Note on the Time Lag for Network Effects

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Occasionally, a question from an intelligent person unfamiliar with network theory or analysis makes you aware of a foundational assumption implicit in how you think. Those questions are a treasured joy from participating in executive education, university teaching, and better dinner parties. I recently received such a question from a free-lance writer in Munich, Rose Jacobs, who had been retained by the Booth School of Business to do a piece for the school magazine on a forthcoming article (Burt, Opper, and Holm, 2021). By email message subsequent to an initial discussion, Rose asked the following question (quoted from Rose's message with her permission):

> "How long does it take for a network to affect a person's behavior? … I think what Table 6 says is that it takes at least a few years for a person's network to affect his penchant to cooperate with strangers … this suggests the structure of our networks during Covid won't do much to affect our behavior going forward — unless we decide to (or are forced to) stick with that structure for some time further."

My assumption has long been that network effects are instantaneous. You live in a structure of relations with and among colleagues. That pattern of social connections predisposes you to predictable behavior, with predictable results.

Rose's inference made me think a little deeper about my assumption. Put aside for another time the interesting question of whether networks are outcome or cause. The preliminary question at issue is "time lag," by which I refer to the interval of time required before we see network associations with known correlates. For simplicity, I will speak as though networks affect subsequent correlates, and use the term "network effects" in the traditional meaning of outcomes that result from a network.

Time lag is typically left implicit in an analysis, perhaps because it is obvious to network cognoscente. However, not making the assumed time lag explicit can create confusion for interested people beyond the cognoscente. More to my interests, making assumed time lags explicit should improve the clarity with which we compare our projects, which should improve the odds that explanations refine one another, and what we know cumulates across projects.

Acknowledgment: I appreciate invigorating reactions from colleagues on drafts of this note: Martin Gargiulo, Alessandro Iorio, Martin Kilduff, Pier Mannucci, Ajay Mehra, Sonja Opper, Mario Small, Giuseppe Soda, Stefano Tasselli, Marco Tortoriello. My friends are not, of course, culpable for the opinions expressed here.

Overview

In reflecting on Rose's question, I settled on six points discussed here. (1) The time lag for network effects has two frames of reference. The effect of established network behavior is instantaneous, but it takes time for predictive network behavior to become established. We know precious little about the latter. Current practice is to assume that whatever network we see is established network behavior. (2) To alleviate the ignorance in that assumption, it would be useful to include in our data collection more information on years one has known each cited contact (already often collected), and key connections formed in past events especially significant for the respondent. (3) In the interest of simple, cumulative theory, focus on the instantaneous effects of network structure separate from the sequence of effects in network evolution, using the former to animate the later. (4) To understand the effect of an event in the field or in a lab (Figure 3), know the established network behavior that is context for the event. (5) To understand momentum effects, ask whether the effect under study is enhanced or inhibited by the effect of another dimension of established network behavior — as illustrated by brokerage contingent on status and reputation, or the relative effects of relational versus structural embedding. (6) For example, we know enough to say that it would be wise to include in our data on manager networks name generator(s) about work content along with name generator(s) about social content. The two broad kinds of relations are often distinguished by managers in their networks (Figure 4), but often distinguished differently by different managers, and the structure of each complements/constrains the other such that they together make better network predictions than either alone (Table 2).

Momentum Effects and Compound Effects

As a tentative beginning, I suggest that we distinguish, and attend in theory, to two kinds of network effects: momentum and compound. Both forms are instantaneous. There is no time lag. However, momentum requires a build-up period to establish a pattern of network behavior, and compound effects are a function of pre-established networks. Rose's question is illustrative of the kinds of questions being asked about social mechanisms that explain how familiar network effects occur (e.g., Burt, 2004, 2010, 2021; Kwon et al., 2020; Obstfeld, 2005; Small, 2009, 2017; Soda, Tortoriello, & Iorio, 2018; Soda, Mannucci, & Burt, 2021; Tasselli & Kilduff, 2021).

"Momentum effects" occur when an established pattern of network behavior predisposes a person to predicted behaviors or outcomes. The established pattern could have been learned, or come to be in any other way that makes it routine, taken-for-granted behavior. In essence, momentum effects are autocorrelations: an established pattern of behavior is used to predict subsequent behavior. Much of network theory and analysis falls into this category. Examples would include the network effect on cooperation that Rose asked about, the network effect hypothesized in network theories of status (Podolny, 1993, 2005), the network effect hypothesized in structural holes theory (Burt, 1992, 2005, 2021), Coleman (1988) and Putnam's (1993, 2000) image of social capital, long-familiar network effects in the diffusion of behavior and opinion (Coleman, Katz, & Menzel, 1957), and the many behavioral correlates of closed networks such as low self-monitoring (Mehra, Kilduff, & Brass, 2001), low creativity (Soda, Mannucci & Burt, 2021), and temporal myopia (Opper & Burt, 2021).

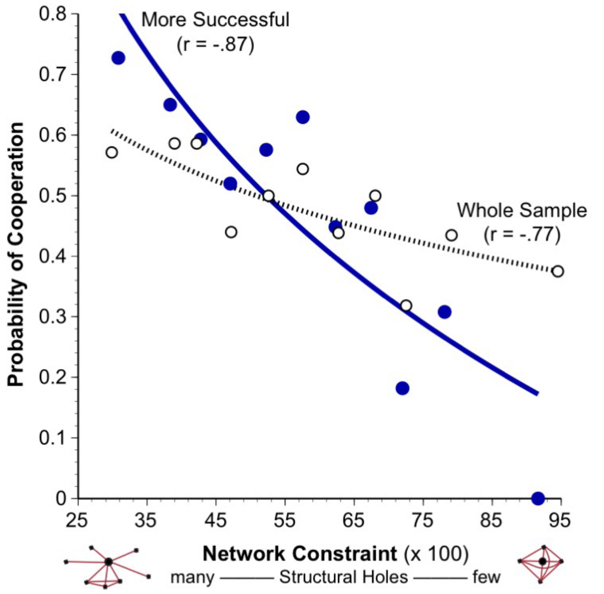
By "compound effects," I refer to behaviors and outcomes predicted to occur from a mixture of multiple momenta (in complement or contradiction), or the combination of momentum with an event that disrupts the momentum. Familiar examples of multiple momenta are returns to brokerage contingent on a person's social standing (Rider, 2009; Burt & Merluzzi, 2016), or the distinct effects of relational versus structural embedding (Granovetter, 1992; Burt, Bian & Opper, 2018), or the complementary effects of brokerage versus closure (Burt, 2005) among a person's colleagues versus friends (to which I return at the end of this note). Familiar examples of momentum disrupted by an event would include the many lab experiments in which restricted network access has predictable consequences (Leavitt, 1951; Cook et al., 1983; Markovsky, Willer, & Patton,1988; Burt, Reagans, & Volvovsky, 2021), or the general task of search in which a person tries to locate something, as when you use an internet browser (Milgram, 1967; Lee, 1969; Granovetter, 1974; Watts & Strogatz, 1998; Kleinberg, 1999, 2000; Lin, 2001; Burt et al., 2019). Covid is another example disruptive event, to which I return later in this note.

