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The role of network embeddedness in film success☆

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ABSTRACT

In the early stage of film development when producers assemble a development team, it is important to understand the means by which different team members may contribute to the film's box office. Building upon theories from marketing and sociology, we propose that these contributions arise from team members' positions, or embeddedness, in a social network weaved through past film collaborations. These collaborations provide team members with opportunities to draw knowledge and skills from the network for new film projects. Our conceptual framework accentuates two aspects of network embeddedness: positional embeddedness (PE)—how well a person is tied to well-connected others, and junctional embeddedness (JE)—the extent to which a person bridges sub-communities in the industry. We examine how the importance of PE and JE varies by functional role (cast versus crew), and is moderated by the film's studio affiliation.

Analyzing more than 15,000 industry professionals over nearly two decades of film collaborations, this research reveals crucial and divergent relationships: while high PE is more valuable for the cast, high JE is critical for the crew. This role distinction also depends on a film's studio affiliation. Managerially, these findings provide guidance to film executives and producers in revenue maximization through strategic team assembly, and to talents in career management.

1. Introduction

The movie industry is a prime example of *Risky Business*. U.S. film studios are estimated to have spent an average of over $40 million to produce and market a single film in 2014, yet these films averaged only $15 million in North American box office. With budgets approaching $200 million to market a film internationally, global box office similarly fails to deliver positive returns for the average global release (McClintock, 2014; Motion Picture Association of America, 2014; Nash Information Services, 2015). To improve returns on investment, film executives and producers are keenly interested in understanding and managing key factors

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in the early stages of film development before making such enormous investments. Given the cost associated with, and the critical contribution of, a film's core team—the principal on-camera cast (e.g. lead actors and actresses) and off-camera crew (e.g. director, cinematographer, and production designer)—to a film's success, it is vital to identify and assemble a high potential core team of collaborators. Past research has focused on box office success as driven by product features, such as genre, and post-development factors such as consumer responses to storyline, advertising, distribution, critics, and word-of-mouth (Eliashberg, Elberse, & Leenders, 2006). We extend this literature by emphasizing the crucial value of the core development team to box office success.

Movie development is characterized by fluid construction and dissolution of development teams on a project-by-project basis (Guimera, Uzzi, Spiro, & Amaral, 2005; Uzzi & Spiro, 2005). For example, when Leonardo DeCaprio and Tom Hanks collaborated in *Catch Me If You Can*, a link between them is established. As they also work with other people on different film projects, more links are generated to form an elaborate collaboration network—a structure consisting of connections among individuals through their prior collaborations in the industry. In light of this networked structure and guided by prior research examining industrial social networks (e.g. Ahuja, Galletta, & Carley, 2003; Cattani & Ferriani, 2008), we take a perspective of interconnected, as opposed to isolated, individuals in the film industry. In particular, we examine two key properties of each person's embeddedness in the collaboration network: positional embeddedness (PE)—the extent to which the person has collaborated with well-connected others in the network; and junctional embeddedness (JE)—the degree to which the person's prior collaborations bridge different network sub-communities (Zukin & DiMaggio, 1990). Intuitively, relations with well-connected others (PE) may increase one's reputation and image, while connections across sub-communities in the network (JE) may represent enhanced access to unique or diverse technical and artistic skills that can benefit future projects (Cattani & Ferriani, 2008; Grewal, Lilien, & Mallapragada, 2006).

Taking the perspective of film producers who are in direct charge of team assembly, we theorize that PE and JE hold differential importance across functional roles in a team, which we classify as the core front-of-scene cast and behind-the-scene crew. For example, a cast member with high PE may have a strong reputation in the industry, helping a movie signal its quality and generate publicity. This network position should be less critical to the crew, whose value arises more from their unique and diverse technical experience. Considering the different responsibilities and skills required across these different functional roles, PE is potentially more valuable to the cast and JE more crucial to the crew.

Furthermore, films affiliated with a major (e.g. Universal), as opposed to an independent (i.e. indie, e.g. Yari Film Group) studio may take advantage of their superior brand recognition in influencing the films' distribution and publicity (Eliashberg et al., 2006). Hence, we propose a film's studio affiliation as a potential moderator of the relationship between box office and team members' network embeddedness. Specifically, given indie studios' typically low marketing budgets and lack of brand recognition among exhibitors, promoters, and consumers, it is likely that high PE among all members will add extra benefits to indie films.

In summary, we construct a conceptual framework to address a number of important unanswered questions of theoretical and managerial significance. *Do cast's and crew's positions in the film industry's network impact their contribution to box office? Does the nature of this contribution depend on functional roles? Should a major versus indie studio assemble its team differently?* These inquiries will not only identify key driving forces underlying the relationship between box office and team members' network embeddedness, but also offer potential answers to one of the most challenging questions facing the film industry—*How does a studio assemble a multi-functional team that maximizes a film's box office potential*?

To address these questions, we analyze the box office revenues of 2110 movies released over a six-year period, leveraging nearly two decades of collaborative histories involving more than 15,000 film industry professionals. Building upon the marketing, management, and sociology literatures, we derive role-level metrics of network embeddedness (PE and JE) for core team members. We then link these metrics to box office while controlling for variations in film quality, talent popularity, and studio resources. The results show that while PE is more valuable for the cast, JE is more critical for the crew. Although past research has focused on the cast's contribution to box office (e.g. Elberse, 2007; Luo, Chen, & Park, 2010), our research highlights the importance and distinct value of the crew. Hence producers may wish to consider assembling a more balanced team involving a crew with diverse experiences rather than a team driven solely by a star cast. Finally, we find that indie, but not major, studios can accrue additional benefits by engaging a crew that is well-connected to prominent (high PE) industry collaborators.

The remainder of the paper is organized as follows. We first construct the conceptual framework. We then describe the two metrics of network embeddedness and our modeling approach. The subsequent section delineates the data, empirical analysis, and managerial implications. We conclude by summarizing the contributions and limitations of this research, as well as suggesting avenues for future research.

2. Conceptual framework

2.1. Film industrial network and functional roles

Prior research focuses on the impact of product characteristics and consumer responses on box office (e.g. Eliashberg et al., 2006). By focusing on the film development team, we expand this literature and aim to provide some answers to one of the most challenging questions facing the motion picture industry—core team composition. Relevant to this inquiry, the literature on new product development (NPD) suggests that NPD team members' functional diversity (Sethi, Smith, & Park, 2001) or specific cognitive skills (Madhavan & Grover, 1998) impact team performance. Moreover, when NPD teams are constructed and dissolved fluidly on a project-by-project basis, team members benefit from their prior collaborations in a variety of ways, such as gaining information, reputation, knowledge, skills, and/or support that can be applied to future projects (Cattani & Ferriani, 2008;

Delmestri, Montanari, & Usai, 2005). That is, team members' structural positions in a collaborative network can critically impact new product success.

Of central interest to us are more nuanced aspects of these relationships, which have been advocated as important directions for future research (e.g. Ahuja et al., 2003; Grewal et al., 2006). Particularly, creative relationships should be examined at the team level beyond a single member or functional role (e.g. director in Delmestri et al., 2005). Our cross-functional role approach may address a vital yet unanswered question—how should a film producer assemble a revenue-maximizing movie *team*?

To accomplish this, we employ social network analysis. This approach examines the interdependence of persons in a structured environment (i.e. network) to identify opportunities for, or constraints on, resources and actions (Wasserman & Faust, 1994). Most relevant to our work is prior research on collaborative networks that involve groups of individuals working together to achieve a common goal. In such networks, individuals are related to one another through a collaborative activity (e.g. a film project); and activities are related to one another through common collaborators (Faust, 1997; see Appendix A for a demonstrative example). Beyond the sheer number of a person's ties (i.e. volume of past experience), the potential impact of an individual's embeddedness in a collaboration network should be informed by the nature of “with whom” one collaborates and the functional role they play in these collaborations.

