Measuring Social Capital in Household Support

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A key problem with social capital is confusion about whether it is a characteristic of the individual or of the family group. A context-effects estimation procedure will be presented that reports both the effect of strong ties between individual kin-related households (the individual level), and the effect of strong ties across all kin-related household in a network (the group level). I find statistically significant coefficients for indicators at both levels of analysis. However, the key finding is an important interaction between the strength of a network and its size. High levels of contact will compensate for the negative effect of network size for between-household support. This study helps to settle part of the debate about the level of analysis for social capital by showing an instance of both levels operating at the same time.

To separate social capital conceptually from other forms of social ties we must ask the question, "what is it about the network itself that changes the outcome or result from a particular tie?" In other words, we should not think of social capital as simply social ties because that is a redundant concept, instead, we should think of social capital as a difference in support from a particular tie based in the surrounding network.

In short, how network-level strength facilitates social support depends on the competition for a particular form of support. When the form of support is plentiful, the effect of network-level strength is positive because it correlates with higher norms and obligations. When the form of support is scarce, the de facto competition forces support to go to the individual with the strongest tie, and so the effect of network-level strength is negative, on average, for all ties. In other words, the actual value of a tie is a positional good, its strength compared to others in that same kin.

Current scholarship in American sociology has two different conceptualizations of social capital (Farr 2003; Field 2003; Schuller, Baron and Field 2000). Each concept is at a different level of analysis, either individual actors or groups of actors. James Coleman made "social capital" salient to the research community with evidence that the extent an actor's immediate network, or group, is interconnected, or has closure, is positively related to the development of human capital (i.e. lower dropout rates and higher academic achievement, 1988). For Coleman, closure in social capital exists "through group process that help members to more easily achieve either collective goods or non-competitive individual interests." This group-based social capital is included in research regarding a quite diverse subject matter that defines a "group" many different ways. For example groups that have social capital can include families, neighborhoods, or nation states. In contrast to the group approach, the individual approach is much more focused on how individual social connections lead to competitive interests e.g. better jobs, faster promotion, or other economic rewards. In general, individuals are hindered by high quality networks for outcomes that are competitive in nature (Burt) while they are helped a great deal by high quality networks for outcomes that are normative, or collective, in nature (Coleman).

However, Burt, one of the leading scholars on this subject, recently defined social capital as a person's "advantage created by [that] person's location in a structure of relationships" (2005 p. 4). This definition is broad enough to encompass both the individual level and the group level concepts of social capital. Wellman and Frank (2001), for example, show that both individual relationships and aggregate properties of networks both provide support benefits for individuals. This paper extends their argument by presenting evidence while benefits exist at both levels of analysis; those benefits follow different patterns based on the competitiveness of the outcome. Thus, the next phase of scholarship surrounding the idea of social capital is to provide synthesis.

My purpose for this paper is to sketch an analytic strategy that includes both paradigms, social capital as groups and social capital as individual relationships. To do this I will frame the social capital problem by juxtaposing individual relationships and group connectedness, then I will outline method for social capital research by reviewing statistical strategies used in the past for similar problems in sociology.

Basic Principles

People exert effort to achieve their goals. Some people, however, are able to achieve their goals with less effort because of certain social ties. The difference between the two cases is a benefit—a discount on effort for individuals—is social capital. A person's benefit from social capital is generally hypothesized to come either from membership in a well-connected group (i.e., group strength and other group measures, see Bowles 1999; Coleman 1988; Coleman 1990; Kawachi and Berkman 2003; Kawachi, Kennedy, and Glass 1999; Pevalin and Rose 2003) or strong relationships with specific individuals (see Astone, Nathanson, Schoen, and Kim 1999; Burt 1992; Burt 2005; Lin 2001; Lin, Fu, and Hsung 2001; Portes 1998; Sandefur and Laumann 1998). To achieve goals that require generalized trust, a benefit of social capital is the ability of a tight-knit group to enforce applicable norms effectively (Coleman 1990). On the other hand a highly connected group will hinder most member's competitive interests. In such instances benefit comes from having the best ties (see Burt 2005 for examples of both). To make sense of these issues methodologically it is useful to define the basic principles often used to discuss social capital. I do not claim that the following definitions are the final word on these concepts. I do believe, however, that having a definition on hand is more useful than hoping the reader is thinking about these words in the same way that I do.

Social Structure

The analysis of social capital must be centered on the social actors that a) have an interest that relates to the social structure and b) perform some behavior that creates the social structure. In other words, they are the social structure and are affected by the social structure. Actors can be individuals, social organizations, or any mutually exclusive social entity that can identify itself in contrast to other social actors. In general, however, I will think of social actors as individuals.

Social structure is comprised of ties between any two actors with the group. For social capital, the central mechanism of these ties is the amount of communication that flows between the connected. There are many different ways to define a tie between any two social actors. In social capital research, however, I believe that communication is generally valid and reliable measure of tie strength. My reasons are twofold. First, the majority of interpersonal social networks that are measured use communication as a mechanism to identify important people in a person's social network (e.g. with who do you discuss important matters).

The second reason for using communication as a fundamental measure of social structure is that it forms the basis of many other social forces. Coleman's concept of trust is based on an individual's perception of a person's trustworthiness, which itself is derived from communication.

Interests

How can we incorporate structure? Benefits or advantages (Sandefur and Lauman) are elements in a social system or contract that are outside the core mechanism. Thus, the second step in thinking about social capital is taking a social system that is already established by a mechanism at one level of analysis, and asking the following question: with the same system, how would the outcome change if we change the social structure at a higher level? Measure the advantage or benefit of social capital and the situations in which the same conditions fed into a mechanism would produce different result. The social capital inquiry, then, is to ask in what situations would a person with the same levels of contact and demographic characteristics provide support at a given rate, and in what situations would the same person with the same levels of contact and demographic characteristics provide less or more?

