Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Repeated Interactions and Improved Outcomes: An Empirical Analysis of Movie Production in the United States

Vishal Narayan, Vrinda Kadiyali

MANAGEMENT SCIENCE
Vol. 62, No. 2, February 2016, pp. 591–607
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2014.2139

Repeated Interactions and Improved Outcomes: An Empirical Analysis of Movie Production in the United States

Vishal Narayan
NUS Business School, National University of Singapore, Singapore 119245, bizvn@nus.edu.sg

Vrinda Kadiyali
Samuel Curtis Johnson Graduate School of Management, Cornell University, Ithaca, New York 14853, kadiyali@cornell.edu

Many marketing activities take place within teams; these team activities often involve repeated interactions among team members over several projects. We study whether and what types of repeated interactions improve current production success, and under what conditions. We use a unique data set of past experience, successes, and pairwise interactions between members of production teams of 1,123 movies and employ dynamic panel data estimation methods. Three unique insights emerge. Interactions between the producer and other team members have a greater effect on revenues than other repeated pairs for which consumers might have preferences. In many instances, repeated interactions with current team members are more revenue enhancing than individual successes in past movies. In fact, repeated interactions between team members improve current revenues even if such interactions were unsuccessful. We discuss theoretical explanations for these results and the managerial implications for successful team formation in movie production.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mnsc.2014.2139.

Keywords: marketing; new products; economics; microeconomic behavior; industries; recreation-sports
History: Received March 21, 2012; accepted November 25, 2014, by J. Miguel Villas-Boas, marketing. Published online in *Articles in Advance* June 26, 2015.

1. Introduction

Several marketing activities take place in teams—new product development (Edmondson and Nembhard 2009), advertising development, brand management, selling, distribution, pricing, allocation of marketing resources, etc.[1] We study the determinants of success of such teams in the context of the U.S. motion picture industry. We focus on an important and under-researched element of team-based production: the impact of repeated interactions across multiple projects. Movie production involves significant artistic and organizational coordination among the producer, director, screenwriter, actors, etc. Members of a production team might have worked in prior movies with the focal team's and other teams' members. Although it might seem intuitive that such repeated interactions among team members is positively related to team production success, much remains unclear and unexplored about the precise role of repeated interactions.

First, movie production teams are composed of members for whom audiences are more likely to have well-defined preferences (actors/actresses) and members for whom audiences are less likely to have preferences (e.g., producer, director, screenwriter, etc.) All repeated interactions (i.e., two team members having worked in movies in the past) could affect the success of the current product (i.e., movie). However, how much of the current success is attributable to/driven by viewer preferences versus supply-side improvements? Second, although successful repeated interactions between team members might positively affect the success of the current product, is it possible that even unsuccessful repeated interactions have positive effects on product success? This is possible if team members learn from failures of repeated interactions. Similarly, it seems likely that repeated interactions have positive effects on product success if the team members are successful in their own right (e.g., repeated interactions between two Oscar winning actors might lead to greater movie success). But can repeated interactions between relatively less

[1] Lazear and Shaw (2007, p. 105) report, "From 1987 to 1996, the share of large firms that have more than 20 percent of their workers in problem-solving teams rose from 37 percent to 66 percent. The percent of large firms with workers in self-managed work teams rose from 27 percent to 78 percent." Such systematic data are not available for more recent time periods.

successful team members also lead to product success? Is it possible that the effect of repeated interactions matters more than the experience and success of individual team members? Third, a member of a movie production team will have worked not just with other members of the focal movie (we term such interactions within-team repeated interactions) but also with several members in the production teams of other movies (outside-team repeated interactions). Both kinds of repeated interactions might enhance product success. However, the difference in magnitudes of these two kinds of repeated interactions is important for understanding how portable success is across team projects with varying team members.

In this research, we empirically address all these questions. The key underlying econometric issue is as follows: how robust are the observed positive effects of repeated interactions on the present movie success after controlling for various factors that are likely correlated with repeated interactions? In other words, we need to distinguish between correlation and causality. For example, current success might be correlated with/caused by success of repeated interactions, or current success might really be a proxy for past individual success. It is also possible that repeated interactions are correlated with other factors unobserved to researchers, making it important to control for potential endogeneity of this measure. Furthermore, arguably all member-specific and pairwise-interaction specific variables are potentially endogenous.

