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Social Networks and Instructional Reform in STEM: The Teaching-Research Nexus

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Abstract
Instructional reform in STEM aims for the widespread adoption of evidence based instructional practices (EBIPS), practices that implement active learning. Research recognizes that faculty social networks regarding discussion or advice about teaching may matter to such efforts. But teaching is not the only priority for university faculty – meeting research expectations is at least as important and, often, more consequential for tenure and promotion decisions. We see value in understanding how research networks, based on discussion and advice about research matters, relate to teaching networks to see if and how such networks could advance instructional reform efforts. Our research examines data from three departments (biology, chemistry, and geosciences) at three universities that had recently received funding to enhance adoption of EBIPs in STEM fields. We evaluate exponential random graph models of the teaching network and find that (a) the existence of a research tie from one faculty member i to another j enhances the prospects of a teaching tie from i to j, but (b) even though faculty highly placed in the teaching network are more likely to be extensive EBIP users, faculty highly placed in the research network are not, dimming prospects for leveraging research networks to advance STEM instructional reforms.

Keywords Evidence based instruction practices · Communication networks · Teaching and research · STEM instructional reforms, exponential random graph models

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Introduction

Universities commonly divide their mission into the areas of research, teaching, and service. Much attention centers on the relationship between the first two, a key issue being whether effective performance in one area enhances or inhibits effective performance in the other. Our work shifts the focus to the social structures in which the day-to-day activities of teaching and research in academia are carried out: the networks of communication and discussion between faculty about research and teaching issues. Specifically, our contributions center on the role that networks of research discussion may play in advancing STEM instructional reforms. We investigate this question in the context of teaching discussion networks and the use of evidence based instructional practices (EBIPs) by STEM faculty. Our research questions concern the extent to which research discussions between faculty are conducive to teaching discussions between faculty and, in turn, how they are related to STEM faculty use of EBIPS in their classrooms.

The next section reviews literature on the relationship between teaching and research in higher education. We find that the literature (a) attends to how a faculty member's research productivity affects student outcomes and (b) does not examine the interplay between research and teaching in a faculty member's interactions with colleagues. We follow this review with a section on methods and description of our data set. The results section addresses several research questions:

RQ1. How do research networks differ from teaching networks;
RQ2. Do individuals occupy similar positions in the two networks;
RQ3. Does the connectivity of tenured and tenure track faculty (those with both research and teaching expectations) differ from that of nontenure track faculty in the two networks;
RQ4. Does a research tie encourage or discourage a teaching tie;
RQ5. Do leaders in the research network engage in evidence based instructional practices to the same degree as leaders in the teaching network, where leadership in both is defined as being often chosen as a discussion partner.

Research, Teaching, and Instructional Reform in STEM

One prominent position on the teaching-research nexus suggests that an overemphasis on higher education's research mission detracts from a proper focus on students and teaching. As characterized by Baker and Zey-Ferrell (1984), this view is zero-sum: engagement in research undermines commitment to teaching and to quality instruction, and time spent on research is time that cannot be spent on teaching (Wilson, 1982; Kline, 1977). Baker and Zey-Ferrell (1984: 83) also take note of an alternative synergistic view, which holds that teaching and research are complementary activities because the creation of knowledge is enhanced by its dissemination and vice-versa (Ratner, 1981; Feldman, 1987). These contrasting views have been revisited over the years, for instance, the chapters in *Faculty Teaching and Research: Is There a Conflict?* edited by Braxton (1996), without any final resolution. More recently, and to the point about research and instructional reform efforts, Bok notes "the growing emphasis on research may also have affected the willingness of faculty members to entertain proposals for fundamental changes in curriculum and teaching methods" (Bok, 2015, p. 335).

Prince et al. (2007) suggest that viewing the relationship between research and teaching as a zero-sum or positive-sum game misconstrues the issue. It is not simply whether research hinders or enhances teaching but, (a) whether it has the potential to support teaching in principle and (b) whether it supports teaching in practice. Evidence from qualitative studies suggests that higher education faculty and administrators agree that synergies between research and teaching can occur in principle (Taylor, 2007; Cadez et al. 2017). But Hattie and Marsh (1996) in their systematic review of 58 empirical studies find little or no evidence of a significant correlation between research and teaching in practice.

Work by Galbraith et al., (2012), Horta et al. (2012), Malcolm (2014) and others address the paradoxical results of studies in which synergies between research and teaching are acknowledged despite evidence showing little or no correlation between research and teaching performance. Prince et al. (2007) posit the absence of a significant correlation between research and teaching performance may be expected because each activity requires a different skillset, but this fact does not preclude faculty members from possessing both skillsets. Horta et al. (2012) point out that most empirical studies supporting the mutually reinforcing synergistic thesis are often qualitative, while those supporting the mutually exclusive nature of research and teaching tend to be quantitative. Reid and Gardner (2020) find that biology graduate students generally believe the synergistic thesis despite being exposed to contradictory messages. Horta et al. (2012) suggest the quantitative analyses fail to show synergy because their conceptual frames of reference for teaching and research are too narrow. Horta et al. (2012) assert that a broader analytical approach is necessary to analyze the linkage. For example, the finding that faculty who do not teach graduate level classes have reduced research output compared to faculty who do teach graduate level courses suggests there is an overlap of teaching-research activities at least with the subset of teaching activities focused on training the next generation of researchers. When research output is adjusted for its quality (high-quality journal publications relative to all publications by a researcher), Cadez et al. (2017) find research quality is positively correlated with teaching quality, while raw research output shows no correlation with teaching quality.[1]

