

# NETWORK OSCILLATION

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The way a network develops over time has implications for the advantage it provides. We find that oscillation between closure and brokerage enhances network advantage. By “network oscillation” we refer to a period of deep engagement in a group (closure), followed by a period of connecting across groups (brokerage), followed by deep engagement in a group, followed by brokering, and so on. For evidence, we distinguish four dimensions to network volatility (churn, variation, trend, and reversal), measure the dimensions with panel data on a population of bankers, then add the volatility measures to models predicting banker compensation from status and structural hole measures of network advantage. Network volatility is not associated with performance directly or

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indirectly—but for one exception: reversals indicate a banker oscillating between closure and brokerage, and that oscillation strongly enhances the performance association with network advantage (measured by status or access to structural holes). In fact, network advantage has no association with performance for bankers who maintain stable brokerage or closure. Our evidence is sufficient to support and illustrate performance contingent on network oscillation, but our data are limited. With an eye to future research, we discuss three mechanisms that could be responsible for the oscillation effect.

#### Editor's Comment

The paper by Burt and Merluzzi provides important insights into the effects of change in an individual's network structure. Do individuals who experience network changes have better outcomes? This is the intriguing question addressed in the paper. Based on simple logic, a few disparate data points, and a bit of intuition, the authors explore the possibility that four different kinds of network change are important for individual advantage over time. With static network analyses dominating the field, Burt and Merluzzi's attention to change is quite important and energizing. To drive home their ideas and to create a vehicle for unpacking empirical findings, Burt and Merluzzi create a stylized example, starring Cat and Bob. Their example is a brilliant communication tool, as are the rich figures presented in the paper. Empirically, the authors find that oscillation between closure and brokerage in the network structure is crucial for advantage as time unfolds. This finding is interesting and impactful given the common belief that consistently strong brokerage is a key source of individual attainment. Overall, the finding has clear implications for future research, instruction in management-development classrooms, and managerial behavior.

C. Chet Miller, Action Editor

## INTRODUCTION

Standard practice in the last 20 years of research on network advantage has been to ask what network structures provide advantage, run studies looking for higher performance from advantaged people and organizations, then talk and teach about building and securing networks that provide known advantage. The practice has worked well. The research literature provides a good sense of how advantage is associated with certain network structures, especially the status of having many well-connected contacts (Podolny, 1993), and the brokerage advantages of those contacts being separated from one another by structural holes (Burt, 1992). The gist of the network story is that the division of labor makes information homogeneous, tacit, and therefore sticky within clusters of densely connected people such that clusters disconnect, buffered from one another by structural holes between them. Two people who have no connection with one another are more likely than connected people to operate in different clusters, working with different ideas and practices. The more disconnected the contacts in a person's network, the more likely the network spans structural holes. An individual whose social network spans

structural holes (call such people network brokers, connectors, hubs, or entrepreneurs) have information diversity, timing, and arbitrage advantages. The network brokers are more familiar with the diversity of surrounding opinion and behavior, so they are more likely to detect productive new combinations of previously segregated information, more likely to identify alternative sets of people whose interests would be served if the new combination were brought to fruition, and more likely to be able to frame their proposals in a way that appeals to target audiences. Thus, a structural hole is a potentially valuable context for action, brokerage is the action of coordinating across the hole with bridge connections between people on opposite sides of the hole, and brokers are the people who build the bridges. Network brokers are rewarded socially and materially for their work decoding and encoding information: People with access to structural holes are paid more than peers, receive more positive evaluations and recognition, get promoted more quickly to senior positions, and are more likely recognized as leaders (Burt, 2005; Burt, Kilduff, & Tasselli, 2013). However, there is an element of trust required to accept a proposed new idea or way of thinking. People have to see the broker as a credible, legitimate source. Where access to structural holes provides production advantage in detecting and developing good ideas, social standing provides an audience advantage in that people are comfortable accepting the broker's proposal. Senior job rank provides the requisite social standing. "The

Author's voice:

How did you get interested in this topic and why is it important



boss asked me to take care of it," is explanation sufficient to make sensible to colleagues your acceptance of a broker's proposal. Network status and reputation can also provide the requisite social standing to be accepted as a broker. "I followed John's advice on this since he is the guy to whom experts turn for advice." Again, extensive evidence has accumulated on status advantages associated with individual and organizational achievement (Podolny, 2005; Sauder, Lynn, & Podolny, 2012; and, Burt & Merluzzi, 2014; Lou & Tang, 2013, on the status interaction with network brokerage).

Given the empirical success of network advantage predicting achievement, theoretical models have been proposed to describe how advantage should be distributed in stable networks (Buskens & van de Rijt, 2008; Corra & Willer, 2002; Dogan, van Assen, van de Rijt, & Buskens, 2009; Goyal, 2007; Goyal & Vega-Redondo, 2007; Jackson, 2008; Reagans & Zuckerman, 2008; Ryall & Sorenson, 2007). The models often imply pessimistic conclusions about the feasibility of stable advantage, though stable advantage is not impossible (Kleinberg, Suri, Tardos, & Wexler, 2008), and in real life, people seem able to muddle through (Burger & Buskens, 2009): The people who have network advantage today are often the people who had network advantage yesterday. Among the bankers to be analyzed here, for example, network status is correlated 0.75 from year to year across four years. Banker access to structural holes is correlated 0.64. Persistent status advantage can be discussed as the familiar "Matthew Effect" (Gould, 2002; Merton, 1968). Stability in access to structural holes is becoming established with results such as Zaheer and Soda's (2009) finding that Italian TV production teams rich in access to structural holes tend to be composed of people who were rich in access several years prior. Sasovova, Mehra, Borgatti, and Schippers (2010) similarly find that continuing individual access to structural holes includes access to many of the same past structural holes along with more access to new structural holes.

These developments emerge against a backdrop of functional theory in which the imprimatur of "social structure" was reserved for stable features of networks. Networks that persist in time have meaning, serve some purpose, and are real in their consequences. Much like human capital that is anchored in enduring education credentials acquired as a person moves up through a stable stratification of grade levels, social capital is studied and taught as a level of network advantage to be developed and preserved. As Laumann and Pappi (1976: 213) expressed the sentiment during the 1970s resurgence of network images in sociology: "Despite differences in nuance associated with 'structure,' the root meaning refers to a persisting order or

pattern of relations among units." And well after network images were again mainstream in sociology, Sewell (1992: 2) broadened the observation as criticism: "structural language lends itself readily to explanations of how social life is shaped into consistent patterns, but not to explanations of how these patterns change over time. In structural discourse, change is commonly located outside of structures."

But we know that networks change and evolve with implications for organizations and the people in them. Our purpose in this paper is to highlight a specific kind of change that we find critical for network advantage. Absent the specific change, there is no advantage. Networks are made volatile by the entry and exit of contacts, the formation of new relations, decay of the old, and realignment of the continuing. Volatility includes random variation from year to year, as well as dramatic transitions and gradual trends in network structure, but we are not thinking about network change in terms of a destination equilibrium or broader context. Given an image of network equilibrium, observed networks can be studied for how they should move, or evolve, toward equilibrium, for example, change toward an equilibrium defined by exchange theory (Burke, 1997; Hummon, 2000; Marsden, 1981), change toward an equilibrium defined by balance theory (Doreian, Kapuscinski, Krackhardt, & Szczypula, 1996; Doreian & Krackhardt, 2001), or change contingent on context (Burger & Buskens, 2009; Johnson, Boster, & Palinkas, 2003). Our purpose in this paper is more modest. We study change as a characteristic property, something akin to the hum of a running engine. There is a certain amount of vibration and wiggle produced by people active in a network. We want to see how that vibration and wiggle affects network advantage.

Characteristic change could be random, corrosive to network advantage, or enhancing. If differences between previous, current, and subsequent networks are random noise, then the change can be ignored (though it would be wise to average out the random noise to focus on stable levels of network advantage—as has been past practice, and as we illustrate with the bankers to be analyzed).

However, even trendless change could be corrosive. Podolny (1993) argued that network status is an advantage because colleagues and clients use status as a visible signal of otherwise difficult-to-read quality. The signal is clear if a person's status is consistently low, or consistently high. The signal is unclear if status bounces up and down. The effect of an unclear signal should manifest as lower returns to a person's level of status. Bothner, Kang, and Lee (2006) show just such an effect among venture capitalists (VCs). Measuring VC status in annual networks of joint investments, they show that

high-status VCs enjoy faster growth, but those whose status bounced up and down over time grow significantly less quickly than would be expected from their level of status (see Bendersky & Shah, 2012, for a similar result in which status oscillation erodes the association between student status and grades). Similar sorts of penalties are evident elsewhere. For example, individuals who move from job to job more than the average are penalized because of unclear identity and an assumption of instability in their careers (Fuller, 2008). At the other extreme, robust, typecast identities can result in job opportunities (Ferguson & Hasan, 2013; Zuckerman, Kim, Ukanwa, & von Rittman, 2003).

On the other hand, certain kinds of change could be important to network advantage. In a structural holes story about brokerage, innovation, and growth, the valuable connections that span structural holes are fragile. Their fragility can be expected for several reasons (Stovel, Golub, & Milgrom, 2011), but regardless of reason, the fact is that bridges are prone to decay (Burt, 2002; Martin & Yeung, 2006; Quintane, Carnabuci, Robins, & Pattison, 2012; Sasovova et al., 2010; Zaheer & Soda, 2009). A certain amount of instability is to be expected in the networks associated with achievement as some projects turn out to be productive, and others not. Again, evidence exists in other contexts. For example, stable identities allow greater audience identification with film actors, but the stable identity is also a barrier to larger, more lucrative opportunities for the actor (Zuckerman et al., 2003). Merluzzi and Phillips (2016) find that investment banking candidates who focus their work experience and activity solely in one functional area (finance) are penalized in terms of lower bonus compensation and fewer job offers when they graduate from business school. Analyzing CEO pay among S&P 1500 firms from 1993 to 2007, Custodio, Ferreira, and Matos (2013) found that CEOs with generalist work histories earned 19 percent more than CEOs with specialist work histories. Employers prefer candidates who learn from varied experience.

Further complicating the situation, network status is not independent of access to structural holes. The people who have extensive access to structural holes tend to have high status; in fact, high returns to brokerage across structural holes are contingent on having an acceptable level of status (Burt & Merluzzi, 2014). Consistent with results in other organizations, network status and access to structural holes are closely correlated across the bankers analyzed here, and year-to-year change in each is closely correlated with the other (see Figures S2 and S3 in the Supplemental Materials). We take advantage of the correlation to refine our measurement.

