Social Capital Across the Life Course: Age and Gendered Patterns of Network Resources*

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Abstract

This paper highlights the usefulness of applying a life course perspective to the study of social capital. To address the dearth of empirical evidence on social capital variation across the life course, we examine age variation in access to social capital in an analysis of nationally representative data on U.S. respondents age 22-65. Analyses identify a statistically significant relationship between age and various indicators of social capital. The results show that resources from occupational contacts tend to increase with age, but eventually level off among older respondents. Changes in voluntary memberships follow a similar pattern, while daily contact is negatively associated with age. The findings suggest that resources embedded in occupational networks tend to accumulate across the career, even in the face of a decline in sociability. Moreover, the relationship between age and social capital is often conditioned by gender.
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Introduction

Sociologists have recently focused much attention on identifying and explaining patterns of resource accumulation across the life cycle (for a review, see DiPrete and Eirich 2006). Researchers have found, for example, substantial divergence in health (Dupre 2007; Willson, Shuey, and Elder 2007) and economic resources (Alon and Haberfeld 2007; Maume 2004) over the course of careers. However, little is known about life course patterns of social capital—i.e., resources embedded within social relationships (Lin 2001). Insight into trajectories of social capital would aid in our understanding how people navigate the various spheres of their lives (e.g., work, family, and educational spheres, to name just a few). Furthermore, life course trajectories of social capital may contribute to broader patterns of cumulative advantage/disadvantage as well as persistent race and gender inequities, as many have suggested (e.g., see Bourdieu 1986).

Some have suggested that social resources tend to accumulate over time (Bridges and Villemez 1986), while others have suggested that social resources tend to depreciate over time (Coleman 1990). Few researchers have explored the nuances of network dynamism across the life course. Rather, most of the research on social networks has remained preoccupied with examining how static network configurations and features explain various outcomes (Smith-Doerr and Powell 2005). The bulk of the evidence on network change comes from the social support literature (e.g., Cornwell, Laumann, and Schumm 2008; Kalmijn 2003). Yet these studies examine strong ties to network contacts which tend to be less salient than weak ties for understanding attainment processes (Granovetter 1973). The few studies that focus on change in work contacts are limited primarily to networks within work organizations rather than more
broadly representative populations. Moreover, analyses of network change are not always embedded within the context of individual’s biographical experiences. Such analyses are often focused on examining changes in networks over time (for example, Time 1 È Time 2 È Time 3) rather than linking changes in networks to aging processes. Consequently, such research lacks sensitivity to the ways that age structures human experiences.

The current investigation attempts to overcome some of the limitations of prior research by using a nationally representative sample of United States residents age 22-65 to examine age variation in social network characteristics. Our examination is focused on (but not limited to) occupational network characteristics drawn from the position generator approach to collecting network data (Lin and Dumin 1986; Lin, Fu, and Hsung 2001). The data are cross-sectional, which limits our ability to distinguish aging trajectories from period and cohort effects. Nonetheless, the findings are consistent with prior research and robust across various indicators of social capital. The results suggest that highly valued work-related social resources tend to accumulate over the course of careers, with diminishing returns among the most senior respondents. Voluntary association membership follows and identical pattern, but non-work daily contact is negatively associated with age. The analyses also highlight many gender differences in the form of the relationships between age and social network characteristics, suggesting that gendered careers structure life course patterns of social capital accumulation.

The first half of the paper begins with a theoretical justification for our study. We link the study of social capital to a life course approach aimed at understanding changing lives within biographical and historical context. Empirical justification follows from a critical review of the relevant empirical literature on network dynamics. We then discuss a set of broad empirical expectations to guide our analyses.
Social Capital and Principles of the Life Course

Noting the static character of network studies, Smith-Doerr and Powell (2005) emphasize the need to incorporate principles of the life course into the study of social networks and economic life. The life course perspective is highly compatible with a relational approach to understanding human behavior (see Emirbayer 1997). A life course perspective helps to embed the network features and configurations possessed by individuals within their broader set of experiences, highlighting the cross-fertilization, intersecting fields, complex motivations, and cross-cutting network affiliations. Moreover, understanding the role that networks play in determining attainment outcomes requires greater attention to life course social processes, the history, timing, and duration of relationships. In this section, we summary the core principles of the life course perspective as they relate to the study of social networks.

