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Decay functions

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Abstract

The tendency for relationships to weaken and disappear I discuss as decay, and functions describing the rate of decay over time I discuss as decay functions. Three conclusions are supported with 4 years of network data on a study population of bankers and their colleagues in a financial organization. (1) Factors known from cross-sectional evidence to be associated with strong relationships are associated with slow decay; decay is slower in relations between colleagues with a strong prior relationship (inertia), working in the same corporate division (homophily), prominent in the social hierarchy of bankers (status), or connected indirectly through many third parties (embedding). (2) Regardless of slower decay in certain relations, decay has a pattern over time similar to the population ecology “liability of newness” attributed to selection and learning, with the added complication of networks and people aging simultaneously. Decay is a power function of time in which the probability of decay decreases with tie age (years for which a relationship has existed) and node age (years for which a banker has been in the study population). (3) Embedding stability is responsible for the greater stability of older relationships. The decay-inhibiting effects of age occur where embedding is disrupted but not where embedding is continuous. The third conclusion is interesting in highlighting the first derivative of social structure as a causal variable: embedding has to be measured for its change, rather than level, to see both of its distinct effects on relationship decay. © 2000 Elsevier Science B.V. All rights reserved.

1. Introduction

As much as change is about adapting to the new, it is about detaching from the old. With respect to change in social networks, adapting to the new is about forming relationships. For reasons of opportunity and interpersonal attraction, relationships

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develop more often and faster between people similar on socially significant attributes such as spatial proximity, socioeconomic status, gender, and age (e.g., Festinger et al., 1950; Lazarsfeld and Merton, 1954; Blau, 1977; Feld, 1981; Pfeffer, 1983; Ibarra, 1992; McPherson et al., 1992; Reagans and Burt, 1998). For reasons of cognitive consistency, relations develop more often and faster between people with mutual friends (e.g., Davis, 1967; Doreian and Mrvar, 1996; Contractor et al., 1998).

This paper is about the second aspect of change, detaching from the old. Relationships end in a great variety of ways. Some last only for the duration of interaction. You walk into a store, are pleasant with the sales clerk for the duration of the sale, and the relationship ends when you walk out of the store. Other relations last well beyond the interaction with which they began. Humiliate someone in a public gathering, and your relationship with the person is forever changed (e.g., Chase, 1980, on the emergence of social hierarchy from nested dyadic conflict). Relations can be so robust that dissolving them requires change in the surrounding network (e.g., Ebaugh, 1988 on leaving high-commitment relationships), but even the simple act of asking someone for information creates a social tie between asker and responder that can survive past the information exchange.

Other things equal, I expect relationships to weaken over time such that some of the relations observed today are gone next year. The tendency for relationships to weaken and disappear I will discuss as decay, and functions describing the rate of decay over time I will discuss as decay functions. Network decay functions would include functions describing change in aggregate network characteristics such as density, reputation, status, or the like, but this paper is about decay in relationships.

More specifically, I expect a “liability of newness” (like the phenomenon described by population ecology models of organizations) in which relations decay over time, and the rate of decay slows with time. Random chance and exogenous factors can be expected to generate relationships, after which processes of selection and learning guide decay.

Many relationships originate from factors, exogenous to the two people involved, that define opportunities for relations to form. These would include population factors that bring together certain kinds of people (such as neighborhoods, office doors close to a main flow of people, or events such as school, entering the labor market, or assignment to the same project team; e.g., Festinger et al., 1950; Coombs, 1973; Feld, 1981), and population factors that limit the availability of certain kinds of people (Blau, 1977; Pfeffer, 1983; McPherson et al., 1992; e.g., there will be no relations with women in a study population that contains no women).

These exogenous factors generate relations regardless of individual preferences. People who would not otherwise seek one another out can find themselves neighbors, or colleagues in the same company, assigned to the same project team, or seated next to one another. It is rude not to strike up a relationship.

Thus, relationships generated by exogenous factors (not all are of course) will often connect people who discover that they do not enjoy one another or cannot work well together, so they disengage in favor of more compatible contacts. This selection process in which new (hoped to be) compatible contacts replace existing (known to be) incompatible ones means that relations on average weaken and decay over time.

The rate of decay can be expected to vary by kind of relation and study population, but all relations should show a liability of newness in which the rate of decay slows over time. The reason is that the longer a relationship has survived, the more likely that the two people involved are compatible, so the higher the probability that the relationship will continue into the future. Compatibility can mean many things, but it would certainly include interpersonal attraction inherent in the relationship and its social context (e.g., Reagans and Burt, 1998), as well as interpersonal attraction built up over time as the two people in a relationship learn a routine of how to interact with one another. Learning the social routines of working together is the mainspring for the liability of newness in population ecology. For example, Hannan and Freeman (1989: 80) write: “As Stinchcombe (1965) pointed out, new organizations typically rely on the cooperation of strangers. Development of trust and smooth working relationships takes time, as does the working out of routines. Initially there is much learning by doing and comparing alternatives. Existing organizations have an advantage over new ones in that it is easier to continue existing routines than to create new ones or borrow old ones (Nelson and Winter, 1982: 99–107). Such arguments underlie the commonly observed monotonically declining cost curve at the firm level, the so-called ‘learning curve’.”

Learning is more than an accompanist to selection processes. There is also learning from your current relationships to identify kinds of people with whom you are likely to be compatible (e.g., Kogut, 1998; Nahapiet and Ghoshal, 1998). Whatever the average probability of a new relationship disappearing next year, that probability should be lower for people more experienced in the study population because experienced people have learned to identify partners with whom they can be compatible.

In sum, network decay is correlated with two kinds of aging responsible for the liability of newness in relationships. There is the age of a relationship, call it “tie age,” for which the liability of newness is evident from slower decay in older relationships. There is second the age of the person citing a relationship, call it “node age,” for which the liability of newness is evident from slower decay in relationships cited by people with more experience in the study population.

In this paper, I describe decay across four annual surveys of colleague relationships for 345 bankers in a large financial organization. My two goals are to determine the functional form of decay with tie and node age, and estimate the relative importance of factors other than time that speed or slow the decay. Other factors would include in the general case the benefits each party to a relationship receives or expects to receive from the relationship, how much effort is needed to sustain it, how much effort is proper to sustain it (e.g., kinship relations can be tiresome, but you are expected to make an effort), and population factors that define opportunities for the relationship (e.g., relations will last longer in a closed study population from which no one exits and no one enters). The decay described here for colleague relationships no doubt varies across organizations (e.g., it would be slower in a static, hierarchical firm) and kinds of relations (e.g., it would be slower in social relations with kin), but the functional form of decay seems to generalize to other kinds of relations, and the conditions that affect decay in the banker colleague relationships are consistent with conditions that affect the strength of relations more generally.

2. Past research

Table 1 contains illustrative results on relationship decay. Decay is measured in terms of ties surviving for a specific period of time.¹ Studies A, B, C, and D were published in the January 1997 issue of *Social Networks*, a special issue on network change. Feld (1997) re-analyzed the network data of Wallace (1966) on 152 men enrolled in a small college at the beginning and end of their freshman year. Of 5345 initial sociometric citations for recognition, 54% were observed again in the second survey. Morgan et al. (1997) describe change in the people cited by 234 recent widows for having the most effect on their lives. Of 4955 people cited in the first interview, 54% were cited again a year later in the seventh interview. Suitor and Keeton (1997) describe change in emotional support relations and socializing for 42 women returning to college at midlife. Of 215 people cited in the initial interview as sources of emotional support, 66.0% were cited again a year later and 33.5% were cited again 10 years later (reported separately for kin and non-kin in Table 1). Of 254 people cited for socializing initially, 36.6% and 23.2% were cited again one and ten years later. The last article in Table 2 from the special issue is the description of change by Wellman et al. (1997) in intimates cited by Wellman's 33 East Yorkers. Of 162 intimates cited in 1968, 27% were cited as intimate ties by the same respondents a decade later; a higher 36.6% if the contact was family, 17.5% otherwise.

What is striking about Table 1 is that it summarizes my canvass of all papers in the journal *Social Networks* and its predecessor, *Sociometry*. The small number of results on relationship decay is silent witness to the fact that we know very little about decay. The editors of the *Social Networks* special issue on change seem to have been justified in their bold claim of offering a (Suitor et al., 1997: 1): “groundbreaking set of studies” that “. . . provides us with the first concerted effort to understand (a) the extent to which personal community networks change over time; and (b) the processes that underlie such changes.”