According to Baker and Faulkner (1993), a “role” can be considered a resource used to pursue interests, enact positions, and claim, bargain for, or gain group membership. It grants access to unique social, cultural, and material capital to be exploited for group interests. We examine a group of individuals widely regarded as the “core” of a film team by the literature (e.g. Cattani & Ferriani, 2008) and based on our conversations with studio executives and producers who recruit team members. The core members are commonly classified into two broad roles: the principal cast (lead actor, lead actress, supporting actor, supporting actress[4]) and crew (director, cinematographer, and production designer). The actors and actresses interpret the dramatic characters on-camera under the guidance of the director. The director controls and collaborates with other crew members on the film's creative and technical aspects. The cinematographer, also known as the director of photography, is responsible for artistic and technical decisions related to the film's visual image. Finally, the production designer identifies and acquires the locations, settings, and styles that help visually tell the movie's story.

While the movie marketing literature has documented the revenue impact of a star cast member, often including it as a control variable operationalized as a power ranking or Oscars dummy (e.g. Ainslie, Drèze, & Zufryden, 2005; Basuroy, Chatterjee, & Ravid, 2003; Elberse & Eliashberg, 2003), it has not examined the impact of the crew or differential contributions across roles. Hence, it cannot speak to one of the most critical decisions facing the industry—the composition of a film's core team. It also views cast members as isolated individuals instead of ones embedded in an elaborate social network. Our research intends to fill these gaps.

2.2. Impact of PE and JE by functional role and studio as a moderator

Positional embeddedness (PE) indicates the extent to which a person is associated with well-connected others in the network (i.e. others who possess high PE). Such connections may engender several benefits to a film, such as enhanced publicity opportunities. How likely these benefits are accrued depends in part on the person's functional role. Consider, a film's box office is partly influenced by the attention that its actors and actresses can attract from the media and general public. By definition, those who enjoy high PE (e.g. George Clooney and Gwyneth Paltrow) should be associated with other powerful, well-connected individuals in the industry (e.g. directors Steven Soderbergh and Robert Zemeckis). These associations may lead to enhanced visibility and broader media coverage, stronger audience appeal, and more effective promotional campaigns for the film. Producers are known to value prominent stars as they generate greater media attention, especially around the releases of their movies (Albert, 1998). Consumers also remember and respond more favorably to advertising that features well-known actors, leading to demonstrable economic benefits to the product (Agrawal & Kamakura, 1995; Erdogan, 1999). Furthermore, high PE actors and actresses may signal a movie's quality to financers and exhibitors, mitigate negative critics' reviews (Basuroy et al., 2003; Eliashberg & Shugan, 1997) and enhance a movie's brand equity through their marquee appeal (Desai & Basuroy, 2005; Luo et al., 2010)

In contrast, high PE may be less important for the crew due to their relatively low profile in behind-the-scenes work. For example, while cinematographer Roger Deakins and production designer Therese DePrez are both winners of multiple technical awards in the industry and possess high JE (as shown in Table 3 later), they are less likely to enhance a film's financing or marketability to the same extent as a high PE cast. In summary, we predict that the cast's PE will have a more positive effect on box office than the crew's PE.

High JE professionals bridge weakly linked clusters or sub-components of a network (Burt, 2000, 2002). Those with higher JE may benefit from the greater diversity in information and resources that they can draw from the collaboration network. They are expected to have greater access to unique and valuable knowledge, skills, and resources that may emerge outside the core of a network (e.g. Cattani & Ferriani, 2008; Cross & Cummings, 2004). Furthermore, those with high JE have been exposed to a broader array of concepts, developmental processes, and collaborative styles (Arranz & Fdez De Arroyabe, 2012). A crew with more diverse experiences may also offer greater novelty and breadth in their abilities to apply unconventional ideas, leading to competitive advantages (Cattani & Ferriani, 2008). Thus, we suggest that high JE should enable a crew to identify and apply movie-making innovations that occur both in the core and the more avant-garde indie or foreign film regions of the industry network. For instance,

[4] We use the highest listed cast members in the film credit database on Oscars.org, reflecting the importance, not the alphabetic order, of the cast in a film. This list is also consistent with the one on imdb.com, arguably the best known movie database.

director Quentin Tarantino is known for borrowing techniques from foreign and indie films (Armstrong, 2013), such as the Japanese animation styles used in *Kill Bill*. In contrast, high JE is less likely to enhance the cast's reputation or value. While being connected with both the core and more peripheral communities may enhance a cast member's artistry, such a position does not necessarily elevate his/her media profile or marquee appeal. In summary, we predict that the crew's JE has a more positive effect on box office than the cast's JE.

We further expect that a film's studio affiliation may moderate the relationship between box office and the cast's or crew's network embeddedness. Film studios enjoy varied degrees of brand recognition and production, marketing, and distribution resources. Studios are commonly classified into *majors* (including mini-majors in our empirical analysis) versus *independents* (i.e. “indies”; Vogel, 2004). Majors release a large number of films each year and command approximately 90% of North American box office revenues. The “Big Six” majors include the 20th Century Fox, Buena Vista/Disney, Sony Columbia, Paramount, Universal, and Warner Brothers. They also have subsidiaries concentrating on art house or niche films, such as Fox Searchlight. Besides the Big Six, well-known mini-majors include studios such as Lionsgate and MGM/UA, which are larger than indies and attempt to compete directly with the Big Six (*Variety*, 2012).

Indies sometimes get their projects picked up by majors after progress toward film completion has been made (Vogel, 2004). They also manage distribution themselves, especially in local and regional markets that are not well covered by majors and mini-majors. As a result, brand recognition is critical for indies when competing for desirable release dates and negotiations for wider distribution. When a studio lacks a strong brand, investors, exhibitors, and consumers resort to the cast and crew's professional brands to assess the film's quality and potential for success (Bettman, Luce, & Payne, 1998). Hence, a cast and crew with strong PE may be particularly important to indie films that are in greater need of brand recognition. We thus propose that higher PE among the cast and crew will add extra benefits to indie films. In contrast, because the behind-the-scene advantages offered by high JE team members do not contribute to brand recognition, we do not expect that the benefits of JE will interact with studio affiliation.

2.3. Summary of predictions

To summarize, team members' abilities to contribute knowledge and skills to new film projects depend on their embeddedness in the industrial network and their functional roles. We predict that (i) high PE is more valuable to the cast; (ii) high JE is more critical for the crew; and (iii) high PE among both the cast and crew will offer incremental benefits to indie studios.

3. Measures and modeling

In our empirical analysis, the collaborative network consists of each film's core team members: the top four cast and the top three crew (director, cinematographer, and production designer). A tie is formed between any dyad of individuals regardless of functional roles, i and i', if they have collaborated on at least one film in the ten years prior to the focal film's release year. We then use PE_{i_m} to denote positional embeddedness and JE_{i_m} junctional embeddedness of individual i working on movie m. For a movie released in year t, the network used to compute PE_{i_m} and JE_{i_m} is constructed from the collaborations on movies released between year $(t-1)$ and year $(t-10)$.