The vast majority of quantitative studies of research productivity and teaching quality use publication records of faculty to measure research productivity and student evaluations to measure teaching quality (Galbraith et al., 2012; Prince et al., 2007; Rodríguez & Rubio, 2016; Taylor, 2007; Cadez et al. 2017). Researchers who cite the

[1] Output was assessed using the method of publication count: the number of publications in journals included in the Web of Science Core Collection database in the period 2006–2011.

strong evidence that student evaluations are not a reliable measure of teaching effectiveness (Boring et al., 2016; Hornstein, 2017) use direct measures of student learning alone or in combination with student evaluations to measure teaching effectiveness. Palali et al. (2018) use a combination of standardized test grades and teacher evaluations to measure teaching quality while research is measured by both output and quality (journal status). They find that graduate students whose mentors produce high quality research score higher on the standardized test but there is no effect for the total number of publications. For undergraduate students, no effects of research measures on teaching measures are found. The authors suggest that these results reflect the more specialized nature of graduate level courses and the higher level of interaction between graduate students and teachers. Galbraith et al., (2012) use a standardized and quantified student learning outcome assessment developed by a faculty committee and using established learning outcomes to measure teaching effectiveness. They find a statistically significant positive correlation between the level of faculty research activity and student learning. Yet, overall, the data suggest diminishing returns on teaching effectiveness from research productivity that the authors attribute to their focus on standardized student learning outcomes as an indicator of teaching effectiveness. Both Palali et al. (2018) and Galbraith et al., (2012) conclude that when teaching quality is measured by standardized tests rather than student evaluations, excellent research performance contributes to a higher teaching quality.

Several qualitative studies (Brew, 2003; Olsen & Simmons, 1996; Taylor, 2007) that find a correlation between research performance and teaching efficiency posit similar relationships. They find that the teaching-research nexus is a strong, mutually beneficial relationship for both students and faculty, while noting that the nature of the relationship can vary depending on disciplines and academic levels, with graduate and post graduate levels sharing the strongest link. Olsen and Simmons (1996) and Prince et al. (2007) go further to suggest that undergraduates should be provided with more opportunities to engage in learning from faculty about their research to strengthen the linkage between teaching and research. Finally, these researchers assert that because teaching and research are both very demanding of time and energy, institutions need to be more proactive in identifying mechanisms and strategies to support the relationship between them.

The idea that networks of teaching and research discussions among faculty may influence the teaching-research nexus occurs rarely in the above research literature with few exceptions. Benbow & Lee, (2019) focus on how faculty members develop social capital through their teaching networks, but leave aside the question of how the same could be done through research networks. Austin argues that "institutions and departments that want to nurture cultures where both teaching and research are valued should consider how they are encouraging conversations about teaching and supporting networks of faculty that emerge around mutual teaching-related interests, as well as those around research projects" (Austin, 1996, p. 64). Empirical research by (Lane et al., 2019) examines how faculty members' knowledge and use of evidence based instructional practices – the focus of many instructional reform efforts – are affected by the knowledge and use of their network partners. Relatedly, McConnell et al. (2020) propose a framework that highlights peer influence effects on the adoption of teaching innovations by instructors. Related to social networks and instructional reform efforts, Shadle et al. (2018) document the social network connections among leaders of the POGIL Project, an NSF funded instructional reform effort in Process Oriented Guided Inquiry Learning. Finally, with respect to the question of the teaching-research nexus connection to instructional reform efforts, Bok observes that the real problem "lies in the effect that graduate (PhD) training and a pronounced research orientation have on the curriculum and on the time available for professors to undertake major improvements and innovations in their courses and methods of instruction" (Bok, 2015, p. 341). Benbow and Lee echo this viewpoint "leaders hoping to foster beneficial ties should tailor instructional initiatives to more closely align with faculty experience and time commitments" (Benbow & Lee, 2019, p. 67).

Overall, previous literature suggests a variety of factors shape the teaching-research nexus: program level, academic discipline, curricula, broad vs. narrow conceptions applied to both research and teaching, and how administrators organize the teaching and research missions (Brew, 2003; Galbraith et al., 2012; Geschwind & Broström, 2015; Olsen & Simmons, 1996; Palali et al., 2018; Prince et al., 2007; Taylor, 2007). Noteworthy is the relative absence of attention to how faculty interact with one another regarding teaching and regarding research. The image conveyed (with noted exceptions) is that of the solitary teacher-scholar going at it alone. Yet, neither teaching nor research takes place in isolation from ties to colleagues upon whom one may rely for both advice and help regarding teaching matters and research matters. It is this interaction-based interplay between teaching and research that we explore with our research questions, which focus on how participation in research ties with colleagues is associated (or not) with the sharing of advice, information, and perspectives about instructional matters.

