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Influence flows in the academy: Using affiliation networks to assess peer effects among researchers

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ABSTRACT

Little is known about how influence flows in the academy, because of inherent difficulties in collecting data on large samples of friendship and advice-seeking networks over time. We propose taking advantage of the relative abundance of "affiliation network" data to assess aggregate patterns of how individual and dyadic characteristics channel influence among researchers. We formulate and test our approach using new data on 2034 faculty members at Stanford University over a 15-year period, analyzing different affiliations as potential influence channels for changes in grant productivity. Results indicate that research productivity is more malleable to ongoing interpersonal influence processes than suggested in prior research: a strong, salient tie to a colleague in an authority position is most likely to transmit influence, and most forms of influence are likely to spill over to behaviors outside those jointly produced by collaborators. However, the genders and institutional locations of ego-alter pairs significantly affect how influence flows.

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1. Introduction

Given the increasingly social nature of academic research, especially in the sciences (Adams et al., 2005; Powell et al., 2005; Wuchty et al., 2007), there is surprisingly little known about how academic colleagues influence one another's professional activities. Rather than examining interpersonal influences, prior research has tended to focus on the individual and institutional characteristics associated with different levels of productivity (Crane, 1965; Long, 1978, 1981, 1990, 1992; Long and McGinnis, 1981; Neumann, 1977; Reskin, 1978a,b; Xie and Shauman, 2003). This has given a somewhat static impression of the factors affecting research productivity; although peer influence has been suggested as a possible mechanism for certain aggregate findings (see Allison and Long, 1990; Azoulay et al., 2008; Bercovitz and Feldman, 2008). The lack of a more fully developed interpersonal explanation is somewhat surprising given the abundant research on the underlying social structures of scientific communities, which implies ongoing influence processes (Breiger, 1976; Friedkin, 1978, 1998; Moody, 2004; Newman, 2001). Research suggests that faculty members' professional contacts are important conduits for the evaluation and spread of specific research practices, and that status and gender are key moderating factors in these processes (Leahey, 2003, 2006). And yet, the general patterns of when "invisible colleges" are most likely to affect research practices remain unclear (Crane, 1972).

Our goal is therefore to begin to formulate and test a social network explanation for short-term changes in researchers' grant productivity, using a sample of faculty members who are regularly involved in grant activity at Stanford University over a 15-year period. Our setting exemplifies the trend toward large well-funded interdisciplinary research, and is therefore indicative of a growing number of research settings. It is therefore well-suited to address questions that are increasingly

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important in understanding the social nature of research: do collaborators and colleagues influence one another's grant productivity? If so, are certain kinds of relationships more important in the spread of productivity norms and practices? Does influence emerge only through synergistic activity occurring in the immediate relationship, or is there evidence that influence spills over into other relationships and independent practices? Do social distances between individuals affect the ways that affiliations channel influence? Our approach offers preliminary answers to these questions, and may be used as a first evaluation of aggregate peer influence patterns in this population. These questions are not only theoretically important to academic researchers, but substantively important for administrators and funding agencies. If research productivity is shaped by ongoing social relations, this suggests that initiatives aimed at increasing collaboration and the collective awareness of productivity gains may be important strategies for increasing organizational productivity. And yet, there are significant obstacles in testing if and when such effects exist.

For many researchers, potential peer effects are threats to causal validity that must be made ignorable through experimental or quasi-experimental designs (Rubin, 1990); while for others, peer effects are analytically important but extremely difficult to quantify (Manski, 1993, 1995). In general, the difficulties in modeling peer influence have led researchers to focus on smaller groups, laboratory experiments and unique quasi-experiments (Azoulay et al., 2008; Christakis and Fowler, 2007; Friedkin, 1998). Many social network approaches are built upon the premise that peer influence is ubiquitous, but complete network information is prohibitively difficult to obtain on large samples over time. And yet, there are many times when researchers would like to know if evidence supports a peer influence explanation for important outcomes in a population and whether or not influence flows as one might expect based upon prior research. Are some types of relationships and types of individuals more influential than others? Given the rarity of natural experiments and the near impossibility of collecting even partially complete information on large peer networks over time, this question is largely unanswered for many important populations and processes.

In this article, we develop an approach that uses "affiliation networks" to assess large-scale patterns of peer influence. Affiliation networks exist whenever actors belong to the same groups (see Wasserman and Faust, 1994). Faculty members, for example, are professionally affiliated with one another through shared memberships in academic departments, dissertation committees, research teams, etc. Our approach assumes that a shared affiliation is a proxy for interpersonal contact, especially if the affiliation group is small and socially cohesive.[1] Affiliation networks tap into how interactions are organized around various "social foci" that transcend physical proximity, and are important in generating and sustaining social ties (Feld, 1981). Using affiliations therefore sacrifices precision in gauging the amount of peer influence involved in a given outcome, but opens research opportunities to assess peer influence in the aggregate and to test when certain individual and dyadic characteristics interact with different social foci in better channeling influence. We also suspect in general that affiliation networks will tend to underestimate peer-influence effects because they will often dilute the influence spread through contacts by including non-significant others.

Our models confront well-known obstacles in causal estimation (see Bramoullé et al., 2007; Hoxby and Weingarth, 2005; Mouw, 2006). There are numerous ways researchers may incorporate affiliation-based information into longitudinal models to gauge influence, and careful consideration should be given in selecting one's strategy. Ultimately, we follow a dyadic approach that is consistent with recent work using directed network data to gauge peer influence on health outcomes (Christakis and Fowler, 2007, 2008; Fowler and Christakis, 2008). We model effects between pairs of academic researchers who share a given affiliation – while incorporating individual-level fixed effects to create more conservative estimates than in prior studies. The limitations of our approach preclude precise assessments of the overall amount of peer influence, while affording *relative* comparisons of effects based upon different group affiliations and dyadic characteristics. As in recent work on health outcomes, we offer further validation of our models by examining certain asymmetries in dyads, because we would not expect effects to be contingent upon directionality if results are uniformly shaped by spurious shifts affecting productivity. Nonetheless, our approach is best suited for more exploratory analyses or for broad confirmatory studies, rather than as a precise estimate of peer influence within a given process.

As a first test of this approach we analyze the associations between affiliation networks and short-term changes in faculty grant productivity. Grant activity is an important and somewhat understudied area of faculty productivity, compared to publication rates. Data on grant activity is relatively available from central offices and therefore easier to collect and more accurate in comparison to publication data, which entails either exhaustive coding of faculty CVs or digitally "scraping" various online article indices.[2] Lag times on publications also vary widely from field to field in ways that could bias models, whereas grant applications and awards tend to have a more uniform annual periodicity. In general, we believe grant activity is a conservative test of our approach because grant applications and awards are less publicly known than faculty publications, and therefore less likely to influence productivity through broadcast effects rather than direct interpersonal contact. We take into account multiple affiliations in assessing: (1) how different relationships may serve as relatively more or less effective conduits

[1] As part of an attempt to validate this assumption, we have completed a survey of all current faculty members at Stanford (with a response rate of 49%). Results confirm that affiliations differ in how likely they are to indicate a subjective understanding of social contact and influence. Shared dissertation committee work is generally not considered a form of social contact, while joint publications are likely to be seen as contact (although this likelihood diminishes if a publication has a very large number of co-authors). More complete results from this survey, which validate our overall understanding of affiliation networks as proxies for social contact, are available from the authors upon request.

[2] At the time of writing, we are still incorporating publication data into our project through a highly involved set of online database scraping and author name disambiguation strategies.

of influence, (2) how peer influence can be associated with actors modifying their behaviors in joint endeavors (synergy) versus modifying them in other endeavors where the specific influential alter is not involved (spillover)[3], and (3) how social distances between individuals can further constrain influence.

In what follows, we begin by outlining in greater detail our theoretical argument for how academic researchers are likely to influence one another's productivity and how affiliation networks can be used to assess if aggregate patterns are consistent with our derived framework. Afterwards, we describe the data used to evaluate this approach before we present our formal model. We then supply a brief outline of the analytical strategy prior to presenting results.