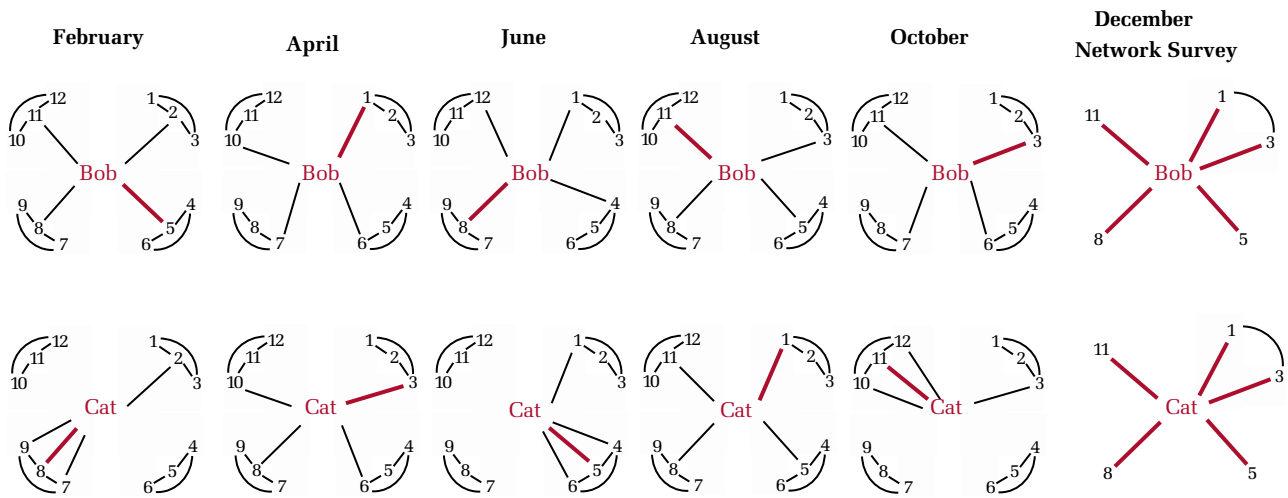
## Network Oscillation

We find that a particular kind of change enhances network advantage. Specifically, we find, and propose as a hypothesis for future research, that oscillation between closure and brokerage enhances network advantage. By “network oscillation,” we refer to a period of deep engagement in a group (closure), followed by a period of connecting across groups (brokerage), followed by deep engagement in a group, followed by brokering, and so on.

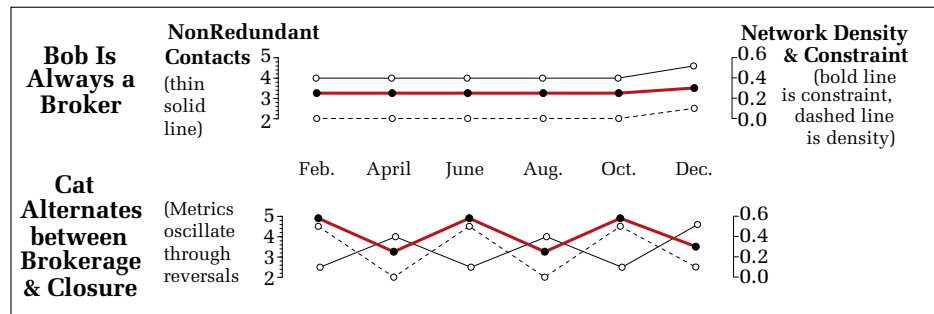
Consider the two hypothetical executives in Figure 1: Robert and Catherine (Bob and Cat for short). An ethnographer has provided bimonthly snapshots of core networks around Bob and Cat. Bob is at all times a network broker—his contacts vary from month to month, but his contacts at each point in time are disconnected. In January and February, Bob spent a lot of his time with contacts 2, 8, 11, and especially 5 (bold-line connection). None of the contacts were connected with each other. In March and April, Bob spent a lot of his time with contacts 6, 7, 10, and especially 1. Again, none of Bob’s contacts were connected with each other. Over the year, Bob focuses on different people, but they are always in different groups and disconnected; Bob is consistently a network broker. A network survey in December asks for the names of people with whom Bob had the most frequent and substantive work contact (assemble the bold line from each bimonthly network). Bob’s end-of-year network consists of redundant contacts into a primary group (colleagues 1 and 3) and bridges into related groups [consistent with the advice often voiced in business to be “T-shaped” (Hansen & von Oetinger, 2001)]. Network metrics in the box at the bottom of Figure 1 show that Bob has continuous high advantage during the year. The number of nonredundant contacts is consistently high; network density and constraint are consistently low. Many students and executives first exposed to a lecture on network advantage walk away thinking that they need to build up their access to structural holes so they look like Bob.

Cat has the same network in the December survey, but her network developed in a way very different from the way Bob’s developed. In January and February, Cat is deeply involved in one of the groups, then she connects across groups in March and April. In May and June, Cat is deeply involved in another one of the groups, after which she connects across groups in July and August. Then again deeply involved in a third group, after which she connects across groups in November and December. Cat’s contacts vary from month to month, but now and again she is found deeply embedded in a group. In the table at the bottom of Figure 1, Cat’s network metrics bounce up

**FIGURE 1**  
**Illustrative network oscillation.**



A period of deep engagement in a group (closure), followed by a period of connecting across groups (brokerage), followed by deep engagement, followed by brokering, and so on



and down over time—identical to Bob’s network in April and August, but when Cat is embedded in a group she has few nonredundant contacts, high network density, high network constraint. Cat illustrates network oscillation. Her network oscillates between closure embedding in a cliquish network and brokerage access to structural holes.

Oscillation should not be confused with network strategies that are stable mixtures of closure and brokerage. For example, initial study of structural holes emphasized the advantage of simultaneous brokerage beyond one’s group with closure inside the group (Burt, 1992, 2005: Ch. 3) and related subsequent work showed the value of heterogeneity in R&D teams (Reagans, Zuckerman, & McEvily, 2004). This research highlights the importance of mixing closure and brokerage, but is not about oscillation. The same caution applies to strategies that are stable mixtures of lagged structures. For example, Soda, Usai, and Zaheer (2004) predict number of people in the audience for a TV show from the team network that produced the show, and conclude that successful shows are produced by teams with current access to structural holes beyond the team, preceded by

dense collaborative ties in the past within the team. In short, successful shows are more likely from teams with brokerage now built on prior closure. The conclusion is intriguingly analogous to network oscillation, and could be the manifestation of oscillation in TV production teams, but closure and brokerage are measured with respect to different networks in the study. Closure is measured by dense collaborative ties within the team. Brokerage is measured by team member collaborative ties to other teams. This is again closure inside the group mixed with brokerage beyond the group. There is a lag in that the closure is valuable if it precedes the brokerage, but it is the resulting mix that is the strong advantage, not oscillation.

On a related note, Carnabuci and Bruggeman (2009) offer an innovative analysis of mixed closure and brokerage in patent production. Dividing patents into aggregate technology domains and aggregating patent citations to measure relations between the domains, Carnabuci and Bruggeman compute network constraint for each domain to measure knowledge specialization. The constraint score for a domain shows the extent to which patents produced

in the domain cite other patents within the same domain or related domains that concentrate their citations in one another. In other words, high constraint indicates a closed network of citations, which indicates high specialization. Carnabuci and Bruggeman (2009) show that growth in future cites to a domain's patents is negatively associated with network constraint, as could be expected from previous work (e.g., Fleming, Mingo, & Chen, 2007), then add an adjustment for closure: as a domain draws more and more on other domains, the domain benefits from focusing in the next time period on fewer domains (cf. Uzzi, 1996, on a possible curvilinear association between performance and closure; Fleming et al., 2007, on brokerage associated with generating patents, closure associated with getting patents cited). In other words, "the domains that accumulate the largest knowledge output within a five-year interval are neither extremely specialized nor extremely brokering, but rather hover around the middle" (Carnabuci and Bruggeman, 2009: 628). Beyond optimum mixtures, Carnabuci and Bruggeman (2009: 630–631) speculate that mixed closure and brokerage could be oscillation: "Whether and to what extent these phenomena are driven by oscillating regimes of knowledge specialization and knowledge brokerage are intriguing questions, as well as opportunities for future research."

More recently, Anjos and Reagens (2013) discuss Bob's behavior in Figure 1 as a "weak commitment" strategy in that Bob quickly moves to new relations, in contrast to consistent closure as a "strong commitment" strategy, and some mixture of strong and weak as a "moderate commitment" strategy. Anjos and Reagens define commitment in terms of ego's constant probability  $\gamma$  of withdrawing from a relationship. Low  $\gamma$  means that ego is committed to his relations; he is unlikely to withdraw if something more attractive comes along. Bob in Figure 1 is an example of high  $\gamma$ , in other words, "weak commitment" behavior. Anjos and Reagens present simulation results showing that "moderate commitment" yields the highest performance scores, more information about potential partnerships, and less frequent coordination failures. In contrast this reasoning from ego's stable probability of leaving or staying, oscillation is about a shifting balance. Cat in Figure 1 lives with low  $\gamma$  in January and February while working in a project. Given her low  $\gamma$ , Cat meets friends of friends and a closed network accumulates around her. Cat's  $\gamma$  is high in March, when she discontinues several relations simultaneously. Over time, her shifts between high and low  $\gamma$  can average into a moderate  $\gamma$ , but what makes Cat's behavior an oscillation sequence is her varying  $\gamma$ , not her average  $\gamma$ . And it is the varying, not the level, that we find associated with performance.

## METHODS

### Data

In keeping with the exploratory nature of the work, we have removed details about our data analysis to supplementary materials available for download (referenced here by an "S" before figures and pages, see acknowledgment note for URL). We analyze 346 investment bankers in a large financial organization during the 1990s. The organization later disappeared when merged into another firm, and nothing is revealed here that would be awkward for the 1990s management, but to honor management's expressed wish for anonymity, we are deliberately vague on job ranks and data categories. The 346 bankers to be analyzed were continuous employees so we know how their networks varied from year to year. By selecting the continuing employees, we narrow the analyzed variation in performance and network advantage because poor performers, and bankers on the social periphery of the organization, were more likely to leave the organization. Tests for selection bias show that the continuing bankers, relative to the excluded bankers, were more senior, more widely connected, and better compensated—just as suspected, but the compensation association with network advantage is the same with or without the excluded bankers (supplementary materials, Section S1).