In this regard, findings from social network analysis on the strong influence of shared background and interaction foci on tie formation (Feld, 1981; McPherson et al., 2001) suggest that the occurrence of teaching ties will follow similarity in organizational and disciplinary affiliation, that is, a teaching tie from i to j should be much more likely if they are in the same university and in the same discipline. Further, social network analysis often finds strong effects of reciprocity (Garlaschelli & Loffredo, 2004), that is, that a tie from person i to person j is much more likely if there is a tie from j to i, and we fully expect to see this with respect to discussions about instructional matters. With respect to the teaching-research nexus, the viewpoint that teaching and research priorities conflict with one another suggests that interaction around teaching matters should be separate and apart from interaction around research matters. That is, a teaching tie from i to j should co-occur with a research tie from i to j at no greater than chance levels. On the other hand, the position that the two complement each other suggests that interaction around teaching matters should overlap with interaction around research matters, that is, a teaching tie from i to j should co-occur with a research tie from i to j more often than would be expected by chance. This phenomenon of tie multiplexity or overlap holds the potential for leveraging support for STEM reform to the extent such reform requires cooperation, a behavioral tendency enhanced by overlapping social ties (Atkisson & Borgerhoff Mulder, 2020).

Methods

The setting for our research is three USA research universities (two R1 and one recent R2 – in 2019) that had received federal grants to promote educational reforms, specifically the adoption of EBIPs, in their science departments. Each university had a different plan for how to accomplish this aim. While these plans did not drive our data collection, the research team was sensitive to the overall concern with STEM education reform, since members of the team from each of the three universities were also main participants in the promotion efforts. This concern was embedded in the more general framework developed above, namely, the core dynamic in research universities involving research demands and expectations on one hand and instruction and program delivery on the other.

Data Collection Data were gathered during the Spring 2018 semester via an online survey distributed to faculty in nine STEM departments across three research universities. A total of 296 faculty gave responses to the survey, a mixture of tenured (61%), untenured-tenure track (14%), and non-tenure track faculty (25%). From each of the three universities, we received a similar number of responses (98—101) and the breakdown by academic discipline was biology (22%), chemistry (25%), geology (20%), mathematics (22%), and physics (12%). The teaching and research networks to be examined are the networks of discussion ties between respondents in biology, chemistry, and geosciences (total $n = 192$) because the response rate in these three fields in all three universities exceeded 70%.[2] Of these 192 respondents, 146 (76%) are tenured or tenure earning (compared to 75% in the total 296 respondents) while the remaining 46 (24%) are in nontenure earning positions.[3]

Attribute data collected include basic demographic information and, of particular interest as an outcome variable, the extent of use of EBIPs measured on a seven-point scale (0–6) for some analyses and on a collapsed binary scale for others. The prompt and response options are (Landrum et al., 2017; McAlpin et al., 2022):

> Please read the following definition of EBIPs and answer Items 1-6 with a yes or no response. What is an EBIP? It is an evidence-based instructional practice or approach that has a demonstrated record of success. That is, there is reliable, valid empirical evidence to suggest that when faculty use EBIPs, stu-

[2] While mathematics faculty, for example, are a sizable percentage of all respondents, the problem is that mathematics departments are typically larger and so the respondents represented an unacceptably small response rate (< 60%) for that faculty. See Agneessens and Labianca (2022) for a discussion of the importance of high response rates in social network analysis.

[3] Specifically, the following ranks are mapped to the first category: Assistant Professor (26), Associate Professor (52), Professor (67), and Distinguished Professor (1); and the following ranks are mapped to the second category: Assistant Professor of Practice (2), Associate Research Professor (1), Clinical Assistant Professor(7), Instructor I (8), Instructor II (6), Instructor III (1), Lab Teacher (6), Lecturer (5), Other (3), Professor of Practice (1), Research Assistant Professor (4), Research Associate Professor (1), and Research Professor (1). Most ranks in this second category, but not all, refer to positions with minimal research expectations.

> dent learning is supported, and it is implied that EBIPs are more effective than standard traditional lecture and discussion methods (Groccia & Buskist, 2011). Active learning techniques are often EBIPs, such as just-in-time teaching, process oriented guided inquiry learning, think-pair-share, cooperative learning, peer instruction, service learning, and many others.

1. Prior to this survey, I already knew about evidence-based instructional practices (EBIPs);
2. I have thought about how to implement EBIPs in my courses;
3. I've spent time learning about EBIPs (e.g. attended workshop, experimented in class, read education literature) and I am prepared to use them;
4. I consistently use EBIPs in my courses;
5. I consistently use EBIPs and I continue to learn about and experiment with new EBIPs; 6. I have evidence that my teaching has improved since I started using EBIPs.

Responses are coded two ways: first, as the number of items checked and, second, dichotomized into a score of 3 or below as low (L) users and a score of 4 and above as high (H) users, an attribute denoted EBIP (H/L). The cutoff represents a division between levels of knowledge of EBIPs and levels of use.[4]

Network data collection uses a roster method to collect ties of discussion about teaching matters and ties of discussion about research matters with departmental colleagues. The specific prompts are:

> During the most recent academic year, I discussed instructional activities (e.g. teaching strategies, student learning, grading, student achievement) with the following colleagues within the [Department]: (Check as many as apply; Please do not select your name)
> [List of faculty provided]
> During the most recent academic year, I discussed research activities (e.g. your research topics, their research topics, mutual collaborations, funding opportunities) with the following colleagues within the [Department]: (Check as many as apply; Please do not check your name)
> [List of faculty provided]

Note that the collection of discussion ties to departmental colleagues leaves the question of whether such ties are mutual or reciprocated to be an empirical matter, that is, symmetry is not enforced by the data collection routine. As we will see shortly, both types of ties are often mutual as an empirical fact.

A recall format is used to collect ties (a) to colleagues in other departments at the same university and (b) to colleagues at other universities. The specific prompts are:

> During the most recent academic year, I discussed instructional activities (e.g. teaching strategies, student learning, grading, student achievement) with the

[4] See McAlpin et al. (2022) for further details justifying this division in light of other measurements.