2. Theoretical framework

2.1. Multiple embeddings and channels of influence

In formulating our network approach we begin by detailing which professional relationships are more or less likely to serve as conduits for influence. Ties can vary in at least three ways: (1) their salience to a belief or behavior, (2) their authority relations, and (3) their overall strength. By examining how different professional affiliations vary in their likelihood of transmitting influence, we acknowledge the "multiple embeddings" (Snow et al., 1980; McAdam and Paulsen, 1993) of academic researchers, and make these an important source for theorizing how ties channel influence.

2.2. Tie salience

Some relations are more pertinent to certain kinds of activities – they have what we term greater *domain salience* by focusing individual behavior more closely around a given activity. Kinship networks, for example, have a greater domain salience with the transmission of caring behavior as compared to professional relationships (e.g. business contacts). Our conception of tie salience is therefore related to a Weberian understanding of social action in that certain relationships are seen as having "elective affinities" with certain beliefs and behaviors (see Howe, 1978). More specifically, we draw on Stryker's (1968) conception of "identity salience" and its application to social networks by McAdam and Paulsen (1993). As in these approaches, we conceive of individuals as having multiple identities, which they invoke in selective ways depending on how relevant an identity is to a specific realm of activity. People tend to compartmentalize their identities and to be more susceptible to influence if the behavior in question is salient to the identity invoked in a relationship. In other words, domain salience suggests that beliefs and behaviors common to a given domain of activity will be more likely to be influenced by relationships specific to that domain than by those formed in other domains.

Researchers' affiliation networks are more likely to successfully approximate social contact networks when the affiliations are salient to a given research activity and focus behavior to that end (Feld, 1981). Within the university setting, academic researchers have multiple identities – teacher, collaborator, committee member – that are sustained through social relationships and are measurable in terms of affiliation networks. In predicting peer effects in grant productivity, we would expect networks of prior grant collaborations to play a particularly salient role. Coauthoring grants with another faculty member has an elective affinity with transmitting outcomes such as grant submissions, success rates, and award amounts. On the other hand, courtesy appointments to departments have little elective affinity with grant activity, and are a nearly random assignment of faculty affiliations in this regard. While those affiliated through courtesy appointments may influence one another in many ways, the lack of domain salience is likely to compartmentalize that influence so that it does not affect grant-related behaviors. Co-involvement in the same dissertation committees has more salience than courtesy appointments because these tend to coalesce around shared projects and topics.

2.3. Authority

Tie salience does not take into account asymmetries of power or authority in relationships; yet, such differences have long been considered important in how beliefs and behaviors spread through communities (see Martin, 1998; Simmel, 1950, p. 184). For example, a long line of sociologists argue that persons in authority positions are higher status players in their networks, and this often translates into greater social influence in diffusion processes (for more recent examples, see Burt, 1987; Fine, 1992; Friedkin, 1998; Kollock, 1994; Leahey, 2005; Lin et al., 1981; Valente and Davis, 1999). Similarly, others argue that persons frequently emulate those higher in status, prestige, or reputation (Bourdieu, 1984; Phillips and Zuckerman, 2001; Podolny, 2005; Simmel, 1957[1904]). While authority differs from status in that it is not derived from an individual's characteristics so much as from a property of specific organizational arrangements, we surmise that relationships involving differences in authority will increase the subordinate's susceptibility to influence from the superordinate. For example, in studying beliefs and behaviors surrounding an ambiguous scientific practice (data editing), Leahey (2003, 2006) found that authority relations matter: academic advisees' attitudes are affected by their advisors, and faculty members in general are more critical of a hypothetical graduate student who employs the same data cleaning strategy as a hypothetical faculty

[3] Our use of the term "spillover effects" differs somewhat from its general usage in economics, which concerns how broader positive or negative consequences can emerge from economic behaviors. Although we share a common interest in "knowledge spillovers" (Jaffe, 1989; Jaffe et al., 1993), we are specifically concerned with spillovers in networks as opposed to spillovers in geographic areas.

member. In our context, we surmise that faculty members who are in lead authorship positions on grants are in positions of greater authority in relation to collaborators, and they will be more influential on the behaviors of subordinate members.

2.4. Tie strength

Network ties have long been considered as varying in their overall *strength* (Granovetter, 1973, p. 1361). Certain types of relationships clearly entail greater commitment in terms of time and emotional intensity, while other relationships are ambiguous in terms of tie strength. For example, it would be difficult to assume that ties among departmental colleagues are on the whole weaker or stronger than ties between grant collaborators. However, looking *within* a single relationship we can discern some variability in tie strength. Looking solely at grant collaborations, for example, we take into consideration *the number of prior collaborations* two faculty members share. Coauthoring a single grant with another faculty member is certainly a salient relationship for future grant productivity; yet, coauthoring *multiple* grants with the same faculty member can be taken as indicating a stronger tie. By making this distinction, we are led to surmise that stronger affiliations will be better conduits for social influence because they represent greater investments in time and trust between individuals and better approximate the intensity of contact.

2.5. Salience, authority, and strength

Combining our understandings of tie salience, authority relations, and tie strength, we develop the following proposition: salient and strong affiliations to individuals with greater authority will be most likely to serve as channels for social influence. While we take this claim as the culmination of our understandings of how ties matter in channeling influence, we believe it can be elaborated upon in two important ways, which we discuss next.

2.6. Synergy and spillover

Prior research on peer influence has not directly accounted for whether peers influence one another primarily through future joint performances and collaborations or if there is evidence that peer effects spill over in a more general way. Azoulay et al. (2008) employ the novel approach of examining productivity drop-offs after unexpected faculty deaths in order to demonstrate that highly productive faculty members generate spillover effects in their home institutions (see also Waldinger, 2010). However, prior research on peer influence has not directly examined possible spillovers in behaviors, most likely because of data limitations. Consider the difficulties involved in estimating whether or not a health-related behavior such as overeating primarily occurs because individuals increase their consumption through shared meals or through general caloric increases apart from one another. We attempt a stronger test of our approach by examining productivity changes that occur outside a specific dyadic relationship.

Fig. 1 illustrates the difference between synergy and possible spillovers for a hypothetical dyad *i* and *j* within an affiliation network of four individuals. All four individuals are connected by directed lines because of their joint affiliation in a given group. Broken lines lead to possible individual and joint products for *i* and *j* at time *t*. In addition to any joint products of *i* and *j* (including products with one or more other researchers) depicted as the broken circle, each member of the dyad is shown to have individual products as well as products they produce with an additional alter (either *z* or *k*). Synergy between the two actors can be said to arise when influence between *i* and *j* results in increases in any jointly produced work; while spillover occurs for focal individual *i* when influence originating from *j* increases *i*'s productivity in activities not directly involving *j*. Spillover effects clearly have greater implications for the diffusion and social "multiplication" of behaviors, since these will tend to spread more rapidly through networks. While spillovers are not an essential element of peer influence, because influence could operate strictly through a relationship, we believe finding evidence of broader spillovers is yet a stronger test of peer influence, and is important to examine in this specific context.

Our strategy is to begin by modeling short-term changes in all *i*'s productivity (synergy and spillover) and then to re-estimate models removing all synergistic activity including both *i* and *j*. This creates a stronger inference for possible peer effects. However, the possibility of complex interrelationships among researchers precludes a definitive test. For example, it is possible that faculty member *k* could affect both *i* and *j* so what appears to be a spillover from *j* to *i* (in y_{ik}) is actually a direct influence from *k* to both *i* and *j*. Such interdependencies are intractable in this case, and will require directed network data over time and a stronger causal research design in order to tease apart. Our goal is to compare models using different affiliation networks and incorporate directionality into these models, and thereby gain a sense of the *relative* importance of various characteristics in both productivity synergies and possible spillovers.[4]

2.7. Social distance

We examine a final element in faculty relationships – social distances – because we suspect such relational factors will alter how peers influence one another net of other effects. Social distances based upon individual characteristics – those

[4] An alternate strategy of modeling only changes in individual activity (y_{ii}) provides a stronger test of spillovers, but severely limits the faculty included in these models. In models not reported here, we did find evidence for this highly limited form of spillover.