We capture positional embeddedness (PE) by using a measure of eigenvector centrality (Bonacich, 1987), which captures how well a person is tied to well-connected others in a social network. PE captures not only the number of a person's direct ties,[5] but weighs these ties according to their importance in the larger ecosystem of the global network (Jackson, 2008, p. 40). In this sense, a tie to a person connected to many others is worth more than a tie to a person who is not as well-connected. Following Bonacich's (1987) formulation of eigenvector centrality, we estimate PE_{i_m} as proportional to the total PE of individual i's past collaborators i' on prior movies m', $\sum_{i'_{m'}} PE_{i'_{m'}}$ over the 10 years prior to the release of movie m:

$$\lambda PE_{i_m} = \sum_{i'_{m'}} PE_{i'_{m'}}, \tag{1}$$

where λ is a proportionality factor between 0 and 1 to ensure a non-zero solution to Eq. (1). The equation is ultimately self-referential in that i_m's PE depends on the PE of i's past collaborators $i'_{m'}$, whose PE depends on the PE of their collaborators; and so on throughout the entire network. The value, λ and PE_{i_m}, for each individual i in movie m are derived by solving a simultaneous linear equation system in the standard eigenvector-eigenvalue formulation:

$$\lambda PE = ePE. \tag{2}$$

Here, PE is a column vector of dimension $[n \times 1]$ that consists of eigenvector centralities of all individuals in the network, where n is the total number of individuals in the network, and e is a $[n \times n]$ symmetric adjacency matrix capturing all prior

[5] The number of a person's direct ties can be described as his or her unweighted degree centrality. While degree is a commonly used social network measure, when applied to collaborative networks with teams that are similar in size, it approximates a simple count of prior collaborations; that is, how many movies that person has worked on. When included together with PE in preliminary models, degree centrality was not significant, despite being significant in the absence of PE. A fourth commonly used measure of network embeddedness is closeness centrality. To our knowledge, there is no theoretical support or prior examination of this variable in a context similar to the present research. Our preliminary analysis found it non-significant in relation to box office.

collaborations of all n individuals in the network. The diagonal elements of e are zero and each off-diagonal element in e is a binary indicator[6] (1 or 0) of whether each person i in movie m has collaborated with another person i' in any movies released in the decade before m. In the language of matrix algebra, λ is the largest eigenvalue associated with the adjacency matrix e, and PE is its corresponding eigenvector.[7]

For JE, we adapt betweenness centrality from network theory (Freeman, 1979) to accommodate our team-level analysis, operationalizing i's JE as

$$JE_{i_m} = \sum\nolimits_{j_{m'} \neq k_{m'} : i_m \notin (j_{m'}, k_{m'})} \frac{Pi(j_{m'} k_{m'})/P(j_{m'} k_{m'})}{(n - g_m)(n - g_m - 1)/2}. \quad (3)$$

Here $Pi(j_{m'} k_{m'})$ denotes the number of shortest paths between collaborators j and k on an earlier movie m' that run through i, $P(j_{m'} k_{m'})$ the total number of shortest paths between j and k; g_m the number of team members on movie m, and n the total number of individuals in the network. We extend the Freeman (1979) equation to our team context by normalizing this proportion by the total number of pairs of individuals in the network (excluding i_m and all others working on movie m) in the denominator of Eq. (3). The intuition behind this JE measure is that information and resources accrued to a given movie team are likely to travel through the social ties established by the team members via prior collaborations. The extent of one's exclusivity over such social paths in the network connotes his/her JE (see Appendix A for an illustration).

We use the igraph package of the R statistical language to calculate PE and JE.[8] When inputting the observed ties to the package, we further account for (a) the number of prior collaborations in a dyad, since one may expect a stronger bond between two individuals from repeated collaborations (frequency); and (b) temporal discounting of the collaborations that took place farther in the past (recency).[9] While (a) is relatively common in examining social and economic networks (Brandes, 2001; Jackson, 2008), (b) is less so. For (b), we use the discount function, $e^{-\beta(t\,-\,1)}$, where t is the year lapse (e.g. $t = 1$ means the collaboration occurred last year) and β a discount parameter. In our context, β should be fairly small such that the network effects do not dissipate rapidly over the 10-year window. We also performed a grid search with different values of β and find that, indeed, large discount rates weaken the effects of JE, but not PE, on box office. This is consistent with the argument that tie values below 1 will statistically over-punish paths through only negligibly weaker ties (Granovetter, 1973; Opsahl, Agneessens, & Skvoretz, 2010). We use $\beta = 0.05$ in our analysis, which results in a discount factor of 0.64 for collaborations that occurred 10 years prior.

To assess PE's and JE's impact on box office, we link the PE and JE values to the logarithm of movie m's cumulative box office in inflation-adjusted U.S. dollars, R_m, as:

$$R_m = \alpha + z_m'\theta + PE_m'\tau_1 + JE_m'\tau_2 + PE_m' I_m \tau_3 + JE_m' I_m \tau_4 + \varepsilon_m, \quad (4)$$

where α is an intercept if movie m is affiliated with an indie studio; and z_m includes control variables commonly used in the movie literature (e.g. Ainslie et al., 2005; Sawhney & Eliashberg, 1996) such as sequel and genre, MPAA rating, Oscars, critics' and consumers' ratings. PE_m (JE_m) consists of the average PE (JE) of movie m's cast and crew after the frequency and recency weighted PE_{i_m} (JE_{i_m}) is calculated for each individual i as discussed earlier. Hence τ_1 and τ_2 capture the main effects of PE and JE, respectively, on box office. This approach both addresses our research questions directly and reduces potential multi-collinearity in individual PE and JE. The grouping of the cast versus crew is further validated by factor analysis which shows that the PEs (and JEs) of the director, cinematographer, and production designer load on one dimension, while those of the actors and actresses load on a second dimension. The scalar dummy $I_m = 1$ if movie m is affiliated with an indie studio, and thus τ_3 and τ_4 examine whether the relationship between box office and network embeddedness varies across majors/mini-majors versus indie studios.

Despite accounting for critics' ratings, consumer ratings, and Oscar nominations above, we may not have adequately captured the heterogeneity in movie quality. A movie with higher quality and financial potential has a greater chance of attracting a cast and crew of higher caliber, leading to higher box office revenue. Failing to properly control for quality heterogeneity can lead to omitted variable bias or potential endogeneity between the movie's box office and the network embeddedness of its team members. To address this potential endogeneity, prior work suggests exploiting the panel data structure and incorporating movie-level fixed effects (Elberse, 2007; Gopinath, Chintagunta, & Venkataraman, 2013). However, only one observation of the cumulative revenue exists for each movie. PE and JE also vary by movie, not by time or geographic area. As a result, using more disaggregate data such as weekly or regional revenues is not plausible. Another possible approach is to use instruments for network embeddedness. However, it is challenging to identify adequately strong instruments for PE and JE—variables that are highly correlated with PE and JE but not with box office revenue.[10] Prior research suggests that using weak instruments not highly correlated with the

[6] We later discuss weighting of this indicator to account for repeated collaborations and temporal discounting of past collaborations.

[7] Readers interested in the standard eigenvector-eigenvalue formulation in matrix algebra may refer to Krishnan (1984) or Abadir and Magnus (2005) for a more detailed, step-by-step derivation. Appendix B also offers a brief, general example of this derivation.

[8] Other network analysis software packages available to facilitate the calculation of the network statistics include the CENTPOW module for Stata, Gephi, Pajek, UCINET, and SocNetV.

[9] The key results also sustain when simple binary (1 = collaborated; 0 = not), instead of weighted collaborations, are analyzed.

[10] For example, potential instruments for PE are family or social connections with well-established individuals in the industry. These connections may lead to movie collaborations with higher PE individuals. However, these connections also likely affect an individual's ability to generate strong box office revenues. Familial connections, unlike PE, also do not vary over time. As for JE, potential instruments include individuals' career diversity (e.g. work in different fields of entertainment, such as music, Broadway, etc.). However, this variable can also have a direct impact on a movie's box office.

endogenous variable can lead to larger inconsistencies in the estimates of the endogenous variable than a model that properly controls for the potential source of endogeneity (Bound, Jaeger, & Baker, 1995; Rossi, 2014). We therefore include multiple control variables in the model to best capture quality heterogeneity across movies.