> following colleagues who are outside the [Department] but at [University] and/or outside {University]: Identify up to 7 individuals in each category; columns indicate whether the individual is at [University] or not.
> During the most recent academic year, I discussed research activities (e.g. your research topics, their research topics, mutual collaborations, funding opportunities) with the following colleagues who are outside the [Department] but at [University] and/or outside [University]: Identify up to 7 individuals in each category; columns indicate whether the individual is at [University] or not.

In the roster method, the respondent sees a complete list of names to which they may indicate a type of tie, whereas in the recall method, no list is provided because the population is too large and open.[5] Answers to the roster and recall questions are used to construct the discussion networks: specifically, there is a tie from i in department X to j in department X if *i* chose *j* from their department's roster, there is a tie from *i* in X to *j* in department Y at the same university if *i* named *j* on the first recall question and there is a tie from *i* in one university to a *j* in another university if *i* named *j* on the second recall question.

Analysis We first characterize the two networks in terms of basic metrics like density (number of actual ties divided by the number of possible ties), reciprocity (the extent to which dyads have both ties in them versus just one tie – from *i* to *j* or *j* to *i*), degree distribution (frequencies of the count of ties sent – outdegree – and ties received – indegree), clustering coefficient (proportion of triples where *i* sends a tie to *k* and *k* sends a tie to *j* that are closed with a tie from *i* to *j*), and mean value of the shortest path (geodesic) between all pairs of vertices. Furthermore, because these networks are ties between university faculty members, we also examine variation in the connectedness of subsets of vertices (representing individual faculty members) defined by whether individuals are in tenured/tenure earning positions and so subject to both teaching and research expectations or in nontenured positions with only instructional assignments (for most of them, see footnote 3).

To examine statistically how teaching ties are related to research ties, we use exponential random graph models (ERGMs). These models evaluate how properties of an observed network are associated with the probability of its occurrence. Technically, they assert that the probability of a graph is proportional to an exponentiated sum of a linear combination of graph features defining the model. Examples of such features are the number of edges (or volume of ties), the number of mutual ties, the number of ties between persons sharing an attribute value (homophilous ties), etc. (Robins et al., 2007). Interpretation of the model can refer to an *ij* pair and how the presence vs absence of an *ij* tie changes the features of the graph included in the model and, via the associated estimated effect coefficients, affects the log odds of its presence. In that sense, an ERGM predicts the probability of an *ij* tie based on effects specified in a model. In our models, effects included are effects of vertex

[5] Pretesting determined that faculty members generally named fewer than 7 persons outside their department or outside their university in response to this recall prompt.

attributes on the volume of ties sent and received, the reciprocation effect on sending a tie if a vertex has received one, the effect of the co-presence of another tie type (edge covariate), and the effects of combinations of attribute values (e.g., EBIP use) for sender and target. Estimation of models is done with the `statnet` package in `R`. This package uses Markov Chain Monte Carlo methods to find maximum likelihood estimates of effect coefficients (Hunter et al., 2008).

In its global form, an ERGM is expressed by Eq. 1 where y is the observed network. In

$$Pr(Y = y|\theta) = \frac{e^{\theta_1 z_1(y)+\theta_2 z_2(y)+\cdots+\theta_p z_p(y)}}{\kappa(\theta)} \tag{1}$$

this equation, θ is a vector of coefficients, one per graph property z_i hypothesized to affect the probability of observing y and $\kappa(\theta)$ is a normalizing constant insuring that the sum of the probabilities over all possible graphs equals 1:

$$\kappa(\theta) = \sum_{y \epsilon Y} e^{\theta_1 z_1(y)+\theta_2 z_2(y)+\cdots+\theta_p z_p(y)} \tag{2}$$

For purposes of interpretation, the ERGM local form expresses the log odds that a tie is present as a function of the changes its presence produces in the graph properties. That form is given in Eq. 3:

$$\left[\frac{Pr\left(Y_{ij} = 1|Y_{-ij} = y_{-ij}, \theta\right)}{Pr\left(Y_{ij} = 0|Y_{-ij} = y_{-ij}, \theta\right)}\right] = \omega_{ij} = \theta_1 \delta^+_{ij,1}(y) + \theta_2 \delta^+_{ij,2}(y) + \cdots + \theta_p \delta^+_{ij,p}(y) \tag{3}$$

In this form y_{-ij} is the observed graph omitting the ij location, Y_{ij} is the random variable associated with the ij location; θ is as defined for the global form; and the k^{th} change statistic $\delta^+_{ij,k} = z_k\left(y^+_{-ij}\right) - z_k\left(y^-_{-ij}\right)$ is the change in the k^{th} graph property when the ij tie is present (y^+_{-ij} is the observed network) versus when it is absent (y^-_{-ij} is the observed network). This form can then be used to calculate the probability of a tie at the ij location using Eq. 4 and given a profile of change statistics corresponding to the presence of a tie at that location:

$$Pr\left(Y_{ij} = 1|Y_{-ij} = y_{-ij}, \theta\right) = \frac{1}{1 + e^{-\omega_{ij}}} \tag{4}$$

We propose and evaluate three models for the teaching discussion network: Baseline, Research, and Research + EBIP (H/L). In all three, there are effects for volume of ties (edges), for which university is sending/receiving ties, for whether ties are within the same university, whether they are within the same STEM field, and for the number of mutual, i.e., reciprocated ties. The second model adds an effect for the number of times a research discussion tie co-occurs with a teaching discussion tie and the third model includes this co-occurrence effect and effects for a dyad's combination of EBIP use with respect to the binary categories high (H) and low (L).