Linked Lives – Life course theory explicitly notes that lives are lived interdependently. An individual’s opportunities are linked to the fortunes of other people with whom they are associated. Status attainment research (e.g., Sewell, Haller, and Ohlendorf 1970) has long recognized that educational and occupational opportunities of individuals are affected by the role played by significant others in their lives: for example, parents (Kim and Schneider 2005), peers (Crosnoe 2000), teachers (Crosnoe, Johnson, and Elder 2004), and mentors (McDonald, Erickson, Johnson, and Elder 2007). Network configurations are therefore consequential for patterns of life course attainment. Because of homophilous network formation and maintenance (McPherson, Smith-Lovin, and Cook 2001), social resources are unequally distributed throughout society (Lin 2000). Resource advantages and disadvantages are consolidated, helping to reproduce existing societal inequities within society (cf., McDonald, Lin, and Ao 2008). Individuals rich in social capital tend to share their good fortune with the people who they know
and care about. Whereas other individuals may be forced to hoard the few available resources (Smith 2005) lest other network members prove to be a drag on opportunities for advancement (Stack 1974). In this way, social capital structures life chances.

**Agency** – The life course perspective also stresses the importance of agency. Individuals construct their life course through the choices and actions that they take. The formation and maintenance of social networks over time is an essential part of this process. The cultivation of contacts has often been viewed as an investment process (Bourdieu 1986; Burt 1992; Lin 2001), such that individuals spend considerable time and effort interacting with others. Some have considered these actions as instrumentally motivated in order to increase wealth, status, and power (Lin 2001), while others have left open the possibility of network actors to socialize for non-goal directed purposes. Both classical (Weber [1922]1968) and contemporary (Bourdieu 1986) scholars have acknowledged that much of social interaction is unconsciously motivated by habit and impulse. Friendships tend to form, at least in part, on the basis of mere spatial proximity (Blau 1963; Verbrugge 1977).

Consequently, Kilduff and Tsai (2003) have argued that interaction within organizational settings can be instrumentally motivated or serendipitous. This distinction, though extremely useful, fails to expose the further complexities of social capital investment. Granovetter (2003) has argued that engaging in social interaction can involve multiplex motivations. For example, graduate students might be inclined to attend a departmental holiday party not only for the requisite “face time” that they can get with faculty members, but also because of the free food. Relationships are also dynamic: the usefulness of relationships is almost certain to change over time. Motivations for relationship formation are likely to differ from the motivations for relationship maintenance. Furthermore, relationships can have unintended consequences. A
friendship forged in youthful debauchery can lead to a job referral later in life. In brief, action is an essential element of the construction of social networks across the life course, though the motivations for engaging in social interaction are multiplex and dynamic.

**Biography** – Aging occurs through processes that are path dependent and cumulative in nature (Elder and Shanahan 2006; O'Rand 2006). Career patterns are constitutive of life course trajectories—that is, sequences of related events or experiences in individual lives. These life course trajectories set individuals on specific paths in life, helping individuals to garner experiences, skills, and resources that ultimately structure future opportunities and decision making. At the same time, individuals are capable of making subtle or even dramatic changes to the paths that they are on. Transitions refer to the distinct events in life that denote changes in the trajectories of social roles. Any given transition in a person’s life needs to be understood within the context of these broader life course trajectories.

Social relationships, too, follow their own unique trajectories over time. Most research on social networks has focused on the presence of social relationships and how relationships affect various outcomes (Smith-Doerr and Powell 2005), but few have examined the ways in which relationships are formed, maintained, erode, go into abeyance, and are rekindled (Burt 2000). Even studies of change in network structures can treat such transitions as independent from larger life course experiences. For example, recent advances in the statistical modeling of network dynamics are derived from Markov chain models, which are based on the assumption that the probability of a future transition in state is dependent on a person’s current state, but independent of past experiences (Snijders 2001). Such an approach is insufficient for understanding divergence in mobility outcomes over time (Fuller 2008) and fails to account for
the ways that prior actions and experiences transform network structures. In this way, lifetime experiences help shape networks and opportunities.

**Timing** – The life course perspective recognizes that the impact of any given event is contingent on its timing. Individuals who fail to follow normative pathways can be labeled as deviant and/or face substantial institutional impediments to accumulating resources. For example, individuals who complete college “off-time” fail to receive the same wage advantages of individuals who complete college “on-time” (Elman and O’Rand 2004). Similarly, the timing of parenthood can have important implications for relationships with children (Heuvel 1988) as well as long term economic consequences for parents (Hofferth 1984). The timing of these life transitions is therefore consequential for life course trajectories, setting some on pathways of advantage while disadvantaging others. Furthermore, the character of social relationships, the resources embedded within those relationships, and the returns to those relationships all vary across the life course. Network composition is linked to age and to specific life course transitions (Bidart and Lavenu; Degenne and Lebeaux; Fischer and Oliker 1983; Kalmijn). The influence of social relationships on life events is also contingent on timing (McDonald and Elder 2006; McDonald, Erickson, Johnson, and Elder 2007; Moerbeek and Flap; Rhee).