While the characteristics of the individual remain constant in our experiment, the surrounding characteristics may be dynamic. Here, I propose that the outcome of dyadic relationships will be different if the surrounding levels of contact are different.

The measure of the surrounding levels of contact used here are average levels of contact within a family group. This paper posits, in part, that for some types of support there in an increase in the rate if the average level of contact increases. For other forms of support the rate decreases if there is an increase in the average level of contact.

Thus, social capital can be the effects of the elements at the group level of analysis that are aggregates of the individual elements. Thus, from the point of view of methodological individualism, aggregate social patterns are a direct result of individual actions (Giddens 1984). Individual actions, however, are not only influenced by factors at the individual level of analysis. Other influences on individual actions come from the group per se (Coleman 1990).

In what situations, then, are aggregate effects positive or negative? Groups with many strong relationships, i.e. high group average, are networks that better enforce norms (Coleman 1990). With effective norms of altruism or reciprocity, group goals such as individual welfare or generalized familial giving are possible. In other words, higher average tie strength in a kin network is more "social capital" by enforcing norms of reciprocity that promote the exchange of favors. This social capital is represented by a positive effect of the group variables. On the other hand, effective norms are a small benefit for individuals seeking limited resources.

Competitions are won by excellence relative to others. Burt writes extensively about how tight networks can be harmful to innovation. High tie strength averages hinder competitors. If all ties are strong, then competition for resources will depend on other things. Also, competitions in which the strongest relationship wins imply a comparison between a focal case and all other group members. A "best" tie is a positional good (Coase 1960), which is only defined relative to all other relationships. Analysis of benefits by individual relationships hinge on relativity—how strong is a tie compared to others. Thus, even for resources garnered through a specific relationship, the process is still dependent on characteristics of the overall network (see Burt 1992; Granovetter 1973; and Granovetter 1985 for examples in economic sociology). So not only can the group have an effect, but this effect can also be negative.

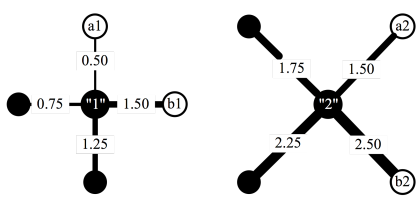

Figure A: Ego networks "1" and "2" with ties to alters including "a1", "a2", "b1" and "b2", each with varying levels of contact

To illustrate the different benefits from both levels of analysis for competitive or normative outcomes, consider figure 1. Imagine two independent families in which no person from either family knows, or is related to, a person in the other family. Let's define these families as "1" and "2". From each family, I pick a single person, an "ego". Each person has the same interests, attributes, and number of ties. Only the strength of each alter's tie varies (the number on the lines in Figure 1). Let us also assume that each group has different average tie strengths.

If each ego were asked for money (a selective process) by each relationship in their group, requester "b1" has the best chance within group "1" and "b2" in group "2" because they have the highest tie strength in that group. However, this is not a social capital story. For social capital, we need to examine the chances for people with the same level of contact but in different contexts. In a selective scenario, "a2" would do worse than "b1", even though they have the same level of contact (1.5) because “a2” is below average for group “2” whereas “b1” is above average for group “1”.

Hence, we can now think of each person’s within status as a relative good. A concept introduced by Coase (1960), a positional good derives value from its position relative to other cases. The worth of a test score is valued based on the overall average when grading by a curve, a race time is evaluated by the other times—these examples illustrate the defining attribute that value is difficult to determine outside a certain context. My framework to interrogate social capital independently examines both a case’s positional good within a network—relative number of connections within—and a group’s average contact compared to other similar groups with similar interests.

The outcome would be different for a cooperative good. If each focal actor wanted to collect a donation of time to a charity from each relationship, the chances would be higher for anyone from group “2”. This is for a simple reason, most relationships in “2” are stronger than in “1”. So any one relationship, picked at random, will generally have a better chance of giving time, over and above the benefit of having a close relationship to that specific person. A social capital effect, however, would be to notice that, in a cooperative scenario, “a2” does better than “b1”, even when they have the same level of contact.

Structure influences interests in a variety of ways. The model’s estimated effects have different patterns for competitive and normative interests. Before I outline the parameters, let me define our measures. The sample consists of J individuals from separate groups, each with nj relationships, for a total sample of N relationships. First, the outcome of the interest relating to the ith relationship with respondent j is Yij. We will replace the term X for C, for consistency with the rest of the study that uses C, or contact, as the main predictor. The level of contact between the ith relationships with respondent j is Cij. The average contact respondent j has across all kin will be referred to as CCj, and is

$$CC_j = \frac{1}{n_j}\sum C_{ij}$$

.

Figure B shows two plots of simulated data. Each plot has data from two types of networks. The +s correspond to data generated from network like “1” in Figure A, and the xs correspond to data generated from a network like “2” in Figure A. The plot on the left shows what these data would look like if social capital had a positive effect on the chances of support, like the left plot in figure B, and the plot on the right shows what the data would look like if social capital had a negative effect on the chances of support, like the right plot in figure B. Each plot in figure B shows regression lines for each group of data. The line from “a1” to “b1” is the regression line for network “1”, and the line from “a2” to “b2” is the regression line for network “2”. The slopes of these within group regression lines are the same. Each graph also has a line from point “z” to point “w”, this is the least squares regression line of all data ignoring the network identities. Finally, each plot draws a line from “b1” to “a2” to illustrate the effect of social capital. Another line from “b2” to a another point “c” is also included in both plots to show the difference between the highest value of contact, “b2” and the outcome of a member of group “1” with the same level of contact.