Finally, additional analyses use simple linear regression methods to assess how overall position in the teaching discussion network and overall position in the

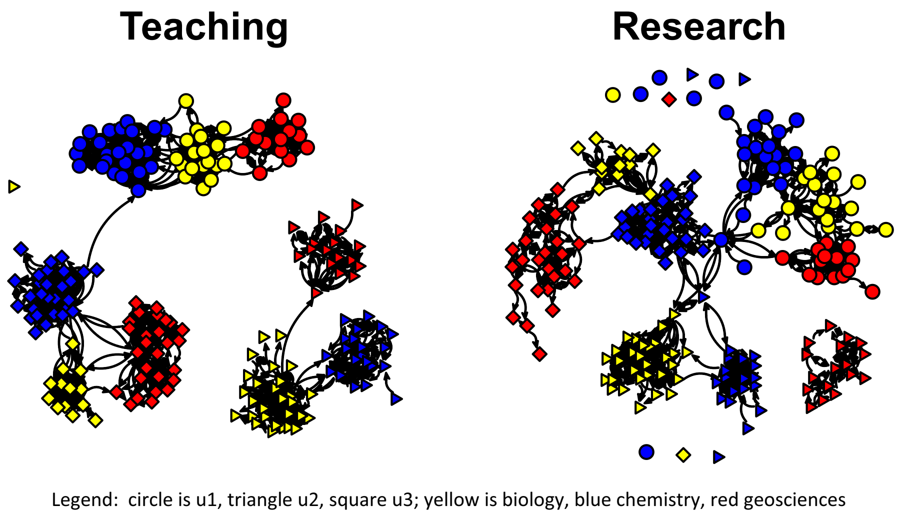


Fig. 1 Visualization of the teaching and research discussion networks of three universities

research discussion network are related to the use of EBIPs. The key measure of position is the number of ties received by a faculty member, i.e. his/her indegree. This quantity is a measure of opinion leadership available through social network analysis, a measure that Valente and Pumpuang's review calls "the most valid and reliable means for identifying opinion leaders but may also be the most costly and restrictive" (Valente & Pumpuang, 2007, p. 888). The motivating question here is how EBIP use is related to leadership positions in the two networks as defined by being named relatively often as a teaching or research discussion partner.

Results

The teaching and research networks are visualized in Fig. 1 with vertices colored by STEM field with a different shape for each university. Simple inspection reveals that both types of ties tend to cluster within university but more so for the teaching ties. Furthermore, all but one respondent is either the target or the sender of a teaching discussion tie, but there are many respondents in the research network who neither send nor receive research discussion ties. We address our five research questions in turn: (1) comparison of the two networks on key metrics; (2) correlations between individual positions in the two networks in terms of ties sent and ties received; (3) comparison of the connectivity of tenured and tenure track faculty with that of nontenure track faculty; (4) whether a research tie encourages or discourages a teaching tie; and (5) EBIP use by leaders vs others in the teaching network as compared to EBIP use by leaders vs others in the research network.

Table 1 Basic network metrics

	Teaching	Research
Density	0.036	0.024
Mean outdegree	6.95	4.50
Katz-Powell reciprocity index	0.606	0.543
Clustering coefficient	0.494	0.407
Mean geodesic	3.15	5.55

see text for explanations of metrics

RQ1 Table 1 compares the two networks in terms of some basic network metrics. First, within this bounded population, the teaching network is denser than the research network, as it appears to be from the figure. That is, there are more teaching ties than research ties. Consequently, Table 1 shows that the average faculty member sends (and receives) more teaching ties than research ties. The third comparison shows that reciprocity is slightly greater among the teaching ties as measured by an index (varying between 0 and 1) that calibrates the number of dyads in which the ties are reciprocated (that is, i sends a tie to j and j to i) relative to the maximum number that could occur, controlling for the outdegree distribution (and so the overall number or density of ties). In effect, in the teaching network as compared to the research network, i sending a tie to j is more likely to be paired with j sending a tie to i, although that pattern is quite common in both networks. Compared to the research network, the teaching network has a higher clustering coefficient (potentially varying from 0 to 1) as measured by the proportion of paths of length two, e.g., from i to k and k to j, that are closed by the third tie from i to j. This difference means that the formation of small, closed circles of vertices is more common among teaching discussions than among research discussions, although, again, it is common in both and well above chance expectations given by the densities (0.036 for the teaching network and 0.024 for the research network). The last row in Table 1 shows that the average shortest path between pairs of connected vertices is shorter in the teaching network than in the research network, indicating the teaching network is more tightly connected through indirect connections (to be expected given its higher average degree).

RQ2 In terms of how positions in the two networks are related to each other, we note that there are positive correlations between outdegree in the teaching network and outdegree in the research network, 0.29, and between indegrees in the two, 0.18. The first correlation means that faculty who send more research ties also tend to send more teaching ties and vice-versa. The second correlation means that faculty who receive more research ties also tend to receive more teaching ties and vice-versa, although this is a weaker tendency.