First, we follow prior research that suggests the decay rate of weekly revenues from the first to second week of release as an indicator of film quality (e.g. Krider & Weinberg, 1998). We include in the vector z_m in Eq. (4) a quality decay variable calculated as the difference between the logarithm of a movie's first- and second-week revenues. Second, each movie project is affiliated with a particular studio (Vogel, 2004). These studios vary drastically in their abilities to finance and market films, with major and mini-major studios enjoying far greater resources than indie studios (Scott, 2005; Waterman, 2005). Greater resources increase the majors' abilities to produce higher quality movies and promote them more effectively to the public. Given that the indie studios we observe (N = 223) produce a much smaller number of movies (73% only produced one or two movies), we include studio fixed effects for the major and mini-major studios (N = 10) to capture heterogeneity in movie quality and financial support.

Finally, production budget may be included to further control for heterogeneity in movie quality and financial support. Budget was not available, however, for a large percentage (72%) of the indie films in the data. If analysis is limited to only movies with budgets, there is insufficient variation in PE and JE to identify their contributions.[11] Considering that a substantial part of a movie's budget is driven by the salaries of the core cast and crew (*Forbes*, 2014), we include popularity of the cast and crew, as measured by the cast's and crew's temporally discounted average cumulative box office over the prior decade, as another set of control variables. We use the temporal discount function $e^{-\beta(t\ -\ 1)}$ to be consistent with the discounted PE and JE measures. As team members who generated higher revenues in the past tend to command higher salaries, the popularity measures help further capture heterogeneity in movie quality and financial support, thereby alleviating the endogeneity issue. Moreover, since high PE and JE members may also be popular, these quality measures also ensure that the network effects are not confounded with cast or crew popularity.[12]

4. Empirical analysis

4.1. Data

We examine the box office revenues of 2110 movies released in the U.S. over a six-year period (1999 to 2004 inclusive) that earned at least \$1000. As new movies are developed and new collaborations established, the network dynamically evolves. Thus, we use a lagged rolling-window approach to define a collaborative network for each of the six release years under investigation. For example, for each movie released in 2004, we use the movies released during the prior decade (1994–2003 inclusive) to construct the collaborative network and compute PE and JE for the cast and crew involved in those 2004 releases. Excluding the focal movie's release year from the network alleviates potential simultaneity between box office and network the statistics. Table 1 provides the descriptive statistics of the variables used in our analysis.

4.2. Network analysis

While this research takes the perspective of the producers who assess the cast and crew's potential contributions when assembling the core movie teams, and thus producers' PE and JE are not key predictors in the model, producers' ties to the cast and crew are also part of the network. We believe that it is important to include producers' ties as the cast's and crew's relationships with producers play a crucial role in determining the cast's and crew's network positions, and hence their PE and JE. Also, for the 5.8% of 16,891 persons in the data that took on more than one role on a particular team, we assign their network embeddedness to each role performed.

Table 2 displays the summary statistics of the six networks analyzed. Each network involves nearly 3000 movies and over 9000 individuals, forming a "giant component" that connects over 85% of all potential collaborators in the industry. Unsurprisingly, further inspection of the data indicates that Hollywood is at the core of this component, while non-U.S. productions and a few isolated U.S. film teams operate outside this dominant "invisible college" (see Appendix C for a sample visualization of the 1994–2003 network used for 2004 releases).

We also observe that an individual wishing to reach a potential collaborator through the latter's prior collaborators would on average need to engage only about four others. That is, the mean "path length" is 4, varying between 3.99 to 4.24 across the six networks. Moreover, we report the clustering coefficient (Watts & Strogatz, 1998) as an indicator of the density of ties, or the proportion of the cases where "a collaborator of my collaborator was also my collaborator." This coefficient is 21% in our data, higher than what would be observed in randomly generated networks of the same size.

The above combination of short path lengths and high clustering coefficients confirms that the film industry can be characterized as a "small-world" network (Watts & Strogatz, 1998). That is, an enormous network (e.g. 9286–11,857 individuals per network in our case) can be quickly traversed through ties among a small number of individuals (e.g. 4 in our data). Such networks tend to be highly conducive to social transmission of information, resources, or influence.

[11] We estimated the proposed model (Eq. (4)) using only those movies with budgets and indeed could not uncover the effects of network embeddedness.

[12] We thank the Associate Editor for this suggestion.

Table 1
Descriptive statistics.

	All movies (n = 2110)		Major studio movies (n = 1229)		Indie movies (n = 881)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Box office ($MM)	20.444	41.688	32.904	49.000	3.062	17.183
Sequel	0.104	0.305	0.146	0.353	0.045	0.208
Foreign movie	0.201	0.401	0.087	0.282	0.360	0.480
Action	0.063	0.243	0.090	0.286	0.026	0.160
Adventure	0.011	0.106	0.013	0.113	0.009	0.095
Animated	0.035	0.184	0.048	0.214	0.017	0.129
Biography/documentary	0.069	0.253	0.023	0.151	0.105	0.306
Black comedy	0.010	0.099	0.009	0.094	0.011	0.106
Comedy	0.225	0.418	0.256	0.437	0.182	0.386
Crime	0.009	0.097	0.005	0.070	0.016	0.125
Drama	0.380	0.486	0.327	0.469	0.454	0.498
Fantasy	0.008	0.089	0.011	0.102	0.005	0.067
Horror	0.030	0.170	0.033	0.180	0.025	0.156
Musical	0.009	0.092	0.006	0.075	0.012	0.111
Suspense/thriller/mystery	0.050	0.218	0.068	0.251	0.025	0.156
Romantic comedy	0.054	0.226	0.072	0.258	0.030	0.169
Science fiction	0.020	0.141	0.028	0.166	0.009	0.095
Western	0.006	0.075	0.007	0.085	0.003	0.058
G-rated	0.027	0.161	0.035	0.184	0.015	0.121
PG13-rated	0.080	0.271	0.107	0.309	0.042	0.201
PG-rated	0.243	0.429	0.359	0.480	0.082	0.274
R-rated	0.475	0.499	0.496	0.500	0.446	0.497
NC17-rated	0.002	0.049	0.002	0.049	0.002	0.048
Consumer rating	6.305	1.149	6.199	1.155	6.453	1.125
Critics rating	5.786	1.310	5.617	1.373	6.020	1.178
Oscar nominated	0.043	0.202	0.066	0.248	0.010	0.101
PE of cast	0.066	0.076	0.092	0.083	0.031	0.043
PE of crew	0.057	0.077	0.083	0.088	0.022	0.037
JE of cast	0.028	0.034	0.039	0.036	0.013	0.023
JE of crew	0.024	0.029	0.034	0.030	0.011	0.020
Popularity of cast	18.376	18.619	25.506	18.496	8.429	13.542
Popularity of crew	14.351	20.505	22.024	22.986	3.646	8.567

Note: a movie is coded as 1 if it belongs to one of the genre categories (such as Drama) or MPAA ratings (such as R for restricted) listed in the data collected from Oscars.org. The average consumers' rating and average critics' rating for each film are from imdb.com and rottentomatoes.com, respectively, both on a 0–10 point scale where 10 = best rated. For Oscar nominations, a movie is coded as 1 if it was nominated for one of the six major award categories: best picture, director, actor, actress, supporting actor, and supporting actress.

Table 2 summarizes the properties of the six ten-year networks. The giant component statistic describes the proportion of the individuals who have connections in the largest connected cluster in the network; the average degree indicates the average number of past collaborators; the average path length captures the number of steps between any two individuals in the network; and the clustering coefficient suggests the tendency of individuals to cluster together such that "the collaborator of a collaborator is also my collaborator."