**History** – Finally, the life course approach examines individual trajectories within the larger historical context. Individual biographies intersect with historical circumstances (Mills 1959). History makes its own unique mark on each cohort of individuals. People traverse life as part of a convoy of social relationships (Antonucci and Akiyama 1987), experiencing historical circumstances and developing collective meanings and memories (Schuman and Scott 1989). Social interactions can only be understood within these historical contexts. The various historical patterns can have a profound impact on the character of social networks. For example, women’s
increased entry into the labor force, the rise of suburban communities and urban isolation, and
the rapid expansion of internet technology (among many other societal trends) have all had major
impacts on the makeup of social networks and their usefulness in society. Social scientists have
only begun to address historical change in network structures (see McPherson, Smith-Lovin, and
Brashears 2006; Putnam 2002).

**Approaches to the Analysis of Network Change Over Time**

A variety of different research fields have explored changes in social networks and social capital
over time. Yet few studies explicitly link changes in social capital to experiences across the life
course. The approaches to studying social network change are briefly outlined here.

*Modeling Dynamic Network Structures*

Recent research has addressed change over time in social networks through the statistical
modeling of dynamic network structures. This branch of research examines the complexity of
network structures via statistical simulations (Doreian 2002; Doreian 2006; Hummon 2000;
Hummon and Doreian 2003). Structural balance theory is used to assess whether or not a set of
social ties (a triad, for example) is “balanced” based upon its configuration and ties with other
groups. This balance reflects a level of stability in that social configuration and is used to
predict changes, or lack of changes, in social ties over time. These mathematically-based models
of social networks are informative because they allow researchers to theorize about change in
social tie arrangements over time. However, this line of research is problematic for a number of
reasons. First, these studies are based on overly simplistic assumptions of rational behavior that
fail to account for multiplex and dynamic motivations for action. Second, the models are based
primarily on simulations and therefore lack an empirical basis. Third, time is de-contextualized
in these studies. In other words, time is divorced from historical context and disembedded from
the life course experiences of individual actors. Current network configurations are presumed to affect future network change independent of individual biographies.

**Changes in Friendship and Social Support Networks**

Research on friendship and social support networks has focused much attention on life course patterns of network resources. Founded in family and community theory, research in this tradition has examined the ways in which age, family transitions, career transitions, and historical events affect network configurations. In general, the results show that life course transitions can result in major network disruption. Friendships are formed quickly and easily at young ages (Cairns and Leung 1995). Drastic transitions, such as those from grade school to junior high for example, result in major upheaval of social networks leaving some individuals vulnerable to a lack of emotional support (Cantin and Boivin 2004).

Prior research suggests that friend networks tend to shrink over time (Kalmijn 2003; Wellman, Wong, Tindall, and Nazer 1997). Labor force participation results in more homogeneous networks (Bidart and Lavenu 2005) and greater network density leads to higher retention of contacts over time (Martin and Yeung 2006). Despite a general decline in contacts across the life course, older individuals tend to experience increases in neighborhood socializing, religious attendance and volunteering from age 57 to 85 (Cornwell, Laumann, and Schumm) and older individuals demonstrate a high level of flexibility and adaptability in the maintenance of ties over time (Wenger and Jerrome 1999).

Gender and family structure also affect friendship networks over time. Married and cohabiting individuals have smaller networks than non-married (Bidart and Lavenu 2005; Fischer and Oliker 1983; Kalmijn 2003). The number of friends and contacts a couple shares increases over the life course, although women tend to have greater contact with friends than
Gendered patterns of labor force participation also influence network characteristics across work careers. Women tend to have more discontinuous work histories than men (Han and Moen 1999). Consequently, men socialize primarily coworkers while women have higher proportions of kin-based ties in their networks (Fischer and Oliker 1983). Women gained more opposite-sex friends in their networks with entrance into the working world while the number of opposite sex friends for men is unaffected by setting (Kalmijn 2002). Women’s social resources, though, are particularly vulnerable to changes in socioeconomic status (Ajrouch, Blandon, and Antonucci 2005). Other structural changes such as retirement may actually benefit female networks as they gain more friendship connections but result in network shrinkage for males (Fischer and Oliker 1983).

This line of research has demonstrated that social networks (1) vary over time, (2) are sensitive to life course transitions, and (3) are structured by gender and family/work career trajectories. There are, however, a number of limitations of this research. First, these studies have also tended to rely on data from age-specific samples (e.g., Cairns and Leung 1995; Cornwell, Laumann, and Schumm 2008), which are unable to fully assess age variation in social network characteristics. Second, the studies have questionable generalizability for the U.S. context, since the samples are typically not nationally representative. Third, few of these studies have directly addressed issues related to changes in occupational networks over time. Most of these studies focus exclusively on changes in close friendship ties rather than work-related ties.

**Changes in Occupational Networks**

An emerging line of research focuses on change in occupational ties over time. Drawing from a sample of investment bankers, Burt (2000) notes that social ties are not stable over time but rather, are subject to a high level of “decay” or disintegration of ties. If a tie is strongly
embedded in a given network then it is less likely to decay or more likely to decay at a slower rate than ties that are not as embedded in a social network. Further investigations reveal that newly formed ties are more vulnerable to decay and the risk of decay is likely to decrease over time as the tie persists (Burt 2002). Social resources tend to accumulate for those who start out with much social capital and decay is less frequent among high performance bankers (Burt 2002).