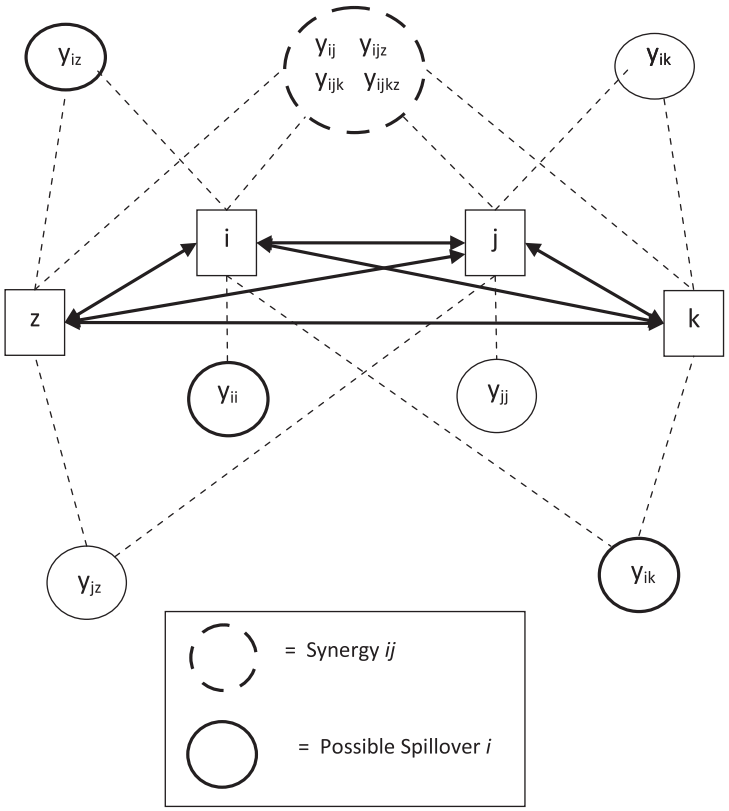

Fig. 1. Illustration of an affiliation network of four researchers (squares) including hypothetical dyad *ij* and "Intellectual Products" (circles) involving *i* or *j*.

thought of as primary cultural frames (e.g. gender) as well as those specific to the academic environment (e.g. institutional location) – may complicate how peers influence one another for two reasons. First, such characteristics serve as cognitive frames for interpreting the salience of an alter's behaviors, and so individuals are likely to weigh their relationships differently based upon such characteristics (see Correll and Ridgeway, 2003). Second, such characteristics also stand in for *social-structural constraints* (e.g. resource distributions), which separate individuals and therefore further complicating the likelihood that researchers will be able to influence one another (Blau, 1977, 1994; Friedkin, 1998). Although the precise mechanisms involved in creating social distances from these characteristics cannot be discerned using aggregate level data, we elaborate our peer influence model by examining how individual characteristics alter the likelihood of peer influence. We re-examine the peer effects among actors sharing a prior grant-writing affiliation, and how gender and institutional location alter the likelihood that peers will influence one another even though each member has recently co-authored one or more grants in the recent past. To the extent that estimated effects change, especially in theoretically consistent ways, we may take this as further support of peer effects and an important elaboration of the contingencies involved in influence flows.

2.8. Gender

Gender is associated with numerous symbolic and material inequalities. As a primary cognitive framework, gender acts as a lens through which women's contributions often tend to be symbolically and materially devalued (England, 1992; Ridgeway, 1991; Ridgeway and Erickson, 2000). An important line of research has directly examined the broader social causes of gender differences in academic research productivity (see Etzkowitz et al., 1992; Reskin, 1978a,b; Whittington, 2007; Xie and Shauman, 2003). Occupational research has shown that women more often than men are caught in the "time bind" of balancing home and work (Hochschild, 1997), and in academia women tend to carry a greater share of the teaching load (Fox, 1992; Long, 1992; Long and Fox, 1995). Here, we are concerned with a related issue of how gender complicates the likelihood that peers will influence one another. Based upon prior research we would expect gender differences in the transmission and reception of influence in academic research. Precisely how these differences will manifest is not entirely clear considering the complexities of peer effects and the distinctiveness of the academic research context; however, we expect in comparison to men that women's influence will be less pronounced. Even within the same salient relationship of having

Table 1
Networks used in models.

Network name	Description	Mean Alters (entire period)
COURTESY	Ego has a courtesy appointment in alter's department at time *t*	43
DEPT	Ego and alter are appointed to the same department at time *t*	43
DISS	Ego and alter are on the same dissertation committee at time *t*	3
DIR_DISS	Alter is the chair of a dissertation committee, which includes ego at time *t*	3
GRANT	Ego and alter are on the same grant application or award at time *t*	6
DIR_GRANT	Alter is the Principal Investigator (PI) on a grant application or award with ego at time *t*	3

written a grant together in the recent past, we expect that because of broader constraints – if not biases – women will tend to be less influential on subsequent productivity changes.[5]

2.9. Institutional location

Academic research occurs within the institutional structure of the university. A researcher's location within this structure (e.g. his or her primary department) is a highly salient indicator of his or her social distance to others. In our setting, as in many others, there has been an increased attention on fostering interdisciplinary work (Abbott, 2001; Brint, 2005; Jacobs and Frickel, 2009). Currently, there is an institutional value placed on forming social ties that span disciplines, because these are thought to foster innovative research. It is possible that such institutional priorities affect how researchers value their prior grant-writing relationships, so that prior interdisciplinary collaborations are a stronger source of influence on future endeavors. However, interdisciplinary ties are more socially distant in the institutional structure. Despite the growth of interdisciplinary institutes, such ties have fewer bases for continued contact and faculty offices and laboratories may be relatively further apart physically. We therefore suspect that comparing interdisciplinary ties to disciplinary ones, even within the same highly salient prior relationship, will reveal constraints on the likelihood of peer effects – what has been called the "30-feet collaboration rule" (Jones et al., 2008; Olson and Olson, 2000) – and that disciplinary ties will be more influential on productivity changes. We therefore re-examine the influence of prior grant-collaborations on productivity changes based upon distances in the institutional structure – dyads within the same department, dyads across departments, dyads within the same school, and finally dyads across schools. We surmise that these will have diminishing levels of influence transmission for grant productivity measures.

3. Data

Data come from central administrative records of grant activity and network relationships of all faculty members who are academic council members at an elite American research university over a 15-year period (1993–2007).[6] A total of 2936 faculty members were considered active (members of the academic senate) in the university during this period. We construct panel data for each faculty member during their active years at the university and include annual time-varying covariates for grant activity and network affiliations for this period.

As discussed in detail below, we largely follow the modeling strategy put forward in recent work on peer effects in public health outcomes (Christakis and Fowler, 2007, 2008; Fowler and Christakis, 2008). Although we experimented with other approaches and alternate ways to incorporate affiliation networks into longitudinal designs, we employ this dyadic approach primarily because it makes no *a priori* assumptions about which actors in an affiliation network are more or less influential and therefore allows for multiple tests and "weightings" by repeatedly fitting models.[7] We begin by constructing dyadic datasets – one for each of six types of network relationships (see Table 1). The units of observation in dyadic datasets consist of pairs (egos and alters) of individuals based upon the existence of a given network relationship. For example, the dataset for departmental affiliations includes all active faculty members and each of their departmental colleagues as dyadic observations. Each faculty member (ego) therefore has multiple observations – one for every faculty member (alter) in their department(s) for a given year. Given that the average department during this period has around 43 faculty members, the full departmental dyadic dataset has approximately 1806 ([43∗43]-43) dyads per year of observation.