There are several noteworthy temporal dynamics in the networks. In particular, positive yearly trends appear in the number of films released, number of unique cast and crew members, average path length, and clustering coefficient. Decreasing over time are the proportion of the individuals in the network's fully-connected giant component and the average number of direct collaboration ties held by an individual. Overall, these findings support the notion that the Hollywood core has become increasingly exclusive (e.g. Scott, 2005). However, they also indicate a growing number of less connected or less experienced individuals entering the more independent sub-communities of the industry. A cursory manual examination of the data suggests the rise of productions from outside North America, such as India's "Bollywood", as a driver of this change.

Table 2
Summary statistics of the six collaboration networks.

Movie released (inclusive)	Movies in network	Persons in network	% in giant component	Mean degree	Mean path length	Clustering coefficient
1994–2003	3,268	11,857	0.858	13.11	4.24	0.217
1993–2002	3,195	11,473	0.868	13.34	4.18	0.215
1992–2001	3,066	10,850	0.886	13.70	4.15	0.212
1991–2000	2,900	10,166	0.895	13.88	4.08	0.211
1990–1999	2,809	9,776	0.904	14.01	4.07	0.211
1989–1998	2,693	9,286	0.894	14.20	3.99	0.209

Table 3
Top 25 cast by PE and Top 25 crew by JE in 2004 releases.

Top 25 cast by PE				Top 25 crew by JE			
Rank	Person	PE	JE	Rank	Person	JE	PE
1	Danny Devito	.406	.610	1	Eduardo Serra	.763	.034
2	Gene Hackman	.231	.196	2	Giorgos Arvanitis	.761	.009
3	Kevin Spacey	.216	.359	3	Thierry Arbogast	.741	.041
4	Samuel L Jackson	.182	.659	4	Christopher Doyle	.687	.019
5	Ben Stiller	.174	.138	5	Elliot Davis	.564	.110
6	Nicolas Cage	.159	.431	6	Benoit Delhomme	.529	.011
7	Robert De Niro	.154	.357	7	Xavier Perez Grobet	.398	.006
8	John Travolta	.151	.289	8	Andrew Dunn	.379	.089
9	Julianne Moore	.150	.507	9	Robert Richardson	.371	.093
10	Meryl Streep	.149	.201	10	Dante E Spinotti	.354	.116
11	Bruce Willis	.148	.429	11	Giles Nuttgens	.343	.012
12	George Clooney	.147	.165	12	Therese Deprez	.335	.063
13	Morgan Freeman	.140	.234	13	David Wasco	.334	.102
14	Julia Roberts	.122	.161	14	Paul J Peters	.320	.059
15	Jim Carrey	.121	.175	15	Denis Lenoir	.306	.020
16	Gwyneth Paltrow	.120	.341	16	Maryse Alberti	.297	.031
17	Laura Linney	.118	.068	17	Ashley Rowe	.293	.021
18	Robin Williams	.116	.459	18	Ellen Kuras	.290	.047
19	Bill Paxton	.115	.084	19	William Chang	.289	.001
20	Drew Barrymore	.115	.264	20	Adam Biddle	.279	.069
21	Billy Bob Thornton	.114	.237	21	Dick Pope	.268	.033
22	Tim Robbins	.113	.202	22	Jane Ann Stewart	.266	.016
23	James Garner	.112	.048	23	Bob Ziembicki	.263	.068
24	Eddie Murphy	.106	.255	24	Kevin Thompson	.255	.048
25	Kevin Bacon	.106	.384	25	Declan Quinn	.255	.052

To offer more concrete examples of PE and JE at the individual level, we list the 25 cast with the highest PE and 25 crew with the highest JE in the 2004 releases with the 1994–2003 network (Table 3).[13] For example, while actors such as Nicolas Cage and Samuel L. Jackson may not spring to mind as among the top 10 on-camera talents of 2004, they held some of the highest PE (and JE) at that time. This is likely due to their exceptional productivity as actors, often in supporting roles, and their collaborations with both diverse (JE) and well-connected (PE) others. For example, Nicolas Cage was credited for 29 movies over the entire observation period, including a diverse range of Hollywood blockbusters (e.g. *National Treasure*), small-budget, artistic independent projects (e.g. *Leaving Las Vegas*), B-movies (e.g. *Kiss of Death*), and foreign productions (e.g. *Tempo di uccidere*, *Zandalee*).

Turning to the list of top crew by JE, we spotlight cinematographer Christopher Doyle, whose incredibly diverse experience is expected to propel his creative and technical contribution to a movie's success. Doyle's variety of experiences across the industry's sub-communities is evident in his work on movies appealing to English, Cantonese, Mandarin, and French language markets, including major studio films (e.g. the 1998 Hollywood re-make of *Psycho* and 2006's *Lady in the Water* with director M. Night Shyamalan), a number of notable Chinese-language films, unusual genre films such as the Japanese-German co-production of “pink-film” *Underwater Love*, and several North American indie films (e.g. *Paranoid Park*, *Passion Play*).

4.3. Model comparison

To demonstrate the contributions of the core cast's and crew's network embeddedness to box office, we estimate a series of models. Building upon the commonly used models in the movie literature that account for product characteristics (e.g. Ainslie et al., 2005; Sawhney & Eliashberg, 1996), Model 1 (baseline) includes the studio fixed effects and other quality measures described earlier, such as critics' and audience's ratings, Oscar nominations, and the revenue decay. Model 2 integrates the cast's and crew's popularity effects without their network embeddedness. Models 3 and 4 add the main effects and interaction effects of network embeddedness, respectively.

Table 4 shows that accounting for cast and crew popularity (Model 2: adjusted R-square = .720) improves model fit beyond the movie characteristics commonly used in the literature (Model 1: adjusted R-square = .683). Importantly, the main effects of network embeddedness explain the variations in box office above and beyond popularity (Model 3: adjusted R-square = .729), and the interaction effects of network embeddedness further improve model fit (Model 4: adjusted R-square = .731). The PE,JE, and popularity measures in Models 2–4 account for frequency and recency discounting using the discount function, $e^{-\beta(t-1)}$. We performed a grid search by varying the values of β from 0.01 to 0.75 for both the network and popularity effects. The best model fit with the same β for both effects is $\beta = .05$. Model fit gets worse as β becomes greater or smaller than .05. As a robustness check, we also estimate and report Model 5 where PE and JE are weighted by the number of prior collaborations between any two persons (frequency), but not the temporal discounting of these collaborations (recency). Model 5 also includes the annual inflation

[13] The values of PE and JE by year for all 16,891 individuals across the six collaboration networks are available from the first author on request.

Table 4
Parameter estimates.