¹ Decay is underestimated by some unknown amount in Table 1, and all other results to be discussed in this paper, because I have no zero point on aging. At initial observation, T0 in Table 1 and Fig. 1 and Table 2, some relationships have existed longer than others and some people have more experience than others. Observed decay is therefore a compound of rapid decay in new relationships cited by inexperienced people mixed in unknown proportion with the slower decay of older relationships cited by people with more experience in the study population. Limiting analysis to relationships not cited in a previous panel does not eliminate the underestimation because it does not adjust for the slower decay in relationships cited by more experienced people and cannot adjust for the presumably slower decay of relationships that are not new so much as renewed (e.g., the 176 positive relations in Table 2 cited in the first panel, not cited in the second, then cited again in the third panel and not cited in the fourth, are evidence of relations continuing over time at different strengths, strong through 1 year then in remission through the next). I hope to control underestimation by adding to the equation predicting decay instrument variables that measure the probability of a relationship between two people (e.g., in-degree, out-degree, homophily, prior relation, etc.) and individual experience in the study population (e.g., age, years in the study population, centrality, etc.).

Table 1
Some rates of decay in interpersonal relationships

Study		Number of ties	Percent kin (%)	Approx. ego age	Years elapsed	Percent ties surviving (%) ^a
(A) 345 bankers in the mid 1990s citing colleagues with whom they had frequent and substantial business during the preceding year (Table 1)	T0 → T1	12,655	0	37	1	24.7
	T0 → T2	12,655	0	38	2	10.1
	T0 → T3	12,655	0	39	3	8.0
	T1 → T2	6964	0	38	1	22.2
	T1 → T3	6964	0	39	2	18.1
	T2 → T3	4081	0	39	1	34.8
(B) 152 college freshmen in the early 1960s recognizing other students (Feld, 1997; from Wallace, 1966).		5345	0	19	0.5	54
(C) 234 recent widows in the late 1980s citing people with a significant emotional impact on their lives (Morgan et al., 1997)		4955	45%	65	1	54.0%
(D1) 42 women returning to college in early 1980s citing sources of emotional support (Suitor and Keeton, 1997)		215	45.8 ^b	39	1	66.0
		215 ^b	100 ^b	48	10	49.5
		215 ^b	0 ^b	48	10	20.0
(D2) 42 women citing people with whom they often socialize (Suitor and Keeton, 1997)		254	35.7 ^b	39	1	36.6
		254 ^b	100 ^b	48	10	25.0
		254 ^b	0 ^b	48	10	22.2
(E) 33 residents of East York citing intimate contacts in 1968 and 1978 (Wellman et al., 1997)		80	0	53 ^c	10	17.5
		82	100	53 ^c	10	36.6
(F) 181 exiting heroin addicts in San Francisco Bay Area citing sources of social support in the early 1980s (Minor, 1983)		2269	63	32	0.5	47.7
		2269	63	33	1	35.8
(G) 69 Jibero Indian men in the late 1940s citing friends and enemies (Danielsson, 1949)		850	75 ^d	? ^d	0.04	94

(a) Percentages rounded to nearest integer were published at that level of precision. (b) The published article only contains rates combining relations with kin and non-kin. The separate kin and non-kin rates here were provided by Jill Suitor. (c) Personal communication from Barry Wellman. (d) Age and percent kin were not reported, but interaction was closely associated with kinship at slightly more than 75% density within groups defined by kinship (Danielsson, 1949: 90, 100), so I use for the purposes here the 75% figure as the percentage of ties that were with kin.

Table 2
Four years of colleague relationships

(T0) Initial observation	(T1) One year later	(T2) Two years later	(T3) Three years later		
			Negative	Not cited	Positive
Negative	Negative	Negative	10	31	3
Negative	Negative	Not cited	8	365	5
Negative	Negative	Positive	4	15	4
Negative	Not cited	Negative	14	35	2
Negative	Not cited	Not cited	10	2503	19
Negative	Not cited	Positive	4	27	5
Negative	Positive	Negative	1	8	4
Negative	Positive	Not cited	5	132	10
Negative	Positive	Positive	4	23	13
Not cited	Negative	Negative	18	65	8
Not cited	Negative	Not cited	25	792	26
Not cited	Negative	Positive	2	40	10
Not cited	Not cited	Negative	76	432	51
Not cited	Not cited	Not cited	554	0	1675
Not cited	Not cited	Positive	51	1088	449
Not cited	Positive	Negative	15	41	14
Not cited	Positive	Not cited	27	2089	214
Not cited	Positive	Positive	12	252	185
Positive	Negative	Negative	7	19	4
Positive	Negative	Not cited	13	211	14
Positive	Negative	Positive	8	19	12
Positive	Not cited	Negative	5	38	1
Positive	Not cited	Not cited	20	6432	153
Positive	Not cited	Positive	7	176	75
Positive	Positive	Negative	9	28	23
Positive	Positive	Not cited	17	1251	215
Positive	Positive	Positive	10	324	300

These are sociometric citations to colleagues with whom the respondent bankers had frequent and substantial business during the year. Colleagues include other bankers and people in other divisions of the company. Negative cites are to colleagues evaluated adequate or poor. Positive cites are to colleagues evaluated good or outstanding. Not cited are to colleagues cited in one of the four years but not in the year for which the relation is listed as not cited.

Of the 365 articles published in *Social Networks* through the end of 1998, 18 used longitudinal data² and all of them except the above four in the January 1997 special

² The count does not include articles with longitudinal data on nodes but network data only in a single panel (e.g., Hirdes and Scott, 1998), nor qualitative discussions of dyadic stability (e.g., Jacobson, 1985; Schweizer, 1996), nor articles on stability in animal networks (though here again interaction data are often aggregated over time to analyze network structure, e.g., Dow and de Waal, 1989; Chepko-Sade et al., 1989), nor articles based on comparisons between independent samples from the same population at two or more points in time (because the stability of individual relationships is unknown from one time period to the next; e.g., Ruan et al., 1997 compare aggregate statistics on a 1986 sample and a 1993 sample of people in Tianjin, China; Lee, 1980, compares aggregate statistics on ties within and between two sections of Hobart, Tasmania before and after a bridge connecting the two sections was destroyed).

issue can be put aside for the purposes of this paper because they do not contain results on the decay of interpersonal relations.³

The small number of articles with longitudinal data in *Social Networks* is not good or bad; it is simply a reminder of how rare such data are. There are studies not published in *Social Networks* that use longitudinal network data. For example, the panel study of Minor (1983) of exiting heroin addicts reported sociometric citations across three panels (study E in Table 1). Communication scholars have been particularly active in studying networks over time. Contractor et al. (1998) is an exemplar of such research, and of 66 network analyses reviewed by Rice (1994) on computer-mediated communication, 47 were based on longitudinal data (71%). But communication studies are the exception. The *Social Networks* inventory revealing few longitudinal studies (18 of 365, or 5%) is closer to my sense of what is typical in the social sciences.

With so little evidence from *Social Networks* on relationship decay, I continued the search back through the journal *Sociometry*.⁴ The article of Mouton et al. (1955) on reliability provided a close reading of *Sociometry* articles published up to that point, after which I searched titles and abstracts for results on reliability, stability, change, or

³ The articles put aside are of three kinds: (1) Four described longitudinal data on relations between organizations not people (Ornstein, 1982, on the reconstitution of broken Canadian interlock ties from 1946 to 1977; Stokman et al., 1988, on the stability and reconstitution of Dutch interlock ties from 1960 to 1980; Berkowitz and Fitzgerald, 1995, on enterprise groups of Canadian firms in 1972 and 1987; Chung, 1996, on the status of investment banks in the American market from 1980 to 1989, cf. Podolny, 1993; Podolny and Phillips, 1996). (2) In another four of the articles, dyads were aggregated to study the stability of summary measures or node variables so I cannot determine rates of change at the dyad level (Hallinan, 1978; Runger and Wasserman, 1980; Barnett and Rice, 1985; Rice et al., 1990; Bearman and Everett, 1993). (3) Six of the articles described longitudinal data on small, bounded networks, which means that relations are much more autocorrelated than in study populations where there are large numbers of people with whom relationships can develop. For example, Freeman (1984) described relations at three points in time over an 18-month period among 16 network analysts in an experimental program on computer communication. Given the selection of 16 people who stayed with the program, it is not surprising to see that relations did not decay. Rather, relations expanded as the 16 people came to know one another within the closed system. The 54 cites for acquaintance at the beginning of the project (0.23 density) expanded to 125 cites at the end (0.52 density). The other five articles use longitudinal data on small, bounded networks for numerical illustration. Doreian (1980) uses the Davis et al. (1941) data on 18 women mentioned in 14 newspaper articles, Iacobucci (1989), Nakao and Romney (1993), and Sanil et al. (1995) use the data of Newcomb (1961) on relations among 17 college students in a residence hall set aside for the study, and Iacobucci (1989) and Doreian and Mrvar (1996) use the data of Sampson (1968) on relations among 18 monks living together.