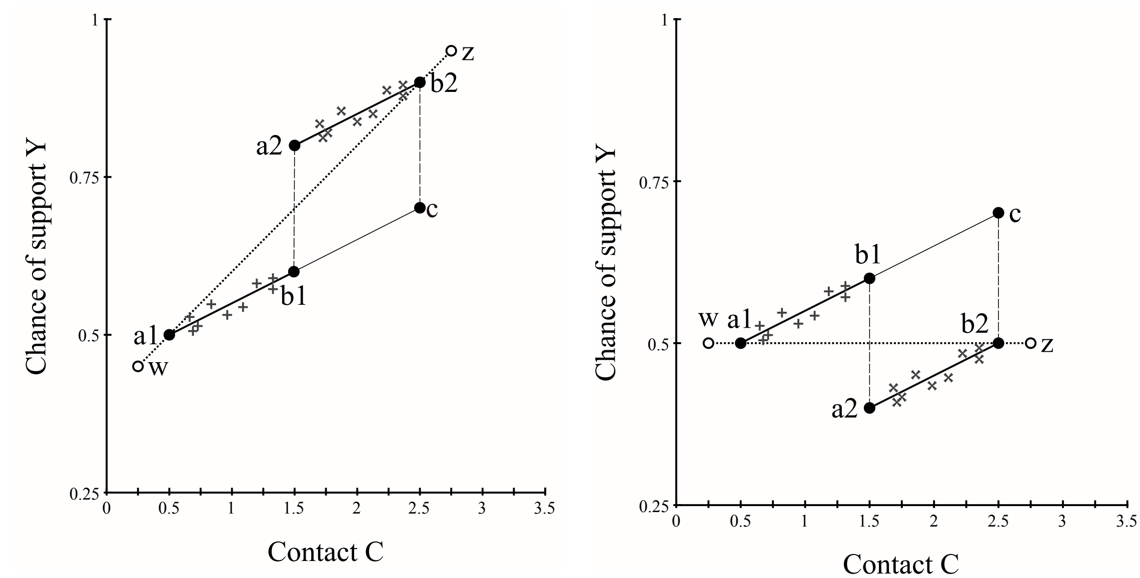

Figure B Simulated data from ego networks similar to figure A with regression lines plotted to show positive and negative effects of social capital

The estimation procedure is quite simple. In order to get a good estimate of the social capital effect, we must use a context effects model. A context effects model measures the effect of contact between respondent j and the ith kin, λ, and the effect of the average contact for all kin of respondent j, γ. However, contact, Cij, and the average contact across kin, CCj, must be centered (or "demeaned" as some econometricians say) on the sample average of Cij (see also Blalock 1984; Duncan and Davis 1953; Goodman 1953; Knapp 1977; Raudenbush and Bryk 1986; Robinson 1950; Willms 1986).

By estimating together the effects of group strength and individual tie strength, it is possible to compare the magnitude and direction of the level's contribution. Patterns of effects are a reaction to whether the exchange is normative or competitive.

Example analysis

The following analysis uses the second wave of the National Survey of Family and Households. Contact between any two individuals is an important predictor of whether social support will be enacted. However, equally important theoretically are effects of contact across the entire group and the size of the group itself. This section presents the competing hypothesizes regarding the effect of group contact and possible effects of group size. While the theoretical propositions are not directly testable with ego-centric data such as our respondent kin-networks, the theory has implications that can be tested.

Social Support Variables

The dependent variable measure the respondent reporting either giving or receiving social support from parents or children that do not live with them during a specified time interval. The specific times of support are not known within the interval relative to the contact and other predictors. This is most likely not a problem, however, because social support is a relatively stable behavior within family networks (Amato 1990). The type of support included favors of household help or transportation.

Contact variables

The NSFH uses two questions to measure the frequency of contact between the respondent and their kin. Each of these questions was asked about all parents and adult children living outside the home. The first question is "During the last 12 months, how often did you see…?" This question measured what I call "face to face" contact. In addition, the NSFH asked a second question, "During the last 12 months, about how often did you talk on the telephone or receive a letter from…?" This question measured other forms of contact outside of actual face-to-face contact. The respondent had six possible answers for each question: not at all, about once a year, several times a year, 1 to 3 times a month, about once a week, and more than once a week. As an aside, the data come from 1994, before the explosion in Internet and email usage. Thus, while such communications would have to be accounted for in a study using recent data, I do not believe that there is a high degree of unobserved contact.

Instead of using each variable by itself in a model, which would cause several statistical problems, it is more parsimonious to create a single composite contact variable (Cij) that is the average of face-to-face (FFij) and phone or letter (PLij) contacts between the ith kin of respondent j. Simply adding the types of contact was not done because it would overplay the level of contact between the respondent and kin in some cases, especially for those with high levels of face-to-face contact that also frequently spoke on the phone:

$$C_{ij} = 0.5\left(FF_{ij} + PL_{ij}\right)$$

The models presented below are the first cut in estimating the effects of contact on intergenerational support at both levels of analysis. These models are context effect models in which both the composite contact measure and the complement mean (the average of the other households) of the composite contact measure are each centered on the sample average of the kin-level average across the entire sample.

The statistical models for the network analysis

The following results present a population average Poisson model in which the chance or rate of support between any ith kin from respondent j is estimated using a typical Poisson link function for a generalized model. The outcome is the number of times, k, the jth respondent named a particular ith kin for various forms of support, generically SUPPORTij. These analyses were repeated for another version of data with the household support without this top-code and the results did not change. In the models below, we will generally use the term SUPPORTij as a placeholder for the probability that each ith kin is named by the jth respondent a number of k times, or Pr(yij|k).