Researchers have also examined the importance of timing for conditioning the effects of social capital. For example, Rhee (2007) demonstrates that the impact of different types of network ties on promotions within a high technology firm is contingent on the duration of time that workers had known their contacts. Moerbeek and Flap (2008) show that, among Dutch household members, access to social resources through relatives has a greater impact on the prestige of first jobs, while access to resources through friends has a greater impact on current job prestige. Analyses of panel data from the NLSY survey show that the use of informal job matching methods (i.e., getting jobs through personal intermediaries) results in divergent outcomes depending on the timing of the job change in people’s lives (McDonald and Elder 2006). The authors find that certain types of informal job matches (i.e., non-searching) are more effective during the middle of the work career than early in the career, implying that workers tend to accumulate social capital across the life course. Then again, research on a sample of white collar workers finds that younger and older network members tended to have the least amount of diversity in their networks (Lambert, Eby, and Reeves 2006), suggesting a curvilinear relationship between social capital and age.

These studies are important because they point to patterns of the accumulation and erosion of work-related contacts over the life course and the contingency of social capital effects
on the timing of employment transitions and relationship formation. However, the evidence is far from conclusive. Like with the social support literature, the studies are subject to questionable generalizability due to non-representative and age-specific sampling. Furthermore, little attention is paid in these studies to gendered patterns of network change over time.

Expectations

The empirical investigation presented here attempts to overcome some of these problems by relying on a nationally representative sample of the United States to examine age variation in social capital and how these life course patterns vary by gender. We explore a number of operationalizations of social capital. To begin with, we focus on resources embedded in occupational networks because (1) relatively little research has examined change in occupational networks over time and (2) these resources are most salient for attainment processes. Social capital resources are examined by using a composite measure of the quantity and quality of occupational networks. We analyze a number of other features of occupational networks: gender, closeness, density, and trust. The age patterns for these occupational network characteristics are compared to changes in daily contact and voluntary association membership.

We anticipate finding that social capital resources vary across the life course. Based on evidence from prior empirical investigations, we expect to find a steady accumulation of resources embedded in occupational networks (McDonald and Elder 2006; Moerbeek and Flap 2008), though the extent of these resources should level out and perhaps even decline at more advanced ages (Lambert, Eby, and Reeves 2006). Research on friendship and social support networks has found the reverse: declining socialization with age (Kalmijn 2003; Wellman, Wong, Tindall, and Nazer 1997). Therefore, we expect the results to show that age is negatively associated with daily contact and voluntary association memberships. Finally, prior research
suggests that men and women display unique patterns of socialization over the life course due to
gendered careers (Fischer and Oliker 1983; Han and Moen 1999; Kalmijn 2002). Consequently,
we expect to find gender differences in the relationship between social capital resources.

**Data and Methodology**

We use data from the Social Capital-USA survey. SC-USA is a national, random-digit dialed
telephone survey of adults in the U.S. age 22-65 who were currently or previously employed.
The survey was specifically designed to examine social capital and was part of a three-society
(U.S.A., China and Taiwan) study, jointly sponsored by Academia Sinica, Taiwan, and Duke
University. The survey was administered from November of 2004 to March of 2005, averaged 35
minutes to complete, and resulted in 3,000 completed interviews. The response rate (43%) is
comparable to other recent national RDD surveys (see Groves, Fowler, Couper, Lepkowski,
Singer, and Tourangeau 2004). To assess the potential bias due to non-response, parameter
estimates from SC-USA were compared to those obtained from the March 2005 Current
Population Survey (limited to respondents age 22-65). Few significant differences were found,
although SC-USA respondents are more highly educated than the CPS respondents. Therefore,
sample weights were constructed (using the rake procedure in STATA) to match the gender,
race, age, marital status, and education characteristics of SC-USA to the CPS estimates. The
sample weights are employed in the analyses presented here to ensure generalizability. Five
cases do not have valid weights due to missingness and are therefore excluded from the analyses.

**Measurement**

The weighted means for the variables used in this analysis are presented in Table 1. This
study focuses on age and gendered patterns of social capital. Age is calculated based on the self-reported year of birth and is reported in years. The sample ranges from age 22-65, with a mean
age of about 42 years. In the analyses, we compute squared and cubic age terms to capture 
curvilinear variation in the dependent variables across age. Gender also serves as an independent 
variable in the analysis and is measured as a dummy variable (female=1, male=0).