⁴ The two journals are closely related in content and function. This is an interesting story in its own right but an aside here. In brief justification of my focus on the two journals as representatives of the same work, I see *Social Networks* providing through the 1980s and 1990s what *Sociometry* provided through the 1940s to 1970s; the most prominent journal devoted to studies of social networks. Both were a rallying point for the interdisciplinary audience of people interested in social networks. When *Sociometry* was discontinued in 1977 and *Social Networks* begin in 1978, *Social Networks* returned to *Sociometry*'s evangelical focus on social networks as a guide to theory and a key to understanding broad social issues. Continuity between the two journals is obscured by the end of *Sociometry*, when it drifted into becoming a psychology journal for sociologists, eventually re-named *Social Psychology* in 1978 and *Social Psychology Quarterly* in 1979. But even in its last year, *Sociometry* contained works true to the journal's initial focus and prominence such as the widely cited introduction to betweenness centrality of Freeman (1977).

longitudinal data. There were numerous studies of children and small groups, but I found only one study of adults akin to the survey network data in Table 1: the study of Danielsson (1949) of 69 Indians citing friends and enemies in a population of 507 people in the western reaches of the Amazon (study F in Table 1). The time interval between the first and second interview was only 2 weeks (0.04 years in Table 2), so the repeated citations could be evidence of reliability more than stability. On the other hand, Danielsson (1949: 92–100) shows that the citations were concentrated (friendships with the “ceremony man” in each village, and repulsion from the “sorcerer” in each village) so concentration could have contributed to the high stability reported (illustrated below by the tendency for relations with prominent colleagues to decay more slowly than relations with peripheral colleagues, Table 5).

3. Four years of colleague relationships

The lack of published results makes all the more exceptional the data I have from four annual surveys of employees in the investment banking division of a large financial organization, and is the reason for making the data available in Table 2 for alternative modeling.

The respondents, who I will discuss as “bankers,” include senior people responsible for making and closing deals, as well as people in administrative positions who manage bankers in lower ranks, or manage analysts who service the bankers. The survey instrument is a roster of employees, in the investment banking division and in other divisions, so change includes both change in the relationships between continuing employees as well as change due to colleagues leaving and entering the organization. Respondents are asked to cite the colleagues with whom they had frequent and substantial business contact in the preceding year, and to evaluate each cited colleague for the quality of working with him or her as *poor* (persons receiving multiple poor evaluations are encouraged to look for a different line of work), *adequate* (a negative evaluation akin to the grade of C in graduate school), *good*, or *outstanding* (persons receiving multiple outstanding evaluations are put on an unwritten list of “stars” for whom special efforts are to be made to prevent them from leaving the organization). The words poor, adequate, good, and outstanding are synonyms for the words actually used in the peer evaluations. Per my sense of how the four levels of evaluation are interpreted within the firm, relations evaluated good or outstanding are positive in Table 2 and relations evaluated adequate or poor are negative. The data are a census in that virtually all eligible employees return the survey questionnaire because responses are used to guide promotion and bonus decisions (Burt, 1997). Quality is also high because the data are routinely studied by a staff of analysts looking for strategic behavior such as blackballing between cliques, or inflated evaluations between friends who had little business with one another (either of which is said to elicit unpleasant retribution from top management).

There is clear evidence of decay. Table 1 contains the survival rates. The data begin with 345 bankers citing 12,655 colleague relationships. Of the 12,655, only 3129 were

cited in the next year's survey (T1) which is the 24.7% survival rate in the first row for study G at the bottom of Table 1. The next row shows that 10.1% of the initial 12,655 were cited in the year after that (T2), and the third row shows that 8.0% were cited in the subsequent year (T3).

There is evidence of the liability of newness in that older relationships and relationships cited by more experienced bankers are less subject to decay. The effect for relations is evident from survival rates in Table 1; there is less difference in the rates for the fourth and third panels (8.0% versus 10.1%) than the first two panels (10.1% versus 24.7%). The oldest relationships are the most likely to survive. Of 883 colleague relations cited in each of the first three annual surveys, almost half were cited again in the fourth survey (47.1%) — a higher survival rate than any reported in Table 1 for this study population. The experience effect for bankers is evident from survival rates for relations cited by bankers who continue working for the firm. Those of the 345 initial bankers who were still employed by the firm in the second panel cited a total of 6964 colleague relationships. The 6964 define a risk set for decay in subsequent years. The fourth row of study G results in Table 1 shows that 22.2% of the 6964 relations were cited in the third year, and almost as many were cited in the subsequent year (18.1%). Decay is least evident in the transition from the third to the fourth panel. Bankers who continued with the firm to the third panel cited a total of 4081 relationships, of which 34.8% were re-cited in the next year's survey — the highest survival rate reported in Table 1 for this study population.

4. Decay functions

Fig. 1A contains decay functions estimated from the survival rates in Table 1. The horizontal axis is time in years; T0 is the year in which relations were initially observed, T1 is a year later, T2 the year after that, and so on. The vertical axis is the portion of relations observed at T0 that are observed again at subsequent times. Solid dots are the survival rates for colleague relations (bottom six rows of Table 1). Hollow dots are the other rates in Table 1.

4.1. Decay as a survival rate

The three decay functions in Fig. 1A show decay as a power function of time in social relations with family (dotted line), social relations beyond the family (dashed line), and colleague relations between the bankers to be studied here (solid line). Decay is described by the following regression equation:

$$Y = \text{portion relations surviving to time } T = (T + 1)^{(\gamma + \kappa \text{ KIN} + \lambda \text{ WORK})},$$

where Y is the vertical axis in Fig. 1A, T is the horizontal axis, KIN is the proportion of relations in a row of Table 1 that are with family (e.g., 0.63 for Minor, 1983), and

WORK is a dummy variable equal to 1 for colleague relations (Table 2). Beginning with all relations observed at T0 (i.e., $Y = 1$ when $T = 0$), the three decay functions in Fig. 1A are defined by substituting coefficient estimates into the regression equation. Ordinary least squares estimates across the 19 rows of Table 1 are -0.716 for γ describing decay over time (-9.2 routine t -test), 0.250 for κ describing the slower decay of social relations with kin (2.2 t -test), and -1.126 for λ describing the faster decay of colleague relations between the bankers (-7.1 t -test). The above power function describes 95% of the variance in survival rates.⁵

I tested the function against some obvious alternative forms. A linear function with slope adjustments for kin and colleagues describes less variance, 70%, which is not surprising since the association between time and survival is visibly nonlinear in Fig. 1A. An exponential function describes the data about as well as a linear function (70.2%).

I do not have consistent data on respondent experience within the study populations so I cannot measure node age, but average respondent age for most of the panels is listed in Table 1. Average age adds nothing to the prediction in Fig. 1B (2.0 t -test for the power function, $P = 0.07$; 0.2 t -test for the linear function, $P > 0.5$), which implies that the positive association sometimes reported between age and relationship stability is limited to older children being more consistent than younger children (e.g., Mouton et al., 1955), or older respondents citing more relations with family (e.g., Marsden, 1987; Burt, 1991), or the experience variable that measures node age is not average age compared across study populations but rather relative age within a study population (see Table 4).