Two models were fit to each outcome. One model uses the raw composite contact variable (Cij) and its complement (CCij), and the second model uses the residual of the composite contact variable (C*ij) and its complement (CC*ij). Both models include a measure for the level of sentiment between the respondent and kin (Sij). In addition, each model for a particular form of support includes a control variable that measures the frequency of any reciprocal support form. Finally, all models use two quasi-fixed effects to control for other factors related to social support. First, respondents may give or receive the same kind of support to friends. Thus, the variable FRIENDj is a dummy variable, specific to each form and direction of support, and indicates whether the support being modeled also occurred with non-relatives. For example, if a particular model is predicting whether the respondent gave financial support, FRIENDj is a dummy that indicates whether the respondent gave financial support to non-relatives. Respondents may give or receive the same kind of support to other family members such as siblings, which are not parents or adult children. Thus, the variable OTHERj is a dummy variable, specific to each form and direction of support, and indicates whether the support being modeled also occurred with relatives other than parents and adult children. For example, if a particular model is predicting whether the respondent gave financial support, OTHERj is a dummy that indicates whether the respondent gave financial support to relatives other than parents or adult children. Each of these effects is notated in the models with a Greek letter δ.

The effects of network size, both directly and as it affects the impact of the complement mean, are noted in the equations with the Greek letter θ. To be consistent with the previous chapter, the effect of the composite contact measure is noted as the Greek letter λ, and the effect of the complement mean of group membership is noted as the Greek letter γ. For each ith kin of respondent j, the rate of support is predicted by one model that uses the composite measure of contact variables (Cij and CCij),

$$SUPPORT_{ij} = \alpha_{ij} + \lambda\left(C_{ij} - \bar{C}_{\bullet\bullet}\right) + \gamma\left(CC_{ij} - \bar{C}_{\bullet\bullet}\right) + \theta_1\left(n_j - \bar{n}\right) + \theta_2\left(\left(n_j - \bar{n}\right) \times \left(CC_{ij} - \bar{C}_{\bullet\bullet}\right)\right).$$

The broad pattern for the effects of contact and complement contact is that, holding network size constant, contact has a large impact on the chances of support while complement contact as little or no effect.

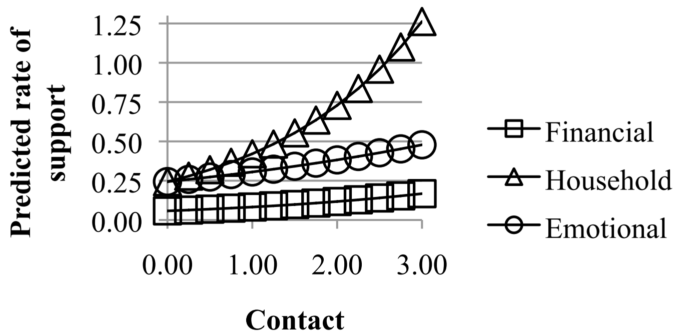

Figure 1: Effect of the composite contact measure on chance or rate of support from the respondent to kin (network model series)

Household support and emotional support have similar chances when there is a low level of contact, but the effects of contact diverge drastically. Looking at Figure 1 and Figure 2, we see that the most extreme effect is for household support, which increases at a much faster rate than emotional support when there are increases in contact. Since each figure looks similar, we can conclude that, on average, the effects of contact are consistent for both giving and receiving support.

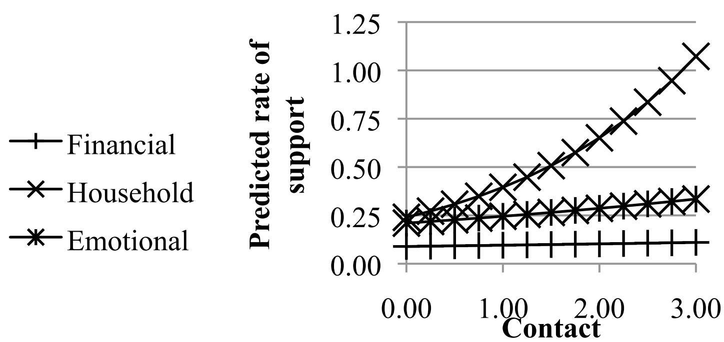

Figure 2: Effect of the composite contact measure on chance or rate of support given to the respondent from kin

Figure 2 depicts the effects of the complement mean on the chance of the respondent receiving support, and Figure 3 depicting the effects of the compliment mean on the chance of the respondent giving support to kin, show that there were effects within the small band of a rate of 0-0.25.

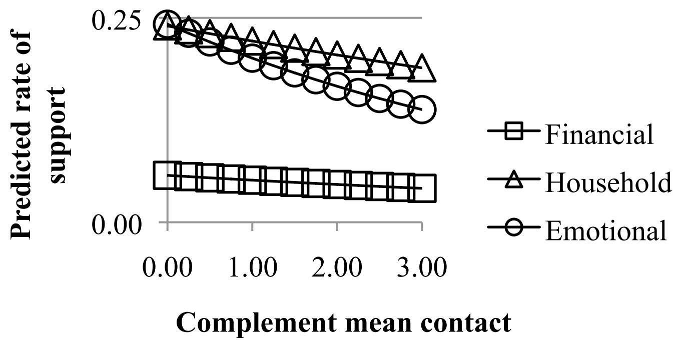

Figure 3: Effect of the complement mean of composite contact measure on chance or rate of support given to the respondent from kin (network model series)

In other words, there were effects but substantively minor. The only notable effect is that an increase in complement average contact decreases the chance that the respondent gives or receives emotional support. However, it should be noted that while the main effects are often null, these effects become dynamic with network size.