[5] Other scenarios are also possible, such as the *homophilous* transmission of influence in which influence tends to be more strongly transmitted through same gender relationships. However, given the lack of research in this area, making strong predictions in this regards seems unwarranted. The strongest evidence points to the unequal influence of women.

[6] Academic council members are voting faculty members. This excludes lecturers, consulting professors, short-term appointments, postdocs, students, and staff.

[7] It is beyond the scope of this article to discuss the strengths and limitations of different longitudinal designs in identifying causal effects. There are clear limitations to the dyadic approach, and these are currently being discussed in a number of articles (see Aral et al., 2009; Cohen-Cole and Fletcher, 2008). However, dyadic models are becoming more standardized (Kenny et al., 2006; Rivera et al., 2010), and are well-suited for the confirmatory approach we have proposed.

3.1. Affiliation networks

Peer relationships are gauged using network affiliation information, which connects faculty members through a shared group membership (Wasserman and Faust, 1994, p. 291). Co-affiliation matrices – also called "two-mode" networks – in departments, dissertation committees and grant proposals require transformation in order to create "one-mode" networks in which faculty members are tied directly to one another. This is accomplished through multiplying matrix **A** by $\mathbf{A^T}$, where **A** is the affiliation matrix and $\mathbf{A^T}$ is its transposition. The resultant network is a co-membership matrix reflecting the number of affiliations each faculty pair shares in common, whether it is a department,[8] dissertation committee, or grant proposal.

Co-membership does not reflect the fact that certain members of a dissertation committee and grant collaboration may be in leadership positions and therefore more authoritative in the relationship. Breiger (1974, p. 95) discusses a transformation process for rendering affiliations into directed graphs, which reflect asymmetries of deference or authority accorded toward leaders or toward a primary group affiliation over a secondary affiliation. Let us assume we still have matrix **A** for faculty affiliations with each dissertation. Next, let us assume we have matrix **B** for dissertation chairs associated with each dissertation. The product matrix $\mathbf{AB^T}$ then results in a directional graph where committee members are subordinate to the chair of the dissertation. This directional network incorporates a hierarchical dimension of commitment and responsibility into the relationship.

3.2. Sample

Our sample consists of a large group of productive researchers in a setting that actively promotes large well-funded academic research. If researchers are influencing one another's productivity, we would expect this setting to be particular likely to exhibit such peer effects. It is therefore well-suited as an initial test of our approach: if we do not find support for our ideas among this group of researchers, it is unlikely that we would find it in settings where academic research is less socially embedded and less exemplary of the trend towards large research teams. However, the generalizeability of these models is somewhat curtailed because of issues of selection. Undoubtedly, researchers at Stanford tend to be highly strategic and oriented toward increasing productivity. Our approach should not be confused with a quasi-experimental design that seeks to mimic a random assignment of researchers to affiliation networks in order to gauge peer influence. Of course, such natural experiments are bound to be informative, but are quite difficult to find and defend. Using statistical techniques for imitating these conditions (e.g. Inverse Probability Treatment Weights [IPTW] and Instrumental Variables [IV]) in the context of affiliations is a stretch of models that are already strained by numerous assumptions. Our goal is to provide an initial test of our framework, and one that can be similarly deployed and elaborated in similar settings.

Our modeling strategy, as we will discuss in detail below, entails omitting dyads of faculty members who do not tend to write grants. In making this omission, we are making an additional assumption, namely that the process motivating faculty members to write one grant (perhaps their first grant) is different from the process shaping how faculty are motivated to write *additional* grants in a given year. We empirically explored and found support for this assumption using zero-inflated negative binomial models, which are not reported here. We suspect that influence operates differently among faculty members for whom grant writing is a common research activity. We therefore limit our analysis to faculty dyads in which both ego and alter wrote at least one grant during a 2-year rolling observation window.[9]

A total of 2034 faculty members wrote at least one grant during this period. The median number of grants written was 2 per year, of which 60% tended to be awarded with a median amount of 246,000 dollars (number of grants written and award amounts are highly skewed because of a few extremely productive researchers). The academic departments most represented in our sample are Medicine (12%), Electrical Engineering (5%), Physics (5%), Biology (4%), Psychiatry (4%), and Mechanical Engineering (4%). Women are 18% of the sample, and tenured faculty members are 60%.

4. Variables

4.1. Dependent variables

We examine changes in faculty grant productivity using three measures: (1) number of grants written, (2) percentage of grant applications awarded, and (3) dollar amount awarded. The number of grants written is a baseline measure of grant activity because higher levels of grant writing are likely to lead to higher award rates and amounts. However, these three measures for individual researchers are not reducible to one another (Cronbach's $\alpha = 0.25$). The percentage awarded indicates something more of the skills and strategies employed in getting grants, while the amounts awarded may also reflected learning processes and are clearly of great institutional interest. We consider each of these dimensions separately in order to assess the ways they may be affected differently by influence through faculty affiliation networks.

[8] Faculty can have multiple departmental affiliations (joint appointments) and this is reflected in the data.

[9] The first-differences approach we employ makes necessary this additional cut in the data. Consider that including non-productive faculty in terms of grant activity (those with zero applications at time t and time $t + 2$) would be conflated with faculty members who are consistent in their grant-writing activity (those with, say, five applications at both periods).

We examine changes in these productivity measures over two-year rolling windows, taking first-differences between time t and time $t+2$ for each faculty member. The dependent variables are therefore designed to gauge short-term shifts in faculty members' productivity, rather than long-term arcs in individual career trajectories. Models also remove from consideration any ingrained tendency to be more or less productive in the first place, using individual-level fixed effects to examine changes *within individuals* as associated with coterminous changes among their network affiliates over time. A two-year window was chosen as an intuitive way to account for annual volatility in grant-activity; however, we also estimated models using rolling two-year averages and these produced very similar results. Taking first-differences also created normally distributed variables from the otherwise skewed productivity measures with distributions peaking around the zero point (i.e. on the whole, faculty members stayed about equally productive over the average two-year window).

4.2. Independent variables

In the aforementioned dyadic differences model, the focal independent variable is essentially constructed in the same way as the dependent variable. However, the independent variable gauges changes in a specific alter's productivity over the same period in which an ego's changes are similarly measured (Allison, 2005; Halaby, 2004). In this case, both ego and alter are included in a given dataset by their sharing a specific group affiliation at time t (and not necessarily time $t+2$). Initial evidence of a peer effect is found when changes in an ego's productivity are associated with changes in his or her alters' productivity scores over the same period, controlling for prior productivity levels as well as ego's stable characteristics (educational background, discipline, etc.), and the average change of a general trend. We discuss model specification in greater detail in the next section.

The strategy we follow is to model changes in each faculty member's productivity as a function of changes in the productivity of their network affiliates over a short window of time. This gauges a certain kind of peer influence process: one that occurs more immediately between social actors with ties to one another. Given that data are left-truncated (we know only about faculty grant productivity beginning in 1993), an alternative strategy to gauge the effects of an alter's *cumulative* grant activity on ego was not possible. While such an alternative specification would arguably be better-suited in testing the effects of reputation and status in the influence process, our model gauges peer influence in the short term. Social influence models suggest that actors monitor the behaviors of others within a reference group, and if one's colleagues begin to work harder, or become more skilled at obtaining grants, it will lead to a diffusion-like spread of productivity gains. To the extent that an affiliation network captures a researcher's academic reference group, we would expect to find evidence of such diffusion-like processes.