The Evidence

To ensure we're firing from the same side of the ship, Figure 1 displays the evidence from which Rose reasoned. Figure 1A is the core result in the research about which Rose was asked to write. The horizontal axis measures network closure by the network constraint index. Small, dense networks are to the right (network poses high constraint). Large, open networks are to the left (network poses low constraint, i.e., network brokers). The data come from a large area probability sample of Chinese CEOs leading small to medium size private companies. The argument in the paper is that the social security created by reputation cost within a closed network makes relations with people beyond the network seem risky in comparison. The more comfortable the network around you, the more risky seem relations beyond the network. The vertical axis in Figure 1A is the probability that a respondent entrepreneur cooperates in a one-shot game of Prisoner's Dilemma with an unknown Chinese CEO similar to the respondent. The downward sloping lines in Figure 1A show the expected effect: the more closed the network around a respondent, the less likely he or she cooperates with the unknown peer outside the network. The association is particularly strong for CEO's leading profitable businesses (solid line). If you've managed to rise above the odds and be successful with a closed network, you are all the more self-righteously uncomfortable cooperating beyond the network.

Figure 1. Evidence.

A. Cooperation and Social Network



NOTE – Plotted data are averages for 5-point intervals on X with thin tails of X truncated for infrequency. Displayed correlations are computed from the plotted data. "More Successful" are CEOs whose businesses had above-median profit last year. Adapted from Burt et al. (2021: Figure 1).

B. Cooperation and Network History

	Events Go Back	Coefficient for CEOs of Successful Businesses	
Only Current Contacts	0.0 years	-.71	(-0.99)
Plus Event-5 Contacts	1.6 years	-1.15	(-1.40)
Plus Event-4 Contacts	3.6 years	-1.57	(-2.01) *
Plus Event-3 Contacts	5.8 years	-2.14	(-2.79) **
Plus Event-2 Contacts	8.2 years	-1.79	(-2.74) **
Plus Event-1 Contacts	10.7 years	-1.90	(-3.00) **
Plus Founding Contacts (whole network)	11.8 years	-2.24	(-3.31) ***

NOTE – Each row contains logit coefficient and test statistic for the slope of the solid line in the graph. Networks in the top row include only current contacts. Networks in the bottom row include all current and all event contacts (which are the networks used for the graph). "Events Go Back" is the average number of years ago that the oldest included event occurred. All controls in the analysis are held constant here. Adapted from Burt et al. (2021:Table 6).

* P ≤ .05 ** P ≤ .01 *** P ≤ .001

The table in Figure 1B contains the results from which Rose made her inference about time. My colleagues and I wanted to show in the paper that the associations in Figure 1A were the result of behavioral patterns established over time — i.e., that the network behavior pre-existed the survey moment at which the respondent chose between cooperation or defection. We traced a respondent's network back in time. Some of the contacts cited by respondents were important contacts in current business. Many were met daily (53%), but a sizable number were met less than monthly (14%). What they had in common was that they were important for the respondent's business this year. Other contacts were cited for helping the respondent deal with significant events that had come up during the history of building the business. Call the latter contacts "event contacts." Event contacts are often people the respondent meets frequently (63% are met daily), but they are not among the people cited as most important for business this year.

We built a sequence of networks around each respondent, beginning with only current contacts, then adding event contacts one at a time, recomputing network constraint at each iteration. The result was seven networks around each respondent (corresponding to the rows in Figure 1B). The first was a network composed only of contacts cited on name generators eliciting current contacts. The second was the current contacts plus the contact cited as particularly valuable in helping the respondent with the most recent event. The most-recent prior event contact was then added to the network, and so on until we reached the whole network composed of a respondent's current contacts plus all of his or her recorded event contacts. The results in Figure 1A are based on the whole network.

The table in Figure 1B shows how the "network effect" on cooperation during the survey becomes stronger as the network around a person is extended further back in time. There is no association with the network of people named as important contacts this year (-.99 test statistic, P ~ .32). The association is statistically significant when the network is extended back more than two years (-2.01 test statistic), and more clearly significant after five years (test statistics of -2.79 to -3.31).

At the bottom of the next page, Table 1 shows what is happening as a person's network incorporates more history. (This background analysis is not in the published paper.) The three rows in the table distinguish CEOs by the extent to which their whole network is open. The third who are most to the left in the Figure 1A graph are in the "Open Network" row of the table. These are the network brokers, the people with the lowest constraint scores (less than 48.6 points of constraint). At the other extreme are the third of the CEOs with the most closed networks (more than 60.3 points of constraint). "Middling" is the third of CEOs in the middle of the distribution. Table 1 contains the 250 CEOs who ran the "more successful" businesses. These are the people who show the strongest network effect on cooperation (solid line in Figure 1A).

The panel to the left in Table 1 shows frequencies when CEOs are assigned to categories based on constraint computed from their whole network. These are the networks in the bottom row of Figure 1B. Two conditions are noteworthy. First, the CEOs running more successful businesses are disproportionately network brokers, as predicted by network theory (101 in the first row versus 78 in the third). Second, the network has a strong association with cooperation (58% cooperation in the first row, 37% cooperation in the third row; statistically significant chi-square for the table).