### Network Structure

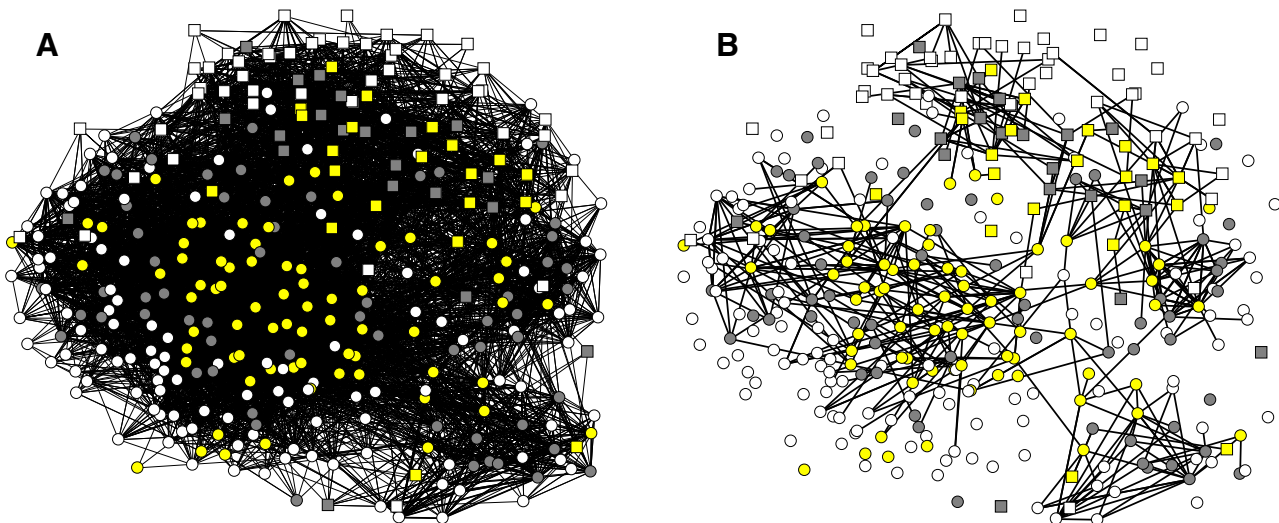
Figure 2 contains two sociograms of the organization. Dots represent bankers. Lines indicate connections between bankers. Each year, the organization conducted a review in which bonus-eligible people were asked to identify colleagues with whom they had worked closely during the preceding year, then asked them to rate their experience with the colleague as poor, good, very good, or outstanding (synonyms for the words actually used). Ratings were given interval scores and the average rating of a banker was used to inform bonus and promotion decisions. As a network datum, each rating is a claim that the person making the evaluation had substantial contact with the person evaluated—they communicated, coordinated, and were otherwise "in touch" during the year. We do not know precisely how a pair of connected bankers worked with each other, or how much they gained from the connection, which

Author's voice:  
Where did you get your data?





**FIGURE 2**  
**Enduring banker relations better reveal social clusters**



Legend: Color indicates banker job rank: top (gold), senior (gray), or other (white). Shape indicates location: US (circle) or elsewhere (square). Lines in sociogram A connect bankers linked by a citation in any of the four years. Lines in sociogram B connect bankers linked by a citation in all four years.

raises a question about how much discretion the bankers had over their connections. At one extreme, bankers could have been assigned to work with certain colleagues, whereupon network decay would be determined exogenously. At the other extreme, bankers could have been free to select the colleagues with whom they worked. The truth is some unknown mixture of exogenous assignment and endogenous choice, with the mix playing out differently for different individuals. An attractive feature of this study population is that the network data on average are probably closer to the endogenous alternative. We cannot prove the point, but we have two reasons for believing it. One consideration is the nature of the work. The bankers received average annual incomes well over a million dollars. They were not paid that level of compensation to take orders. They were expected to find ways to create value. In fact, the company invested substantial resources in annual peer evaluations precisely because it is otherwise difficult to keep track of collaborations since the bankers often cut across vertical chains of command, making it difficult for supervisors to know at any one time how direct reports worked with other employees. Second, evaluations determined by exogenous assignment should be symmetric and correlated within dyads. People assigned to the same project would evaluate each other and project factors they have in common would create correlation between their evaluations (more positive evaluations perhaps, in more successful projects). Instead, the evaluations are asymmetric and contradictory. Less than half of the

peer evaluations were reciprocated (38 percent), and when reciprocated, they were inconsistent with one person saying the relationship was good while the other said it was ok (0.27 correlation between reciprocated evaluation scores 1–4). In short, we believe that the bankers had wide latitude in naming colleagues with whom they had substantial work contact.

The sociograms in Figure 2 are based on different treatments of network stability, but both shows the bankers connected in a dense network spanning the globe. To facilitate comparisons across the two sociograms, each banker's location in Figure 2A is the same location in Figure 2B. In Figure 2A, the connection between two bankers is the number of years they were connected: 4 if either or both bankers cited the other in each of the 4 years, 3, 2, 1, or 0 if neither banker cited the other in any of the 4 years. Two bankers are close together to the extent they were strongly connected with each other and the same colleagues ["spring embedding" algorithm, NetDraw, (Borgatti, 2002)]. Connections are slightly more dense in the lower left of Figure 2A, corresponding to the U.S. headquarters, but the overall impression is density everywhere. It is difficult to see anything but connections in Figure 2A, black at the center, fading to distinguishable connections at the periphery.

The underlying social structure is more visible when the network is limited to stable connections. In Figure 2B, a line indicates bankers connected in all 4 years. It is now more apparent that the bankers were organized with respect to five dense clusters,

corresponding to centers of activity in New York, London, two cities on the European continent, and a city in Asia. It makes sense that enduring relations would be more likely between bankers in the same location, and the bankers explained their movement through the organization in terms of time they spent in the cities corresponding to the geographic clusters in Figure 2B. In sum, the bankers were socially differentiated, but it is equally true that the bankers were densely connected across their differences.

### Baseline Performance, Network, and Control Variables

Stable clusters facilitate stable advantage. Stable advantage would be visible as strong correlations between repeated network measures of advantage, which is what we report in a factor analysis of status and structural hole measures across the 4 years (Table S1). One could conclude that the four panels of data are not different observations of the bankers so much as they are test–retest replication observations of an underlying stable structure—distorted at random by circumstances unique to individual bankers in specific years. In this view, annual deviations from the typical would be noise. Such noise can be removed from the network predictors by pooling the data across years to define the relative network advantage typical for a banker through the 4 years.

Regression models in Table 1 provide a baseline for our analysis and further support the image of a stable

underlying social structure. The models predict banker compensation, under certain controls for banker differences, from measures of network advantage aggregated in different ways over time.

We present results for two often-used measures of network advantage: the network eigenvector index measuring banker centrality and status (Bonacich, 1972, 1987; Podolny, 1993), and the network constraint index measuring a banker's lack of access to structural holes (Burt, 1992).

The eigenvector index increases with the number of a banker's contacts, adjusted for the status of the contacts. Given two bankers with the same number of contacts, the one with higher status is the one with stronger connections to higher-status contacts. Following Podolny (1993), the status story about network advantage is that colleagues and clients use status as an indicator of quality. The more able the banker, the more likely he or she will be sought out by able colleagues. In populations where quality is difficult to measure objectively, judgments about quality are inferred from status as a visible correlate of quality, so returns to effort are higher for higher-status people and products (Podolny, 1993, 2005). We measure status each year as the ratio of a banker's status relative to the average banker (see pp. S2–3 in the supplementary materials), where a score of 1.00 indicates a banker with average status.

Structural hole advantage is about information access and control. We measure access to structural holes with the network constraint index, which increases from 0 to 100 with the extent to which a banker

TABLE 1  
Compensation Returns to Network Advantage

|                              | All Years     |                | Within Years  |                | Between Years |                |
|------------------------------|---------------|----------------|---------------|----------------|---------------|----------------|
|                              | I             | II             | III           | IV             | V             | VI             |
| Network status               | 0.41 (0.05)** | —              | 0.47 (0.05)** | —              | 0.33 (0.04)** | —              |
| Network constraint           | —             | −0.31 (0.07)** | —             | −0.41 (0.08)** | —             | −0.27 (0.04)** |
| Job rank 2                   | 0.20 (0.08)*  | 0.20 (0.09)*   | 0.20 (0.08)*  | 0.21 (0.09)*   | 0.23 (0.03)** | 0.24 (0.03)**  |
| Job rank 3                   | 0.48 (0.09)** | 0.51 (0.09)**  | 0.50 (0.08)** | 0.52 (0.09)**  | 0.59 (0.06)** | 0.62 (0.06)**  |
| Job rank 4                   | 1.48 (0.10)** | 1.64 (0.11)**  | 1.37 (0.10)** | 1.58 (0.11)**  | 1.55 (0.10)** | 1.74 (0.11)**  |
| Colleague evaluation         | 0.17 (0.04)** | 0.18 (0.04)**  | 0.13 (0.04)** | 0.17 (0.04)**  | 0.12 (0.02)** | 0.14 (0.03)**  |
| Years with the organization  | 0.004 (0.01)  | 0.008 (0.01)   | 0.001 (0.01)  | 0.006 (0.01)   | −0.003 (0.01) | 0.002 (0.01)   |
| Minority (gender or race)    | −0.07 (0.07)  | −0.08 (0.08)   | −0.05 (0.07)  | −0.07 (0.07)   | −0.07 (0.04)  | −0.09 (0.05)   |
| U.S. headquarters            | −0.11 (0.06)  | −0.06 (0.06)   | −0.14 (0.06)* | −0.07 (0.06)   | −0.09 (0.05)  | −0.04 (0.05)   |
| Intercept                    | −0.91         | 0.21           | −0.91         | 0.78           | −0.81         | 0.31           |
| Multiple correlation squared | 0.71          | 0.68           | 0.74          | 0.70           | 0.71          | 0.66           |
| Number of observations       | 346           | 346            | 346           | 346            | 1,038         | 1,038          |

Note. Unstandardized ordinary least squares (OLS) regression coefficients are presented with standard errors in parentheses. Compensation is measured as a z score. Network status is an eigenvector score normalized to the average banker. Network constraint is the log of constraint. Models I and II predict compensation summed across years from network indices computed from relations pooled over time (relation is 1 if it occurs in only 1 year, 2 if 2 years, etc.). Models III and IV predict annual compensation averaged across years from network indices computed for each year then averaged across years. Models V and VI predict compensation next year from network indices this year (with standard errors adjusted for autocorrelation between repeated observations of the same bankers using the “cluster” option in STATA).

\* $p < .05$

\*\* $p \leq .001$



had few colleagues and those colleagues were interconnected, either directly or indirectly through central contacts in the banker's network (Burt, 1992, see page S4 in the supplementary materials). The higher the network constraint on a banker, the more interconnected the banker's contacts, so the less opportunity the banker had to broker connections across structural holes. To capture the nonlinear association between performance and constraint, we use the natural log of raw constraint scores.<sup>1</sup>

Performance is measured by annual compensation, which varied across the 4 years from a few hundred thousand dollars to several million (Eccles & Crane, 1988: Ch. 8, on deliberations over banker compensation). To obscure dollar amounts, we standardize within year. A score of zero on the z-score compensation variable indicates a banker who received an average level of compensation for that year. A score of 1.0 indicates a banker with compensation 1 standard deviation higher than average, and so on. Means, standard deviations, and correlations for the variables in Table 1 are given in the supplementary materials (Table S2 in the supplementary materials). The compensation and control variables come from company personnel records.