4.2. Decay as a hazard rate

Beyond aggregate survival rates available from published studies, I can use the panel data on colleague relationships to study decay more precisely as function of year-to-year

⁵ Assume for a moment that the decay-function parameter estimates in Fig. 1A are true of networks generally. (The estimates are limited to *Social Networks*, *Sociometry*, and the study population of bankers, so there are many studies not represented.) Then the function could be used to corroborate network inferences with respect to time. For example, Volker and Flap (1995) gathered survey network data in 1992 from 189 East German respondents on several dimensions of socializing then re-interviewed the respondents in 1993. In a personal communication, Flap said that 941 of the 2332 contacts cited in 1992 were cited again in 1992 (40.4% survival rate) and 31.8% of the contacts cited in 1992 were kin. The 1992 interview, however, asked respondents to cite relationships from three years ago, in 1989. The time interval between the network panels is either 1 year (if current relations shaped respondent memory of 1989 relationships) or 4 years (if respondents were able to think back to 1989 as instructed). If I add the Volker and Flap study to Table 1 assuming a 1-year interval, I obtain estimates for the now 20 observations of -0.73 for survival over time (γ , -9.1 t -test), 0.26 for the kin adjustment (κ , 2.2 t -test), and -1.11 for the work adjustment (λ , -6.9 t -test), predicting 94.5% of the survival variance. If I assume the 4-year interval, I get estimates of -0.71 for γ (-9.6 t -test), 0.25 for κ (2.3 t -test), and -1.13 for λ (-7.4 t -test), predicting 95.1% of the survival variance. Either set of estimates is similar to the results in Fig. 1A, but the set assuming a 4-year interval is a slightly better fit to the model — from which I infer that the interval between the panels is closer to four years than 1 year, implying that respondents were able to respond with retrospective 1989 data as instructed.

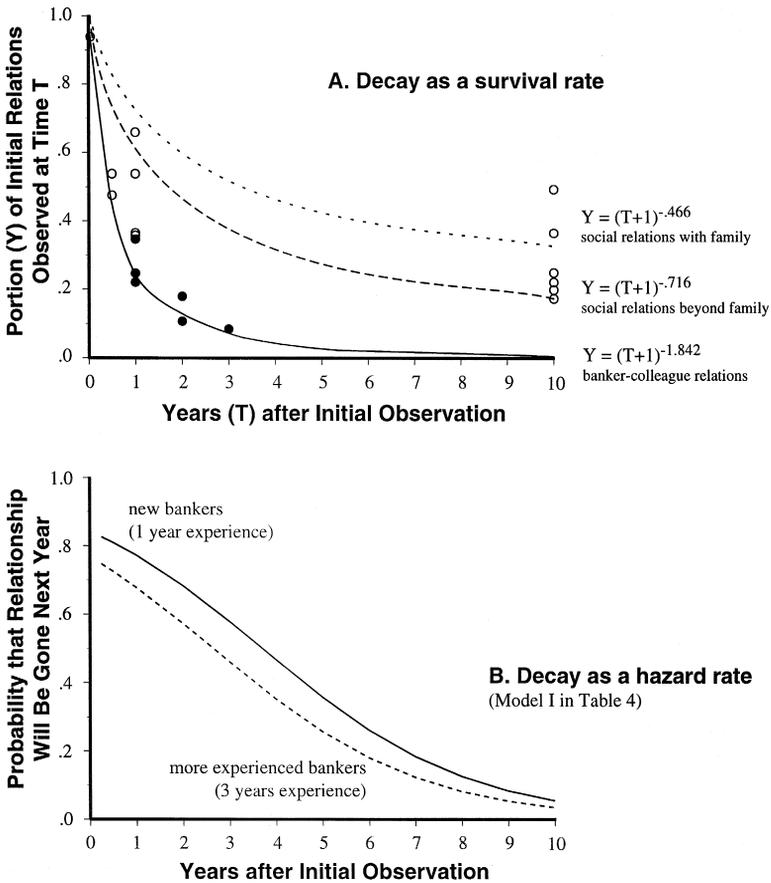


Fig. 1. Decay functions.

variation. The hazard rate for a relationship is the probability that it will be gone next year. Hazard rates for the colleague relations are given in Table 3, predicted by logit equations in Table 4, and graphed in Fig. 1B. Test statistics in Table 4 are adjusted down for autocorrelation between relations cited by the same respondent (e.g., Kish and Frankel, 1974).

Decay is high on average. Three in four of the 22,709 colleague relations at risk of decay in Table 3 are gone next year.

Model I, in the first column of Table 4, shows that tie and node age are both statistically significant factors in the liability of newness. As expected for tie age, the hazard of decay is lower for older relationships. Hazard rates are lower in Table 3 for older relationships (e.g., 0.753 vs. 0.529), there is a statistically significant -6.7 z-score test statistic in Model I for tie age T in Table 4 ($P < 0.001$, and $\log T$ yields no stronger effect, -6.3 z-score), and there is a negative slope to the predicted hazard rates in Fig. 1B. A colleague relationship that survives for a decade is almost sure to survive into the future (the predicted hazard rate is near zero).

Table 3

Decay hazard rates

(a) This row describes colleague relationships cited in the first panel. (b) This row describes relations cited in the second panel, but not in the first panel. (c) This row describes relations cited in the third panel, but not in the second. (d) These are the relations cited this year that are at risk of not being re-cited next year. (e) These are the relations at risk that were not re-cited. (f) This is column (e) divided by (d), the proportion of relations at risk that were not re-cited.

Years observed (<i>T</i>)	Panel in which first observed (<i>P</i>)	Relationships at risk ^d	Relationships that decay ^e	Hazard rate ^f
1	1 ^a	12,655	9526	0.753
2	1 ^a	3129	2246	0.718
3	1 ^a	883	467	0.529
1	2 ^b	3835	3173	0.827
2	2 ^b	662	398	0.601
1	3 ^c	1545	865	0.560
Total		22,709	16,675	0.734

As expected for node age, the hazard of decay is lower for relations cited by more experienced bankers. Hazard rates are lower in Table 3 for relations cited by more experienced bankers (e.g., 0.753 for 1-year-old relations cited by bankers in the first panel versus 0.560 for one-year-old relations cited by those of the bankers who continue to the third panel), there is a statistically significant -3.8 test statistic in Model I for node age *P* in Table 4 ($P < 0.001$; and log *P* yields no stronger effect, -3.2 *z*-score),

Table 4

Predicting the hazard of decay

	I	II	III
Intercept	1.910	3.180	2.906
<i>Tie age</i>			
Years tie has been observed (<i>T</i>)	$-0.451 (-6.7)^*$	$-0.399 (-6.0)^*$	$-0.365 (-5.4)^*$
Positive strength of relationship	–	$-0.300 (-5.4)^*$	$-0.314 (-5.7)^*$
Negative strength of relationship	–	0.007 (0.1)	$-0.001 (-0.0)$
<i>Node age</i>			
Panel in which tie is first cited (<i>P</i>)	$-0.238 (-3.8)^*$	$-0.223 (-3.5)^*$	$-0.203 (-3.2)^*$
Banker age (years)	–	$-0.027 (-2.7)^*$	$-0.004 (-0.3)$
Banker seniority (years)	–	0.002 (0.2)	0.007 (0.6)
Banker job rank	–	–	$-0.335 (-4.4)^*$
Chi-square	79.45*	141.99*	175.55*
d.f.	2	6	7

These are logit coefficients predicting decay with test statistics in parentheses (*z*-scores adjusted for autocorrelation between relations cited by the same respondent). Estimation is across all 22,709 relationships in Table 3 at risk of decay next year. Unless otherwise indicated, predictor variables are measured for this year predicting decay next year (year *T*). * $P < 0.01$.

and the predicted decay rates in Fig. 1B for relations cited by new bankers (solid line) is higher than the rates for more experienced bankers (dashed line).

5. Decay functions, *ceteris paribus*

I can study decay in finer detail by holding constant factors that could speed or slow decay.

5.1. *Direct measures of node and tie age*

Model II in Table 4 adds direct measures of prior relationship. I do not know when a colleague relationship began, but *ceteris paribus*, stronger relations could be expected to have existed longer than weak relations to the extent that relationships grow stronger with their duration in time. Prior relationship is measured on a three-category scale for positive and negative strength. Positive strength is a relationship evaluated (2) outstanding, (1) good, or (0) less than good (see Table 2), and more positive relations are significantly less likely to decay (-5.4 *z*-score, $P < 0.001$). Negative strength is a relationship evaluated (2) poor, (1) adequate, or (0) more than adequate, but more negative relations are neither more or less likely to decay (0.1 *z*-score). Regardless of prior strength, positive or negative, relations decay more slowly with the years for which they have been observed (-6.0 *z*-score for *T* in Model II).