The panel to the right in Table 1 shows frequencies when CEOs are categorized by their network of current contacts (using the same category boundaries of 48.6 and 60.3). These are the networks in the first row of Figure 1B. Again, two conditions are noteworthy. First, CEOs are disproportionately in the "closed network" category (197 of 250 have constraint scores over 60.3 so they are assigned to the third row of the table). Second, the network association with cooperation is obscured (the chi-square for the table is negligible, consistent with the result in the first row of Figure 1B).

In other words, limiting a CEO's network to contacts important to business this year makes the CEO look like he or she lives in a network more closed than it is. Asking for event contacts distinguishes the CEOs who have broader networks than they are currently using this year. The closed-network CEOs in the panel to the right in Table 1 sort into two groups in the panel to the left: (1) CEOs whose event contacts are in their closed network of current contacts. These CEOs remain in the closed-network category of CEOs, unlikely to trust beyond their network. (2) CEOs whose event contacts come from groups outside their closed network of current contacts. These CEOs were erroneously assigned to the “closed network” category. They are network brokers when we know their event contacts, which moves them to the first row of business leaders, the people likely to cooperate beyond their immediate network.

Momentum Effect Is Distinguished by Build-Up Period

Rose asks whether it is reasonable to infer that the network effect “kicks in” after two or three years. Her question raises two questions rarely discussed: How much time does the network effect take to occur? And how long does a network have to be in place before it has its effect?

The answer to the first question is assumed to be “no time at all.” The network effect is instantaneous. Once we know a respondent’s established pattern of network behavior, we expect that behavior to shape current behavior. The point in Figure 1 is that business leaders in closed networks have a knee-jerk response of defecting in cooperative games with kindred leaders beyond the network. That knee-jerk

Table 1. Limiting Networks to Current Contacts Make Some Networks Look More Closed than They Are

	All Contacts (Whole Network) 9.99 chi-square, 2 d.f., P ~ .007			Only Current Contacts 0.23 chi-square, 2 d.f., P ~ .89		
	Defect	Coop-erate	Total	Defect	Coop-erate	Total
Open Network	42 (42)	59 (58)	101 (100%)	8 (47)	9 (53)	17 (100%)
Middling	29 (41)	42 (59)	71 (100%)	16 (44)	20 (56)	36 (100%)
Closed Network	49 (63)	29 (37)	78 (100%)	96 (49)	101 (51)	197 (100%)
Total	120 (48)	130 (52)	250 (100%)	120 (48)	130 (52)	250 (100%)

NOTE — These are frequencies for the 250 CEOs who ran the “more successful” businesses. The three rows distinguish the whole sample of CEOs by the third who had the most open networks (bottom 33% in constraint scores), a middling category, and the third who had the most closed networks (top 33% in constraint scores). The panel to the left shows frequencies when constraint is defined by all contacts (bottom row in Figure 1B). The panel to the right shows frequencies when constraint is defined by current contacts only (first row in Figure 1B). Row percentages are in parentheses.

response is a violent soccer-kick for business leaders who have been successful within a closed network.

The evidence in Figure 1B addresses the second question highlighted by Rose's query: How long does the network have to be in place before the pattern of behavior in it is established? Our purpose in presenting the evidence was to show that the prediction in Figure 1A depends on a pattern of network behavior established back in time. How far back was the empirical question. From the table in Figure 1B, I infer that a respondent's pattern of network behavior for two or three years is a good indicator of the respondent's behavioral predisposition in a game played today.

Thus the action question for the kind of network theory and analysis in Figure 1 is not: "How long does it take for a network effect to happen?" In most such predictions, the effect is instantaneous. The action question is: "How long does it take for network behavior to become established, routine?" In this, the network effect comes from the momentum of established network behavior.* That is the assumption, but I know of no direct evidence on the question. It can take time to establish a pattern of network behavior. But it can happen quickly too. Having myself just immigrated from Chicago to Milan, I can testify that the network context for one's behavior can change very much, very quickly.

Momentum Versus Evolution

Social networks are the accretion of interpersonal behavior in the context of current structure. Repeated or cathartic behavior can establish a pattern of network behavior such that it has momentum predisposing a person to think or behave in a predicted way. Whatever the predicted effect of network momentum, individuals can go with the momentum or resist it. The effect is our response to the momentum. The network is no more an actor than the dock on which the fish flops.

When we go along with the momentum, we reinforce current structure. An outsider shunned strengthens the bonds within a closed network. Resisting momentum can modify the structure — former friends no longer invited, new acquaintances full of promise, casual acquaintances given new significance by that unanticipated, intimate exchange. Engaging the outsider weakens bonds within a closed network, moving the engaged a little closer to an open network. In short, network structure evolves.

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*By "momentum," I have in mind that the interdependent elements in a network, in motion via the behavior of its inhabitants. The more numerous and interconnected the elements, the greater the network mass. The more frequent and unquestioned the behavior in the network, the greater the network velocity. Momentum increases with mass times velocity (https://en.wikipedia.org/wiki/Momentum, or for thoughtful exploration of the analogy, see Martin's, 2003, Rosetta-Stone discussion of field theory in the natural and social sciences, focusing on uses in social psychology, stratification, and organization theory).

This is familiar imagery. We have evidence that illustrates the imagery (Padgett and Ansel, 1993; Powell et al., 2005; Kossinets & Watts, 2006; Padgett & McLean, 2011; Van Wijk et al., 2013; Small, 2017), and ambitious efforts that try to systematize it (Stokman & Doreian, 2001; Jackson & Watts, 2002; Padgett and Powell, 2012; Tasselli & Kilduff, 2020). Network evolution is fascinating in its possiblities.