RQ3 In these networks there are, as noted earlier, 146 tenured/tenure track faculty and 46 nontenure track faculty. They differ from one another with respect to sending and receiving of the two types of ties in ways consistent with intuition. Specifically,

Table 2 Estimation results for three ERGMS for the teaching network

		Estimates		
Effect	Interpretation	Baseline	Research	Research + HL EBIP
edges	Volume of ties	–12.468***	–12.063***	–12.547***
nodefactor	Volume adjustments per university			
u2		–0.245***	–0.328***	–0.284***
u3		–0.198***	–0.236***	–0.174***
nodematch	Homophily – same university and same field			
univ		7.430***	7.065***	7.135***
field		3.724***	3.484***	3.524***
mutual	Reciprocated ties	2.196***	2.015***	1.981***
edgecov	Presence of research tie			
research		–	1.505***	1.493***
mix.ebipHL	Pair combination of EBIP use			
H.H		–	–	0.597***
L.H		–	–	0.279*
H.L		–	–	–0.015 ns
AIC		5231	4829	4767
BIC		5282	4889	4852

*$p < .05$ ***$p < .001$

tenured/tenure earning faculty send fewer teaching discussion ties on average (6.69 vs 7.78) and receive fewer such ties on average (6.40 vs 8.70) than nontenure earning faculty. As expected, given the difference in research expectations, the pattern is reversed for research discussion ties: tenured/tenure earning faculty send many more research ties on average (5.29 vs 1.98) and receive many more research ties on average (5.40 vs 1.65) than nontenure earning faculty. Clearly tenure earning faculty are far more engaged in research discussions than nontenure earning faculty. But note that the latter, despite minimal research expectations, do participate in the research discussion network, albeit at understandably reduced intensity.

RQ4 The results of the exponential random graph models for the network of teaching ties are found in Table 2. In the first column, the Baseline model, included effects capture the overall volume of ties (edges), differences among universities in the volume of ties (nodefactor("univ")), being in the same university, i.e., university homophily (nodematch("univ")), being in the same field i.e., field homophily (nodematch("field")), and the sending of a tie to target who has sent the same type of tie to the sender, thus reciprocating that selection (mutual). Figure 1 makes it clear that most teaching ties are within a university and, within a university, within a field represented by the department at that university. Table 1's reciprocity index makes it clear that reciprocity in the teaching network is substantial (60% of its maximum possible value). Furthermore, and not obvious from Fig. 1, is the fact that there are differences among universities (u1, u2, and u3) in the volume of ties their faculty participate in. Coefficients in the Baseline model (Table 2) associated with all these factors capture these impressions. First, they are all significant beyond $p<0.001$. Second, in absolute magnitude the coefficients for homophily by university and for homophily by field and for mutuality are much larger than the coefficients for the adjustments to volume for u2 and u3 relative to u1 (whose tie volume is captured in the edges coefficient).[6] These differences mean that the chances of a teaching tie from i to j are more closely linked to sharing university or field affiliation or to when j has sent a tie to I than they are to differences among universities in the volume of ties sent and received.

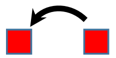
To understand these results better, we use eqns. 3 and 4 to calculate the probability of an *ij* tie for a particular model from a profile of changes in modeled effects associated with the presence of a tie versus its absence. The profiles in Table 3 begin with the profile associated with the tie that has the lowest probability. That profile is for a pair *ij* where i is in u2, j is in u3, they are in different fields, and j does not send a tie to i.[7] The profile associated with the highest probability is depicted in the last row of the table. It is a pair of vertices in u1 (the R2 university) where both are in the same field and there is a tie from *j* to *i*. This probability, 0.704, would be the chance, for example, that faculty member *Smith* sends a teaching tie to faculty member *Jones* when both are in u1 and both are in biology (or both in chemistry or both in geosciences) and *Jones* has sent a teaching tie to *Smith*. In line with the sizes of coefficients, the most probable ties occur between faculty in the same university, the same field, and where *j* has sent a teaching discussion tie to *i*. On the other hand, given identical circumstances except both faculty members are in u2, one of the R1 universities, the probability that *i* sends a teaching discussion tie to *j* is 0.596. These are baseline probabilities of a teaching tie without considering the effect of a research tie from *i* to *j* and as baselines, allow us to demonstrate clearly the effect of such a research tie by comparison.

The model in the Research column of Table 2 assesses the association between the research network and the teaching network, specifically, whether an *ij* teaching tie is more common when there is an *ij* research tie. This pattern is called entrainment (Lusher et al., 2013) and in other literature multiplexity (Skvoretz & Agneessens, 2007). It is useful to begin with an understanding of how often research and teaching ties co-occur. Given there are 192 respondents, there are $192 \times 191 = 36{,}672$

[6] An additional node factor effect contrasting the volume of ties between tenured/tenure earning and nontenure earning, suggested by the descriptive comparison, was in the full baseline model. Although the effect of being tenured/tenure earning was negative, it was not statistically significant and was dropped from consideration.

[7] The logic behind this analysis is that the least likely tie is one that avoids homophily effects (being in the same university and being in the same field) which would increase the chances of a tie since these effects have positive coefficients and the positive effect of mutuality. Thus it must be a tie that goes between universities with the vertices being in different fields. There are three possibilities: a tie between vertices in u1 and u2, between u1 and u3 and between u2 and u3. The first tie is affected by the overall edges effect and an increase of 1 in the nodefactor.u2 effect, the second by the overall edges effect and an increase of 1 in the nodefactor.u3 effect, and the last by all three effects. Therefore the tie that has the lowest probability is between a vertex in u2 and one in u3 in a different field and not paired with a second tie that would make the dyad a mutual dyad. This is a dyad with just one edge in it either from a vertex in u2 to one in u3 or from a vertex in u3 to one in u2 and in either case one that is between fields.