Models II and III in Table 4 contain direct measures of banker experience. Bankers who are older, have more years with the firm, or have achieved senior job rank are in various ways more experienced. Decay is slower in the relationships cited by older bankers (-2.7 *z*-score in Model II), regardless of their years spent in the study firm (0.2 *z*-score), but neither measure of age in years matters relative to job rank. The bankers were stratified across three broad job ranks; senior (rank = 1), more senior (rank = 2), and most senior (rank = 3). Decay is slower in relations cited by bankers in higher ranks, and rank is the variable responsible for more stable relations from older bankers (effect of banker age reduces to -0.3 *z*-score when job rank is held constant).⁶ One could infer from Models II and III that the stability associated with node age (*P*) is less a function of experience accumulated over time (banker age, or years with the firm) than it is experience legitimated by promotion to senior rank (cf. Krackhardt, 1990; Han, 1996). However, none of the direct measures of banker experience eliminates the strong

⁶ The equal intervals between job ranks is sufficient for the purposes of this paper. If dummy variables are entered to distinguish the two higher job ranks, the coefficient for the more senior rank is -0.311 (-2.3 *z*-score) and for the most senior rank is -0.332 (-2.5 *z*-score), so the two higher job ranks are more similar to one another than either is to the first rank. Entering job rank as a dummy variable that distinguishes the first from the two higher job ranks also reveals the statistically significant rank effect on decay (-3.9 *z*-score).

Table 5
Contingent decay

	IV	V	VI	VII	VIII	IX
Intercept	3.244	3.558	3.216	3.479	3.450	1.881
<i>Tie age</i>						
Years tie has been observed (<i>T</i>)	−0.417 (−6.0)*	−0.346 (−4.9)*	−0.450 (−5.9)*	−0.361 (−4.7)*	−0.355 (−4.6)*	0.246 (2.9)*
Positive strength of relationship	−0.239 (−6.1)*	−0.225 (−5.7)*	−0.294 (−6.4)*	−0.258 (−5.6)*	−0.232 (−5.9)*	−0.236 (−5.9)*
<i>Node age</i>						
Panel in which tie is first cited (<i>P</i>)	−0.193 (−2.9)*	−0.421 (−6.1)*	−0.320 (−4.5)*	−0.500 (−6.6)*	−0.502 (−6.7)*	−0.592 (−8.2)*
Banker job rank	−0.377 (−5.1)*	−0.386 (−5.1)*	−0.300 (−3.7)*	−0.322 (−4.0)*	−0.320 (−4.0)*	−0.271 (−4.3)*
<i>Population marginals</i>						
Cites from banker in year <i>T</i>	0.004 (1.7)	0.008 (2.8)*	0.005 (1.7)	0.010 (3.2)*	0.010 (3.1)*	0.008 (3.5)*
Cites to colleague in year <i>T</i>	−0.025 (−19.6)*	−0.027 (−19.2)*	−0.051 (−21.2)*	−0.048 (−19.6)*	−0.048 (−19.6)*	−0.043 (−14.7)*
<i>Homophily</i>						
Colleague is outside banking division	–	0.566 (10.5)*	–	–	–	–
Colleague job rank (in banking division)	–	–	0.358 (9.3)*	0.408 (9.7)*	0.409 (9.6)*	0.365 (7.9)*
Banker and colleague have same job rank	–	–	−0.121 (−1.9)	−0.056 (−0.9)	−0.058 (−0.9)	−0.068 (−1.0)

Banker is a woman	–	–	–0.045 (–0.2)	–0.071 (–0.4)	–0.076 (–0.4)	0.062 (0.4)
Banker and colleague are both men	–	–	–0.298 (–3.5)*	–0.312 (–3.6)*	–0.314 (–3.6)*	–0.164 (–1.2)
Banker and colleague are both women	–	–	–0.046 (–0.2)	0.167 (0.8)	0.167 (0.8)	–0.031 (–0.2)
Same age (\pm four years)	–	–	0.299 (3.2)*	0.216 (2.4)	0.218 (2.4)	0.262 (3.2)
Same age \times Odd age within job rank	–	–	–0.045 (–2.2)	–0.028 (–1.4)	–0.028 (–1.4)	–0.027 (–1.5)
<i>Embedding</i>						
Number of third-party (TP) ties	–	–0.049 (–7.3)*	–	–0.063 (–8.3)*	–	–
Positive TP ties (positive-positive)	–	–	–	–	–0.075 (–6.2)*	–
Positive TP ties (negative–negative)	–	–	–	–	–0.124 (–4.0)*	–
Negative third-party (TP) ties	–	–	–	–	–0.032 (–2.3)	–
Disrupted embedding (Number TP ties in year T-1, no TP ties in year T)	–	–	–	–	–	0.383 (11.7)*
Continuous embedding (TP ties in year T – 1 \times TP ties in year T)	–	–	–	–	–	–0.007 (–12.3)*
Chi-Square (d.f.)	582 (6)*	721 (8)*	590 (13)*	565 (14)*	630 (16)*	835 (15)*

These are logit coefficients predicting decay with test statistics in parentheses (z -scores adjusted for autocorrelation between relations cited by the same respondent). Models IV and V are estimated across all 22,709 relations in Table 3 at risk of decay next year. All other models are estimated across the 15,600 relations with banker colleagues for whom colleague rank, age, and gender are known. Unless otherwise indicated, predictor variables are measured for this year predicting decay next year (year T). * $P < 0.01$.

node age effect of the panel in which a relationship was first observed. In other words, there is an effect of experience over time not captured by banker age or job rank.

5.2. Controls for the exogenous probability of a relationship

Ceteris paribus, relations more likely to occur because of conditions outside the dyad could be expected to be less subject to decay within the dyad. Table 5 contains decay models with controls for the exogenously determined probability of a relationship.⁷

5.2.1. Population marginals

Model IV in Table 5 adds controls for the marginals of the choice matrix. If in year T a banker cites many colleagues (row marginal) and a colleague is often cited (column marginal), then by random chance (independence model of a two-way tabulation) the hazard of decay in their relationship should be less than it would be in an otherwise similar relationship between a banker who made few citations and a colleague rarely cited. The results in Model IV show that decay is independent of how many colleagues a banker cites (1.7 z -score), but is strongly associated with how often the colleague is cited (-19.6 z -score). There are two parts to the column-marginal effect indicating colleague availability; the increased probability of a relation being cited by random chance with an often-cited colleague, and the impossibility of citing a colleague who has left the firm (and so cited zero times in year T). I cannot add a control variable for colleague exit because there is no decay variance in relations with colleagues who have left — all relations with them have decayed. However, the strong negative association between decay and number of citations to the colleague is more than just exit. If I re-estimate Model IV from only the relations at risk of decay that were with colleagues who continued in the firm to time T , the -19.6 z -score in Table 5 is reduced but still strong at -7.0 ($P < 0.001$).

The valuable point here is not the statistical significance of colleague availability; that seems obvious. What is valuable is knowing that the liability of newness exists despite variation in colleague availability. A panel study involving survey network data provides row marginals measuring the number of people cited by each respondent in each panel, but does not provide column marginals measuring contact availability in each panel. It would be possible to ask about decayed relationships (e.g., “You cited Robert last year, but not this year. What happened to Robert?”), however, the added survey cost would be substantial. The Model IV results are valuable, therefore, in that they show no effect on decay from the number of contacts cited by a respondent (a point of comparison with any network panel study since row marginals are always available), and show the liability of newness despite controls for contact availability (which typically is not known). Above and beyond the constraints of limited banker citations and limited

⁷ Table 5 is long, so I do not include the three predictors from Table 4 that had negligible direct association with decay (*viz.*, negative strength of relation, banker age, and banker seniority). None of these three variables have a statistically significant association with decay in any model in Table 5.

colleague availability, decay is slower in older relationships (-6.0 z -score test statistic for T effect) and slower in relationships cited by more experienced bankers (-2.9 z -score for P effect).

5.2.2. Homophily

Homophily effects refer to the tendency for relationships to develop between socially similar people (Lazarsfeld and Merton, 1954). To the extent that strong relations are more likely to develop between socially similar people (as they do in this study population, Reagans and Burt, 1998), relations between socially similar people could be less subject to decay.