I highlight the imagery only to keep it separate from the topic at hand. I want to keep network theory simple to facilitate replication and knowledge cumulation. In the current state of development, I believe it wise to keep the effects of network structure at any one moment separate from the chain of events set in motion by how people respond to structure. The momentum of established network structure has predictable effects. The way people respond to that momentum is a function of personal history, intentions, and other people present — easy to describe, but difficult to predict. The evolution of network structure is a sequence of momentum, response, new momentum, new response, and so on. That is even more difficult to predict. Therefore, my aspiration for network theory in this note is to capture network momentum at a moment in time pressuring a person to think or behave in a predicted way. I leave it to the more adventurous to use bits of that theory to animate theories of network evolution. There could very well be sequences of momentum and response that occur frequently with predictable effect (e.g., Burt and Merluzzi, 2016, on oscillation; Mannucci and Perry-Smith, forthcoming, on network sequences; or the example in Table 2 at the end of the note on momentum from a manager's work versus social network). But much like theories of molecules built from atoms, it is productive to distinguish the molecules from the component atoms.

Compound Effect Resulting from Interrupted Momentum

Suppose you have an established pattern of network behavior, then an exogenous shock occurs inconsistent with the pattern. The shock of that disruptive event in combination with the established pattern can have its own effect. For example, how long does it take for a stressful conversation with a co-worker to affect your behavior? It is instantaneous. You are usually content in your exchanges with colleagues. Then you have a stressful conversation with that new guy. You are unhappy after, and that spills into your next few conversations. Smith, Menon & Thompson (2012) illustrate the point: Just having subjects in a lab read a stressful story is enough to produce a bias toward reporting that their network is a supportive circle of interconnected friends.

Disruptive events are commonplace, but they are particularly exposed for study in network research based on laboratory experiments, where disruption is defined by design. Subjects can be assigned to pre-defined networks to see how behavior is a function of network structure. In the classic Bavelas, Leavitt, and Smith experiments with team networks (Leavitt, 1951), subjects assigned at random to the star network (Figure 2) performed their work quickly due to the coordinating role of the central person, and the person assigned to the central role was happier with his work in the experiment than were his four teammates assigned to the peripheral roles. Cook et al. (1983) show further, with slightly more elaborate networks, that the person assigned to the central role earns more from exchanges with his teammates because the teammates have one person with whom they can exchange, while the center person has four possible exchange partners.

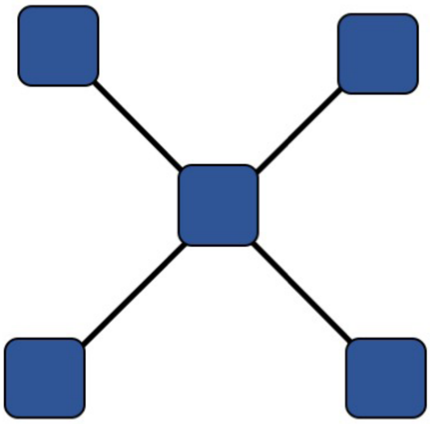


Figure 2. Bavelas-Leavitt-Smith Wheel Network

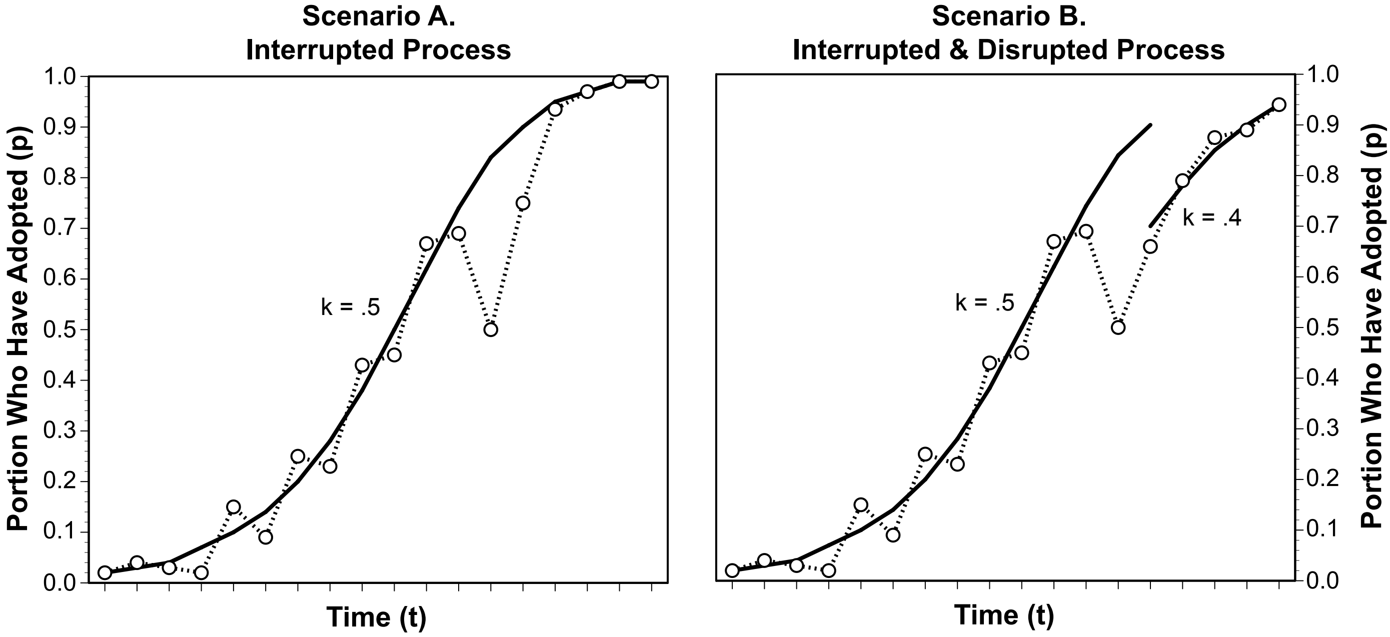
The event's effect is instantaneous, at whatever strength the event has. In fact, the effect of constraints imposed by a disruptive event is likely to diminish as people adapt to, and work around, the constraints (see Guetzkow & Simon, 1955; Burt et al., 2021, regarding the Bavelas-Leavitt-Smith team networks). In contrast, momentum effects are likely to be stronger for people whose current network becomes more established. Given two panels of data, the effect of network closure is likely to be stronger for people whose networks were closed during both the first and second panels. That is the idea behind the evidence in Figure 1B.