5. Estimation

Our estimate of peer effects measures if a change in ego's productivity is related to a change in alter's productivity. The general dyadic model can be written as follows:

$$(y_i^{t+2} - y_i^t) = \beta(y_j^{t+2} - y_j^t) + \mu_i + \tau_i + \varepsilon_i \quad (1)$$

where $(y_i^{t+2} - y_i^t)$ gauges a change in ego's productivity over a two-year window, $(y_j^{t+2} - y_i^t)$ gauges a change in alter's same measure of productivity over the same window, β is an estimate of the peer-influence effect, μ_1 is a fixed-effect for faculty member i, τ_t is a period fixed-effect for time t, and ϵ_i is an individual specific error term. The validity of a similar specification has been widely discussed and tested in accounting for public health outcomes (see Christakis and Fowler, 2007, 2008; Fowler and Christakis, 2008; Couzin, 2009; Trogdon et al. (2008)Trogdon and Pais, 2008). While the general approach is not without its shortcomings, it has certain advantages over other available possibilities. For one, the individual-centered peer influence approach tends to use *averages* from all alters for each ego, which either makes the highly doubtful assumption that influence from one's affiliations is "linear-in-means" or tests a specific *a priori* weighted average of others' influences.[10] We favor the general dyadic approach because it allows flexibility for one to empirically test the significance of various "weightings" of alters in networks, based upon our proposed framework (e.g. tie strength), rather than averaging across all ties. In addition, we make two modifications to the dyadic approach, which, as we discuss below, making for a more conservative set of tests.

Lacking experimental or quasi-experimental conditions, peer effects research must at minimum statistically minimize interpersonal selection effects and spurious associations (Allison, 2005; Halaby, 2004; Winship and Morgan, 1999). For example, in terms of interpersonal selection effects, it is reasonable to assume that faculty members select (or are selected into) affiliations in part based upon shared productivity norms (professional homophily). Rather than using lagged dependent variables to account for prior productivity, which may be insufficient controls for unmeasured heterogeneity in panel data (see Halaby, 2004; Mouw, 2006), we minimize factors about individuals that lead to initial selection of affiliations using

[10] Friedkin's (1998) elegant structural approach is an example of using a weighted average where each ego is presumed to be more or less influenced by his or her alters depending upon their structural location. Something like a test of these ideas could be incorporated into our models by seeing if any additional influence stemming from an alter's structural location within a grant collaboration network. In formulating our approach, we first experimented with the weighted average approach in addition to the dyadic lagged variable approach of Christakis and Fowler (2007). Although we did not pursue our preliminary models in as great of detail as reported models, we found significant and substantively similar peer-influence effects.

fixed effects. As Christakis and Fowler (2008, p. 9) note with a re-estimation of their models, using fixed effects will tend to bias results downward in significance (see Nerlove, 1971; Nickell, 1981). By restricting our analysis to the changes *within* individual faculty members' networks over time, we account for factors that initially bring faculty members together, as well controlling for all stable characteristics of those individuals over time (gender, academic specialization, etc.). Fixed effects for time periods account for time-varying characteristics that affect all researchers equally (e.g. inflation rates, university-wide research mandates). Because we observe the same ego across multiple years and ego-alter dyads, we correct for standard errors that could be biased downward using robust standard errors (as suggested by Allison (2005, p. 19)).

Two issues are not directly accounted for in the basic model. First, there remains the possibility that time-varying exogenous factors, such as the founding of a specialized funding initiative in a certain area of research or complex interdependencies of influence, are correlated with increases in both ego and alter's grant productivity. Period fixed effects account for exogenous events that affect *all* faculty members equally; however, there is the possibility that other external factors will affect more local faculty clusters in which faculty members also tend to share affiliations. Complex interdependencies cannot be directly accounted for in our models. We follow the now established strategy of re-estimating Eq. (1) for multiple types of network relationships, including the *directionality* to assess the presence of spurious causes. To the extent that spurious factors produce changes in both individuals, we would expect more or less uniform effects that vary little based upon the type or direction of a network tie connecting faculty members, as well as the status characteristics of ego and alter. However, if peers are influencing one another, we would expect these to be highly significant for the transmission of influence and to vary in ways that are consistent with our theoretical framework (see Bramoullé et al., 2007).

Second, unlike in prior work, we test the robustness of our estimation by exploring a type of spillover effect, re-estimating models that remove shared productivity between ego-alter pairs. Spillover gauges the extent to which an increase in an alter's productivity is associated with an increase in an ego's productivity *independent* of joint endeavors. In order to estimate possible spillover effects, we replicate models for the three productivity measures net of dyad specific gains. We do so by subtracting, for example, the number of grants that ego wrote with alter at time $t+2$ from the total number of ego's grants at that time prior to taking the first difference of this measure. This can be written as:

$$(y_i^{t+2} - y_{ij}^{t+2}) - (y_i^t - y_{ij}^t), \tag{2}$$

where y_i is a measure of ego's productivity and y_{ij} gauges the amount of ego's grant productivity with alter. Re-estimated models therefore can be interpreted as gauging the extent to which an alter's productivity shifts are associated with an ego's shifts net of their collaborative efforts. While this is not a definitive test for spillover effects, because it is impossible to know the exact source of the influence responsible for a given portion of a researcher's productivity changes, it does provide a more rigorous approach than prior research on peer influence by gauging changes that do not include direct collaborations.

6. Results

Table 2 assesses how network affiliations are more or less effective channels for peer influence. Coefficients are from separate and non-nested models in the form of Eq. (1), so that a one-unit change in an alter's productivity predicts a *beta* change in ego's productivity for the average two-year window. For example, consider faculty grant relationships (GRANT). For each additional grant that an ego's prior co-author wrote over the average two-year window, results predict an increase of 0.06 grants from ego over the same period. This can be seen as a 6% greater likelihood of writing an additional grant for each additional grant a colleague writes. For a 1% increase in the number of grants awarded to an ego's co-author over the average

Table 2
Affiliation Networks and Peer Effects on Grant Productivity.

Network	*Number of grants written*	*Percent of grants awarded*	*Dollar amount awarded*
COURTESY	0.000	0.004	-0.008
	[0.007]	[0.010]	[0.009]
DEPT	0.021**	0.009**	0.071**
	[0.003]	[0.003]	[0.010]
DISS	0.031**	0.065**	0.114**
	[0.011]	[0.012]	[0.026]
DIR_DISS	0.039*	0.073**	0.107**
	[0.017]	[0.022]	[0.041]
GRANT	0.058**	0.138**	0.362**
	[0.008]	[0.011]	[0.034]
DIR_GRANT	0.125**	0.157**	0.398**
	[0.046]	[0.021]	[0.067]

Note: Coefficients are from separate models using fixed-effects in the form of Eq. (1). Robust standard errors clustered on individual faculty members are reported in brackets. In addition, all models include $t-1$ dummy variables to control for period effects.

* $P < 0.05$.

** $P < 0.01$.

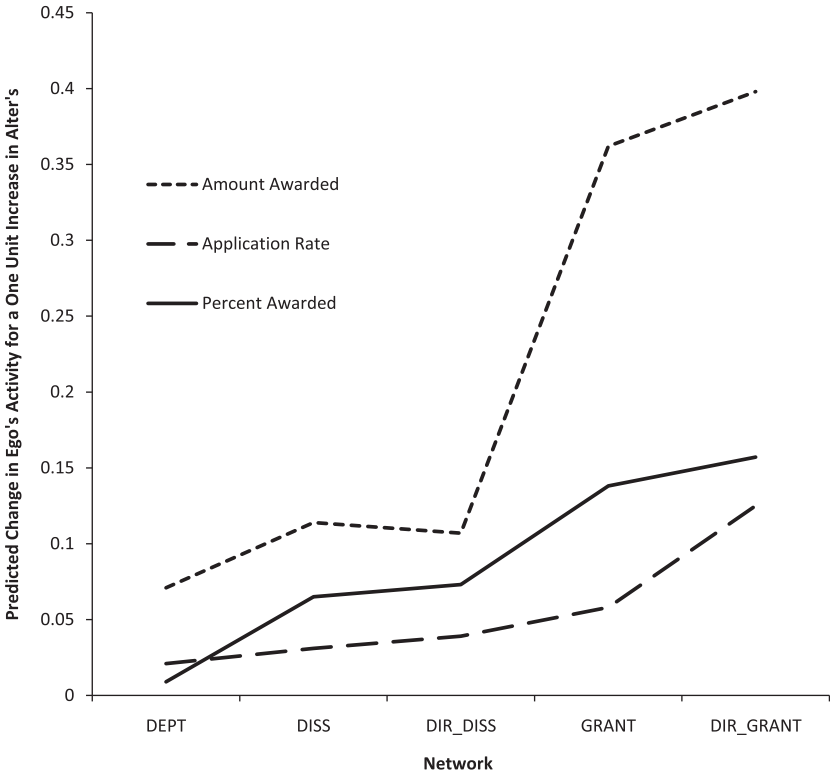

Fig. 2. Network salience and authority as predictors of changes in ego's grant activity.

two-year window, the model predicts an increase of 0.14% in ego's own award rate over the same period. This suggests that a researcher's award rate will increase by 14% if a grant co-author doubles their initial award rate. For a one dollar increase in the amount awarded to an ego's co-author over the average 2-year window, we predict an increase of 0.36 dollars for ego over the same period. If a co-author doubles their prior award amount, it is associated with an increase in a focal researcher's award amount of 36%.