	Baseline	(1) + popularity	(2) + network main effects	(3) + network interaction effects	(4) based on # collaboration-weighted PE and JE
	(1)	(2)	(3)	(4)	(5)
Intercept: indie studios	10.249**	9.972**	10.308**	10.525**	10.540**
Sequel	1.618**	1.284**	1.321**	1.311**	1.317**
Foreign film	−0.952**	−0.575**	−0.487**	−0.470**	−0.478**
Action	1.389**	0.960**	0.974**	1.022**	1.024**
Adventure	0.628	0.403	0.413	0.371	0.353
Animated	0.587**	0.252	0.440*	0.444*	0.428*
Black comedy	0.870**	0.659*	0.541	0.544	0.569
Comedy	0.404**	0.267*	0.252*	0.279*	0.272*
Crime	−1.184**	−1.425**	−1.451**	−1.435**	−1.427**
Drama/romance	0.162	0.020	−0.027	−0.005	−0.027
Fantasy	0.736	−0.248	−0.107	−0.036	0.054
Horror	1.555**	1.646**	1.733**	1.737**	1.741**
Musical	0.392	0.382	0.272	0.312	0.322
Romantic comedy	0.870**	0.684**	0.592**	0.637**	0.642**
Suspense/thriller/mystery	1.180**	0.896**	0.794**	0.822**	0.805**
Sci-fi	1.196**	0.705**	0.661**	0.660**	0.645**
Western	0.957*	0.210	0.210	0.223	0.309
G-rated	1.765**	1.566**	1.680**	1.613**	1.620**
PG13-rated	1.639**	1.448**	1.495**	1.325**	1.386**
PG-rated	1.767**	1.447**	1.381**	1.429**	1.339**
R-rated	0.613**	0.569**	0.551**	0.473**	0.461**
NC17-rated	0.894	0.850	0.811	0.724	0.644
Consumer rating	0.129**	0.107**	0.086*	0.092*	0.103**
Critics rating	0.113**	0.146**	0.159**	0.156**	0.147**
Oscar nomination	1.470**	1.171**	1.072**	1.068**	1.135**
Quality decay	−0.285**	−0.281**	−0.275**	−0.273**	−0.277**
Studio fixed effects	Y	Y	Y	Y	Y
PE: cast			0.287**	0.265**	0.157**
PE: crew			0.076	0.040	−0.016
JE: cast			−0.073	−0.059	0.000
JE: crew			0.186**	0.169**	0.225**
PE: cast × indie				0.216	0.055
PE: crew × indie				0.441**	0.813**
JE: cast × indie				−0.111	−0.033
JE: crew × indie				−0.010	−0.165
Popularity: cast		0.024**	0.019**	0.018**	0.015**
Popularity: crew		0.023**	0.019**	0.019**	0.014**
Adjusted R-square	0.683	0.720	0.729	0.731	0.729

Notes:
[1] Both PE and JE are standardized so that their corresponding parameters are comparable.
[2] Significance at 0.05 is denoted by ** and at 0.10 by *.
[3] The baseline genre is biography/documentary. The baseline MPAA rating is unrated.

discounted popularity measures of the cast and crew. Overall, we see that the same pattern of results holds. However, Model 4 (.731) fits slightly better than Model 5 (.729).[14]

4.4. Parameter estimates

4.4.1. Effects of movie characteristics

Parameters of movie characteristics make intuitive sense across all models: sequels, MPAA rated, Oscar nominated, and those receiving favorable consumers' and critics' reviews accrue higher revenues. In contrast, foreign films, crime genre films, and those with faster revenue decay generate lower revenues. All of the studio fixed effects except for that of United Artists, are significant and positive, confirming our expectation that movies released by larger studios accumulate higher box office. We omit reporting the studio fixed effects for simplicity of exposition. Popularity of the cast and crew significantly affects movie box office (Model 2).

4.4.2. Effects of PE

To assess the relationship between network embeddedness and box office, we start with Model 3. Note that since PE and JE are standardized in the analysis, we can directly compare the magnitude of their effects within and across functional roles. Model 3

[14] Although not reported in Table 4, two additional models were estimated: Model 1 plus the main effects of PE and JE, and Model 1 plus the main and interaction effects of PE and JE. Comparing these two models with Models 3 and 4 shows that when popularity effects are considered, unsurprisingly, the effects of PE remain significant, although they become smaller in size.

reveals that the PE effect for the cast is positive ($\tau_{1,cast} = .287$) and significant at 0.05, after controlling for the cast and crew's popularities, indicating that higher PE for the cast is associated with elevated revenues. However, the PE effect for the crew is not significant. The positive PE effect persists in Model 4 where interaction effects between network embeddedness and the type of studio are taken into account. These findings indicate that, again, PE of the cast, but not of the crew, contributes to revenues. Echoing our earlier discussions, we attribute this result to cross-functional differences such that ties to well-connected others provide the cast with heightened image and reputation, which in turn may enhance media attention and marquee appeal. However, such capabilities are significantly less important for the crew.

4.4.3. Effects of JE

Model 3 shows that the effect of the crew's JE ($\tau_{2,crew} = .186$) is positive and significant at 0.05, while the cast's JE is non-significant. These results persist even when the interaction effects are accounted for in Model 4. These findings reveal that the crew's, but not the cast's, JE contributes to box office success. As reasoned earlier, a crew occupying a position that bridges sub-communities of the network may draw greater technical knowledge, creativity, and methods from more varied sources, potentially boosting product quality to a higher level.

4.4.4. Moderation by studio affiliation

As predicted, we observe a significant and positive interaction between the crew's PE and studio affiliation (e.g., $\tau_{3,crew} = .441$ in Model 4). This result indicates that the crew's PE provides a much needed extra signal of a film's quality for indie films that lack the brand recognition enjoyed by major studio films. However, we did not find the predicted interaction of PE for an indie film's cast, suggesting that the cast's connections to well-connected others (PE) are important regardless of the studio's overall marketing resources. In other words, PE of an indie film's cast does not add extra benefit beyond its main effect contribution to box office. Lastly, as expected, we did not find interaction effects of the studio affiliation and JE of the cast or crew.

In summary, this analysis reveals that a film achieves greater box office if developed by a high PE cast who has collaborated with well-connected others and a high JE crew who bridges diverse sub-communities in the industry. While the movie literature has focused on the effects of product- and consumer-related factors on box office, we demonstrate the important contributions of the movie's core development team, whereby each team member draws knowledge and skills through prior collaborations to support his or her role-driven contribution to a film's revenues. These previously undocumented findings represent important considerations for critical managerial decisions on product team formation before millions of dollars in development costs are incurred.

4.5. Managerial implications

The proposed conceptual framework and methodology lead to important and practical guidance to film studios and talents, and more broadly, for new product team assembly in other industries. First, faced with a large and constant flux of talents, how do producers (or senior managers) assess the cost/benefit involved in hiring a new-comer (i.e., a person with limited network embeddedness) versus an "old hand" (i.e., a person with high network embeddedness) in the industry? Our approach offers a model-based evaluation of this and related tradeoffs by predicting the cumulative revenues based on either scenario. In the same vein, when one talent becomes unavailable and alternatives are considered, our approach can readily forecast the potential revenue gain or shortfall when considering alternative team members.

For a second example specific to the film industry, when deciding among a roster of potential candidates for the cast and crew, producers may utilize the proposed approach as an effective decision aid to assemble a "dream team" that complements auditions, interviews and the recommendations of professional talent agencies. With insider information on budget, salary cap, and negotiation stance, a producer who has a revenue goal in mind may conduct a tradeoff analysis or optimization exercise to derive a team with a minimum salary and maximum box office potential.

Related to the above, a third question is whether the producer faced with skyrocketing salaries should resort to a "star strategy" focusing only on a star cast or a more "balanced" strategy involving a more modest cast (lower PE) but high-value (higher JE) crew? Our research suggests the potential of the latter strategy to help producers assemble an optimal movie team in this cost environment.

In addition to offering managerial guidance to studio executives and producers, our findings shed light on career management by the cast and crew themselves in a highly competitive industry. Theoretically and empirically, this research reveals that an actor or actress should focus on collaborating with well-connected others, while a crew member may be better-off seeking diverse collaborations. Thus, when selecting which film projects might maximize one's own career trajectory, an industry professional should be cognizant of how his/her potential team mates' collaborative history could influence his/her own future success.