Disruptive event and established pattern both matter. Suppose your stressful conversation with the new guy occurs in the context of a workplace characterized by stressful conversations. One more stressful conversation is not much of a shock. The established pattern sets the stage for whatever results from the exogenous shock. The effect of that stage is a thing to distinguish from the effect of the shock. As social psychologist Solomon Asch (1952:61) said early on: "Most social acts have to be understood in their setting, and lose meaning if isolated. No error in thinking about social facts is more serious than the failure to see their place and function."

Let me illustrate by going back further to an early bit of empirical research rarely cited in contemporary work (12 Google cites at the end of July 2021). Pemberton (1937) describes four examples of disruptive events affecting the process of social diffusion. In a population of people who have access to one another, diffusion from one time period to the next can be modeled as: $dp/dt = k(1-p)p$, where p is the proportion of the population that has adopted, and k is the average probability of an individual adopting (e.g., Coleman et al., 1957:261). The change in proportion expected during a unit of time equals the average probability of an individual adopting (k) times the proportion of the population available to adopt ($1-p$) times the proportion of the population that has already adopted (p). The model describes a familiar S-shaped curve in which there are few adoptions initially as people are nervous about early adoption (low p), followed by a rapid bandwagon spread of adoptions as neighbors adopt, followed by a decrease in adoptions as their are few

Figure 3.
Interrupted Versus Disrupted Diffusion Processes.

Solid line is diffusion in theory (dp/dt = k(1-p)p). Dashed line is diffusion observed.



people remaining who have not already adopted (high p).

Figure 3 contains two examples. The bold line in Figure 3A is the theory prediction in a population where the typical person is 50/50 about adoption (k = .5). There is slow initial diffusion, followed by a rapid bandwagon of adoptions as more of the population adopts, concluded by slow diffusion among the few remaining people yet to adopt.

The dashed line in Figure 3A shows a hypothetical observed diffusion curve. The observed line hovers around the theoretical line across time — until it reaches a point at which the observed drops well below expected. The drop in adoptions is what Pemberton observed when World War I or the Great Depression constrained the availability of adopters during ongoing diffusion processes. Pemberton's point is that the momentum of the diffusion process is quickly re-established subsequent to the event, such that adoptions continue along the initial theoretical prediction — as illustrated by the dashed line reverting to the solid line in Figure 3A. The exogenous event merely interrupted the momentum of an established pattern of behavior.

The graph in Figure 3B describes a hypothetical event that interrupts and disrupts established behavior. Activity is the same in the two graphs up to the event. Subsequent to the event, Figure 3A shows a return to the prior pattern, while Figure 3B shows a new pattern consistent with theory, but at a lower level resulting in slower diffusion. If Figure 3A is an interrupted momentum effect (IM for easy reference), Figure 3B is an interrupted and disrupted momentum effect (IDM).

We know the difference between an IM and an IDM effect retrospectively. Given disruption by some event, the effect is an interruption if the momentum of pre-event network behavior is re-established after the event. The event is IDM until prior momentum is re-established.

Compound network effects raise a question for any experiment reporting a network effect. Since subjects are almost never randomly assigned to treatment with respect to their established network behavior, treatment effects can be affected by network behavior established before the experiment. For example, Freeman (1992) ran an experiment showing that people have difficulty learning a network that contains a structural hole, but Janicik and Larrick (2005) show that subjects experienced with such networks have a much easier time with the task. Burt et al. (2021:44) describe lab networks defined to allow every teammate to communicate with every other teammate. But subjects on one team performed as though they had been assigned to a wheel network (Figure 2). It turned out that one subject kept teammates so busy with messages that he transformed the network from a clique into a wheel network, whereupon the team performed like it had been assigned to a wheel network.
I expect that the person who hijacked the assigned clique network entered the experiment with an established pattern of network broker behavior. In a display of good practice, Mannucci and Perry-Smith (Forthcoming: 21-22) show that their lab network effect on creativity is robust to the network with which subjects entered the lab. Subjects with dense networks outside the lab show less creativity in the lab, as expected from network theory, but the dominant effect is from the network in the lab.

Back outside the lab, in our day-to-day lives, we often expect the disruption in Figure 3B when living through an event because we take for granted the established pattern waiting to re-assert itself. How many strategies intended to change behavior are advanced on the basis of the IDM effect in Figure 3B, but end up frustrated by the IM effect in Figure 3A? Management changes get made, public policy changes get made, all to be undone when managers revert to old habits. People participate in programs to eliminate self-destructive habits in their many forms (smoking, drinking, other drugs, eating, abuse, etc.), then return to their pre-program established behavior. Nevertheless, Pemberton's examples all show the IM pattern in Figure 3A. Even constrained by the severe events in Pemberton's examples, the pre-event diffusion process re-asserts itself. Perhaps this is the reason for immigrants being disproportionately the source of good ideas that develop into intellectual property (Maddux and Galinsky, 2009; Godart et al., 2015; Weiner, 2016). Established network behavior cannot reassert itself when it is left behind, in a distant place.

It would be reasonable to speculate that a process has to be well-established to survive events as severe as war or depression, let alone the usual modest events in network experiments. If the bandwagon period in a diffusion process indicates established behavior, then the speculation is supported by Pemberton's examples. In three of Pemberton's four examples, the interrupting event occurs well after the bandwagon began. However, Pemberton's fourth example is one in which the interrupting event occurs during the initial period of slow adoptions.

It would be reasonable to speculate that positive events contribute to an established process, while negative events are responsible for the interruption or disruption illustrated in Figure 3. It is often said that positive reputation builds slowly, but one instance of bad behavior can destroy a positive reputation. On average, however, stories exchanged among people in a closed network build and sustain positive reputations pretty much as they build and sustain negative reputations (Burt, 2005:198; 2010:163-171).