The remaining 8 variables are measures of social network characteristics and serve as the 
dependent variables for the analyses. Most of the social network variables are drawn from the 
position generator methodology, which measures the characteristics of occupational networks 
(Lin and Dumin 1986; Lin, Fu, and Hsung 2001). The position generator measures quantity and 
quality of embedded resources in occupational social networks by identifying access to contacts 
in a list of 22 occupations. Each respondent is asked, “Do you know anyone among your 
relatives, friends, or acquaintances that has one of the following jobs? (“Knowing” means that 
you and the person can recognize and greet each other. If you know several persons that have a 
particular job, please name the person that comes to mind first.”) The list of jobs is designed to 
capture the scope of positions in the occupational hierarchy: from janitors and hairdressers to 
lawyers and CEOs. Upon identifying a contact with a particular job, respondents are asked a 
series of follow-up questions about the characteristics of the position occupant.

We calculate a number of variables based on these questions. First, we calculate a 
measure of social capital based that taps into the quantity and quality of social resources 
available in occupational networks. Extensity is a measure of the total number of positions 
accessed by respondents. The quality of contacts is measured by upper reachability of network 
contacts, calculated by selecting the highest prestige score of the occupations to which 
respondents had access (using the Standard International Occupational Prestige Scale). This 
variable spans from 0 (for respondents who have access to zero positions in the generator) to 85 
(for respondents who said they knew a Congressperson). Extensity and upper reachability are
highly correlated (r=.62) and are therefore combined into a single social capital index using principle component factor analysis with varimax rotation. The factor score was recoded such that values range from 0 to 5.96, with a mean value of 3.36.

We also include a measure of the proportion of contacts mentioned in the position generator. The variable ranges from 0 to 1 and is equal to the number of male contacts mentioned divided by extensity. Respondents were also asked about how close they are to each person they mentioned. The closeness variable was recoded (such that 1=not close at all, 2=not close, 3=so, so, 4=close, and 5=very close) and the average closeness of all contacts mentioned in the position generator was calculated. The resulting continuous variable ranges from 0 (for individuals with access to zero positions in the generator) to 5 (for people who reported only very close occupational contacts).

Density of occupational networks is gleaned from a question asking, “Among the above people you mentioned [in the position generator], how many know each other?” Higher values on the density variable indicate a greater degree closure among network contacts. This ordinal level variable ranges from a value of 0 (no contacts know each other) to 4 (all contacts know each other). Trust is measured in a similar way. Respondents were asked, “Among the above people you mentioned [in the position generator], how many can be trusted?” The values on the trust variable range from 0 (all can’t be trusted) to 4 (all can be trusted).

We also examine a question on daily contact, which identifies the number of people that each respondent interacts with in a typical day. The variable spans from a value of 1 (0-4 people) to 6 (more than 100) and has been shown to be related to expressive and instrumental network dimensions of other social capital indicators (Fu 2005). A follow up question asked, “Among those [daily contacts], how many of those do you make contact with because of work?”
Responses vary from “almost none” (0) to “almost all” (4). Finally, we include a measure of the number of memberships in voluntary organizations, which is a count of up to 10 different types of organizations.

In the subsequent analyses, the sample size depends on the missing values on the dependent variables, since the independent variables (age and gender) contain no missing values. The only variable with substantial missing data (i.e., greater than 7%) is the work-related contact variable, which is explained by the fact that responses from non-employed individuals were coded as “not applicable.” Therefore, when interpreting the results, it is important to recognize that valid responses refer only to currently employed individuals.

**Analysis**

The analysis is divided into three steps. First, the relationship between age and social network characteristics is presented graphically to provide a visual representation of how social capital varies across the life course. Second, the form of the relationship between age and social capital is modeled using ordinary least squares regression (for the continuous dependent variables) and ordinal logistic regression (for ordinal dependent variables). Third, analyses are split to identify gender similarity/difference in the form of the relationships between age and social capital. The figures and tables are organized according to these three steps, but we describe all three steps for each dependent variable before moving to the next variable.

**Results**

Figures 1 and 2 present visual evidence of how social network characteristics vary across different age groups. The first figure (1a) graphs the relationship between age and the social capital factor score. Social capital increases steadily with age, though additional returns to age tend to diminish to the point where social capital peaks (age 46-50) and then drops off among the
50+ population. This pattern is generally consistent with our expectations. Interestingly, there is a slight uptick in social capital scores among the oldest age group. This finding might be explained by life course patterns of career renewal. Moen (Moen 2005) notes that careers often involve “second acts” in which people retire from high pressure jobs to take on more flexible enriching work roles. Alternatively, the higher levels of social capital could be reflective of generational differences, reflecting the greater overall civic involvement of the World War II “greatest generation” (Mettler 2007).

The functional form of the relationship is modeled using ordinary least squares regression (see Table 2). The best fitting model includes both a linear age term and a squared age term. The significant positive age effect captures the pattern of social capital accumulation with age, while the significant negative age-squared effect highlights the diminishing returns to age among the older respondents. The summary from Table 3 shows that this pattern holds for both males and females in the sample. This is illustrated by the positive linear age term, negative squared age term, and insignificant cubic age term.