5. Discussion

This research contributes to the literature on movie marketing, collaborative networks, and new product development along several important dimensions. Theoretically, our conceptual framework accentuates the importance of the development team to product success, moving beyond the conventional focus on product or consumer traits in the movie marketing literature. It takes a network perspective by proposing that team members' contributions to a film arise from their positions in the industrial network, and thus their opportunities and capabilities to draw knowledge and skills accrued from past collaborative experiences. The conceptual framework also reveals an important, potentially divergent relationship between box office and network embeddedness of the cast versus the crew. In doing so, it expands the marketing and sociology literatures' focus on a single function and allows us to address a key managerial challenge of team assembly. It further proposes and partially validates a moderator (studio affiliation) in the relationship between box office and a team's network embeddedness. While past research offers evidence of the value of a star cast, this research reveals a more nuanced picture, suggesting a crew that has worked in diverse "regions" of the industry can be as important as a well-connected cast.

From a substantive perspective, the proposed methodological framework provides producers and movie studios with a new decision making tool in assembling an optimal movie team. The conceptual framework and methodology may also be generalized to other entertainment, media, and technology industries, or firms sharing characteristics similar to the movie industry, such as relatively fluid formation and dissolution of product development teams and distinct roles within each team.

Despite these contributions, this research has limitations and thus points to promising avenues of future research. For example, future research may investigate the evolution of network embeddedness within an individual and further address self-selection into teams. This is a complex yet intriguing area of research as it involves dynamic and endogenous network evolution, a challenging topic that is receiving growing research attention in the marketing and statistics communities. Our research is also limited in scope by focusing on a team member's connections to others outside, instead of within, the team. This focus was driven by the existence of research that has already examined past collaborations among team members in collaboration networks (i.e. team cohesion; Mehra, Dixon, & Brass, 2006; Sparrowe, Liden, Wayne, & Kraimer, 2001; Uzzi & Spiro, 2005).

Furthermore, while our modeling tactics alleviate endogeneity of the network measures, additional control variables such as advertising spending were not available for analysis; other potential sources of endogeneity may exist as well. Readers therefore should keep in mind that our results may remain subject to some endogeneity bias. Nonetheless, we believe that this research takes an important step toward quantifying team members' contributions as they arise from their network positions and across functional roles, shedding a critical light on film (and more generally, new product) team formation in the early stages of product development.

Appendix A. Illustrative collaboration network and calculation of network statistics

As is typical in the analysis of large social networks, the complexity of the data we observe makes it cumbersome to demonstrate how our statistics of network embeddedness are derived from the actual data. For brevity, we offer an illustrative example of a collaboration network focusing on two hypothetical movies released in 2004 (Movies A and B) by extracting a collaboration history for these movies and their NPD team members from four hypothetical movie released in the lagged 10-year network over 1994–2003 (Movies C–F). Figure A1 presents the hypothetical data observed and PE and JE that would result from this data set. Figure A2 presents visualizations of the two- and one-mode networks generated from this data. The "two-mode" visualization connects people (circles) to the movie teams on which they collaborated (squares). The one-mode projection on persons (circles) presents ties between persons who have worked together on at least one movie. The one-mode projection on movies (squares) connects movies that share at least one team member.

Illustrative Data of A Collaboration Network

Raw Data

Person	Name	Movie	Year
1	Smith	A	2004
2	Wong	A	2004
3	Fleur	A	2004
4	Li	B	2004
5	James	B	2004
6	Ortega	B	2004
1	Smith	C	2002
7	Page	C	2002
8	Nayar	C	2002
1	Smith	D	1999
2	Wong	D	1999
9	Gold	D	1999
8	Nayar	D	1999
2	Wong	E	1997
4	Li	E	1997
6	Ortega	E	1997
2	Wong	F	1995
4	Li	F	1995
5	James	F	1995

2004 Individual-level Embeddedness

Person	Name	JE	PE
1	Smith	0.03	0.70
2	Wong	0.43	1.00
3	Fleur	0.00	0.42
4	Li	0.00	0.30
5	James	0.00	0.50
6	Ortega	0.00	0.59

2004 Team-level Embeddedness

Movie	JE	PE
A	0.15	0.71
B	0.00	0.46

Fig. A.1. Illustrative data of a collaboration network.

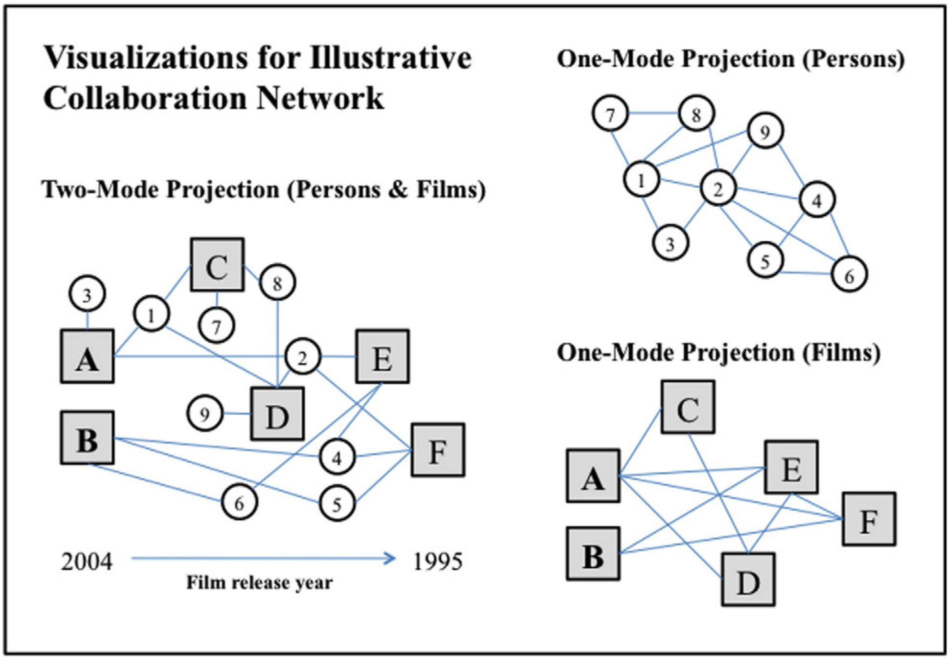


Fig. A.2. Visualizations of the two- and one-mode networks generated from the illustrative data.

Junctional embeddedness (JE)

To calculate JE in Eq. (3) for persons on the Movie A team, we first find the proportion of the shortest paths between all pairs of persons (i.e. dyads) who are not members of the Movie A team that pass through Movie A's team members. The shortest paths are those that require the fewest steps between any dyad independent of Movie A's team members. For example, the two shortest paths between Persons 4 and 7 are "4-2-1-7" and "4-2-8-7" (with path length = 3). Movie A's team member, Smith (Person 1), lies on the shortest path for three dyads (the paths connecting Persons 4 to 7, 5 to 7, and 6 to 7). For each of these three dyads, Smith is on 50% of the shortest paths (the rest go through Nayar (Person 8)), providing the numerator in Eq. (3) for Smith. Calculation of Smith's denominator in this equation requires the number of persons in the network ($n = 9$) and Movie A's team size ($g = 3$). It is hence $(9 - 3) \times (9 - 3 - 1) / 2 = 15$. Following Eq. (3), Smith's *JE* is $3 \times (.5 / 15) = .03$. As can be observed in the one-mode projection for persons in Figure A.2, Wong (Person 2) holds an even stronger junctional position in the network than Smith as Wong lies on shortest paths for nearly all collaborations bridging the two sides of this network. In contrast, all other persons lie on the "outside edges" of the network, and do not bridge other collaborators.