These results offer the necessary preliminary basis of support for the presence of peer effects. The remainder of our analysis elaborates upon these findings by examining the *relative* changes in these effects based upon several theoretically motivated subsets of the data, which have the potential to offer further support for our theoretical perspective on the ways that peer influence is channeled through affiliations.

Fig. 2 summarizes findings with respect to our theoretical motivation concerning tie salience and authority relations. First, it demonstrates that the salience of the network tie is a strong predictor of transmission across all three productivity measures (affiliation networks are ordered along the *x*-axis in terms of our *a priori* understanding of their increasing salience and authority). Relationships that have a greater social focus that is salient to the grant-writing process are particularly important in channeling influence in grant productivity, while courtesy appointments, for example, do not channel influence in this regard and are therefore omitted from the figure. This suggests an elective affinity between ties and behaviors – faculty members are more likely to cognitively reference and socially interact with colleagues in their grant-writing network in ways that influence their own productivity. As expected, courtesy appointments, which are nearly random assignments of ego-alter pairs with respect to grant productivity, are not significant in terms of social influence.

Second, the figure shows that authority relations tend to intensify the likelihood of peer effects for actors in subordinate positions. Dissertation committee members tend to be more influenced by the committee chair (apart from amounts awarded, which is largely unchanged in this regard). Grant co-authors tend to be more influenced by the Principal Investigator (PI) across all productivity measures. This is highly consistent with our proposition that authority relations within a given dyad help solidify the transmission of social influence, particularly if the relationship is more salient to the activity in question. Finally, because the direction of relationships in these models alters the magnitude of peer-influence effects in our proposed manner, we take this as indicating that spurious external causes are not leveraging our results.

Fig. 3 examines how tie strength within prior grant collaborations changes the likelihood of peer influence in affiliation networks. Findings indicate that tie strength matters in creating a more effective conduit of influence across all productivity measures. If ego and alter have written or received more than one grant together at time *t* the estimation of peer influence is considerably stronger than if they had only one grant connecting them. Ties that are both salient and strong are clearly the best predictors for how peer influence is channeled. This is consistent with the understanding that stronger ties represent

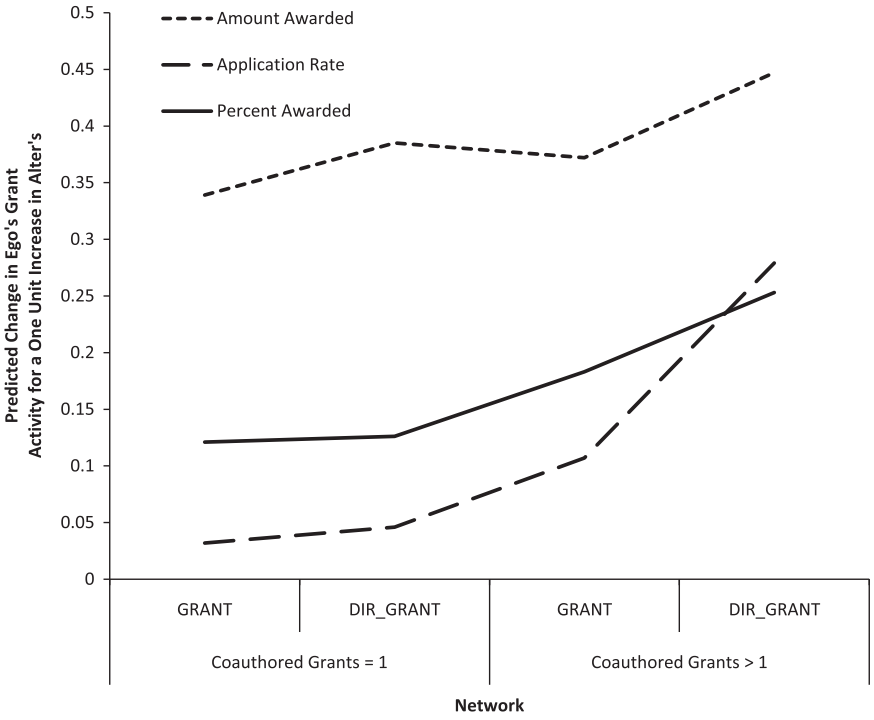

Fig. 3. Strength of grant affiliation tie as a predictor of changes in ego's grant activity.

Table 3
Affiliation networks and potential spillover effects on grant productivity.

Network	*Number of grants written*	*Percent of grants awarded*	*Dollar amount awarded*
COURTESY	−0.004	0.007	−0.008
	[0.007]	[0.006]	[0.008]
DEPT	0.014**	0.006**	0.061**
	[0.003]	[0.002]	[0.009]
DISS	0.009	0.042**	0.112**
	[0.011]	[0.008]	[0.025]
DIR_DISS	0.017	0.045**	0.105**
	[0.016]	[0.015]	[0.032]
GRANT	0.029**	0.106**	0.334**
	[0.007]	[0.007]	[0.035]
DIR_GRANT	0.073	0.119**	0.346**
	[0.043]	[0.013]	[0.065]

Note: Coefficients are from separate models using fixed-effects in the form of Eq. (1). Robust standard errors clustered on individual faculty members are reported in brackets. In addition, all models include $t-1$ dummy variables to control for period effects.

* $P < 0.05$.

** $P < 0.01$.

greater commitments of time and emotional intensity, and that more significant others within a salient domain are likely to serve as social contacts and reference group members for transmitting interpersonal influence.

Having established support for our general understanding of which types of ties matter most in transmitting influence, we now turn to two final elaborations. Table 3 shows results from models that re-estimate those reported in Table 2, removing all synergistic increases in faculty productivity, following Eq. (2) above to create the dependent variable. Significant coefficients suggest the possibility of numerous spillover effects, although the magnitude of effects tends to be smaller than when including synergies. This is consistent with the idea that peer influence induces broad changes in individual behavior in addition to encouraging further joint endeavors. Furthermore, we compare likely spillover effects across networks and productivity measures. Figs. 4–6 compare re-estimated coefficients to those reported in Table 2, thereby illustrating the presumed amount of the overall network effect (which includes both synergy and spillover) that is *not* synergistic, and could therefore potentially be a spillover effect. In general, more salient ties are more likely to have larger potentials for spillover effects; although department ties have a consistent, albeit relatively weaker, effect on general changes in a faculty member's