From a theoretical standpoint, there are various supply-side reasons for there to be a causal relationship (rather than correlational) between repeated interactions and current success. Consider agency first. In team situations, three types of agency are possible: agent's (team member's) agency, principal's (or team organizer's/team leader's) agency, and between-agent agency. Repeated interactions might provide ways to mitigate these team agency issues. The second pathway of improved productivity via repeated interaction is greater investment in relationship-specific assets. These investments might be central to the production process; the bigger, more irreversible they are, the less likely they are to be incurred in single-time interaction. Finally, repeated interactions might lead to productivity improvement through learning by doing as team members learn to work with each other. Intuitively, it might appear that learning by doing is most likely in homogeneous production scenarios (e.g., assembling airplanes in a factory) where production is a linear process and there might not be as much team coordination. However, learning might happen in even more complex nonhomogeneous tasks because production comprises not just routine manufacturing tasks but also learning to work with team members. In §2, we elaborate on these three pathways of improved productivity via repeated interactions and discuss in §3 how they specifically apply to the movie industry.

Note that careful estimation of the magnitude and path of the impact of repeated interactions is substantively and managerially important. Increase in movie success despite unsuccessful repeated interactions will have different movie team casting implications than if this were not the case. Increase in movie success due to repeated interactions even between relatively less successful team members should be reassuring for studios and financiers, given the large payments commanded by successful team members in Hollywood. If within-team repeated interactions matter more for movie success than outside-team repeated interactions, then casting decisions should depend less on how "collaborated" potential team members are in general and more on the level of repeated interactions within specific potential team members. If within-team repeated interactions matter more than individual success factors, it makes economic sense to have sticky movie production teams rather than bringing in new members who might have achieved high individual success in other movies.

Our empirical work proceeds as follows. We assemble a data set of 4,117 individuals who feature in 1,123 movies released in the 1999–2005 period. We measure the repeated interactions and experiences of five team members in each movie—producer, director, screenwriter, lead actor, and lead actress. Consistent with the movies literature, we measure a team's production output by box office revenues. In addition, we also include a variety of other descriptors of movie revenues (like advertising expenditure, production costs, seasonal dummies, etc.)

To deal with the endogeneity issue while still accounting for unobserved heterogeneity across movies, we apply GMM style estimators of dynamic panel data models that exploit lags and lagged differences of explanatory variables as instruments.[2] These methods have the advantage of not relying on the availability of robust exogenous instruments. These methods were pioneered by Anderson and Hsiao (1982) and further developed by Arellano and Bond (1991) and Blundell and Bond (1998). They were introduced to marketing by Clark et al. (2009) to study the effect of advertising expenditures on brand awareness and perceived quality. To study the effect of social network structure on the popularity of online videos, Yoganarasimhan (2012) extends these methods to enable the identification of the effects of time-invariant endogenous covariates. Methodologically

[2] We thank an anonymous reviewer for suggesting these methods to resolve the endogeneity issue.

our work is most closely related to this paper since our endogenous variables of interest do not vary over time either.

Our findings are as follows: (1) repeated interactions have an economically significant impact on movie revenues; (2) the number of within-team repeated interactions influences revenue even after controlling for success of these interactions, experience, and success of individual team members as well members' overall team experience (with those not in this focal team) and various movie characteristics; (3) the number of within-team repeated interactions matters more than the number of outside-team repeated interactions; (4) within-team repeated interactions matter more than experience or success of individual team members; and (5) the producer's within-team repeated interactions matter more than other members' within-team repeated interactions. An obvious view of how the producer affects movie success would be via her role of organizing the production process, e.g., by obtaining financing and distribution for a movie. However, this route of the producer's impact of movie success is likely to be measured by her individual descriptors (number of movies made, success of past movies, etc.). We find that the producer's repeated interactions with team members are most salient for movie success. This is consistent with the following view: the three drivers of improved outcomes in team production (lesser agency, lower transaction costs, and learning by doing) are most salient in pairwise repeated interactions featuring the producer. This finding points to the role of leaders in teams (the producer is akin to the CEO) rather than the day-to-day operational head (the director is akin to the COO). This finding also underlines the relative importance of the revenue-enhancing role of team members who consumers do not view on the screen.