The results in Table 1 show compensation increasing with network advantage. Whether measured across all of the years (Models I and II), or within years then averaged across years (Models III and IV), network advantage is closely associated with compensation. For these four models based on network data pooled across years, we predict annual z-score compensation averaged across years 2, 3, and 4. A one-unit increase in network status is associated with half a standard deviation increase in banker compensation (with *t*-tests of 7.65 and 9.64 for status measured across versus within years), and compensation is higher for bankers whose networks spanned structural holes (*t*-tests of  $-4.62$  and  $-5.35$  for the lower compensation received by bankers in constrained networks measured across versus within years). The results are consistent with Gargiulo, Ertug, and Galunic's (2009) analysis of cross-sectional data on a larger population of investment bankers spread into job ranks below the bankers analyzed here. Gargiulo et al. (2009: 319) show that

annual bonus decreases with increasing network density among colleagues citing the banker in the annual review.

Models V and VI preserve annual variation with a pooled cross-section design that allows us to estimate returns with a time delay. Next year's compensation is predicted from this year's network advantage. Number of observations increases from 346 to 1,038 because each banker is observed three times: year 1 network predicting year 2 compensation, year 2 network predicting year 3 compensation, and year 3 network predicting year 4 compensation. Hannan and Young (1977) outline the costs and benefits of pooling cross sections. We want the statistical power of repeated observations over time, but compensation is strongly correlated between adjacent years, so repeated observations of the same banker are not independent observations. In theory, compensation can vary widely between years because most of a banker's compensation is bonus, which can vary widely with annual business (in the years observed here). However, banker gossip ensures stable reputations (Burt, 2005: Ch. 4), which means bonuses guided by reputation are correlated over time. We find that annual compensation is 0.96 correlated between adjacent years. If we hold constant the control variables in Table 1, even the residual correlation is 0.85 between compensation in adjacent years. Therefore, standard errors in Models V and VI are adjusted for autocorrelation between repeated observations of the same bankers ("cluster" option in STATA). On balance, our conclusions with pooled cross sections are the same as our conclusions with scores averaged over time: Compensation increases with status (8.05 *t*-test) and decreases with low access to structural holes ( $-6.23$  *t*-test for log network constraint). However, the coefficients for network status and constraint are smaller with year-to-year variation preserved than the corresponding coefficients when annual scores are averaged across years (0.33 and  $-0.27$  in Models V and VI versus 0.47 and  $-0.41$  in Models III and IV, respectively), which again implies that some year-to-year network variation can be discarded as noise.<sup>2</sup>

Job rank and colleague evaluations are the important control variables, dwarfing performance associations with years employed in the organization,

<sup>1</sup> The association between constraint and achievement is often nonlinear such that achievement is better predicted with the log of raw constraint scores. We tried both. The  $-5.35$  *t*-test for log network constraint in Model IV (Table 1) is  $-3.61$  with raw constraint scores. The  $-6.28$  *t*-test for log network constraint in Model VI is  $-5.30$  for raw constraint scores. The associations are negative and strong for raw or log scores, but consistently stronger for the log scores, so we report log-score results.

<sup>2</sup> We also estimated fixed-effects versions of Models V and VI in Table 1 (excluding race and gender, which are constant for each banker over time). The 0.33 coefficient for network status in Model V drops to 0.03 (*t*-tests of 6.05 and 1.55, respectively). The  $-0.27$  coefficient for network constraint in Model VI drops to  $-0.04$  (*t*-tests of  $-6.23$  and  $-1.75$ , respectively). Year-to-year variation in network advantage adds negligible prediction to the prediction available from banker differences stable across the 4 years.

minority status (gender/race), and whether the banker worked in the U.S. headquarters. The bankers occupied four job ranks. Beginning with job rank 1 as a comparison group, compensation is higher for rank 2 bankers (0.20–0.24 increase in *z*-score compensation), more so for rank 3 bankers (0.48–0.62 *z*-score increase), and much higher for rank 4 bankers (1.37–1.74 *z*-score increase, corresponding to *t*-tests of 13.55 and 16.32). “Colleague Evaluation” in Table 1 is the average standardized evaluation of a banker in the annual review process. The average rating of a banker is computed for each year (as was done in the organization to inform promotion and bonus decisions), converted to a *z* score to measure relative evaluation for each year (for Models V and VI), then averaged across the 4 years (for Models I–IV). The more positive the colleague evaluation of a banker, the higher the banker’s compensation relative to others in the same job rank with the same network advantage (*t*-tests of 3.68–5.92 in Table 1). It is not surprising to see that compensation is higher for bankers in higher job ranks and for those who receive more positive evaluations (since the evaluations were included in bonus decisions), but it is useful to know that those are the key control variables (of the controls available). We hold all five of the control variables constant in subsequent predictions, but their coefficients do not vary greatly from the results in Table 1 and they are not our primary interest, so further details on them are removed to the supplementary materials (Table S6 in the supplementary materials).

### Measuring Network Volatility

Given clear social clusters, autocorrelated levels of network advantage, and coefficients reduced when year-to-year differences in structure are retained, it would be reasonable to analyze the annual banker networks as repeated observations of a stable underlying social structure, as illustrated in Table 1, and as is typical in research on network advantage, and as published on these bankers (Burt, 2005).

Still, stable summary statistics can hide changes significant for individuals and groups. For example, Moody, McFarland, and Bender-deMoll (2005: 1227–1229) argue the point using Newcomb’s (1961) panel network data on a small group of students. The group is typically discussed as an example of network structure converging to stability. On average, relations within the group converge quickly to a high level of reciprocity and become increasingly transitive over time. However, convergence only characterizes two of three clusters in the network. In the third cluster,

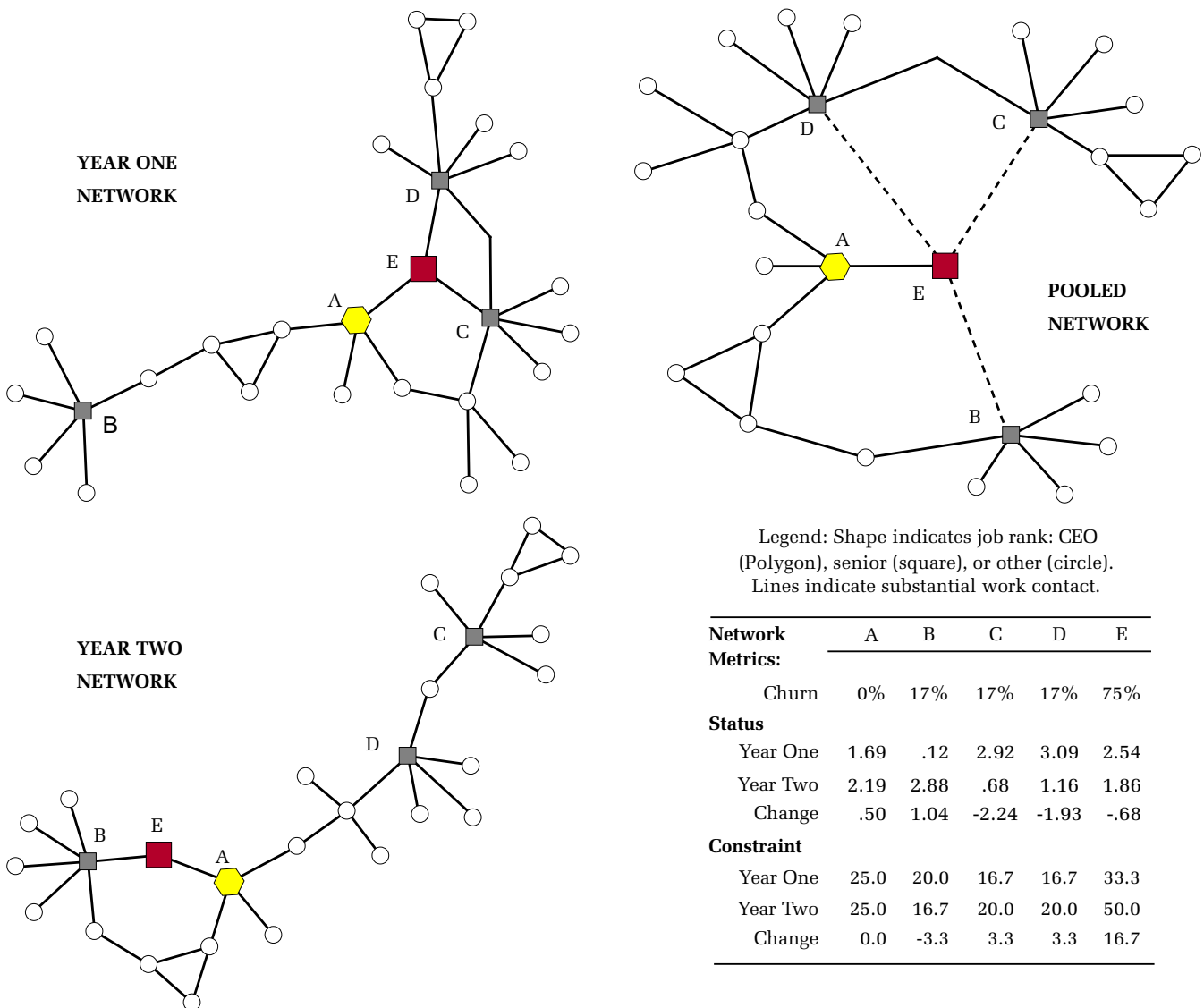
extensive change continues throughout the observation period (Moody et al, 2005: 1232).

More generally, normal business operations can generate change significant for the relative network advantage of individuals and groups within an otherwise stable aggregate structure. For example, the sociograms in Figure 3 describe senior people in a hypothetical organization for first year, then a second year, then both years. The sociograms are hypothetical, but not uncommon: Person A in the United States manages three people—B, C, and D—who each run a business overseas. The businesses are different and run independently, but A has a trusted overseas colleague E who leads projects across the businesses where such projects could be valuable. When the organization is first observed, E is leading a project that involves A, C, and D. In the second year, E is leading a project that involves A and B. The network pooled across the 2 years shows no change except for three relations with E (indicated by dashed lines). This is an illustration of a senior person, A, using a network broker, E, for flexible coordination across business units. Business units are not tightly coordinated through formal authority. They benefit from the occasional loose coupling that a network broker can provide.

Only three relations change during the 2 years, but those three changes trigger unequal change in the networks around individuals. The first row of the table in Figure 3 shows churn—the percentage of a person’s contacts over a time period that change during the period. Person A has zero churn. He is connected to the same four people in both years. Churn is most apparent in E’s network. He developed one new relationship (B) and lost two (C and D), for a total of three changed contacts. With a total of four contacts (A, B, C, and D) during the 2 years, 75 percent of his contacts changed. High churn is to be expected, of course, in the network around a person moving from project to project. Persons B, C, and D experience some churn. One in six of their contacts change.

The two panels in the table in Figure 3 illustrate change in network status and constraint across the 2 years. Person B was relatively peripheral in the first year, but rose to a central position when she became involved in the second-year project. Person E’s status decreased when he shifted from a project coordinating three network hubs in the first year to a second-year project coordinating two hubs. Person B becomes slightly less constrained in the second year, when her network expands to include central broker E, whereas E is slightly more constrained because his year-two project coordinates fewer leaders. The networks around the white dots in Figure 3 show no change. The white dots continue to be connected

**FIGURE 3**  
**Illustrative churn and variation**



to the same people and the same opportunities (zero change in network constraint scores).