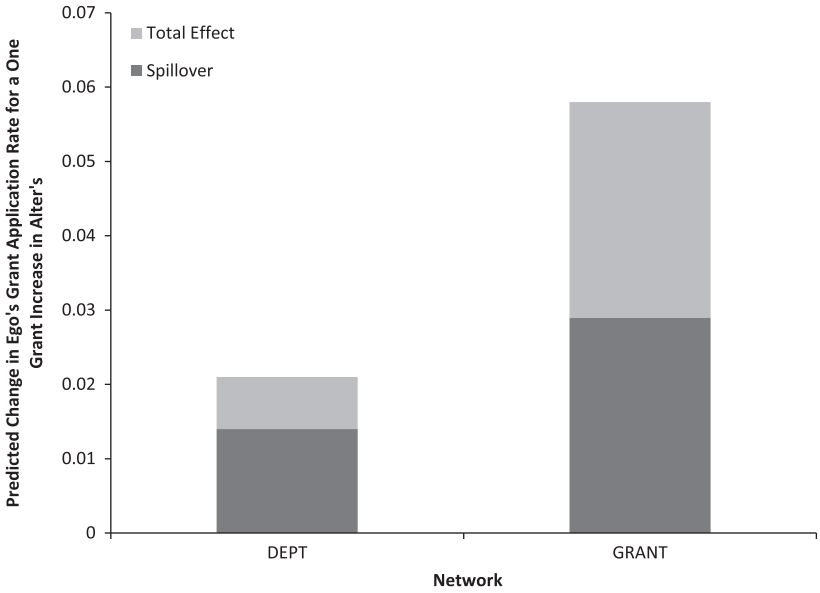

Fig. 4. Potential spillover effects of affiliation networks on number of grants written.

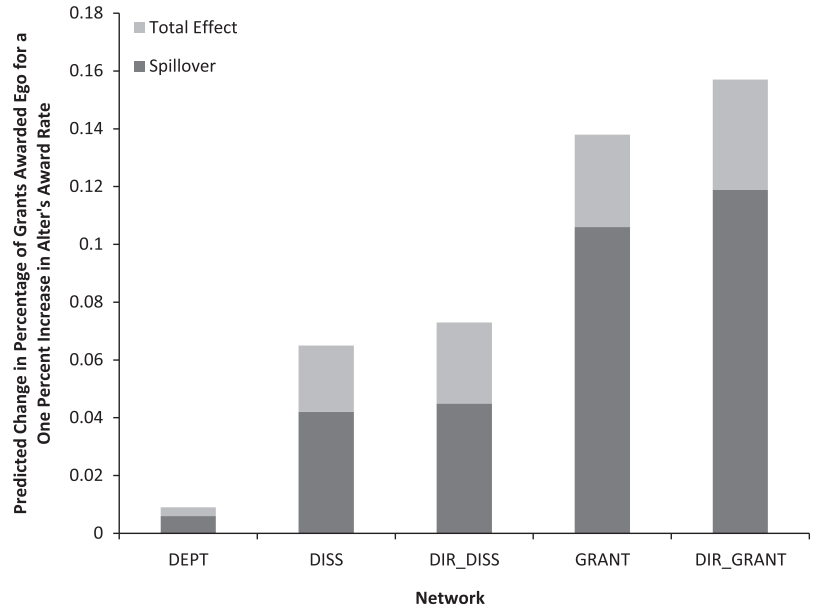

Fig. 5. Potential spillover effects of affiliation networks on percentage of grants awarded.

productivity. These findings dovetail with how salient ties act as more effective conduits of influence in general and offer a stronger test for peer effects because they remove joint productions. However, it is worth noting that peer influence is possible even in the absence of likely spillovers. Although neither necessary nor sufficient for testing for the presence of peer effects, these re-estimated models do offer greater evidence that faculty influence one another through their affiliation networks than if no potential spillovers were identified.

We have posited that gender and institutional location act as both cognitive frameworks and indicators of social-structural constraints on network relationships. To assess how strongly these characteristics alter peer effects, we subset from the grant-writing affiliation network, using characteristics of ego and alter to create new datasets. We use the grant co-authorship network because it is the most highly salient network to our outcome, and therefore provides the strongest test for the importance of social distances. In examining the role of gender, we create four subsets for each network relationship, where (1) ego and alter are both female, (2) ego is female and alter is male, (3) ego is male and alter is female, and (4) both ego and

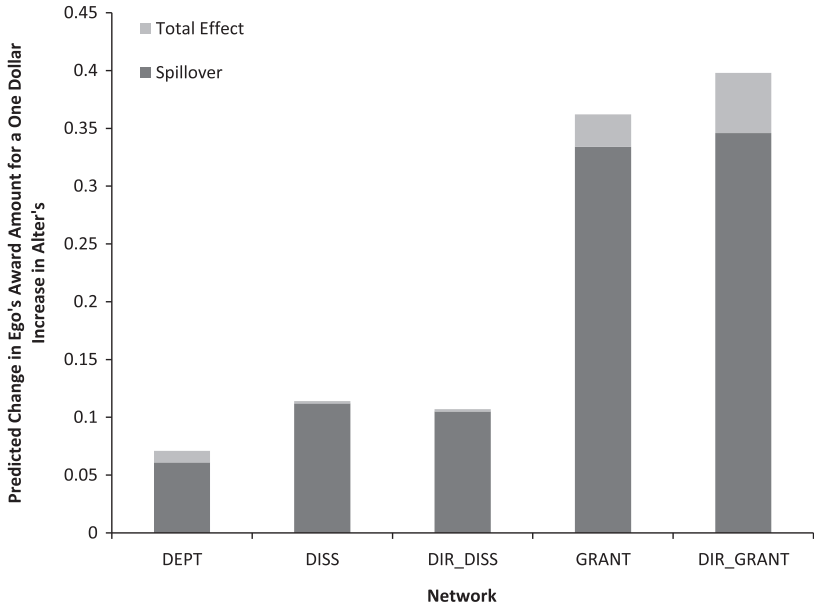

Fig. 6. Potential spillover effects of affiliation networks on grant amount awarded.

Table 4
The combined effects of social distance and prior grant-writing collaboration on changes in ego's number of grant applications (*t, t + 2*).

	Network	
Social distance (ego-alter)	GRANT	DIR_GRANT
Overall effect	0.058**	0.125**
	[0.008]	[0.046]
Gender		
Male ← male	0.056**	0.066**
	[0.009]	[0.020]
Male ← female	0.061**	0.111
	[0.014]	[0.086]
Female ← female	0.014	0.282
	[0.032]	[0.231]
Female ← male	0.068	0.295*
	[0.035]	[0.146]
Institutional location		
Same department	0.111**	0.221**
	[0.018]	[0.085]
Interdepartmental	0.037**	0.071*
	[0.008]	[0.037]
Same school	0.060**	0.154**
	[0.010]	[0.059]
Between schools	0.037**	0.059
	[0.008]	[0.036]

Note: Arrows indicate direction of influence from alter to ego. Coefficients are from separate models (see Eq. (1)) using fixed-effects for ego. Robust standard errors clustered on individual faculty members are reported in brackets. In addition, all models include $t - 1$ dummy variables to control for period effects.
* $P < 0.05$.
** $P < 0.01$.

alter are male. In examining the role of institutional distance, we create the following subsets: (1) ego and alter are in the same department, (2) ego and alter are within the same school, (3) ego and alter are in different departments, and (4) ego and alter are within different schools. While sharing a department affiliation is examined as its own form of association in prior models (ego-alter pairs in the same department are thought to share an affiliation network), here, we consider a researcher's department as measuring their social proximity to individuals with whom they have previously collaborated with on a grant. To the extent that gender and institutional location change the results for pooled models with all dyads in the grant-writing network, we may consider this evidence of a type of interaction effect between social distances and network affiliation.

Table 4 re-estimates models predicting changes in ego's number of grant applications. The overall effect is taken from pooled models in Table 2, and the remaining coefficients report how this overall effect changes according to the social distances between ego and alter. First, we consider gender. For the undirected grant-writing affiliation network (GRANT), men are more susceptible than women to influence from both their male and female prior collaborators. However, for women there is no longer evidence of statistically significant peer effects. Men seem to be most strongly driving the overall peer effects found in the pooled model. The directed grant-writing network (DIR_GRANT), where alter is PI, shows women to be considerably more susceptible to influence from authority relationships with men, and there is no longer strong evidence for peer effects from women in authority positions to either male or female prior collaborators. On the whole, these findings are consistent with a social-structural constraints explanation of how gender alters peer influence: in most cases, women are less likely to transmit influence, while men are both more likely to transmit as well as receive peer effects. Evidence of male bias is weak, considering that men tend to be as strongly influenced by their female colleagues (although this does not extend to female PIs for reasons that may have to do with the relative rareness of such relationships).