The effects of repeated interactions on revenue are likely to be a combination of demand-side and supply-side effects. In further research, we collect additional data from a viewer survey to understand viewer preferences for specific team members. This analysis indicates that revenue improvements can be attributed largely to supply-side effects of repeated interactions rather than to viewer preferences of seeing pairs of team members in a movie. In the remaining sections, we discuss the relevant literature (§2), present industry and data features (§3), describe our estimation model (§4), discuss results (§5), and conclude (§6).

2. Literature Review

Why might repeated interactions among team members affect production success? To address this, we first discuss the literature on agency in teams and team productivity and then on investing in relationship-specific assets and learning by doing.

Consider first the types of agency situations that can arise in teams. First, if an agent's (team member's) interests are not aligned with the principal's (the owner or manager), the agent might reduce effort in her task. We term this agent's agency.[3] Second, if awards are team-based and effort is not completely observable by the principal, an agent might free ride on the effort of her team mates (Alchian and Demsetz 1972, Holmstrom 1982). We refer to this phenomenon as between-team agency. Third, in an attempt to underpay agents, the principal might underreport profits and output if these are not fully observable to agents (MacLeod 2003, Levin 2003) or use nontransparent evaluation criteria resulting in underpayment of agents (Baker et al. 1997, among others). The principal may also be maximizing her own maximand that is directly at odds over agents' maximand. This is the principal's agency.

These three kinds of agency (agent's agency, between-team agency, and principal's agency) might be reduced over repeated interactions in teams (i.e., interaction in previous projects) in at least two ways. First, despite imperfect observability of agency, there is a higher probability of observing these behaviors over repeated interactions. Over time, teams might eliminate team members whose agency comes to light. Second, teams might learn to better manage bad behavior from team members (who might be valuable despite these behaviors), for example by spreading responsibilities to other group members.

Although the theoretical literature in economics elucidates agency issues in teams, empirical research on the impact of team structure on team output has been rarer. Knez and Simester (2001) show that despite a team performance goal, Continental Airlines was able to avoid free riding in teams, likely because the organization of teams enabled mutual monitoring (of and by agents). Hamilton et al. (2003) show improved productivity in a garment plant that adopted team-based compensation; they also find more heterogeneous teams to be more productive, a finding consistent with mutual team learning. Heywood and Jirjahn (2009) isolate the effects of complementarity of effort in increasing team output relative to when effort inputs are independent. As we discuss in §3, the movie production process offers a setting where team agency might be a salient issue. Also, we

[3] There is a rich history of examining agents' agency issues in marketing, including the following influential papers: theory papers include Basu et al. (1985) and Lal and Staelin (1986), and empirical papers include Lal et al. (1994), among others. However, we were unable to find any papers dealing with agency and performance issues in teams, the focus of our research.

are not aware of research where all three types of agency have been explored.

The second mechanism for improved team productivity via repeated interactions is improved incentives to invest in relationship-specific assets. Classic empirical papers in this stream of literature include Joskow (1985), Monteverde and Teece (1982), Anderson and Schmittlein (1984), and Masten (1984). The insights relevant to our context are the following—in production processes with high uncertainty, complexity, connectedness, and timeliness requirements, contract parties fear investing in relationship-specific assets that have limited value outside the relationship. If these transaction costs are not borne by one or both of the contracting parties, production cannot take place (as effectively or not at all). Long-term contracts or vertical integration are solutions to these high transaction costs situations. Extending these insights in to a team context, there are multiple pairwise production processes. Each of these pairwise production processes might need investments by both parties to successfully execute the team-wide and pairwise production process. As might be expected, some pairwise repeated interactions might be more critical than others in a team production process. Note that although we have discussed transaction costs as a separate mechanism from agency mitigation as the driver of team productivity, they are empirically indistinguishable in our data situation. This is not a serious issue for us since the primary purpose of this research is to document the impact and conditions of repeated interactions on team productivity, regardless of the specific mechanism for improved productivity and to understand that these mechanisms can occur concurrently and perhaps even reinforce one another.