In light of Figure 3, consider Rose's inference about the network consequences of Covid. One can say that the Covid lockdown was a special hardship for parents living with children and for people living alone, but what is the effect post-Covid? Will network effects be weaker post-Covid (IDM effect), or will they be briefly stronger than ever from people rushing to re-establish pre-Covid life (IM effect)? For people who engaged pre-Covid in frequent exchanges with diverse, new acquaintances, lockdown was an exogenous shock inconsistent with their established network behavior. Suddenly life was drained of its vitality, talking with the same people about the same things again, and again, and again. Happy memories of activity pre-Covid were blown out of proportion by the longing for them. Release from lockdown into the world will be welcome — but likely disappointing relative to positive memories exaggerated into myth.

At the same time, there are people for whom lockdown became their established network behavior. You, your partner, and the dog lived happily safe at home, watching the world from your computer screen. For you, release from lockdown will be difficult as you once more take up the challenge of trying to find your place in the world — now that you know what happy feels like. Here are the people who would like to continue with the pandemic's detached lifestyle.

In short, Covid's effect on network behavior depends on who you were pre-Covid, and what you became over the span of the pandemic. It will be easy to record how people react to the pandemic's retreat, but I expect surprises for prognosticators who predict how people will react.

I find exhilarating how little we know about the interrupted momentum of compound network effects. There is a world of important work to be done here.

Compound Effect Resulting from Multiple Momenta

A simple network analysis involves a person in a network. As the person spends more time in the same network, the network behavior becomes more established, and its consequences more likely. The association with time need not be linear. A pattern of behavior can be established quickly, say for a person new to a situation (Li & Tangirala, 2021), or in response to a significant event (Burt and Opper, 2017), or it can emerge slowly as a by-product to other activity (Festinger, Schacter, & Back, 1950). On average, however, longer time in the same network is expected to more firmly establish a pattern of network behavior. Hence the statement earlier in this note that, with two panels of data, the effect of network closure is likely to be stronger for people whose networks were closed during both the first and second measurement.

The complication is that networks vary on multiple dimensions. Different aspects of the same network structure can have different effects. There are also differences in composition: Who are the other people in the network? And differences in content can matter: What is the substance of relations in the network? Each dimension of a network can have its own momentum. How established is the structure? Has this person's network been closed for a long time? The composition? Has this person been dealing with contacts socially similar to himself for a long time? The content? Has the stability of this person's social network tempered the chaos in her professional network? With multiple potential sources of effect, potentially contradicting one another, network effects are often compound effects resulting from the relative momentum of more than one network characteristic. The puzzle is to disentangle the components.

With respect to network structure, for example, the above statement about the effect of closure increasing with time spent in a closed network seems to be true, but not the reverse. The success associated with open networks can be diminished for managers who have consistently open networks. Open networks provide information benefits different from the reputation benefits of closed networks. Burt and Merluzzi (2016) show for a population of investment bankers that bankers on average are more successful with more open networks. But the most successful bankers oscillate between closed and open networks to get the benefit of both. Success is generally associated with access to structural holes (Burt, 2021), but not for would-be brokers with low status (Burt, 1997, 2005:156-162; Rider, 2009; Burt & Merluzzi, 2014).

Closure too has its variations. It is well-known in economics (e.g., Greif, 1989), law (e.g., Ellickson,1991; Bernstein, 1992), and sociology (e.g., Granovetter, 1985) that closed networks facilitate trust by creating a reputation cost for bad behavior (Burt, 2005: Chps. 3-4, for review). Granovetter (1992) terms this "structural embedding" to refer to a relationship embedded in a network of mutual contacts. But trust can also result from a history of positive experience with someone (Granovetter, 1992, on "relational embedding"), or positive behavior in a significant event (Burt, Bian, & Opper, 2018, on Chinese "guanxi"). Time is a key difference between the two network predictors. Relative to accumulating a positive history with someone, activating mutual contacts can occur quickly. Not surprisingly, structural embedding is especially consequential for trust in new relations (Burt, 2005:214-191, 2010:181-191; Dahlander & McFarland, 2013).

Continuing with respect to who is in the network, trust and cooperation are more likely between socially similar kinds of people (McPherson, Smith-Lovin, & Cook, 2001; Dahlander & McFarland, 2013). On the success association with network structure, Soda et al. (2021) show for TV production teams that individuals who have an open network do more creative work, but the effect of the open network is diminished if it is not refreshed with new teammates. It is not enough to work repeatedly with the same initially-diverse teammates.

With respect to network content, I will go into a little detail here because content issues are readily solved empirically, and good evidence is available. The core of what follows is a recommendation to routinely gather manager network data on both work and social relations.

Standard data-collection procedure is to identify a core set of people connected to a manager by some criterion kind of relationship defined by a name-generator question, then flesh out the network with name-interpreter questions about characteristics of the cited people, and relations with and among the cited people (how long known, how often met, how close to, family, same organization, etc.). Perry, Pescosolido, and Borgatti (2018) offer broad discussion of generators and interpreters. The name-generator criterion used in a study is typically mentioned in published reports with little or no discussion of why that criterion was selected. Popular options for manager networks are: job ***buy-in*** (“Who are the most essential sources of support, buy-in, for success in your job?”), **career value** (“Who have been the people most important for your career success?”), ***advice*** (“Who are the people to whom you turn for advice on work-related matters?”), or just ***work contact*** (“Who are the people with whom you most often discuss your work?”, or “Who are the people with whom you have had the most frequent and substantive work contact?”).

The above content criteria all have face validity in that each concerns important work relations. The guide to making informed choice between alternative criteria is a content map. Ask a set of informants in the target population to respond to multiple name generators using alternative criteria to see which alternatives elicit the same names. The data can be used to generate a content map: a spatial display of the extent to which two kinds of relations connect the same people. Kinds of relations then appear clustered together in the map. The more often two kinds of relations connect the same people, the more ambiguous the distinction between them as two kinds of relations. Friendship is easy to distinguish from business relations for people who never do business with friends. The distinction is more difficult for people who typically do business with their friends. Content maps are simple to construct, so I focus here on conclusions rather than procedure (see Burt, 1983, 2010:286-288).