The relationship between age and the proportion of male contacts is displayed in Figure 1b. Again, the results reveal a curvilinear relationship: initial steep decline in male contacts followed by a steady increase to the oldest age group. Overall, this evidence is consistent with what one might expect to find. Female dominated occupations (e.g., service and clerical) are common in the early part of careers, while increasing occupational attainment may lead individuals to male dominated workplaces, which offer greater wages and benefits (not to mention male contacts). However, the pattern could also reflect changing labor market conditions over time. For example, the decline in male dominated manufacturing jobs, the rise in the female-dominated service sector, and increasing female labor force participation could all
contribute to lower proportions of male contacts in occupational networks among younger cohorts. The relatively high proportion of male contacts among young adults age 22-26 is more difficult to explain. This may be related to gender differences in labor force participation or in networking behavior among this age group. The best fitting form of this relationship, though, is a positive linear relationship that captures the steady increase in male contacts with age. The results in Table 3, however, show that this relationship is significant for women only. For men, the relationship between age and proportion of male contacts is statistically insignificant.

The closeness of contacts tends to diminish over time (see Figure 1c). After an initial rise in the closeness of contacts from 22-26 to 27-30, closeness declines and tends to level off around age 46-50. This suggests a general weakening of occupational ties across the life course. As individuals gain greater work experience, their occupational networks expand and diversify, resulting in broader yet more weakly tied networks. The significant negative linear age effect best captures this pattern of declining closeness across age groups (see Table 2). The relationship between age and closeness, however, is conditioned by gender. Only men experience this significant decline in closeness across the life course.

Patterns of network density across age are similar to closeness. Figure 1d shows a general decline in density, with a particularly steep drop between ages 27 to 40. The negative relationship between network density and age provides further evidence of the accumulation of social capital resources across the life course. Dense networks lack structural holes (Burt 1992), which are useful for procuring non-redundant information and for brokering exchanges. Furthermore, the similarity between the closeness and density graphs is consistent with what one might expect. Both factors are empirically associated and strength of ties has often been used as a proxy measure of network density (Burt 1992). Using ordinal logistic regression, we find that
the best fit for the form of the relationship between age and density uses both linear and squared age variables. The significant negative effect captures the rapid decline in density in the first half of the work career, whereas the positive squared term illustrates the leveling off of the effects during the second half of the work career. The gender-specific models (see Table 3) indicate that the curvilinear relationship is best for men only. For women, density declines across the career with less leveling at the end of the career than men.

Figure 2a shows that, in general, older respondents are more likely than younger respondents to perceive their occupational contacts as trustworthy. This pattern could reflect a social process by which individuals develop greater trust in their contacts over time or that individuals eventually rid their networks of untrustworthy contacts. The increase in network trust across age categories provides further support for the notion that social resources tend to accumulate across the work career. However, the increase in trust is not consistent across all age groups. There is an early rise in trust from age 27 to 45, followed by a sharp drop in trust for the 46-50 age group, and then a steady rise in trust again among the oldest age groups. The sharp drop in the levels of trust at age 46 might be reflective of a historical shift in trust, but the trend does not mesh with prior assertions that trust in others has declined in successive cohorts (Putnam 2002), which would predict that the later cohorts would have substantially higher levels of trust in their network contacts than earlier contacts. The linear pattern of increasing trust across age is confirmed with ordinal logistic regression (see Table 3). The results show that, on average, each additional year is associated with higher levels of trust in occupational networks. Splitting out the results by gender, however, shows that increasing trust with age is significant for women, but not for men.
The results also show a general decline in the amount of daily contact in which people engage, though again the pattern is not entirely linear (see Figure 2b). The highest levels of daily contact are among the youngest age group. Daily contact dips among 27 to 35 year olds, then rises among 36 to 40 year olds, and steadily declines thereafter. Using OLS regression, the age pattern of daily contact is best captured by a negative linear term for age (see Table 3). The overall decline in daily contact is consistent with prior research that shows a general decline in network contacts over time (Kalmijn 2003). Further analyses summarized in Table 4 reveal gender differences in the form of the relationship between age and daily contact. For men, the daily contact relationship is best described as linear. For women, the best fitting model contains a negative linear age term, a positive squared age term, and a negative cubic age term (all of which are statistically significant). This model predicts an S-curve characterized by an initial decline, then increase, and finally a decline in daily contact across age. This suggests greater fluctuation in the daily contact of women across the life course.

Age patterns of daily social interaction are distinct from changes in occupational network characteristics over time. Indeed, Figure 2c tracks the proportion of daily contact that is work-related and shows a pattern that is more consistent with what was found for the variables constructed from the position generator. That is, the proportion of work-related contact tends to increase with age and levels off around age 46. In spite of the apparent diminishing returns, the ordinal logistic regression model with a single linear age variable produced the only statistically significant coefficients. However, both men and women display similar linear increases in work-related contact across age.