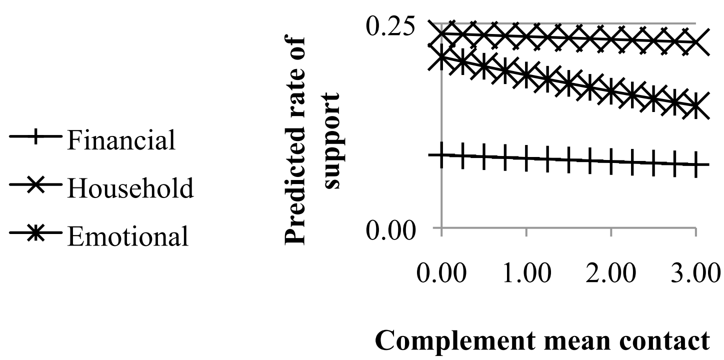

Figure 4: Effect of the complement mean of composite contact measure on chance or rate of support given to kin from the respondent (network model series)

If we consider the effect of complement mean as something that depends on size, we see an interesting pattern. Figure 5 presents the rate-ratios of the complement mean of contact predictor from the models predicting whether the respondent gave kin financial, household, or emotional support, on the vertical axis, and on the horizontal axis are the most common occurring network sizes ranging from two to six kin members. Each point is a rate-ratio (RR) that is calculated by taking the exponent of a formula that uses the effect of the complement mean, γ, the size of the network, n, and the effect of the network size/complement mean interaction, θ_2.

$$RR_n = \gamma + \theta_2 \left(n - \bar{n} \right)$$

Rate-ratios work in a similar fashion as odds-ratios. They represent the comparative in the rate support for a one-unit change in a predictor. Rate-ratios of less than one (the bottom half of the graph) represent a reduction in the occurrence of the outcome, rate-ratios of one represent the same rate and thus no effect, and rate-ratios of greater than one (the upper half) represent an increase in the rate of support. When networks are small, an increase in the average contact between the respondent and their kin reduces the chance of giving any one of them household support. As we can see in Figure 5, the effect of the compliment mean of household support is negative (below 1) when the network is 4 or less members large. Yet, in contrast, the effect of complement mean is positive for larger network sizes of 5, 6, or greater. This means that when networks are large enough, the effect of increasing the average contact is positive.

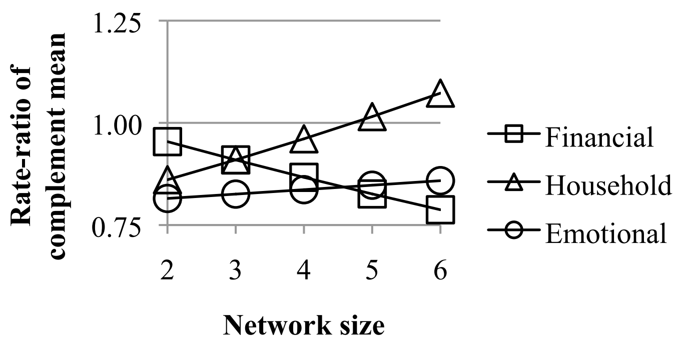

Figure 5: Effect of complement mean on rate of support given to kin by respondent as a function of network size (network model series)

Although the relevant coefficients are non-significant in the tables below, it is worth mentioning that there is a negative pattern for rate of the respondent giving kin financial support. Increasing the average contact always has a negative impact on financial transfers, but according to the figure this effect is exacerbated with increasing network size. While these patterns are very clear in modeling whether the respondent gives kin support, the effects are not easily detected in the reverse direction of support; in general, no effects are detected (see Figure 6).

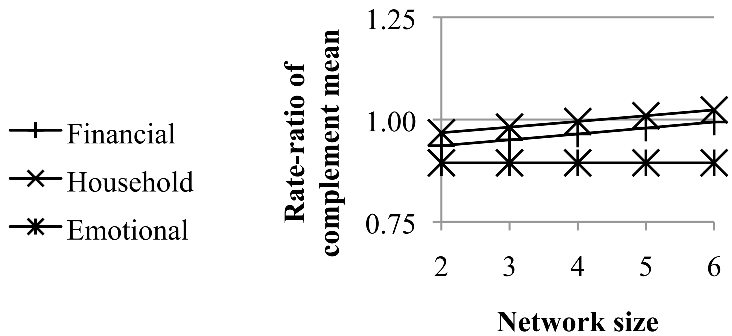

Figure 6: Effect of complement mean on rate of support given to respondent by kin as a function of network size (network model series)

The results also control the reciprocity and support with other family and friends. The effects of each were generally positive and quite strong. Reciprocity will be discussed per outcome, but the effects of other support will be discussed here. There were strong positive effects for financial support, meaning that if respondents gave or received financial support to either friends or other family, there was a substantial increase in the rates of financial support to parents and adult children. I do not believe there is a network story here simply because the effects are so large. Instead, I believe that these effects are picking up the ability to exchange money. A similar pattern is evident with emotional exchanges. Similarly, I believe these effects pick up unobserved effects that correlate with emotional supportive behaviors.

There was a large effect for giving household support to other family, meaning that if the respondent gave household support to other family, there were also much more likely to give support to parents or adult children. This was also found with the models predicting whether the respondent received household support from parents or children, meaning that if a parent or adult child gave them support, some other relative was also more likely to give support. Interestingly, whether the respondent received household support from friends was also highly predictive of whether the respondent received support from parents or adult children. If people are receiving household support from friends, they are probably in such a need as to also receive it from family as well.

In all, including these effects in the model is important as a blunt method to pick up other unobservable characteristics of these respondents, their networks, and how respondents manage their support needs and obligations. The results we observe with other variables, then, are shown to be even more robust as they are detected in models that include these variables.

Finally, there is a consistent pattern across all outcomes when we compare the raw contact variable and the residualized predictor. Once we use only the residual contact variable, the effect of distance and sentiment tend to change. Also, the effects of contact are reduced when we enter the residuals because they have less explanatory power. Thus, this confirms that multicolinearlity between contact and other predictors can causes problems for these models, and using residuals in later chapters allow for these problems to be suppressed. The next sections will present outcome-specific results for the network models.

Results for financial transfers

The results for both giving and receiving financial transfers are presented in Table 1 and Table 2. The most striking effect in predicting whether respondents give kin support is the effect of reciprocity, labeled in the tables as "frequency of any kind of support given to respondent." While the descriptive results above indicate little or no effect of reciprocity in predicting whether respondents will give kin financial support, the models in Table 1 show a negative effect. In the first model that controls for the raw composite contact scale, and not the residuals, each instance of kin giving support to the respondent reduces the rate that respondent's provide financial support to kin by 12 percent. This effect is somewhat lower in the second model, in which the rate is only reduced by 11 percent. I suspect that this result indicates more about where in the life course the respondent and kin are located, since providing financial assistance is generally rare, and happens only in specific circumstances.