The formal structure of jobs is the most obvious place to look for homophily effects. I have two levels of data on jobs in the study population. There is first a distinction between bankers and non-bankers. Of the 22,709 relations at risk of decay in Table 3, 15,600 were between bankers and 7109 were between bankers and non-bankers. Model V shows that relations with colleagues outside banking are much more subject to decay (10.5 z -score, $P \ll 0.001$). Second, I know for the bankers which of the three broad job ranks they held within the organization; senior, more senior, or most senior. If I regress decay across banker rank and colleague rank, holding T and P constant, decay is significantly slower in relations with higher-rank people (-3.6 z -score for banker rank, -2.3 z -score for colleague rank). In Model VI, however, colleague prominence in the informal network is held constant and the positive association between decay and colleague job rank shows that decay is increased in relationships with colleagues who have a prominent rank in the formal structure of the firm, but low prominence in the informal structure.⁸ Rank-homophily is a minor consideration beyond the direct effects of banker and colleague job rank in that decay is negligibly slower in relations between bankers at the same rank (-1.9 z -score in Model VI, weaker in later models).

Gender is an often-discussed criterion for social similarity in organizations and there is sufficient evidence to expect that gender could be associated with the development and consequences of informal networks (e.g., Kanter, 1977; Brass, 1985; Ibarra, 1992; Milkman and Townsley, 1994; Ibarra, 1997; Burt, 1998). Fig. 2 contains decay functions for banker-colleague gender combinations. The graph is the same as Fig. 1B in showing the hazard of decay over time (except here, node age P is set to its average for each gender mix rather than the extremes of 1 or 3 as in Fig. 1B). The two solid lines in Fig. 2 show decay in relationships cited by men. Relations between men are less subject to decay on average, but all relations cited by men show the liability of newness in which

⁸ Colleague job rank is closely associated with prominence in the informal network (0.40 correlation between the three levels of colleague job rank and number of citations to the colleague), so multicollinearity is an issue for separating direct effects on decay. To be sure of the interpretation in the text, I looked at decay rates for colleagues at each job rank separated into high-citation colleagues (cited more often than average for their rank) vs. all others as low-citation colleagues. Decay rates for the low-citation colleagues are 0.77, 0.80, and 0.81 for the senior, more senior, and most senior job ranks. Decay rates for high-citation colleagues in the three job ranks are 0.68, 0.61, and 0.59 respectively. Being a low-citation colleague in the most senior job rank increases decay more ($0.22 = 0.81 - 0.59$) than being a low-citation colleague in the least senior job rank ($0.09 = 0.77 - 0.68$).

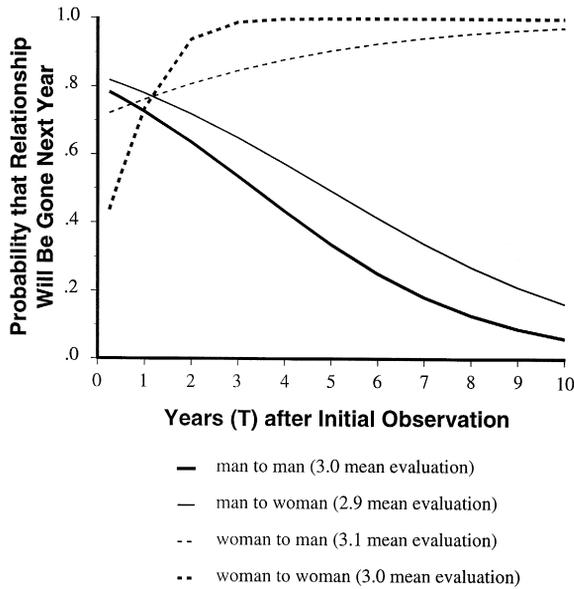


Fig. 2. Decay functions by gender.

decay is less likely in older relationships. The two dashed lines in Fig. 2 show a contrary effect in women's relationships; the hazard of decay increases to almost certain decay after three years. The higher rate of decay in women's relations is statistically significant (3.6 z -score, $P < 0.001$), but holding constant the Table 4 measures of tie and node age shows that banker gender is less important than the fact that banker and colleague are both men (-3.5 z -score for "both men" in Model VI). Relations that involve women either as banker or colleague are more subject to decay.

Age is another often-discussed criterion for social similarity, correlated with period and cohort effects inside and outside an organization (e.g., Pfeffer, 1983). Age differences between bankers are less powerful than job rank in measuring banker experience (Model III in Table 4), but the question remains of age homophily affecting relationships.

The results in Model VI show decay is associated with age homophily, contingent on a banker's relative age within his or her job rank. There are two age variables in Table 5. "Same age" is a dummy variable equal to 1 if banker are within four years of one another in age.⁹ The second variable is same age multiplied by the difference in years

⁹ The age homophily effects are fragile in that they are weaker for homophily defined by an interval one year longer (± 5 years generates a 2.2 z -score instead of the 3.2 in Table 4) or 1 year shorter (± 3 years generates a 2.0 z -score). Continuous years of difference between banker and colleague yield no homophily effect (1.7 z -score), but that makes substantive sense in that homophily refers to similar age, not degree of similarity. I do not study age homophily in detail here because the effects disappear when controls for embedding are introduced in Model IX and my only purpose is to show that homophily factors which are associated with stronger relations in cross-sectional data are also associated with slower decay.

between a banker's age and the median age at his or her job rank. Thus, the same-age effect on decay in Table 5 describes the effect of same age for bankers at the median age for their job rank. The effect of "Same age \times Odd age within job rank" describes the effect of same age for bankers older or younger than is usual for their job rank. Reagans and Burt (1998) show a negative bias in peer evaluations between same-age bankers at the median age for their job rank, and attribute the negative bias to competition between the many bankers that cluster around the median age. Consistent with that finding, Model VI shows increased decay in relations between same-age bankers at the median age for their job rank (3.2 z -score). Reagans and Burt (1998) also show a positive bias in evaluations between same-age bankers who are much older or younger than the median for their job rank, which they attribute to the legitimacy that same-age people of an unusual age lend one another. Consistent with that finding, Model VI shows decreased decay in relations between same-age bankers much older or younger than the median age for their job rank (-2.2 z -score).

5.2.3. *Embedding slows decay*

For reasons of information flow and enforceable social norms, relationships embedded in dense networks are more likely to reach extremes of trust and distrust (e.g., Bott, 1957, for a preliminary discussion; Granovetter, 1985 on structural embedding and trust; Coleman, 1990 on social capital and trust; Burt and Knez, 1995 and Burt, 1999 on gossip and trust). To the extent that embedding facilitates the development of strong relations, it could be expected to slow their decay.

Embedding turns out to be relevant in three ways. First, it has a strong association in the expected direction with decay. Model VII shows slower decay for relations embedded in dense networks (-8.1 z -score, $P < 0.001$). Embedding is measured by the number of third parties through whom banker and colleague were connected last year. The count increases by one for a banker-colleague relationship each time the banker cited someone who in turn cited the colleague.

The effect is primarily from positive connections. In Model VIII, the count of all third-party ties is disaggregated into three components: the number of positive-positive ties (banker made a positive evaluation of third party who made a positive evaluation of the colleague), negative-negative ties (banker made a negative evaluation of third party who made a negative evaluation of the colleague), and negative ties (banker's evaluation of the third party was the opposite of the third party's evaluation of the colleague). Decay is most clearly slowed by third-party ties composed only of positive evaluations (-6.2 z -score, $P < 0.001$). Positive third-party ties composed of two negative evaluations have a less obvious, but still strong, association with decay (-4.0 z -score, $P < 0.001$). Negative third-party ties have the weakest association with decay, though they too slow decay (-2.3 z -score, $P = 0.02$).

5.2.4. *Embedding explains decay-inhibiting effects of homophily*

Second, embedding explains the decay-inhibiting effects of homophily. There are no significantly negative effects on decay for the homophily variables in Model IX. Specifically, the age-homophily effect that is significant in Model VI (-2.2 z -score) is

negligible in Model IX (-1.3 z -score). In other words, the slower decay in relations between same-age bankers of unusual age for their job rank can be attributed to such bankers having more mutual contacts with other colleagues.