Finally, we examine age variation in the number of voluntary organization memberships. Here the pattern with steady increases in memberships early in the life course, diminishing
returns and a reversal of the trend during the middle years, followed by a slight uptick in
memberships among the oldest age group. This increase in voluntary association membership is
consistent with recent evidence that shows an increase in community participation and
volunteering among older individuals (Cornwell, Laumann, and Schumm 2008). Furthermore,
the pattern is strikingly similar to what was found for social capital. Results from OLS regression
show that the relationship is best described with a positive linear age term and a negative squared
age term. This captures the parabolic form of the relationship between age and organizational
memberships. Further elaboration by gender in Table 4 shows that the relationship is similar for
both men and women.

Discussion

Drawing from nationally representative U.S. data, we investigate age variation in social
capital and the extent to which these patterns may be conditioned by gender. As such, this paper
provides a number of important contributions to the research literature. First, we apply a life
course perspective to the study of change in social capital over time. This study demonstrates the
importance of embedding studies of network change within the context of individual
biographies. The results show that social capital resources indeed vary by age, as each of the
eight social resource indicators is significantly associated with age. Second, we employ a
multidimensional approach to examining social capital. Third, this research fills a gap in
knowledge about age-related patterns of occupational networks and compares these patterns to
changes in other forms of socialization (daily contact and voluntary association memberships). In
general, occupational network resources tend to accumulate as individuals age, but have a
tendency to taper off (and sometimes diminish) at older ages. The same is true for voluntary
association memberships. However, daily contact tends to decline across the life course. Finally,
the results explore the moderating influence of gender on age-based patterns of social capital. There remains some consistency in the relationships between age and the social network measures by gender, but gender divergence in these relationships is more common.

The analysis presented here was designed to overcome some of the limitations of previous research literature on network dynamism, but retains a number of critical limitations. Most importantly, this study relies on cross-sectional data, which does not allow for the separation of age, period, and cohort effects (Glenn 2003). Our own interpretation of the age-related patterns emphasizes aging processes by which resources tend to accumulate or dissolve, but alternative interpretations cannot be ruled out. The greatest impediment to understanding variation in social capital across the life course is a lack of longitudinal data on social networks. The data presented comes from the first wave of a larger panel study. As these and other panel datasets become available, researchers should explore these empirical findings in greater detail to distinguish aging process from changes in historical circumstances and enhance understanding of these life course processes.

The findings presented here are primarily descriptive and therefore provide many additional opportunities for further elaboration. First, age-based patterns of social capital are more orderly and consistent during the middle years and are more erratic earlier and later in adult lives. This presumably reflects the transitional character of these times in people’s lives. The youth labor market involves considerable “churning” or “milling about” (Gardecki and Neumark 1998) as individuals complete education and attempt to settle on a career. The late career period also contains numerous transitions out of primary careers and into retirement, secondary careers, and volunteering (Moen 2005). Relatively little is known about the role that social capital plays in these particular transitions. Second, the findings presented here reveal a striking congruence
between age-related patterns of social capital and those of voluntary association memberships, which seems to suggest that participation in voluntary associations may be causally linked to the expansion of occupational networks. Recent empirical analyses have found little support for an overarching causal relationship between social capital and association membership (Song 2008), but it remains possible that the relationship is contingent on timing. In other words, voluntary associations may be critical for developing diverse occupational contacts for older individuals only, helping to explain the uptick in social capital among the 56-65 age group in the SC-USA sample. Third, the gender differences in age-related patterns of social capital identified in this paper were not examined in any real detail. Future research should examine how family and work events/histories contribute to gender-specific social capital trajectories. Finally, future studies should not only clarify trajectories of social capital accumulation across the life course, but also examine how these trajectories are associated with other forms of resource accumulation. Social capital likely serves as a social mechanism that reproduces social inequality (cf., McDonald, Lin, and Ao 2008) by contributing to broader patterns of cumulative advantage and disadvantage across the life course.
References