The changes illustrated in Figure 3 are to be expected as people move in and out of projects. It is a sign of vitality, of participating in central projects, in a broader context of stable structure. It is the vibration and wiggle of an active network. Network broker E is the key change agent. Leader status goes up and down as individuals move in and out of projects with network broker E. For example, the people attached to person B have slightly higher status in the second year because their leader, person B, is involved in the year-two project.

The situation depicted in Figure 3 is familiar in organizational life, but the network story in Figure 3 is more general than organizational life. The structures

in Figure 3 come from the biochemistry of energy in proteins. Csermely (2008: 573) uses the structures to illustrate “active centers” in protein dynamics. The analogy is sufficiently fertile to warrant a brief aside. Proteins are strings of amino acids folded into specific three-dimensional structures defined by amino acid sequence. Folding into the correct structure is essential to protein function. There are myriad ways in which a string of amino acids can be folded. The energy landscape argument is that folds occur so as to minimize the energy required to maintain the structure (Bryngelson, Onuchic, Socci, and Wolynes, 1995, esp. pp. 173–175). Csermely’s “active centers” are places where elements such as E in Figure 3 connect hubs in a molecule (e.g., A, C, and D), pulling them together to create a fold, then

detaching and re-attaching elsewhere (e.g., A and B).<sup>3</sup> The folding process involves repeated attaching, pulling together, and detaching by elements such as E. Multiple active centers, each creating folds as needed, enable folding to progress along any of many alternative pathways to reliably reach in a practical length of time a native protein structure. By analogous process, network broker E in Figure 3 facilitates coordination among leaders A, C, and D, then moves away and facilitates coordination between leaders A and B, then moves away and facilitates coordination elsewhere. He is a corporate white corpuscle targeting locations in the organization where coordination is problematic. Over time, business units can be refreshed and coordinated within the organization without incurring the costs of tight coupling.

With the Figure 3 illustration in mind, we explore the implications of network volatility in four dimensions. The usual regression models used to estimate returns to network advantage are of the form:

$$P = a + b_n N + \sum b_x X$$

where  $P$  is a measure of performance,  $N$  is a measure of network advantage (in this paper, eigenvector status or log constraint), and various control variables,  $X$ , are held constant. The regression models in Table 1 are such models. We now add adjustments for network volatility. We measure volatility with binary variables  $V$  (1 for high volatility over the 4 years, 0 for low), then add volatility level and slope adjustments to the usual model:

$$P = a + (b_n + gV)N + b_v V + \sum b_x X$$

where  $b_n$  is the return to network advantage for bankers with low-volatility networks,  $g$  is the higher or lower average return for bankers with high-volatility networks, and  $b_v$  is the compensation associated with high-volatility networks, holding constant level of network advantage and the control variables  $X$ . We get the same results with continuous measures of volatility (summarized in a footnote to the results), but results with binary measures are easier to interpret and sufficient for this exploratory analysis.

<sup>3</sup> Csermely (2008: 571) describes active centers to highlight his analogy to network brokers: “The network analysis showed that active centers: (i) occupy a central position in protein structure networks; (ii) most of the time, but not always, are hubs (i.e., have many neighbors); (iii) give nonredundant, unique connections in their neighbourhood; (iv) integrate the communication of the entire network; (v) are individual and do not take part in the dissipative motions of ‘ordinary’ residues; and (vi) collect and accommodate most of the energy of the whole network.”

**Wide variation in advantage.** As a summary measure of change in the network structure around a banker, we use the standard deviation of a banker’s network scores across the 4 years. “Wide variation in advantage” is a dummy variable equal to one for bankers whose network scores varied more than the median standard deviation, zero otherwise. High average scores can vary more widely from year to year, so it is not surprising to see that bankers whose network status varies widely tend to have high average status (1.34 mean status for bankers with high-variance status, versus 0.65 mean for low-variance bankers, 9.05  $t$ -test), and bankers whose access to structural holes varied widely from year to year tend to have high average network constraint scores (43.58 mean network constraint for bankers with high-variance constraint, versus 25.71 mean for low-variance bankers, 9.83  $t$ -test). Thus, bankers with high-variance status enjoy higher compensation on average (0.33 mean z-score compensation for bankers with high variance in status, versus  $-0.33$  for low-variance bankers, 6.49  $t$ -test), and bankers with high-variance network constraint receive lower compensation on average ( $-0.24$  mean z-score compensation for bankers with high variance in constraint, versus 0.24 for low-variance bankers,  $-4.63$   $t$ -test). The empirical question is whether high variance in advantage adds anything to predicting compensation from level of advantage.

**Productive churn.** As a summary measure of change in the contacts around a banker, we use the percent of a banker’s contacts added or dropped during the 4 years (additions and departures are highly correlated, see Section S4 in the supplementary materials). For example, churn is 75 percent for person E in Figure 3. Most bankers experienced high levels of churn. The median level is 90 percent, which can seem high. Sasovova et al. (2010) report a much lower 57 percent churn in their study of friendship, personality, and brokerage within the Radiology Department of a Dutch hospital.<sup>4</sup> However, churn levels have to be compared with caution. The churning banker ties represent substantive work relations between bankers scattered across the

<sup>4</sup> Sasovova et al. (2010) do not report the 57 percent churn rate. We infer it from their text. They report an average of 16.94 friends per person in the initial network, 6.09 friends gained on average in the network 9 months later, and an average of 7.15 friends lost (p. 653). The average total number of friends during the period is therefore 16.94 initial friends plus 6.09 new friends: 23.03. The average turnover is 6.09 friends added plus 7.15 lost: 13.24. Churn is 13.24 divided 23.03, which is the 57 percent we report in the text. In personal communication, Ajay Mehra confirmed the 57 percent churn in Sasovova et al.

world, from Asia, to Europe, to North America. The churning radiologist ties in Sasovova et al.'s analysis concern friendships between co-located colleagues. International collaborations could be expected to be less stable than co-located friendships. Arguing for the opposite expectation, the 90 percent banker churn is across 4 years, whereas the 57 percent radiologist churn is across 9 months. Per-year churn is 30 percent for the bankers versus a much higher 76 percent for the radiologists. The higher churn among radiologists could be due to their networks being measured just before and after the introduction of a disruptive technology. The point is simply that time frame, content, and context all warrant consideration when comparing churn across studies. More, it is not difficult to reach 90 percent churn in 4 years. Imagine that you worked closely with 10 people over the course of 4 years. The first 2 years were on a project with five people. The second 2 years were on a project with one continuing person from the first project and four other colleagues not in the first project. That is 90 percent churn across the 4 years.

Exploratory analysis reported in the supplementary materials shows that there are two unproductive churn conditions for the bankers (Table S5 in the supplementary materials). A volatility variable we name "productive churn" equals zero if a banker falls into either of the unproductive combinations, one otherwise. The first unproductive combination is complete stability: churn is low and structure varies little (cell 1,1 in Table S5). These are bankers who continued for 4 years connected to the same people and the same opportunities. They are trapped, perhaps hiding, in a stagnant job. The second unproductive combination is excessive churn in a stable structure (cell 3,1 in Table S5). Sales and service managers are particularly subject to this trap: always a broker, but with continually new contacts. With respect to status, an example would be a person who manages a department in which turnover is extremely high: always the boss, but continually working with new subordinates. On average, bankers with productive churn enjoy higher compensation (0.19 mean *z*-score compensation for those with productive churn versus  $-0.42$  for bankers with unproductive churn, 5.57 *t*-test).

**Trend and reversal.** The standard deviation of network scores over time is a summary measure of network volatility, but it obscures substantively interesting patterns of change. To explore those patterns, we studied network scores as a profile, or sequence (Stark & Vedres, 2006 provide a rich substantive example). For illustration, Figure 4 displays sequences of status scores for seven bankers. The simplest sequence is banker E. His 0.74 average status

Author's voice:  
How did the paper evolve and  
change as you worked on it?



Author's voice:  
What was the most challenging aspect  
of this research project?



score across the 4 years (to the left in Figure 4) accurately describes his status in each year. Banker F is similar, but with a little more variation. Bankers E and F are in the low-variance category of the "wide variation in advantage" variable defined by status.

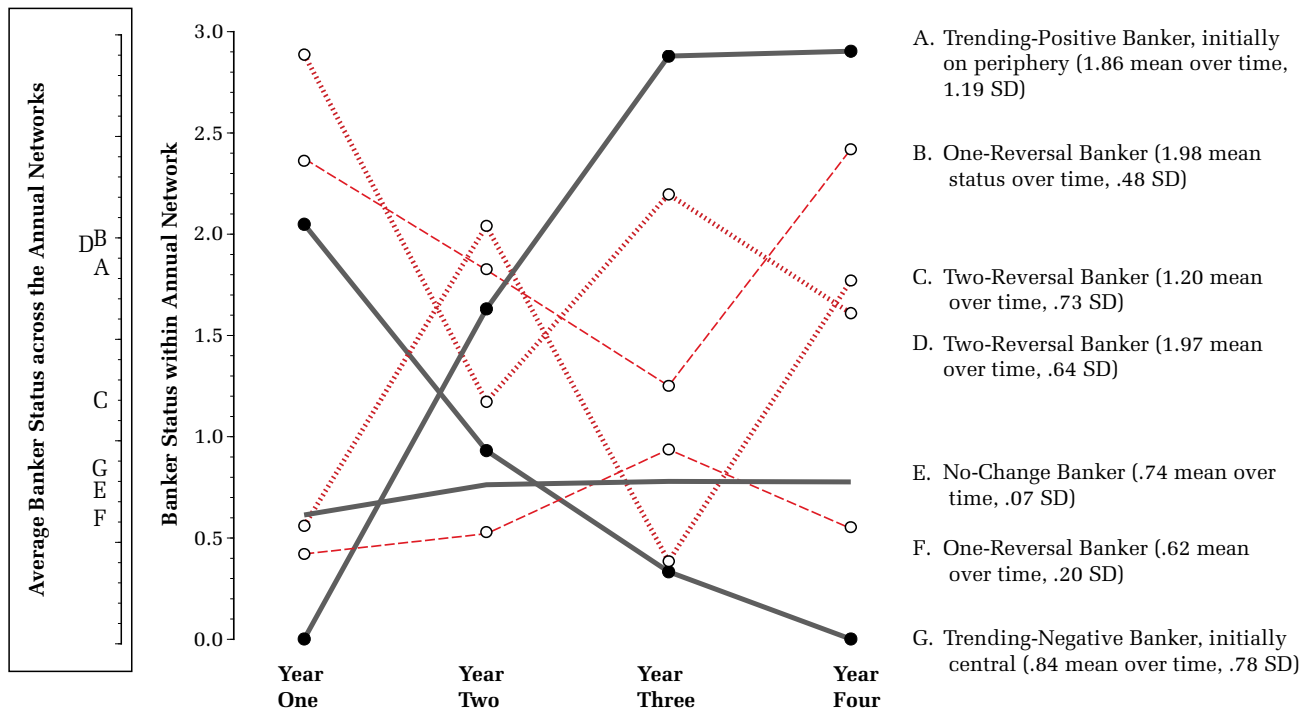
The other five bankers in Figure 4 have high-variance status. Their average status scores across the 4 years are poor description of scores in any 1 year. Although all five bankers experience high status variation, the patterns of change they experience are different in ways that could yield different returns to status.