Positional embeddedness (PE)

Since a simultaneous linear equation system is used to produce the standard eigenvalue and eigenvector calculations underlying PE in Eq. (2), it is not feasible to manually demonstrate the development of this measure. However, intuition for this measure can be gained by comparing the individual statistics for *PE* presented in Figure A.1 against the one-mode (person) visualization in Figure A.2. For instance, Wong (Person 2) holds the maximal positional embeddedness in this network ($PE = 1$) due to both the number of collaborations he holds (ties = 7) and the "connectedness" of his ties (e.g. Persons 1 and 6 also possess high *PE*). In contrast, the person with the lowest *PE*, Li (Person 4), has several ties (ties = 4), but has collaborated with poorly-connected others. In most physics-based network visualizations, nodes with high PE (or other eigenvector-based centrality measures) will appear deep in the network's core, as can be observed for Wong (Person 2) in Figure A.2.

Appendix B. Calculating eigenvalues and eigenvectors

Let e be an $n \times n$ matrix. And λ is an eigenvalue of e if there exists a non-zero vector v such that

$$ev = v.$$

In this case, vector v (or PE in our context) is called an eigenvector of e corresponding to λ. We can rewrite the condition $ev = v$ as follows:

$$(e - I)v = 0,$$

where I is the $n \times n$ identity matrix. For a non-zero vector v to satisfy this equation, $e - I$ must not be invertible. That is, the determinant of $e - I$ must equal 0. Call $p(\lambda) = \det(e - \lambda I)$ the characteristic polynomial p of e. The eigenvalues of e are the roots of the characteristic polynomial of e.

For example,

$$Let\ \ e = \begin{bmatrix} 2 & -4 \\ -1 & -1 \end{bmatrix}.$$

$$\begin{aligned} Then\ \ p(\lambda) \ &= \ \det \begin{bmatrix} 2-\lambda & -4 \\ -1 & -1-\lambda \end{bmatrix} \\ &= (2-\lambda)(-1-\lambda)-(-4)(-1) \\ &= \lambda 2-\lambda-6 \\ &= (\lambda-3)(\lambda+2) \end{aligned}$$

Thus, $\lambda_1 = 3$ and $\lambda_2 = -2$ are the eigenvalues of e.

To find the eigenvectors corresponding to these eigenvalues, solve the system of linear equations given by

$$(e - \lambda I)v = 0.$$

For example, to solve for the eigenvectors corresponding to $\lambda_1 = 3$, let $v = [\begin{smallmatrix} v1 \\ v2 \end{smallmatrix}]$. Then $(e - 3I)v = 0$ gives us

$$\begin{bmatrix} 2-3 & -4 \\ -1 & -1-3 \end{bmatrix} \begin{bmatrix} v1 \\ v2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix},$$

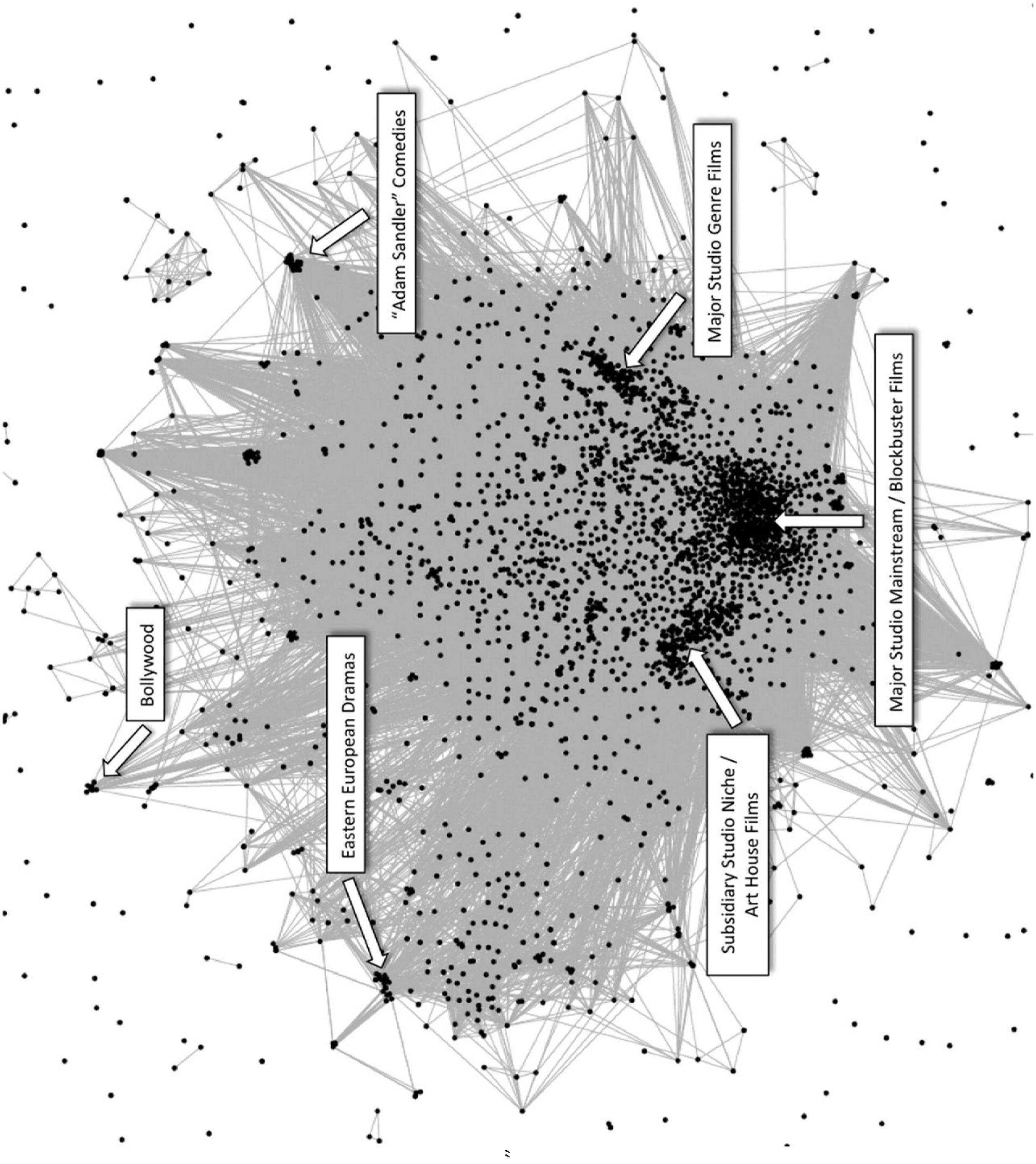
from which we obtain the duplicate equations

$$\begin{aligned} -v_1 - 4v_2 &= 0 \\ -v_1 - 4v_2 &= 0. \end{aligned}$$

If we let $v_2 = t$, then $v_1 = -4\,t$. All eigenvectors corresponding to $\lambda_1 = 3$ are multiples of $[\begin{smallmatrix} -4 \\ 1 \end{smallmatrix}]$ and thus the eigenspace corresponding to $\lambda_1 = 3$ is given by the span of $[\begin{smallmatrix} -4 \\ 1 \end{smallmatrix}]$.

Appendix C. Visualization of the 1994–2003 network

The graph visualization below shows the 1994–2003 network used to evaluate the impact of network embeddedness on the revenues of 2004 movie releases. The image is a one-mode graph projection of movies (n = 3268; see Appendix A for alternative mode examples). Here, movies are represented as black dots, with grey lines linking movies shared by common collaborators. The visualization is physics-based (OpenOrd using Gephi); that is, the distance between any two movies depends on the number of collaboration ties among the core team members on those two movies. Labels describe selected examples of major visible clusters in the network. Movies for which no core team members have worked on a movie project with others in the network appear as isolated dots.


"Adam Sandler" Comedies
Major Studio Genre Films
Major Studio Mainstream / Blockbuster Films
Bollywood
Eastern European Dramas
Subsidiary Studio Niche / Art House Films

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