Table 3 Probabilities of a teaching discussion tie under various conditions, baseline model

Condition	Diagram*	Change Profile**	Prob
i in u2 to j in u3, diff field, no tie from j to i		⟨1,1,1,0,0,0⟩	2.5e-06
i and j in u2, diff field, no tie j to i		⟨1,2,0,1,0,0⟩	0.004
i and j in u3, diff field, no tie j to i		⟨1,0,0,2,0,0⟩	0.004
i and j in u1, diff field, no tie j to i		⟨1,0,0,1,0,0⟩	0.006
i and j in u2, same field, no tie j to i		⟨1,2,0,1,1,0⟩	0.142
i and j in u3, same field, no tie j to i		⟨1,0,2,1,1,0⟩	0.152
i and j in u1, same field, no tie j to i		⟨1,0,0,1,1,0⟩	0.211
i and j in u2, same field, tie j to i		⟨1,2,0,1,1,1⟩	0.596
i and j in u3, same field, tie j to i		⟨1,0,2,1,1,1⟩	0.615
i and j in u1, same field, tie j to i		⟨1,0,0,1,1,1⟩	0.704

*Vertex i is left, j right; circle is u1, triangle u2, square u3; yellow is biology, blue chemistry, red geosciences; solid arc is teaching discussion tie

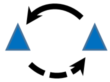
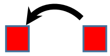
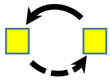
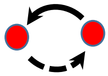
**⟨*edges*, *nodefactor.u2*, *nodefactor.u3*, *nodematch.u*, *nodematch.f*, *mutual*⟩. For example, the entry in the second to last row ⟨1,0,2,1,1,1⟩ means that an *ij* teaching discussion tie that occurs in the diagrammed pair increases by 1 the number of edges, by 2 the number of vertices in u3 that send or receive such a tie, by 1 the number of edges involving two vertices from u3, by 1 the number of edges involving two vertices in chemistry, and by 1 the number of mutual dyads (a pair of reciprocated ties)

Table 4 Faculty pairs by presence/absence of teaching tie and research tie

		Research tie		
		Present	Absent	Total
Teaching Tie	Present	510	825	1335
	Absent	354	34,983	35,337
	Total	864	35,808	36,672

pairs of vertices, i.e., locations at which either a teaching tie or a research tie or both could appear. A cross-tabulation of the outcomes in Table 4 shows that at 510 of these locations both types of ties occur. If the co- appearances of research and

Table 5 Probabilities of a teaching discussion tie under various conditions, research model

Condition	Diagram*	Change Profile**	Prob
i and j in u2, same field, teaching tie j to i, no research tie i to j		⟨1,2,0,1,1,1,0⟩	0.460
i and j in u2, same field, teaching tie j to i, research tie i to j		⟨1,2,0,1,1,1,1⟩	0.799
i and j in u3, same field, teaching tie j to i, no research tie i to j		⟨1,0,2,1,1,1,0⟩	0.513
i and j in u3, same field, teaching tie j to i, research tie i to j		⟨1,0,2,1,1,1,1⟩	0.831
i and j in u1, same field, teaching tie j to i, no research tie i to j		⟨1,0,0,1,1,1,0⟩	0.625
i and j in u1, same field, teaching tie j to i, research tie i to j		⟨1,0,0,1,1,1,1⟩	0.886

*Vertex i is left, j right; circle is u1, triangle u2, square u3; yellow is biology, blue chemistry, red geosciences; solid arc is teaching discussion tie, dotted arc research discussion tie.

*⟨*edges*, *nodefactor.u*2, *nodefactor.u*3, *nodematch.u*, *nodematch.f*, *mutual*, *edgecov.r*⟩

teaching ties were independent, we would expect only 31 such cases. So clearly, a teaching tie is much more likely if there is a research tie and vice versa. To properly assess this apparent association controlling for other important effects represented in the Baseline model, we add an effect for an edge covariate, the edge covariate being whether or not there is an *ij* research tie.

Results in the Research column of Table 2 show that all effects in the Baseline model remain statistically significant. Furthermore, net of these effects, a research tie has a positive, substantial, and statistically significant effect. The presence of such a tie in the *ij* pair enhances the prospects of an *ij* teaching discussion tie nearly as much as a *ji* teaching discussion tie (reciprocity). Table 5 illustrates how much enhancement by calculating probabilities for various profiles. Selected conditions from Table 3 for a particular profile are divided into two subgroups, those having no *ij* research tie and those having such a tie. Clearly, the probability of a teaching discussion tie is much greater in the latter group than the former although it is, relatively speaking, large in both groups. In terms of our previous example of Professors *Smith* and *Jones*, the presence of a research tie from *Smith* to *Jones* makes the probability of a teaching tie from *Smith* to *Jones* equal to 0.886 whereas it is 0.625 in the absence of that research tie.

The final model in Table 2 adds a dyadic attribute to the prediction of a teaching tie based on the combination of each vertex's high (H) or low (L) use of EBIPs.

Table 6 EBIP use as a function of leadership

	EBIP Use	
Effect	Teaching	Research
constant	2.934***	3.816***
indegree	0.148***	0.033 ns
R^2	0.084	0.003

***$p < .001$

The additional effects are not as large as either the reciprocity effect or the research tie effect, but two of them nevertheless contribute statistically to the presence of a teaching discussion tie.