Overtime variation was greatest for bankers A and G (1.19 standard deviation in annual status scores for banker A, and 0.78 for banker G), but their patterns of change do not obscure so much as clarify status. Banker A shows continuous upward mobility. She begins at the periphery of the network with a status score of zero, jumps to a status greater than the average banker in year two, jumps by another unit of status in year three, then continues to the top of the status hierarchy in year four. Banker A goes through a dramatic magnitude of change in status, but the change is consistently up; easy to read as a positive signal. It would not be surprising to see rising-star banker A receives higher-than-expected returns to her network status. Banker G is the opposite extreme. Like banker A, banker G experienced a dramatic magnitude of change in status that is easy to interpret because the change is a consistent trend. Unlike banker A, the trend is negative. Banker G seems not to be the quality guy he once was. From a central position of high status in the organization, banker G progressed to a position in year four of zero status on the periphery of the organization. It would not be surprising to see banker G, tainted by downward mobility, receive lower-than-expected returns to network status.

Bankers B, C, and D experienced the status-obscuring ups and downs implicit in Bothner et al.'s (2006) argument. We discuss these patterns in terms of reversals. A reversal occurs when change in 1 year is contradicted by change the next year, requiring colleagues to re-assess the direction in which network advantage is moving. Single-reversal sequences are indicated in Figure 4 by dashed thin



**FIGURE 4**  
**Illustrative variation, trend, and reversal**



Reversal refers to change this year contradicted next year, as when banker status decreases this year after increasing last year (e.g., bankers C and D). No reversals means that banker status was stable from year to year (e.g., banker E), or changed in one direction (e.g., banker A's increasing status)

lines. Banker B's status decreased from the first to the second year, then again to the third year. He was on a path of downward mobility akin to banker G. Then things turned around for him in the fourth year with a status score higher than the score with which his sequence began 3 years earlier. The course on which Banker B was moving reversed. Colleagues who thought of Banker B as on the decline had to re-think their opinion of him.

Two sequences in Figure 4 contain double reversals, indicated by thicker dashed lines. Banker C's status increased sharply in the second year, then dropped even more sharply in the third year, then turned around by increasing sharply in the fourth year. The annual changes are more than a full unit of status, which is associated in Table 2 with half of a standard deviation in compensation—a lot of money in this population of investment bankers. Banker D shows a similarly volatile sequence. His status dropped sharply in the second year, turned around in the third year, then dropped again in the fourth year.

Reversals could dampen, or enhance, returns to a banker's network advantage. Bothner, Kang, and Lee (2006) make the dampen argument. If status is valuable because it serves as an indicator of quality,

then status ambiguity cast doubts on quality. Quality uncertain is quality diminished. Reversals disrupt how colleagues think about you. A person who was coming along is now off the radar. A person who was fading comes back strong. Having to re-think status creates an element of ambiguity, which could be expected to erode the returns expected for whatever the current status. Returning to Figure 4, it would be difficult to infer banker C's quality from his status sequence. He is way up, then way down, then back up.

On the other hand, reversals could enhance returns. These are financial advisors during a period of economic growth. In a structural hole story about brokerage, innovation, and growth, stability is a stigma. People exploring the opportunities presented by new combinations of knowledge can be expected to have unstable status as their novel ideas are sometimes productive and sometimes not. Reversals bring you to colleague attention and highlight your vitality. If stability is a virtue, then banker C looks unreliable. If growth and trying new ideas are a virtue, then banker C is a guy to watch when he is on the ascendance.

We use change in adjacent years to distinguish bankers by trend and reversal. The following

**TABLE 2**  
**Compensation Returns to Network Advantage and Volatility**

|   | Network Status Predictions |               |               | Network Constraint Predictions |               |                |
|---|----------------------------|---------------|---------------|--------------------------------|---------------|----------------|
|   | III                        | VII           | VIII          | IV                             | IX            | X              |
| Volatility level adjustments<br>(at median network advantage) |                            |               |               |                                |               |                |
| Productive churn  |                            | -0.00 (0.09)  |               |                                | -0.10 (0.10)  |                |
| Wide variation in advantage                                   |                            | 0.07 (0.08)   |               |                                | 0.10 (0.10)   |                |
| Positive trend in advantage                                   |                            | 0.02 (0.08)   |               |                                | -0.03 (0.12)  |                |
| Negative trend in advantage                                   |                            | -0.07 (0.10)  |               |                                | -0.19 (0.11)  |                |
| Reversal in advantage   |                            | -0.00 (0.08)  | -0.00 (0.06)  |                                | 0.07 (0.08)   | 0.12 (0.06)    |
| Network advantage slopes                                      |                            |               |               |                                |               |                |
| Network status (at low volatility in VII, VIII)               | 0.47 (0.05)**              | 0.06 (0.14)   | 0.25 (0.07)** | — —                            | — —           | — —            |
| Network constraint (at low volatility in IX, X)               | — —                        | — —           | — —           | -0.41 (0.08)**                 | -0.26 (0.13)* | -0.28 (0.09)** |
| Volatility slope adjustments                                  |                            |               |               |                                |               |                |
| (Productive churn) × (Network-median)                         |                            | -0.02 (0.16)  |               |                                | -0.16 (0.18)  |                |
| (Wide variation) × (Network-median)                           |                            | 0.15 (0.12)   |               |                                | 0.11 (0.18)   |                |
| (Positive trend) × (Network-median)                           |                            | 0.13 (0.18)   |               |                                | -0.10 (0.22)  |                |
| (Negative trend) × (Network-median)                           |                            | 0.22 (0.15)   |               |                                | 0.20 (0.19)   |                |
| (Reversal) × (Network-median)                                 |                            | 0.38 (0.14)** | 0.31 (0.08)** |                                | -0.31 (0.15)* | -0.33 (0.12)** |
| Intercept   | -0.91                      | -0.67         | -0.79         | 0.77                           | 0.33          | 0.33           |
| R <sup>2</sup>  | 0.74                       | 0.76          | 0.76          | 0.70                           | 0.71          | 0.71           |

*Note.* OLS regression coefficients are presented with standard errors in parentheses. Z-score compensation, network status, and network constraint are average annual scores as in Models III and IV in Table 1. All models include the seven Table 1 control variables for job rank, colleague evaluation, years with organization, minority, and U.S. headquarters (coefficients are given in Table S6). Level adjustments show change in compensation associated with the five binary volatility measures defined in the text. Slope adjustments are interaction terms between volatility variables and network advantage as a deviation from its median.

\* $p < .05$

\*\* $p \leq .01$

cross-product measures change in a banker's status across 3 years:  $(S_{t+1} - S_t)(S_{t+2} - S_{t+1})$ , where  $S_t$  is the banker's status in year  $t$ . Positive values of the product indicate trend. Negative values indicate reversal. Each banker had two such products in the 4 years of data. Here is the product for banker A in Figure 4 as she moved from year one to three:  $(1.64 - 0.01)(2.89 - 1.64)$ , and here is the product for her move from year two to four:  $(2.91 - 2.89)(2.89 - 1.64)$ . Both products are positive, indicating that the trend was positive with no reversals during the 4 years (which we see visually with the upward sloping line in Figure 4 for banker A). Here is the product for banker D in Figure 4 as he moved from year one to three:  $(1.18 - 2.90)(2.21 - 1.18)$ , and here is the product for him going from year two to four:  $(2.21 - 1.18)(1.62 - 2.21)$ . Both products are negative. Banker D went through two status reversals during the 4 years.

Bankers are assigned to trend categories if both cross products are positive beyond a .001 confidence interval around zero. We found 119 trend sequences in network status, 81 in network constraint. Positive trend is distinguished from negative by regressing network scores across the 4 years. Binary network-

volatility variable "positive trend in advantage" equals one for a banker whose two cross products are positive and whose regression coefficient for change over time is greater than zero (73 with respect to status, 36 with respect to constraint). These are bankers whose network advantage has an upward trajectory across the 4 years, as illustrated by banker A in Figure 4. At the other extreme, there are bankers whose network advantage had a downward trajectory across the 4 years, as illustrated by banker G in Figure 4. "negative trend in advantage" equals one for a banker whose two cross products are positive and whose regression coefficient for change over time is not greater than zero (46 for status, 45 for constraint).

Binary network-volatility variable "reversal in advantage" equals one for a banker if either of his or her two cross products is negative beyond a 0.001 confidence interval around zero. Of the 346 bankers, 138 experienced a reversal sequence in network status and 157 experienced a reversal sequence in network constraint. Bankers who had a reversal in status often had a reversal in network constraint (58.7 percent), but many had only one or the other: 62 bankers experienced a reversal in status without a corresponding reversal in access to structural holes (17.9 percent), and

81 bankers experienced a reversal in access to structural holes without a corresponding reversal in network status (23.4 percent). We also measured reversals in terms of number (one versus two) and magnitude (largest negative cross product). For example, banker B in Figure 4 experienced one reversal, whereas bankers C and D experienced two. Relative to a median negative cross product of  $-0.26$  for network status, banker F experienced a minor reversal in moving from year two to four ( $-0.06$  cross product), whereas banker B in the same period experienced a major reversal ( $-0.67$  cross product for his deep drop moving from year two to three, then a sharp recovery moving from year three to four).

## RESULTS

Table 2 contains regression models predicting banker compensation from the controls and network advantage variables in Table 1 now including level and slope adjustments for network-volatility measures. We begin with the baseline Table 1 Models III and IV predicting compensation from level of network advantage, then introduce the network-volatility predictors. Means, standard deviations, and correlations for the Table 2 predictions are available in the supplementary materials (Tables S3, S4). The seven control variables from Table 1 are included in estimating the models, but not shown in Table 2 since the table is already large and the control variables continue to show strong job rank and colleague evaluation effects, as in Table 1 (Table 2 coefficients for control variables are given in the supplementary materials, Table S6).<sup>5</sup>

<sup>5</sup> We tested for volatility spillover between adjacent networks, but as there is no spillover effect from neighbor levels of network advantage (Burt, 2010), there is no spillover effect from neighbor volatility, so spillover is not discussed in the text. The intuition was that having volatile neighbors could create some amount of volatility in ego's network regardless of ego's behavior, which could mean that neighbor-induced volatility is an important control variable. We computed neighbor volatility for the two reversal measures (the two volatility measures found in the analysis to affect compensation above and beyond level of network advantage). We computed neighbor volatility for banker  $i$  as follows:  $nv_i = \sum_j p_{ij}v_j$ , where  $v_j$  is a volatility measure for neighbor  $j$ 's network, and  $p_{ij}$  is the proportion of banker  $i$ 's evaluations over the 4 years that were with neighbor  $j$  ( $p_{ij} = (\sum_t a_{ijt}) / (\sum_t \sum_j a_{ijt})$ , where  $a_{ijt}$  is a binary score equal to one if there is an evaluation between  $i$  and  $j$  in year  $t$ ). Neighbor volatility has negligible association with compensation when added to the network status prediction in Model VII (0.45  $t$ -test for neighbors going through status reversals), and when added to the prediction from network constraint in Model IX (0.71  $t$ -test for neighbors going through constraint reversals).