The gender-homophily effect is similarly explained. In Model VI, the faster decay in relationships involving a woman could be due to the fact that women received less positive evaluations on average (means in the Fig. 2 legend, -3.0 t -test for lower evaluations of women), and less positive evaluations are more subject to decay. However, this is not sufficient since strength of positive evaluation is held constant in Model VI, and adding strength of negative evaluation from Table 4 has no effect on the -3.5 z -score for “both men” in Model VI (0.3 z -score for strength of negative evaluation). Prominence in the organization would be another reasonable explanation for the gender effect. Women were less prominent than men on average — a job rank lower than men (0.82 ranks, -8.2 t -test) and cited six fewer times as a colleague (5.85 fewer, -2.3 t -test) — and decay is faster for less prominent people. But this too cannot be the whole explanation because job rank and citations received are held constant in Model VI. Embedding is the explanation. Women were less likely to be connected indirectly through third parties (-3.8 t -test), and the “both men” association with decay significant in Model VI (-3.5 z -score) is negligible in Model IX (-1.3 z -score). In other words, the slower decay in relationships between men can be attributed to men having more mutual contacts with other colleagues.

5.2.5. Embedding stability explains decay-inhibiting effects of age

The third way in which embedding is relevant is that its stability explains the slower decay in older relationships.

Chains of relations define the indirect connections that are the substance of embedding, the individual relations in the chains decay at a fast rate in this study population, so third-party ties can be expected to change from one year to the next.¹⁰ Consider Table 6. Parentheses contain counts of relations, followed by a loglinear z -score test-statistic for the extent to which the count is higher than would be expected if embedding in year T were independent of embedding in year $T-1$.¹¹ Embedding stability is evident from the large positive z -scores in the diagonal (12.2 z -score shows that “none” this year tends to be “none” next year, 21.1 z -score shows that “five or more” this year tends to be “five or more” next year, etc.) and large negative z -scores far away from the diagonal (-5.3 z -score shows that “none” this year is unlikely to be

¹⁰ As first reported by Feld (1997), embedding is more stable than individual relationships since embedding is an aggregation across third parties. Across the 22,709 relations at risk of decay, there is a 0.50 correlation between third-party ties from banker to colleague in years T and $T-1$, vs. a 0.30 correlation between the banker’s evaluation of the colleague in years T and $T-1$. Still, a correlation of 0.50 means that 75% of the variance in embedding this year cannot be predicted from embedding last year.

¹¹ The four levels of embedding are arbitrary in the sense that decay rates plotted against third-party ties show a continuous linear decline with an increasing number of third-party ties, but the categories are sufficient to illustrate the effect of stability on embedding’s effect to be tested with continuous measures in Tables 5 and 7.

Table 6
Decay by lagged embedding

Number of third parties in year $T - 1$	Number of third parties in year T				
	None	One or two	Three or four	Five or more	Total
None	0.931 (667, 12.2)	0.702 (141, 5.7)	0.652 (23, -3.4)	0.667 (9, -5.3)	0.882 (840)
One or two	0.932 (2101, 5.2)	0.647 (788, 7.1)	0.609 (258, 0.7)	0.505 (99, -6.3)	0.823 (3247)
Three or four	0.940 (2149, -9.9)	0.675 (949, -1.5)	0.581 (559, 4.9)	0.499 (337, 1.7)	0.789 (3994)
Five or more	0.957 (5385, -27.9)	0.701 (1963, -21.7)	0.610 (2055, 2.9)	0.444 (5225, 21.1)	0.691 (14,628)
Total	0.947 (10,303)	0.683 (3841)	0.605 (2895)	0.449 (5670)	0.734 (22,709)

Entries are hazard rates (portion of relations at risk of decay in year T that were not cited in year T). Parentheses contain the number of relations from which hazard rates are computed, followed by the loglinear z -score indicating the extent to which the frequency is higher than would be expected if the number of third parties around a relationship in year T were independent of the number in year $T - 1$.

“five or more” next year, -27.9 z -score shows that “five or more” this year is unlikely to be “none” next year). Embedding instability is evident from the fact that two of every five relationships are more than a category away from the diagonal (42.4%, e.g., 5385 relations were embedded in five or more third-party ties last year but none this year).

The interesting point is what happens to decay when embedding is not stable. The Table 6 entries not in parentheses are decay rates. The row and column marginals of the table show slower decay in relations more embedded in third-party ties in either year.

Within the table, decay rates systematically decrease and increase with embedding. To the right in the table, more third-party ties at time $T - 1$ protect a relationship from decay at time T . For example, decay rates decrease from 0.667 to 0.444 down the rows of the “Five or more” column in Table 6, and the decrease is statistically significant (-2.4 z -score). In contrast, decay rates increase down the rows of the “None” column in Table 6. The increase is slight, from 0.931 to 0.957, but it is statistically significant (3.2 z -score) in clear contradiction to rightmost column in the table. Column one describes an effect of what can be termed “disrupted embedding” in the sense that any third-party ties embedding a relation in year $T - 1$ are stripped away to no third-party ties by year T . Decay is slower in a relation consistently unsupported by third-party ties (0.931) than it is in an embedded relationship stripped of third parties (0.957).

Guided by these results, two embedding variables are specified in Model IX in Table 5: Disrupted embedding is the count of third-party ties from banker to colleague this year multiplied by a dummy variable equal to 1 if there are no third-party ties from banker to colleague next year. High scores indicate a large number of third-party ties “disrupted” between year $T - 1$ and year T . Continuous embedding is the count of third-party ties from banker to colleague this year multiplied by the count of third-party ties next year. High scores indicate a relationship embedded in a dense network through year $T - 1$ and year T . The specific colleagues involved as third parties could be different in the 2 years. This is a measure of embedding continuous in volume, not constituent third parties.

Stability is critical to embedding's effect on decay. Disrupted embedding speeds decay (11.7 *z*-score, $P < 0.001$), while continuous embedding slows decay (-12.3 *z*-score, $P < 0.001$). The strong positive association in Model IX for disrupted embedding means that the decay associated with disrupted embedding increases with the strength of the embedding disrupted. More disrupted third-party ties in year $T - 1$ create a larger increase in decay by year T .

Some portion of the disrupted-embedding effect is due to colleagues leaving the firm. If a banker has an embedded relation in year $T - 1$ with a colleague who leaves the firm by year T , then the relationship and the embedding are both gone at year T . The cause of the relationship decay is not disrupted embedding; it is the simultaneous termination of the relationship and embedding by the colleague's exit. The first two columns of Table 7 contain estimates for Model V in Table 5 computed for (a) colleagues known to be with the firm in year T , then computed for (b) all colleagues some of whom left the firm before year T . Both columns show a statistically significant positive association between decay and embedding in year $T - 1$. In other words, the disrupted-embedding effect on decay is not due to colleagues leaving the firm. In fact, the only model in

Table 7
Decay functions by lagged embedding

	Number of third parties in year T				
	None ^a (continuing colleagues)	None ^b	One or two	Three or four	Five or more
Intercept	8.370	9.210	2.347	0.610	-0.049
Years tie has been observed (T)	-2.014 (-11.0)*	-2.092 (-11.6)*	0.162 (1.5)	0.536 (4.0)*	0.641 (6.9)*
Positive strength of relationship	-0.048 (-0.6)	-0.076 (-1.0)	-0.135 (-2.2)	-0.201 (-3.4)*	-0.260 (-5.6)*
Panel in which tie is first cited (P)	-1.511 (-11.8)*	-1.609 (-12.3)*	-0.827 (-11.9)*	-0.491 (-4.7)*	-0.088 (-0.7)*
Banker job rank	-0.447 (-4.1)*	-0.532 (-4.3)*	-0.281 (-4.1)*	-0.207 (-2.9)*	-0.256 (-2.9)*
Cites from banker in year T	0.004 (1.0)	0.004 (1.3)	0.006 (3.4)*	0.009 (3.9)*	0.008 (2.9)*
Cites to colleague in year T	-0.008 (-3.3)*	-0.023 (-11.5)*	-0.007 (-3.3)*	-0.004 (-1.4)	-0.022 (-11.2)*
Colleague outside banking division	0.172 (1.3)	0.438 (3.4)*	0.227 (2.7)*	0.070 (0.7)	0.570 (7.3)*
Number of third-party (TP) ties	0.033 (2.1)	0.039 (2.4)	-0.009 (-0.9)	-0.006 (-0.5)	-0.017 (-2.4)
Chi-square (8 d.f.)	306.5*	427.4*	252.9*	103.5*	378.4*
Number of relations at risk (N)	6655	10,303	3841	2895	5670

These are logit coefficients predicting decay with test statistics in parentheses (*z*-scores adjusted for autocorrelation between relations cited by the same respondent). Relationships in the None columns are to colleagues with whom the banker had no indirect connections through third parties in year T ; column None^a relations are with colleagues still employed in the firm, column None^b relations are with all colleagues, some of whom left the firm during the year before time T . * $P < 0.01$.