Figure 4 on the next page shows four content maps. Specific question wording is available in the cited source publications. Figure 4A is a content map of the manager relations analyzed in *Structural Holes* (Burt, 1992, 2005:52). A sample of 284 senior managers in a large, American computer manufacturer cited 3,854 contacts in a network survey. The managers responded to nine name generators (listed in Burt, 1992:123), indicated in Figure 4A by solid dots. The managers also responded to four name interpreters (indicated by hollow dots) concerning the frequency with which they speak with each person named (daily, weekly, monthly, less often), how many

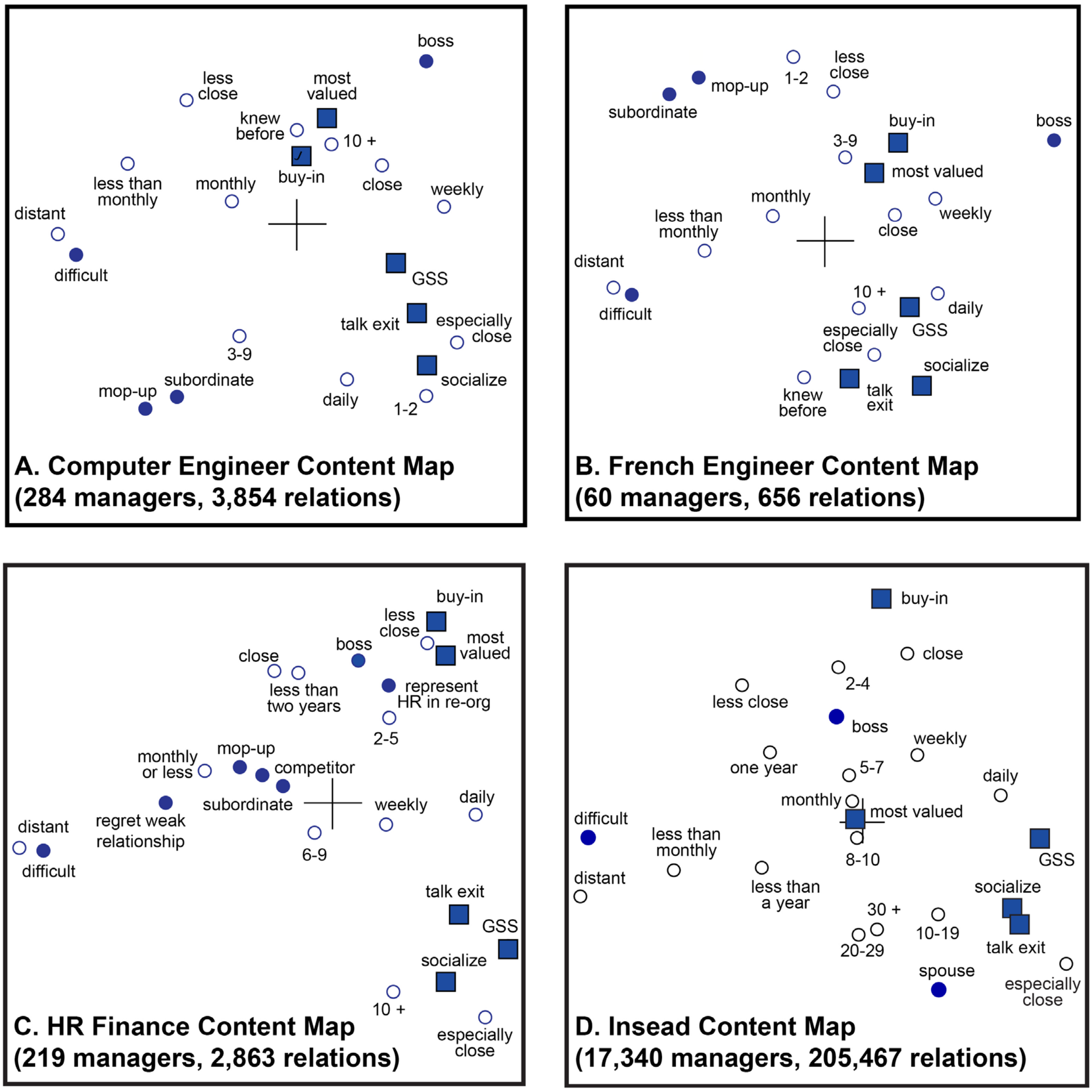


Figure 4. Content Maps

The images are classical multidimensional scalings of joint probabilities (in A and B) or Jaccard coefficients (in C and D) measuring the co-occurrence of contents. A, B, C respectively are adapted from Burt (1997:364), Burt, Hogarth, and Michaud (2000:136), and Burt (2010:287). D is new here. Name generator contents are indicated by solid dots. Five core generators are indicated by solid squares. Name interpreter contents are indicated by hollow dots. Number labels indicate years known. Crosshairs mark the center of the space, and axes are proportional in length to the eigenvalues defining them.

close, close, less close, distant), and how close each cited person was to each other cited person (especially close, strangers/distant, or something between).

The map shows two dimensions. The horizontal axis distinguishes positive relations to the right (especially close relationships, most-valued colleagues), and negative relations to the left (most difficult colleague, distant relationships). The vertical axis distinguishes work relations from social. To the northeast are the boss, ***essential sources of buy-in***, and most ***valued contacts***. To the southeast are the General Social Survey (***GSS***) generator ("Who are the people with whom you most often discuss matters important to you?"), ***socializing*** ("Who are the people with whom you most often get together for informal socializing such as going out to lunch, dinner, drinks, visiting one another's homes, etc."), and ***talk about exiting*** ("If you were considering another job, who are the people with whom you would most likely discuss your job options?").

The same two dimensions are apparent in the other content maps. Figure 4B is a map of relations cited by the managers in a division of a large, French chemical company. The map is not presented as typical of French managers. It was obtained as part of an effort to test for differences between American and French managers using a translation into French of the instrument used to gather the data in Figure 4A (Burt et al., 2000:135-137). The map is similar to the map in Figure 4A — a dimension of evaluation varying from positive at the right versus negative at the left, and a content dimension with work relations at the top and social relations to the southeast. (Points in the space are fixed distance from one another. Each space is rotated so that social relations are in the southeast of each map.)