We also see a slight negative effect for the size of network, with both models showing a 10 percent reduction in the chance that the respondent provides financial assistance to kin for each additional kin member. In the first model, physical distance increases the chances of the respondent gives financial support, but this is holding constant the raw level of contact. Thus, when people are in contact at least one day a week, increased distance may result in substitution of financial support in lieu of other forms of support.

Table 1: Poisson regression coefficients and rate ratios, in alphabetical order, predicting financial support given to kin from respondent

	Model 1	Ratio	Model 2	Ratio
Complement mean of composite measure of interaction	-0.108*	0.898	.	.
Complement mean of composite measure of interaction times size of household kin network	-0.048	0.953	.	.
Complement mean residual of composite interaction measure	.	.	0.026	1.026
Complement mean residual of composite interaction measure times size of household kin network	.	.	-0.015	0.985
Composite measure of interaction	0.354***	1.425	.	.
Financial support given to friends from respondent	0.530***	1.699	0.522***	1.685
Financial support given to other family from respondent	0.652***	1.919	0.646***	1.908
Frequency of any kind of support given to respondent	-0.137***	0.872	-0.119**	0.888
Ln-miles between respondent and alter	0.083***	1.087	0.026*	1.026
Residual of composite measure of interaction	.	.	0.253***	1.288
Sentiment for kin	0.068	1.07	0.154***	1.166
Size of household kin network	-0.092***	0.912	-0.108***	0.898
Constant	-2.856***	0.057	-2.697***	0.067
N Kin	13914		13914	
N Respondents	6535		6535	
Average kin per respondent	2.129		2.129	
R-Square (deviance-based)	0.044		0.038	

Notes: * p < 0.050, ** p < 0.010, *** p < 0.001, two-tailed tests. Coefficients and standard errors estimated using a population average model. Source: National Survey of Families and Households wave 2, 1994.

In the first model, there is a very strong positive effect for respondent-to-kin contact; each additional day of contact increases the chance or rate of support by over 40 percent in the first model. However, the first model appears to confirm the selection-process hypothesis. A higher complement mean in the raw contact measure reduces the chance or rate of support by 10 percent. These results were not totally reproduced in the second model, which used only the residuals of contact. First, the effect of contact is reduced by a great deal. In the first model, a day increase in contact increased the chances of financial support by over 40 percent, in the second model this increase was reduced to less than 30 percent. Second, the effect of the complement mean was also reduced to statistical insignificance.

Next, we turn to models predicting whether the respondent received support from kin. There were no effects of contact or distance in predicting whether the respondent received financial assistance from kin. There were positive effects for reciprocity in both models, each estimating a 20 percent increase in the chances that the respondent received support. There was, however, strong support for the selection process. The results for these two effects were consistent given across model specifications. Each additional network member reduced the rate of financial support given to the respondent from kin by 19 percent.

Table 2: Poisson regression coefficients and rate ratios, in alphabetical order, predicting financial support given to respondent from kin

	Model 1	Ratio	Model 2	Ratio
Complement mean of composite measure of interaction	-0.047	0.954	.	.
Complement mean of composite measure of interaction times size of household kin network	0.015	1.015	.	.
Complement mean residual of composite interaction measure	.	.	-0.011	0.989
Complement mean residual of composite interaction measure times size of household kin network	.	.	0.008	1.008
Composite measure of interaction	0.07	1.073	.	.
Financial support given to respondent from friends	0.579***	1.784	0.582***	1.79
Financial support given to respondent from other family	0.871***	2.389	0.872***	2.392
Frequency of any kind of support given to kin	0.186***	1.204	0.181***	1.198
Ln-miles between respondent and alter	0.006	1.006	0	1
Residual of composite measure of interaction	.	.	0.078	1.081
Sentiment for kin	-0.021	0.979	-0.01	0.99
Size of household kin network	-0.209***	0.811	-0.207***	0.813
Constant	-2.417***	0.089	-2.411***	0.09
N Kin	13914		13914	
N Respondents	6535		6535	
Average kin per respondent	2.129		2.129	

R-Square (deviance-based)	0.048	0.048

Notes: * p < 0.050, ** p < 0.010, *** p < 0.001, two-tailed tests. Coefficients and standard errors estimated using a population average model. Source: National Survey of Families and Households wave 2, 1994.

Results for household support

The main effects of contact for both giving and receiving household support were consistent across models and outcomes. Reciprocity has a large effect on household support, generally increasing its rate by 60 to 70 percent. The size of the household kin network also has a negative effect, where additional kin reduce the rate that the respondent gives kin support by 10 percent (see table 3), and the chance that kin give the respondent household support by 3 percent (see Table 4).

Table 3: Poisson regression coefficients and rate ratios, in alphabetical order, predicting household support given to kin from respondent

	Model 1	Ratio	Model 2	Ratio
Complement mean of composite measure of interaction	-0.080*	0.923	.	.
Complement mean of composite measure of interaction times size of household kin network	0.055***	1.057	.	.
Complement mean residual of composite interaction measure	.	.	-0.042	0.959
Complement mean residual of composite interaction measure times size of household kin network	.	.	0.062***	1.064
Composite measure of interaction	0.549***	1.732	.	.
Frequency of any kind of support given to respondent	0.254***	1.289	0.264***	1.302
Household support given to friends from respondent	0.078	1.081	0.069	1.071
Household support given to other family from respondent	0.317***	1.373	0.294***	1.342
Ln-miles between respondent and alter	-0.071***	0.931	-0.157***	0.855
Residual of composite measure of interaction	.	.	0.508***	1.662
Sentiment for kin	0.072**	1.075	0.208***	1.231
Size of household kin network	-0.103***	0.902	-0.108***	0.898
Constant	-1.425***	0.241	-1.148***	0.317
N Kin	13914		13914	
N Respondents	6535		6535	
Average kin per respondent	2.129		2.129	
R-Square (deviance-based)	0.201		0.193	

Notes: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$, two-tailed tests. Coefficients and standard errors estimated using a population average model. Source: National Survey of Families and Households wave 2, 1994.