Table 7 in which embedding significantly slows decay is the final model, for relations in which embedding is continuous or increasing from year $T - 1$ to year T .

There is more at issue here than aggregating effects that contradict one another. At the top of Table 5, decay is slower in older relations in all of the models except the last one. In Model IX, which controls for embedding stability, decay is faster in older relationships (4.0 z -score). Table 7 more clearly shows the association between embedding stability and the liability of newness. The “None” column describes the effect of disrupted embedding, which speeds relationship decay (2.4 z -score). The “Five or more” column describes the effect of continuous embedding, which inhibits relationship decay (-2.4 z -score). Across the columns, with increasing embedding at time T , the significantly negative (-11.6 z -score) effect of tie age (T) in the “None” column shifts to negligible, then to significantly positive (6.9 z -score) in the “Five or more” column. The negative effect of node age (P) shifts more slowly, but it too shifts from negative in the “None” column (-12.3 z -score) to negligible in the “Five or more” column (-0.7 z -score).

In other words, the decay-inhibiting effects of age occur where embedding is disrupted but not where embedding is continuous. The aggregate negative effects of tie age and node age in Table 5 occur in this study population because there were more relations with disrupted embedding (“None” column in Table 7) than with continuous embedding (“Five or more” column in Table 7).

6. Conclusions

There is pattern to the dissolution of relationships. The tendency for relations to weaken and disappear I discussed as decay, and functions describing the rate of decay over time I discussed as decay functions.

I draw three conclusions from the analysis. The first is that factors known to be associated with strong relationships are associated with slow decay. In the study population of bankers and their colleagues within a large financial organization, decay is slower in relations between colleagues with a strong prior relationship (path dependence), working in the same corporate division (homophily), prominent in the social hierarchy of bankers (status), or connected indirectly through many third parties (embedding). Decay also varies by kind of relationship, again showing consistency between the decay and formation of relationships. The equations in Fig. 1A can be used to state decay in a more intuitive way. Set Y equal to 0.5 and solve for T to determine the number of years after which half of relationships observed today will be gone. Half of social relations with family can be expected to disappear within three and a half years (3.42). Decay is faster in social relations beyond the family, two and a half years (2.63). These rates highlight the speed with which the colleague relations decay; half disappear within 6 months (0.46 years).

Second, regardless of slower decay in certain relationships, decay has a pattern over time similar to the population ecology “liability of newness” attributed to selection and learning, with the added complication of networks and people aging simultaneously. Decay is a power function of time in which the probability of decay decreases with the

years for which a relationship has existed (tie age) and the years for which a banker has been in the study population (node age). Summary decay functions are plotted in Fig. 3A for parameter estimates in Model V in Table 5. As in Fig. 1B and Fig. 2, the vertical axis is the probability of a relationship disappearing next year, and the horizontal is the years for which the relation has been observed (tie age). The solid line at the bottom of the graph describes decay in the relations least subject to decay; bankers are experienced ($P = 3$, job rank = 3), there is a strong prior relationship (score of 2), the colleague is prominent in the informal social structure of the company (cites to colleague set to the 75th quartile of the distribution, which is 32 cites), the colleague is another banker, and the relationship is embedded in a dense network (third-party ties set to the 75th percentile of the distribution, which is 11 ties).¹² The dashed line at the top of the graph describes decay in the relations most subject to decay; bankers are inexperienced ($P = 1$, job rank = 1), there is no prior relationship (score of 0), the colleague is peripheral in the informal social structure of the company (0 cites to the colleague), the colleague works in a division outside banking, and the relationship has no supporting third parties. The bold line in Fig. 3A describes decay in the average relationship. The extreme rates of decay are clearly distinct, but all three lines in the graph show the liability of newness in which decay slows in proportion to the age of a relationship.

Third, the decay-inhibiting effects of age can be attributed to embedding stability. Decay slows with age when embedding is disrupted, but increases with age if embedding is continuous. This point is illustrated in Fig. 3B, again using Model V in Table 5 but with the aggregate measure of embedding in Model V replaced by the separate measures of disrupted embedding and continuous embedding. The bold line in Fig. 3B is, as in Fig. 3A, decay in the average relationship. The dashed line describes relationship decay with disrupted embedding; the relationship is almost certain to decay within a year or two, but if it manages to survive for a few years, the hazard of decay drops quickly (this is the strong anti-decay effect of relationship age in the first column of Table 7). The solid line in Fig. 3B describes relationship decay with continuous embedding; the relationship is almost certain not to decay for several years — but exogenous shocks over time increase the hazard of decay over the long run (this is the strong positive effect of relationship age in the last column of Table 7 and in Model X in Table 5).

There are practical and theoretical implications. Since continuous embedding enhances survival, but speeds decay if the embedding is disrupted, the implied strategy for building stable relationships is to build them free of third parties when the stability of third parties is uncertain. A theoretical implication is that the decay-inhibiting effect of age described as the “liability of newness” in population ecology need not be about learning or selection processes. It could instead be about the continuity of the social structure in which aging occurs (cf. Tilly, 1996: 592–593, on the “invisible elbows” that sustain social structure).

¹² The number of colleagues cited by a banker, out-degree, is control variable set equal to its average value (53.160 cites) for Fig. 3A and combined its effect with the intercept term. Similarly, intercepts for the equations in Fig. 3A contain the effects of all predictors but tie age (T).

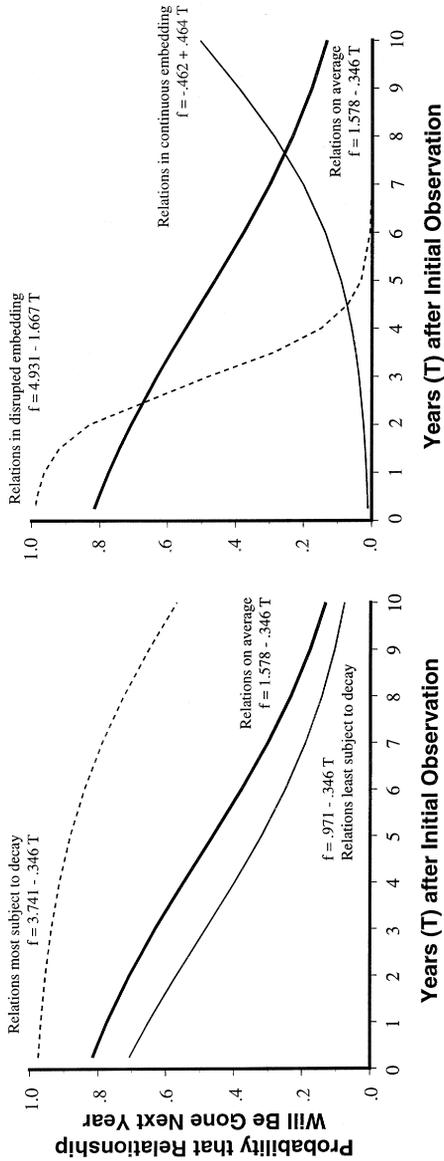


Fig. 3. Summary decay functions.

There is a broader implication for theories of social structure. Social structure is typically discussed in terms of levels; this network compared to that one is larger, or more balanced, or more constraining, or more dense, or more hierarchical, and so on. Thinking in terms of levels is consistent with available network data, which are typically cross-sectional. Theories focused on levels of social structure offer little incentive to incur the costs of gathering network data over time.

It is productive, therefore, to note decay taking two dramatically different routes as a function of embedding being continuous (whereupon decay is extremely unlikely and of increasing probability over time) or disrupted (whereupon decay is extremely likely and of decreasing probability over time). The two decay functions cannot be distinguished from the level of embedding in which a relationship began. The two functions are distinguishable only from change in embedding. In other words, it is the first derivative of social structure, not the integral, that is the critical factor in relationship decay. How many other aspects of social life will become apparent when the level variables in terms of which we think about social structure are replaced by change variables?

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