RQ5 Finally, we address the question of how EBIP use relates to being a leader in the two networks by virtue of being often named as a discussion partner. As noted earlier, social network analysis commonly identifies opinion leaders by the number of ties they receive (their indegree). Such individuals are ones sought out by many others and thus, presumably, their opinions and practices matter more than the opinions and practices of those not often sought out. Given the findings of the last ERGM with respect to EBIP use, we expect what Table 6 shows: a significant positive relation between EBIP use and indegree in the teaching discussion network. That is, colleagues in the teaching network who are more often sought out for advice and discussion have significantly higher EBIP use. On the other hand, even though the presence of a research tie contributes positively to the chances of a teaching tie, Table 6 shows that indegree in the research network is unrelated to EBIP use. That is, those who receive many research advice/discussion ties are no more likely to be high EBIP users than those who receive few such ties. If high EBIP users are likely to be advocates for EBIPS, such advocacy is no more likely to be found among leaders than among non-leaders in the research network. There is, however, a glimmer of hope with respect to leveraging research networks to advance instructional reforms in STEM: if influential actors in the research network became high EBIP users, that could open additional channels of influence in the teaching domain. These additional channels correspond to the teaching ties that co-occur with research ties at greater than chance levels. In this optimistic scenario, influential actors in the research network, those who receive many research discussion ties, are the target of induced teaching ties and it is through those ties that their high-level use of EBIPS could exercise peer influence and motivate adoption.

Discussion

There has been long-standing interest in the relationship between teaching and research in universities. As we have reviewed, some scholars argue for the complementarity of the relationship, in short, excellence in teaching and in research go hand-in-hand. Others claim teaching and research compete for the time and energy of faculty and so the attention needed to be successful in one domain detracts from the attention needed to be successful in the other. Research findings on the issue have been mixed. Our finding that the existence of a research tie from one faculty member to another significantly increases the chances of a teaching tie in the same direction, net of other powerful effects, means that teaching and research complement one another in the social infrastructure of departments. This finding aligns with the synergistic view of the teaching-research nexus; however, it is silent on the issue of whether excellence in teaching contributes to excellence in research and vice-versa.

From the point of view of reform efforts, an important question is whether networks of research discussion can be leveraged to advance instructional reforms in STEM, especially, the adoption of evidence based instructional practices. The evidence we have suggests the answer is negative. We find that leaders in the research network are no more or less likely to be high-level adopters of EBIPs than the average faculty member and so cannot be counted on to advance the adoption of EBIPs through their leadership position in the research discussion network. The upside is that at least at the three institutions studied, research leaders are not uniformly low-level EBIP users who might be less than supportive of such instructional practices. And the fact that research ties encourage teaching ties points to unrealized potential for advancing instructional reforms if leaders in the research network become EBIP adopters. In that case, the overlap or multiplexity of the ties among faculty provides a precondition for cooperative action to overcome perceived costs to the adoption of EBIPs (McAlpin et al., 2022).

When we look at how EBIP use directly relates to teaching discussion ties, we find a basic consistency with previous work (Lane et al., 2020). High-level users are significantly more likely to have a tie to other high-level users (net of all other important effects in the model) than they are to have a tie to low-level users. So consistent with the main conclusion of Lane et al. (2020), the high-level users are "preaching to the choir" even when the presence of research ties is controlled. The current model also suggests that low-level users are also significantly more likely to have a tie to the high-level users than to other low-level users. This finding is a bit of good news because such connections between low-level and high-level users could facilitate the diffusion of EBIP usage.[8]

Finally, it is worth mentioning some limitations of the analysis. A key limitation is that our data cover only three fields (biology, chemistry, geosciences) in three universities so the generality of the results is necessarily limited. To be fair, complete network data are quite difficult to collect. While there are other studies of faculty networks focused on teaching advice and discussion, none of them also collected data on research discussions nor did they have an outcome measure related to use of evidence based instructional practices. In terms of the research interest in STEM instructional reform initiatives, our work provides the sole source of insight into how faculty research discussion networks might contribute.

A second limitation is that the settings for our work are two R1 and one R2 universities. For institutions that are not R1 or R2, we think our main findings would

[8] Previous work did not find this effect because its models did not control for the presence of a research discussion tie from i to j. That the effect shows up once the contribution of research ties is taken into account has to do with the differing proportions of LL vs LH pairs that have a research tie.

replicate, in particular the finding that an *ij* research tie enhances prospects for an *ij* teaching tie. However, we expect a substantial difference in the volume of research ties overall between R1/R2 institutions and others in favor of the former. When such ties do occur in non-RI/R2 institutions, we think they are likely to be associated with teaching discussion ties. At the very least, our results provide a comparison for future work that examines similar questions in non-R1 institutions. Overall, we think our findings are intriguing enough to motivate additional data collection for other STEM fields and universities and at other types of institutions to build a larger database to address how networks play a role in STEM educational reform efforts.

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Data Availability Anonymized version of data used in analysis can be made available upon request and with consent to appropriate confidentiality safeguards.

Code Availability Available.

Declarations

Ethical Approval BSU IRB approval number 936-SB19-038; UNL IRB project ID: 16000 (exempt status); USF IRB: Pro00025701.

Consent Participants provided informed consent on the first page of the survey.

Conflicts of Interest All authors certify that they have no competing interests.

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