Table 4 also shows that although interdisciplinarity has been heavily encouraged in many academic settings, including the one studied here, peer effects are still mainly channeled through traditional disciplinary relationships (see Brint, 2005). This is true for both the undirected as well as the directed versions of this affiliation network. Consistent with our initial assumptions regarding the "30 feet collaboration rule," interdisciplinary relations are more socially distant and therefore tenuous in many ways. Research institutes and other university initiatives may have begun to build bridges, yet the divides still remain in terms of channeling influence in grant productivity. Because peer effects vary by the genders and institutional locations of ego and alter in ways that are consistent with prior research, we take this as both further evidence of peer effects as well as an important elaboration of the contingencies of such effects.[11]

7. Discussion

Using various affiliation networks, we have assessed evidence that suggests specific patterns of peer influence in academic research. Changes in behaviors that are fundamental to research productivity – number of grants written, percentage of grants awarded, and grant award amounts – are all importantly associated with the changes occurring among one's local network affiliates. Evidence suggests that researchers monitor one another's grant activity, and that researchers improve grant writing skills by working with more skilled writers. In short, our models indicate that a researcher tends to become more productive at grant-writing as his or her professional affiliates become more productive, and these increases are in general independent of increases that arise solely from jointly produced work. However, we also found that this process varies in important ways based upon social distances at the individual level, which was largely consistent with our theoretical framework. Our findings that the magnitude of peer effects varies according to tie salience, tie strength, authority relations, and social distances – all in ways that are highly consistent with related research and general theoretical expectations – offers strong evidence that academic researchers influence one another's ongoing professional behaviors in important ways.

This offers a more malleable view of researchers' professional behaviors than offered by prior research on research productivity, which has tended to focus on stable individual characteristics – aspects of prior training, current academic department, and gender. Our strategy holds constant such individual characteristics to focus on ongoing changes within a focal researcher's affiliation networks, and finds that, far from being stable producers of grants and awards, researchers change in ways that suggest influence and learning. To the extent that researchers monitor and learn from their current professional contacts, and become better and more productive grant writers through such contacts, this suggests that organizational initiatives focusing on increasing awareness and promoting collaboration may be effective tools in increasing organizational productivity. Rather than simply hiring highly motivated and competent researchers, which may be a necessary component, universities may be able to promote learning and a social ratcheting of productivity through initiatives aimed at "thickening" grant collaboration networks.

Several of our findings invite more detailed analyses before such initiatives could be more targeted. First, we took into account individuals' multiple embeddings and found that some types of affiliations act as better conduits than others in channeling influence. We advanced a theory of elective affinities between ties and activities through the notion of domain salience to account for why some types of ties serve as more effective channels. This was supported by findings that prior grant relationships are considerably better at channeling influence on grant activity. We take it as further support of our notion of domain salience that courtesy appointments have non-significant findings. Courtesy relations have very little to do with grant writing processes, but are very common forms of association in our setting; yet they do not act as conduits of influence for these outcomes. At minimum, this refutes any notion that the modeling strategy *induces* the appearance of peer influence (see Cohen-Cole and Fletcher, 2008). We also surmised that authority relations and tie strength will separately and jointly help to further consolidate channels of influence, which was also largely supported in our findings, along with the corollary proposition that strong, salient ties to alters in relational positions of authority act as the most effective influence channels.

[11] We also examined these effects on the other two dependent variables (the award rate and award amount) and found similar patterns. Tables and figures available upon request.

Second, we tested the robustness of effects by assessing the possibility that affiliation networks channel influence through global changes in individual behaviors (spillover) versus more local changes specific to a given relationship (synergy). We did so by re-estimating our models for changes in an ego's productivity, looking only at productivity that is independent of joint endeavors with a given alter. This also revealed that some networks and grant activities are more likely to produce spillover effects – i.e. networks with stronger total peer-influence effects also tended to have larger potential spillovers. Our findings also suggest that learning processes (award rates and amounts) have greater spillover than do changes in routine behaviors (application rates). These findings have clear implications for research concerned with intra-organizational diffusion processes. Although more research is merited, the potential for significant spillovers suggests that relatively small incentives to increase grant productivity at the organizational level may have an additional "multiplier effect" as information and influence concerning productivity gains diffuses through underlying faculty networks. For example, it is possible that our findings are heavily dependent upon a few exceptionally productive and well-connected researchers who initiate the ratcheting effects rather than a diffuse influence emerging from many individuals in one's network. Future research using Friedkin's structural weights and "one-mode" network data may be able to discern such differences.

Finally, we found that some network channels are more volatile than others in how they transmit influence, and that peer effects are heavily dependent upon the social distances between individuals. While we were unable to identify the precise mechanisms behind this volatility, prior research suggests that status characteristics may act as cultural and institutional lenses through which behaviors are differently interpreted. These may combine with additional structural barriers associated with status characteristics to further limit the transmission of influence and social learning within certain types of dyadic relationships. By examining the same effects across multiple relationships and productivity measures, we also helped to rule out the possibility that our findings are driven by exogenous shifts affecting both ego and alter (see Christakis and Fowler, 2007, p. 373). If "broadcast effects," such as the creation of a new research initiative, were entirely responsible for what we have characterized as endogenous effects we would not expect different network types of network ties to dramatically vary our overall findings. Certainly, it would make little sense that directionality in a relationship would significantly alter effects in our proposed manner.

Nonetheless, there are some limitations to our approach. Even with our conservative strategy, the precise magnitude of peer effects is not clear because of the unknown possibility of uncontrolled spurious factors. However, our primary goal has not been to specify *how much* productivity results from peer influence, so much as to find initial support for peer effects and to elaborate these in theoretically guided ways. Future research should focus more specifically on comparing individual, institutional and relational sources for productivity. Our study is limited in a second way because it focuses on a single university, and one that is strongly oriented toward grant writing. While a single-institution study does have the advantage of implicitly controlling for institutional effects on productivity, it limits generalizeability to a larger population of researchers in unknown ways. Given that our setting is in many ways ideal-typical of the trend towards large, interdisciplinary research teams, it is a highly suited test case for examining the role of peer influence, but we should exercise caution in applying these findings to settings where researchers may be less initially oriented towards increasing their grant productivity.

Our approach uses affiliations networks to assess how influence flows in the aggregate. Such information is relatively easy to collect in a number of research settings where more complete network data is lacking, and already exists in many publicly available datasets. For example, research on adolescence is particularly concerned with peer influence in shaping risky behaviors or positive aspirations. These outcomes have been studied at a number of levels, and prior to the completion of the Add Health dataset (see Harris et al., 2009) there had only been small network-type studies of peer influence. Understanding aggregate patterns of influence, for instance within a large public high school, has been limited. If one's research goals are to understand *if* peers matter at all, then our approach is unnecessary because of the prominence of ethnographic findings. However, if one wishes to better understand what types of relationships or individuals act as stronger conduits of influence for a given population of interest, then affiliation networks can act as proxies in the absence of large, comprehensive network datasets. Students belong to a number of groups (school and non-school based), and these may provide useful information on social contact. Co-membership in certain kinds of clubs (academic versus non-academic) may act as stronger channels of influence because of what they suggest for the quality of the relationship between students. The quality and strength of ties may combine with other properties of individuals in ways that support or disconfirm notions of how influence should flow. While affiliation networks are unlikely to provide the kind of precise estimates of peer effects sought by econometric analysis, they offer numerous opportunities for assessing how influence flows. For academic researchers, aggregated influence flows suggest that peer effects continue to shape important practices throughout one's career.

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