The first model also shows an effect of complement contact on the rate of the respondent giving kin household support. For each day of contact in which the complement mean increases, the rate at which any one kin member receives support is reduced by 8 percent. However, as discussed above, there is a positive statistical interaction between network size and the complement mean, creating the pattern in which the complement mean has a negative effect in small networks but a positive effect in large networks. Thinking about this issue in terms of how the effect of one variable depends on the value of another can be difficult, especially when both variables are continuous.

Another method to think about this result is to consider the framing of social capital, given in a previous chapter. Consider the process in which household support is a function of network size, and from the model we can say that network size has a measureable negative effect on the chances of any one kin getting support. In fact, each member reduces the rate by 10 percent. Next, we think of the level of contact between the respondent and kin members as a form of social capital. To understand the effects of social capital, we then simply ask ourselves how the relationship between size and support differs across different levels of "social capital", or in this case, different levels of contact.

Figure 7 shows the rate of the respondent given household support to kin as a function of network size. However, this figure presets these rates for three distinct hypothetical household kin networks. The rate for each is calculated assuming the average levels for distance, contact between kin and any particular respondent, reciprocity and giving household support to other family and friends. Three rates were calculated for each network size by taking the exponent of the fitted value for three values of complement mean (W).

$$r_n = \exp\left(\left(\beta_0 + \gamma W\right) + \left(\theta_1 + \theta_2 W\right) \times \left(n - \bar{n}\right)\right)$$

One line represents a household kin network with a complement mean equaling the average contact for all respondents in the sample (W=0). The downward trend of this line is the effect estimated by θ_1. The second line is for a low complement mean. For this set of rates, I set the complement mean to be equal to 1 day below average (W = -1). Thus, for any network size n, the rate had a different constant (β_0-γ instead of β_0), and a different effect for network size (θ_1-θ_2 instead of θ_1), which becomes

$$r_n = \exp\left(\left(\beta_0 - \gamma\right) + \left(\theta_1 - \theta_2\right) \times \left(n - \bar{n}\right)\right).$$

The third line is the opposite of the second in that it is set for a high complement mean (W=1) Thus, for any network size n, the rate had a different constant (β_0+γ instead of β_0), and a different effect for network size (θ_1+θ_2 instead of θ_1), which becomes

$$r_n = \exp\left(\left(\beta_0 + \gamma\right) + \left(\theta_1 + \theta_2\right) \times \left(n - \bar{n}\right)\right)$$

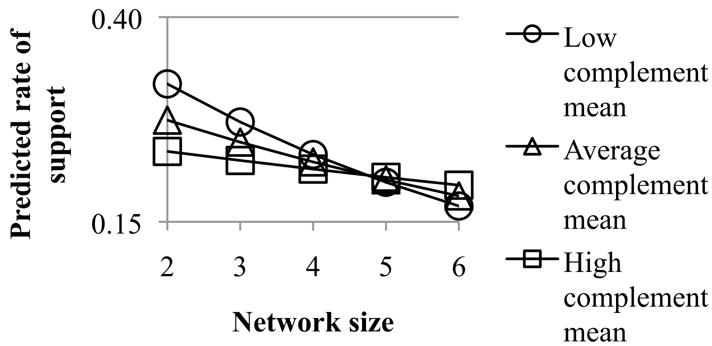

Figure 7: Predicted rate of household support given to kin by the respondent as a function of network size for networks with low complement mean contact, average complement mean contact, and high complement mean contact.

We can then see that across three families with differing complement means, that the effect of network size is also different. In families with a low complement mean, the effect of network size is much steeper than the effect of network size for families with high complement means.

However, having a high level of contact does not reverse the effects of network size, but only reduces the negative effect of network size. To be clear, no kin member receives more support than a kin member in a small family with a low complement mean of contact, assuming they have a sample-average level of contact with the respondent. However, if that person was in a large family, they would have the same rate (or a little less) as another person in a large family with the sample average level of contact with the respondent, but instead in a family with a high level of complement contact.

Table 4: Poisson regression coefficients and rate ratios, in alphabetical order, predicting household support given to respondent from kin

	Model 1	Ratio	Model 2	Ratio
Complement mean of composite measure of interaction	-0.015	0.985	.	.
Complement mean of composite measure of interaction times size of household kin network	0.014	1.014	.	.
Complement mean residual of composite interaction measure	.	.	-0.037	0.964
Complement mean residual of composite interaction measure times size of household kin network	.	.	0.025	1.025
Composite measure of interaction	0.499***	1.647	.	.
Frequency of any kind of support given to kin	0.204***	1.226	0.216***	1.241
Household support given to respondent from friends	0.318***	1.374	0.307***	1.359
Household support given to respondent from other family	0.692***	1.998	0.676***	1.966
Ln-miles between respondent and alter	-0.090***	0.914	-0.177***	0.838

Residual of composite measure of interaction	.	.	0.530***	1.699
Sentiment for kin	0.069**	1.071	0.206***	1.229
Size of household kin network	-0.025	0.975	-0.044*	0.957
Constant	-1.437***	0.238	-1.155***	0.315
N Kin	13914		13914	
N Respondents	6535		6535	
Average kin per respondent	2.129		2.129	
R-Square (deviance-based)	0.217		0.218	

Notes: * p < 0.050, ** p < 0.010, *** p < 0.001, two-tailed tests. Coefficients and standard errors estimated using a population average model. Source: National Survey of Families and Households wave 2, 1994.