We draw three conclusions from Table 2. First, network volatility does not affect performance directly. All volatility adjustments in Table 2 for level of compensation are negligible. The same is true for the several alternative volatility measures we explored. When level of network advantage is held constant and the model includes slope adjustments for volatile networks, compensation is not higher or lower for bankers with stable or volatile networks across any of the five volatility measures. That is, the measures for the different types of network volatility (churn, variability, trend, and reversal) are not statistically associated with compensation for these bankers using either network status or network constraint.

However, and this is the second conclusion, network volatility is a significant slope adjustment enhancing returns to level of network advantage. We draw this conclusion from two patterns in Table 2: The multiple correlations are virtually identical before and after introducing the network-volatility measures, whereas the direct association between compensation and level of a banker's network advantage decreases from very strong before adding the volatility measures, to weak or negligible after adding the measures. On the first point, the variance explained by the models remains constant at about 0.75 for network status and 0.70 for network constraint.<sup>6</sup> On the second point, the initial association between network status and compensation is a 0.47 regression coefficient with a 9.64  $t$ -test (Model III), which drops to 0.06 and a 0.31  $t$ -test when volatility measures are added for churn, variability, trend, and reversal (Model VII). For network constraint, the cross-sectional association is a  $-0.41$  coefficient with a  $-5.35$   $t$ -test (Model IV), which drops to  $-0.26$  and a  $-1.96$   $t$ -test when volatility measures are added for churn, variability, trend, and reversal (Model IX).

Third, the network volatility that enhances advantage is a very specific kind. It is not a matter of making new contacts in place of old. Churn should be moderate in that it should be what is typical for the median person. Nor is the volatility

<sup>6</sup> To keep the substantive meaning of the models simple, we estimate level and slope effects with binary measures of volatility. When we add five continuous measures of trend and reversal to Model VII, the 0.76  $R^2$  in Table 2 increases to 0.77. The five continuous measures are number of reversals (0, 1, or 2), level and slope adjustments for the  $\beta$  describing a banker's status change across the 4 years, along with level and slope adjustments for the maximum negative cross product a banker experienced. When we add the five continuous measures for network constraint to Model VIII, the 0.71  $R^2$  in Table 2 increases to 0.73. The prediction improvements are negligible relative to the added complexity continuous variables would introduce, so we only report the results with binary measures.

effect a matter of trend. The negligible slope adjustments for trend in Models VII and IX show that compensation was no higher or lower for bankers trending up or trending down in network advantage.

The critical volatility is reversals. Reversals enhance network advantage. The slope adjustments for reversals are the only statistically significant network-volatility effects in Models VII and IX. The effect on compensation from reversals in access to structural holes is a little larger than the direct effect of a banker's level of access ( $-0.26$  coefficient for level in Model IX versus  $-0.31$  for reversal). Returns to network status are more dramatically contingent on reversals. The effect on compensation from reversals in network status is six times the direct effect of status level ( $0.06$  coefficient for level in Model VII versus  $0.38$  for reversal). In fact, the  $0.06$  coefficient with its  $0.14$   $t$ -test says that a banker's level of network status had no association with compensation unless the banker experienced reversal during the 4 years.

Oscillation in either network status or access to structural holes will generate oscillation in the other. Status and access to structural holes are closely correlated and have a co-dependent relationship with achievement (Burt & Merluzzi, 2014). Here too, bankers with high status tend to have extensive access to structural holes (Figure S2 in supplementary materials). More relevant to network oscillation, year-to-year change in network status is closely correlated with change in access to structural holes (Figure S3 in supplementary materials). Given a banker with broad access to structural holes and high status, oscillating into a closed network increases the banker's constraint score, and proportionately decreases her status score as she disconnects from other groups ( $t$ -test of  $-4.72$  for change in network status associated with increase in network constraint, holding constant the banker differences in Table 1 and adjusting for correlation between changes by the same banker, see Table S7 in supplementary materials). When the banker oscillates out of the closed network by connecting again across groups, her constraint score decreases and her status increases proportionately ( $t = -9.06$  for change in network status associated with decrease in network constraint, holding constant the banker differences in Table 1 and adjusting for correlation between changes by the same banker, see Table S7).

We use correlated changes in status and access to structural holes as alternative indicators of network oscillation. The two forms of change are combined in Figure 5. The horizontal axis in Figure 5 is average annual network constraint and the vertical axis is average z-score compensation (Models IV, IX, and

X in Table 2). To provide a sense of the data distributions while highlighting associations, average scores are plotted in Figure 5 within five-point intervals on the horizontal axis. For example, each of the three symbols second from the left in Figure 5 are average network constraint scores for the bankers with scores between 15 and 19 points, and average z-score residual compensation scores for those bankers. The bold line in the figure describes the association between compensation and brokerage for bankers whose networks definitely oscillated over the 4-year period. These bankers had one or more reversals in network constraint and network status. The thin solid line describes the compensation-network association for bankers whose networks showed some oscillation. These bankers had reversals in either network constraint or network status, but not both. Finally, the dashed line describes the compensation-network association for bankers whose networks did not oscillate. These bankers had reversals in neither constraint nor status.

Figure 5 is a summary illustration of network advantage contingent on oscillation. Oscillation is irrelevant to bankers embedded in networks more than 30 or 40 points constrained. The lines to the right in Figure 5 overlap with one another. Oscillation matters a great deal for the bankers who were brokers. The three lines fan out to the left of the graph, with oscillating brokers receiving compensation much higher than bankers whose networks showed some oscillation, who were in turn better compensated than bankers whose networks showed no oscillation. Bob and Cat in Figure 1 would be at 30 points of constraint, just where the three lines begin to diverge for the bankers. Cat would be on the bold line. Bob would be on the dashed line. The expected difference in compensation would be small for Bob and Cat. However, as Bob and Cat expanded their networks to a scale more appropriate to an investment banker, Cat could expect to see substantial increases in compensation, whereas Bob would be expected to see no improvement at all.

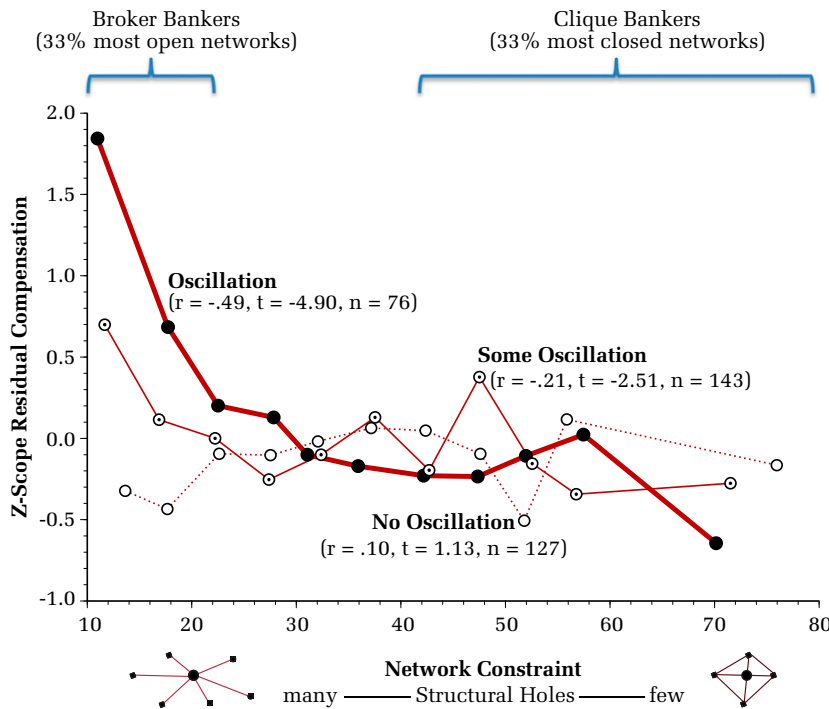
## DISCUSSION

Our results could be limited to dynamic kinds of work, such as the investment activity in which our bankers were involved. Replication is needed in

Author's voice:  
If you were able to do this study again,  
what if anything would you do  
differently?



**FIGURE 5**  
Returns to brokerage are contingent on oscillation.



**How Much Does Oscillation Matter for Each Category of Bankers?**

|                  | N   | t-test | P     |
|------------------|-----|--------|-------|
| Broker Bankers   | 111 | 4.38   | <.001 |
| Middling Bankers | 116 | 0.08   | .94   |
| Clique Bankers   | 119 | -0.84  | .84   |

Vertical axis is a banker’s z-score annual compensation—adjusted for the banker’s job rank, evaluation by colleagues, years with the bank, gender, race, and geographic location—averaged across the 4-year observation period. Horizontal axis is annual network constraint averaged across the 4 years. Symbols indicate averages of individual scores on the horizontal and vertical axes, within five-point intervals of network constraint. The three lines distinguish bankers by the extent to which oscillation across the 4 years is visible in their annual networks: Definite oscillation refers to bankers who experienced reversals in network status and constraint. Some oscillation refers to bankers who experienced a reversal in status or constraint, but not both. No oscillation refers to bankers who experienced no reversals. The table shows tests for association between relative compensation and oscillation using a contrast of 1 for oscillation, 0 for some oscillation, and -1 for no oscillation. Average z-score compensation across 4 years is predicted from average network constraint, holding constant job rank, seniority, peer evaluations, gender, race, and geography (Model IV, Table 1)

other kinds of populations. Pending that replication, however, there is sufficient evidence here to say that the way a network develops can have implications for the advantage it provides. Specifically, the importance of network reversals implies that advantage is not solely a result of high status or broad access to structural holes. Advantage depends on a banker behaving such that his or her network metrics rise and fall through time, a process we propose to term “oscillation,” a sequence in which a period of deep engagement in a group (closure), is followed by a period of connecting across groups (brokerage), which is followed by deep engagement, followed by brokering, and so on.