Figure 4C is a map of relations cited by HR managers within a large, American financial services organization (Burt, 2010: 285-288). Again, a dimension of evaluation runs from positive at the right to negative at the left, with a pronounced distinction between various work relations at the top and a cluster of personal positive relations to the southeast.

Figure 4D is a content map based on network data obtained by Martin Gargiulo's network diagnostic website (executive-tools.insead.edu/socialcapital). I am grateful to Martin for sharing the citation data (anonymized). The respondents are managers in executive education programs and EMBA students at diverse universities (MBA students are excluded). The data summarized in Figure 4D are from 17,340 managers who cited a total of 205,467 contacts. The network instrument used in the website is similar to the generators and interpreters in *Structural Holes*, so the content map in Figure 4D is readily comparable to the other maps. Again, a dimension of evaluation runs from positive at the right to negative at the left, with a distinction between various work relations at the top and a cluster of social positive relations to the southeast, although the distinction between work and social contacts is least distinct in this heterogeneous assembly of relations.

Managers on average distinguish work from social relations, but the extent to which they do so varies tremendously between individuals. The average HR manager in Figure 4C cites 28.8% of her social contacts as work contacts, but the range goes from many managers who have no overlap between work and social, up to some managers whose cited social contacts are all work contacts. The average person in Martin Gargiulo's extensive diagnostic data (Figure 4D) cites 24.1% of his social contacts as work contacts, in a range that goes from many managers who have no overlap between work and social relations (2,570), up to just five with 100% overlap.

My reason for showing the maps to you is not to prove that social relations can be distinguished from work relations. It is to show that managers on average distinguish the two kind of relations, and that the two together offer better prediction than either alone, presumably because momentum for brokerage can build in either social setting. The distinction point is illustrated in Figure 4.

The prediction point is illustrated below in Table 2. The data in Table 2 are from the HR population in Figure 4C. Compensation, measured as a z-score, is predicted by a manager's job rank (higher compensation to managers in higher rank), years with the organization (higher compensation to managers longer in the organization), and network constraint (cf. plot and predictions in Burt, 2010:84-85). As expected, compensation decreases as the network around a manager closes, whether the closure happens in the manager's work relations (-2.20 t-test for Model 2, P ~ .02) or

Table 2.
Work versus Social Name Generators

	Predict Compensation			Correlations					
							Network Constraint		
	Model 1 (.62 R^2)	Model 2 (.60 R^2)	Model 3 (.61 R^2)	Comp.	Grade	Seniority	All Ties	Work Ties	Social Ties
Grade	.48 (13.21)	.50 (13.44)	.50 (13.74)	.75	1.00				
Seniority	.02 (3.19)	.03 (4.34)	.03 (4.55)	.43	.33	1.00			
All Ties	-.30 (-3.72)	—	—	-.49	-.41	-.40	1.00		
Work Ties	—	-.27 (-2.20)	—	-.36	-.35	-.17	.45	1.00	
Social Ties	—	—	-.34 (-2.72)	-.31	-.27	-.08	.25	.64	1.00

NOTE — Statistics are computed across 219 HR managers whose relations are mapped in Figure 4C. OLS regression models predict compensation from the indicated row predictors (routine t-tests are given in parentheses). "Comp." is the z-score level of annual compensation. "Grade" is a five-category variable distinguishing job ranks. "Seniority" is years employed by the organization. The log score of network constraint is used for the calculations to capture the nonlinear performance association. Network constraint for "All Ties" is computed from the network among all alters named on the 12 generators in Figure 4C. Constraint for "Work Ties" is computed from the network among the subset of alters named on the nine work generators at the top of Figure 4C. Constraint for "Social Ties" is computed from the network among the subset of alters named on the three social generators at the bottom of Figure 4C.

in the manager's social relations (-2.72 t-test for Model 3, P < .01). The test statistic for social relations is slightly stronger because constraint from social relations is slightly less associated with job rank. However, the strongest prediction comes from combining work and social relations in an aggregate network around the manager (-3.72 t-test in Model 1, P < .001). The magnitude of association is about the same for work (-.27), social (-.34), and work combined with social (-.30), but the clarity of the association is strongest for the combined relations, which means the network effect estimated from work and social relations will be more robust to variation in control factors. The same conclusion holds for the *Structural Holes* managers in Figure 4A; a single network of work and social relations together provides better prediction of promotions than either alone (Burt, 1997). In short, momentum for brokerage at work can build in a manager's work or social network.

Precious little evidence is available on which name generators to use, but what evidence we have is sufficiently consistent to recommend that any study of managers would be wise to gather network data on at least one work generator and one social generator. For comparability with past work, the safe course would be to use (1) a buy-in generator or general work discussion generator to identify core work contacts, plus (2) the GSS generator or a general socializing generator to identify core social contacts. To add a broader time frame to work relations, the content maps in Figures 4A, 4B, and 4C imply that a good secondary generator would be to ask for contacts most valuable to a manager's career. To add a broader frame of reference to social relations, all four content maps in Figure 4 imply that a good secondary generator to use is the informal socializing generator. If it feels awkward to ask about informal social activities, a more work-relevant relation that is clearly social in Figure 4 is the name generator that asks for people with whom a manager would discuss job options. Martin Gargiulo's popular network-diagnostic website includes all four of the above generators plus others. Marissa King's open-access network-diagnostic website also spans the work-social space, using a buy-in generator along with a GSS-like generator and a socializing generator (assessyournetwork.com).

I suspect that the reason why work and social relations together provide better prediction than either alone is because managers can hone brokerage skills in either one to compensate for closure in the other. A manager locked into a closed network of colleagues at work can perhaps develop brokerage skills among her diverse social contacts. A manager with a network of interconnected friends perhaps has the social support to engage in brokerage at work. With the attention given to work-life balance, I'm surprised at the lack of research on success as a function of the balance a manager draws between work and social relations.

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