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<th>Description</th>
<th>Mean</th>
<th>Range</th>
<th>N</th>
</tr>
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<td>In years</td>
<td>42.38</td>
<td>22-65</td>
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<tr>
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<td>.51</td>
<td>0-1</td>
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<td>Factor score combining number of contacts with highest prestige from position generator (PG)</td>
<td>3.36</td>
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<tr>
<td>Male contacts</td>
<td>Proportion of male contacts in PG</td>
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<td>Closeness of contacts in PG</td>
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<td>Density</td>
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<tr>
<td></td>
<td>0= None know each other</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1= Only a few know each other</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2= About half know each other</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3= Most know each other</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4= All know each other</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>Trust in contacts in PG</td>
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<td></td>
<td>0= All can’t be trusted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1= Most can’t be trusted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2= Some can be trusted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3= Most can be trusted</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4= All can be trusted</td>
<td></td>
<td></td>
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<tr>
<td>Daily contact</td>
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<td></td>
<td>0=0-4</td>
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<td>1=5-9</td>
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</tr>
<tr>
<td></td>
<td>2=10-19</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
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</tr>
<tr>
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<td>4=50-99</td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>5=100+</td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>Proportion of daily contact that is work-related</td>
<td>2.74</td>
<td>0-4</td>
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<tr>
<td></td>
<td>0= Almost none</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1= Few</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2= About half</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3= Most</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4= Almost all</td>
<td></td>
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<td>Organizational members</td>
<td>Number of organizational memberships</td>
<td>1.73</td>
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## Table 2. Multiple Regression of Social Capital, Male Contacts, Closeness, and Density on Age

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<td>Age</td>
<td>.078 ***</td>
<td>.001 *</td>
<td>-.006 ***</td>
<td>-.080 **</td>
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<tr>
<td></td>
<td>(.016)</td>
<td>(.001)</td>
<td>(.002)</td>
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<tr>
<td>Age squared</td>
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<td></td>
<td>.0008 *</td>
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<tr>
<td></td>
<td>(.0002)</td>
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<td>(.0003)</td>
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<tr>
<td>Constant</td>
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<tr>
<td></td>
<td>(.332)</td>
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<td>(.086)</td>
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<tr>
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<td></td>
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<tr>
<td></td>
<td></td>
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<td></td>
<td>(.626)</td>
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<tr>
<td></td>
<td></td>
<td></td>
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<td>(.618)</td>
</tr>
<tr>
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<td>-1.161</td>
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<td>(.616)</td>
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<tr>
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<tr>
<td>R-squared</td>
<td>.021</td>
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* p<0.05, **p<.01, ***p<.001
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<thead>
<tr>
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<td>.008 *</td>
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<td>.123 ***</td>
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<tr>
<td></td>
<td>(.004)</td>
<td>(.003)</td>
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<tr>
<td>Age squared</td>
<td></td>
<td></td>
<td></td>
<td>-.0013 ***</td>
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<tr>
<td>Constant</td>
<td></td>
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<td>-.963 *</td>
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<tr>
<td></td>
<td></td>
<td>(.137)</td>
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<td>(.472)</td>
</tr>
<tr>
<td>Cut1 constant</td>
<td>-3.619 ***</td>
<td></td>
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<td>(.223)</td>
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<tr>
<td>Cut2 constant</td>
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<td></td>
<td>(.188)</td>
<td></td>
<td>(.183)</td>
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<td>.135</td>
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<tr>
<td></td>
<td>(.170)</td>
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<td>(.184)</td>
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<td>(.168)</td>
<td></td>
<td>(.187)</td>
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</tr>
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<td>N</td>
<td>2904</td>
<td>2995</td>
<td>2652</td>
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<tr>
<td>R-squared</td>
<td>.001</td>
<td>.004</td>
<td>.004</td>
<td>.014</td>
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* p<0.05, **p<.01, ***p<.001
<table>
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<th>Male contacts</th>
<th>Closeness</th>
<th>Density</th>
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<td></td>
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<td>Male Female</td>
<td>Male Female</td>
<td>Male Female</td>
</tr>
<tr>
<td>Age</td>
<td>+ +</td>
<td>n.s. +</td>
<td>– n.s.</td>
<td>– –</td>
</tr>
<tr>
<td>Age squared</td>
<td>– –</td>
<td>n.s. n.s.</td>
<td>n.s. n.s.</td>
<td>+ n.s.</td>
</tr>
<tr>
<td>Age cubed</td>
<td>n.s. n.s.</td>
<td>n.s. n.s.</td>
<td>n.s. n.s.</td>
<td>n.s. n.s.</td>
</tr>
<tr>
<td></td>
<td>Trust</td>
<td>Daily contact</td>
<td>Work contact</td>
<td>Org. memberships</td>
</tr>
<tr>
<td></td>
<td>Male Female</td>
<td>Male Female</td>
<td>Male Female</td>
<td>Male Female</td>
</tr>
<tr>
<td>Age</td>
<td>n.s. +</td>
<td>– –</td>
<td>+ +</td>
<td>+ +</td>
</tr>
<tr>
<td>Age squared</td>
<td>n.s. n.s.</td>
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<td>n.s. n.s.</td>
<td>– –</td>
</tr>
<tr>
<td>Age cubed</td>
<td>n.s. n.s.</td>
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<td>n.s. n.s.</td>
<td>n.s. n.s.</td>
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</tbody>
</table>
Figure 1. Social capital, male contact, closeness, and density by age
Figures 2. Trust, daily contact, work-related contact, and organizational membership by age