The results display network advantage as episodic in time. Network advantage need not evolve toward equilibrium, or change in any continuous way over time. What matters for network advantage is sequenced transitions in and out of closed networks. Given our annual panels of data, we have little to say about the periodicity of the transitions, a defining feature of oscillation as the term is used in other sciences. How long do people focus on closure or brokerage? Is there an optimum time interval for shifts between the two? Intriguing questions, but there is too little research to answer with any confidence, and experience suggests there might not be correct answers in so far as timing depends on contextual factors defining when the time is right to leave or enter a group. Still, Quintane et al. (2012) study network data across time intervals of a day, a week, and several months showing that contact volatility around network brokers, on average over time, is concentrated

Author’s voice:  
Was there anything that surprised you about the findings?



in the shorter intervals as brokers move from project to project. Our annual data bar us from digging into such temporal detail. All we can say at this point is that the absence of oscillation signals a problem for our bankers.

Suppose replication shows that oscillation is critical to network advantage. We still only have an empirical finding; an interesting finding, but a finding. The mechanism responsible for the oscillation effect on network advantage has not been explicitly discussed. And we cannot test a mechanism with the data we have available. We can, however, suggest at least three plausible mechanisms, each of which could be a portal for research into why oscillation has its effect on network advantage.

### Reputation

Bob's continuous brokerage offers the usual advantages of information breadth, timing, and arbitrage associated with spanning structural holes, but Cat's oscillation between closure and brokerage offers those plus reputation. Reputation as a trusted contact depends on closed networks. Without closure, reputation evaporates over time. For the bankers analyzed here, reputation without closure evaporates by the time the next annual evaluation occurs (Burt 2005: Ch. 4; 2010: Ch. 6), supporting Coleman's (1988: S107–S108) early surmise: "Reputation cannot arise in an open structure, and collective sanctions that would ensure trustworthiness cannot be applied."

Oscillation involves a broker embedding himself in a closed network for a period, which can be sufficient to launch the gossip that establishes a local reputation for the broker as a trusted contact. Local reputation becomes important when a broker tries to move an idea or practice from one group into another. Getting information from a group is typically easy to do, but getting another group to accept the new information as a good idea is greatly facilitated by the positive reputation of the person introducing it (Centola & Macy, 2007), so it is not surprising to see higher returns to network advantage for people with high status or a positive reputation (Burt & Merluzzi, 2014; Hillmann & Aven, 2011; Rider, 2009). It is one thing to hear about a new concept from a scholar in another discipline, quite another thing to hear a trusted colleague describe how the concept is useful in your area of research. Bob in Figure 1 has ready access to diverse information. Cat has the same ready access—and has in addition reputation within each of the groups. Her time spent working closely with people on the other side of her bridge

relations means she is more likely to understand and have established a reputation with people on the other side of the bridge, both of which make it easier for her to move new information across the bridge and to have her new information find welcome reception. As Rider (2009: 578–579) explains: "a broker's reputation for consistently representing actors of high quality is a valuable, intangible asset that enables a broker to realize future rents on the brokerage position. . . . If a positive reputation reduces the costs of assuaging potential exchange partners' concerns, then the returns to brokerage should be positively related to a broker's reputation." More, being known in a target group facilitates bridge relations into the group. Kleinbaum (2012) shows that bridge relations tend to emerge between people who had prior time together in closed networks. He defines relations using e-mail messages among several thousand people in a large information technology and electronics company of about 130,000 employees. The dependent variable is whether or not e-mail messages occur to bridge the gap between people extremely unlikely to communicate with each other. Kleinbaum (2012: 434–435) reports that bridge relations between distant people are more likely if the two people had prior time together in the same function, office, or business unit—and bridges are especially more likely if the two people spent time in a closed network together (measured by the number of mutual contacts with whom they have communicated in the past).

The above is a story about network brokerage enabled by positive reputation, where status is one indicator of positive reputation. The story is less clear about the salutary effects of oscillation in status. However, we know that an association between oscillation and returns to network brokerage ensures an association between oscillation and returns to network status because of the close correlation between status and access to structural holes. Managers who have large, open networks providing access to structural holes tend to have high network status (Figure S2 in supplementary material), and changes in banker status mirror changes in a banker's access to structural holes (Figure S3 and Table S7 in supplementary material). At a minimum, oscillation will be correlated with enhanced returns to network status as a by-product of oscillation enhancing returns to work brokerage. Oscillation in status can be argued to have its own positive effects on colleagues—"Despite his high status, he's not afraid to join us down here working as a member of the team." However, we are content for the moment with the reassurance that oscillation will improve returns to network status if for no other reason than

oscillation's positive effect on returns to network brokerage.

## Two Other Possible Mechanisms

Network advantage has production and audience dimensions. Network brokerage concerns production—brokers have information breadth, timing, and arbitrage advantages in detecting and developing opportunities. Network status concerns the audience—high status groups and individuals are more likely to be sought out and accepted as the source of a key service or new course of action. By the above reputation mechanism, oscillation has its effect through the audience. By a second and third mechanism, oscillation enhances advantage through production.

A second mechanism is that oscillation could exercise and develop a person's ability to quickly and effectively respond to developments in the surrounding organization and market. Oscillation involves moving in and out of groups. Bob and Cat in Figure 1 both know the variety of activity around them, but Bob experiences this as an outside observer. Cat has the deeper experience of insider. Beyond insider knowledge, Cat experiences engaging and disengaging from groups as an insider. Experience with change is preparation for change. Cat can be expected to be flexible in moving between identities (Ibarra, 2003, on brokers changing identity; Ebaugh, 1988, on people in closed networks changing identity), and so develop the adaptive self-monitoring associated with network brokers (Mehra, Kilduff, & Brass, 2001). The image that comes to mind is people who grew up in multiple countries, or in families that frequently moved between cities. There is an apocryphal story about a commander sent to the U.S. Army Staff College to be tested in the College's sequence of nine war-game scenarios. The commander and his team were successful in all nine scenarios. No commander before or after was successful in all nine, despite the fact that the successful commander's actions were recorded in a "battle book" closely studied by subsequent commanders tested at the college. When asked years later to explain his success, the commander said that for 6 months prior to attending the college he assembled his team regularly to present them with a hypothetical battle scene, and discuss how they would respond. By the time the team arrived at the college, they had experienced hundreds of hypothetical scenarios and learned a great deal about how to respond and reason together. The wisdom communicated by this story, and perhaps the reason why it continues to circulate, is that the secret was not what to do. The secret was being ready to do whatever needed

to be done.<sup>7</sup> As Eisenhower quipped regarding national defense, "The plan means nothing, but planning is everything." On a related informal note, Tom Elfring sent an update by e-mail (March 19, 2013) on his study of 32 entrepreneurial start-ups in the United Kingdom. Tom followed the founders for 10 years after the initial network data on them were collected (described in Elfring & Hulsink, 2007). Thirteen of the start-ups were described as having volatile networks (network revolution), whereas the others had varying degrees of more stable networks (network renewal and evolution). Ten years later, only 1 of the 13 start-ups with volatile networks had gone bankrupt—versus half of the start-ups with comparatively stable networks. Reinforcing the "adaptive response" point, the high-volatility network start-ups were "able to move from one niche market to another when the original one appeared to be less lucrative than originally perceived." Moving up to larger organizations, the concept of organizational identity, like social structure earlier, was proposed as something manifest in everyday life, but deeper and fundamental—features that are the central essence of an organization, distinctive, and to some degree continuous over time (Albert & Whetten, 1985; a formulation that applies to people as well as organizations, Whetten, 2006). Gioia, Schultz, & Corley (2000) argued against the received wisdom in favor of what they termed "adaptive instability," and offered as evidence positive instances of short-run identity instability. When an organization operates in a turbulent environment, short-run identity instability can be an asset for adapting to exogenous shocks. When faced with a disruptive event, such as a merger (Clark, Gioia, Ketchen, & Thomas, 2010), short-run identity instability facilitates weathering the disruption (especially interesting in that organizational identity was originally developed in explaining seemingly irrational responses to a disruption at one of the author's university, Whetten, 2006: 229). In sum, oscillation could enhance network advantage by strengthening a person's ability to flexibly engage new opportunities in the surrounding environment.

Third, and finally, oscillation could enhance advantage simply by enabling a person to maintain a larger, more diverse network. Relations can be understood as ongoing or episodic investments. The traditional focus on stable, enduring relations lends itself to an understanding of relations as ongoing investments. This understanding encourages network models of equilibrium structures as function of connections

<sup>7</sup> The commander's story was told to one of the authors by Don Ronchi, then the Executive Vice President of Six-Sigma and supply chain in Raytheon Company.

maintained within a budget of network time and energy (Winship, 1978). In network oscillation, relations are episodic investments. A person invests in a relationship for a period, spending time and energy, then withdraws, allowing the relationship to go into remission, available to be re-animated at a future date. Levin, Walter, and Murnighan (2011) articulate an episodic understanding of relations, ground it in a review of previous work, and illustrate it with an exercise asking EMBA students to re-animate dormant relations. A classic reference for the episodic understanding of relationships is Granovetter's (1974) dissertation on job search. Granovetter began by asking respondents to name close contacts, then asking who among the contacts had helped the respondent obtain his current job. The typical response was "none." On asking whether any personal contacts had helped, respondents named a friend from school, a colleague at a former job, and so on. In other words, respondents had re-animated a good relationship gone dormant. With respect to Bob and Cat in Figure 1, both could be building relations that could go into remission, but Cat's relations are embedded in mutual contacts—which makes them easier to re-animate (Kleinbaum, 2012). The point is related to the fact discussed earlier that Cat's reputation is more likely to endure within the closed networks in which she participates, but the mechanism here is distinct. If oscillation enhances network advantage by preserving a person's reputation, then oscillation has its effect through audience perceptions of the person. Alternatively, oscillation could enhance network advantage merely by allowing a person to accumulate a larger population of dormant contacts to be re-animated as future needs require, whereupon oscillation has its effect by enhancing a person's capability for future action.<sup>8</sup> Reputation, adaptive response, and large network maintenance are three

<sup>8</sup> We do find that the cumulative number of colleagues with whom a banker works is larger for bankers whose networks oscillate. Cumulative number of colleagues is the number of colleagues with whom a banker worked in the first year, plus any additional colleagues in the second year, plus any additional in the third year, plus any additional in the fourth year. The average banker who showed no oscillation in Figure 5 was connected with 30.4 colleagues over the 4 years. The average banker whose network showed oscillation was connected with an additional seven colleagues (3.03 *t*-test,  $p < .01$ , holding constant the individual differences in Table 1). However, the additional colleagues are captured by our measures of network status and constraint. If status and constraint are added to the prediction, the bankers whose networks oscillate have only one more colleague contact than the bankers whose networks do not oscillate, which is a negligible difference (1.09 additional colleagues, 1.80 *t*-test,  $p = 0.07$ ).

possible explanations for oscillation enhancing network advantage. At this writing, reputation is the best documented of the three as a contingency factor for advantage, so reputation is our preferred explanation pending future research.

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Recent examples are a book on advantage spillover, *Neighbor Networks: Competitive Advantage Local and Personal* (2010, Oxford), an analysis of personality affecting advantage (2012 *Am. J. Sociol.*), and a review of network advantage (2013 *Ann. Rev. Psychol.*).

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