This network size and contact pattern is not replicated when we consider household support given to the respondent, from kin, however. While there are strong effects for interaction, the effect of network size was small and there was no main effect or interaction effect with the complement mean of contact.

Results for emotional support

Emotional support is the most common of all the types of intergenerational support. Emotional support is also the most affected by reciprocity when we examined the basic tables above. The effects of reciprocity are maintained in the models presented below. The specification of the model did not alter the effect of reciprocity (see

Table 5). In both cases, reciprocity increased the rate of the respondent giving kin emotional support by 40 percent. Likewise, the chances of the kin giving the respondent emotional support were also increased by a similar amount; there is also a 40 percent increase (see

Table 6).

Table 5: Poisson regression coefficients and rate ratios, in alphabetical order, predicting emotional support given to kin from respondent

	Model 1	Ratio	Model 2	Ratio
Complement mean of composite measure of interaction	-0.188***	0.829	.	.
Complement mean of composite measure of interaction times size of household kin network	0.013	1.013	.	.
Complement mean residual of composite interaction measure	.	.	-0.106***	0.899
Complement mean residual of composite interaction measure times size of household kin network	.	.	0.031*	1.031
Composite measure of interaction	0.224***	1.251	.	.
Emotional support given to friends from respondent	0.249***	1.283	0.258***	1.294
Emotional support given to other family from respondent	0.335***	1.398	0.328***	1.388

Frequency of any kind of support given to respondent	0.369***	1.446	0.381***	1.464
Ln-miles between respondent and alter	0.021***	1.021	0.004	1.004
Residual of composite measure of interaction	.	.	0.143***	1.154
Sentiment for kin	0.116***	1.123	0.151***	1.163
Size of household kin network	-0.091***	0.913	-0.092***	0.912
Constant	-1.414***	0.243	-1.381***	0.251
N Kin	13914		13914	
N Respondents	6535		6535	
Average kin per respondent	2.129		2.129	
R-Square (deviance-based)	0.161		0.156	

Notes: * p < 0.050, ** p < 0.010, *** p < 0.001, two-tailed tests. Coefficients and standard errors estimated using a population average model. Source: National Survey of Families and Households wave 2, 1994.

Emotional support is the best candidate to be affected by sentiment on face value. How friendly people feel towards each other can both lead people to seek out emotional support. Conversely, emotional exchanges can also reinforce sentimental feelings. This hypothesis was confirmed in the models that predicted whether the kin would give respondents emotional support. Looking at

Table 6, we see that for each standard deviation increase in sentiment, the likelihood that the respondent received emotional support from kin increased by 35 percent. This was the largest effect of sentiment across all the models for each form of support.

Table 6: Poisson regression coefficients and rate ratios, in alphabetical order, predicting emotional support given to respondent from kin

	Model 1	Ratio	Model 2	Ratio
Complement mean of composite measure of interaction	-0.112***	0.894	.	.
Complement mean of composite measure of interaction times size of household kin network	0	1	.	.
Complement mean residual of composite interaction measure	.	.	-0.018	0.982
Complement mean residual of composite interaction measure times size of household kin network	.	.	0.018	1.018
Composite measure of interaction	0.155***	1.168	.	.
Emotional support given to respondent from friends	0.414***	1.513	0.421***	1.523
Emotional support given to respondent from other family	0.427***	1.533	0.424***	1.528
Frequency of any kind of support given to kin	0.353***	1.423	0.367***	1.443
Ln-miles between respondent and alter	0.008	1.008	-0.007	0.993
Residual of composite measure of interaction	.	.	0.079***	1.082

Sentiment for kin	0.299***	1.349	0.328***	1.388
Size of household kin network	-0.096***	0.908	-0.098***	0.907
Constant	-1.563***	0.21	-1.540***	0.214
N Kin	13914		13914	
N Respondents	6535		6535	
Average kin per respondent	2.129		2.129	
R-Square (deviance-based)	0.192		0.191	

Notes: * p < 0.050, ** p < 0.010, *** p < 0.001, two-tailed tests. Coefficients and standard errors estimated using a population average model. Source: National Survey of Families and Households wave 2, 1994.

In both models, of course, we see an effect for contact. For each extra day of contact, the rate for the respondent to give emotional support to kin increased by 25 percent in the model using the raw contact measure, but there was only a 15 percent increase in the model that used the residualized composite measure.

The effect of complement contact was negative on predicting whether the respondent receives emotional support from respondents, indicating a selection mechanism at work. Whether this means the respondent selects the best kin to ask for support, or these models pick up that they are more likely to get emotional support out of anyone else, it hard to tell. Either way, like with household favors, this selection effect is not constant across all network sizes. There is also a negative effect of network size. As the network gets larger, the rate of kin members to receive or give emotional support is reduce by 9 percent. The combination of the effects of network size and complement mean are show in Figure 8.

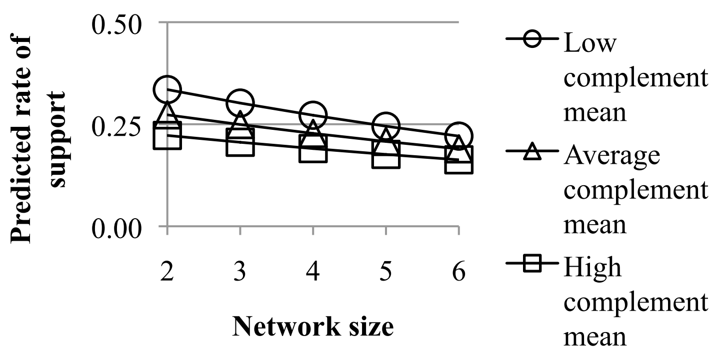

Figure 8: Predicted rate of emotional support given to kin by the respondent as a function of network size for networks with low complement mean contact, average complement mean contact, and high complement mean contact.

Discussion

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