Researchers have examined learning by doing in teams, the third important mechanism for team productivity in repeated interactions. Huckman and Pisano (2006) find that when surgeons perform a procedure across several hospitals, their performance in any hospital is a function of how often they have worked in that hospital rather than overall experience across all hospitals (see also Huckman et al. 2009). Kellogg (2011) finds that joint teams from drilling rig companies and oil companies work best if they have experience working together rather than histories of independent work experiences (with other firms). It is important to note that these demonstrations of learning by doing are in the context of homogeneous production. In other words, learning by doing in production processes is driven by repetition of the same set of actions over and over. We will discuss later to what extent such a model might apply to movie production. Additionally, although not discussed in existing literature, from our research perspective, learning by doing might also be intertwined with learning about agency. For example, learning by doing might proceed faster after "bad" team members have been eliminated or teams have developed routines to work better with such "bad" team members. As discussed in the previous paragraph, our results must therefore be seen as testing for support for any and all three of these mechanisms of repeated interactions for improving production success potentially via greater team productivity.

3. Industry Background and Data

3.1. Industry Background

The U.S. movie industry has a high rate of product failure and an expensive production process; "industry estimates reveal that 60 percent or more of movies produced each year are box-office flops" (Schwartz 2010). Therefore, any insight on improving team production is likely to be valuable.

In earlier times (until the 1950s), studios had teams of producers, directors and actors who interacted repeatedly within the boundaries of any studio (Chisholm 1993). After the studio system loosened, team members were no longer contractually bound to work only for certain studios with certain combinations of team members (Baker and Faulkner 1991). With these free markets for talent, there is greater need, and greater financial incentive, for better managing team production. Free market for talent means that movie production teams are fluid; i.e., teams are formed afresh for each new movie. These teams do not operate inside the boundaries of a firm; i.e., team members are not contractually obligated to work with one another.

Movie production typically begins with the producer selecting from several versions of multiple screenplays and then finalizing a screenplay to take to production. The next step is to arrange for finances to produce the movie, for which the producer enters into a contract with a studio or obtains financing from other sources. During the process of obtaining financing, the producer chooses the director, who then assists in assembling the rest of the cast and crew. Production budgets are also decided at this stage. Distribution contracts with studios/distributors are negotiated by the producer. After this preproduction stage, the actual production of the movie commences (Eliashberg et al. 2006). Research shows that business and artistic domains are fairly distinct in movie production. As Baker and Faulkner (1991, p. 290) discuss, the producer has more of "deal maker" or organizing role in the moviemaking team (akin to a CEO). The producer's specialization in entrepreneurial, financial, and administrative abilities "increases the producer's credibility, acceptance and bargaining power in the creative and financial communities." Consequently, the producer plays a central role in the (longevity and success of) careers of team members and in distributor/studio financial success. The director's role is to manage the artistic domain (akin to the COO of the production process).

Movie production has the "O-ring property" where each team member has to perform at a sufficiently high level to help achieve a high level of team output (Kremer 1993; the phenomenon is named after the space shuttle Challenger disaster where a single weak link had catastrophic consequences). Although this O-ring property might ensure some alignment of interests among team members, agency, transaction costs, and lack of learning by doing might get in the way of optimal production. Consider first agency issues. In production, individual and team goals overlap and conflict. For example, there are individual and movie-level industry awards, and it is hard for a movie to be successful based on just one team member's effort. Yet careers are typically built individually. Members who have interacted with each other in the past might form an unobservable coalition to jointly try to maximize their visibility in a movie with an eye to their own future career and earnings. Agents might expect accommodation from team members in other ways, e.g., demanding bigger trailers to rest during production, appropriating more lines from the screenplay to maximize their individual rewards from the movie, finding ways to save their time over others' time (such as by arriving late after others have arrived and prepared), etc. Although some of these (e.g., on the set) behaviors are observable, other behaviors, like an artist conducting private conversations with the director on the direction of movie, are not. These between-member agency behaviors can have adverse effects on movie success.

The producer's agency in underreporting profits has been discussed in Cheatham et al. (1996); they discuss how *Forrest Gump* supposedly earned negative net profits despite being the fourth highest grossing movie of all time. The manipulation of the net profit figures allegedly occurred because the writer had been promised 3% of net profits. Such agency might be detectable ex post and therefore, theoretically, going forward, optimally contracted, making such agency a nonissue.

In addition to increased probability of detection of reducing bad behavior, both the principal and agents might have incentives to signal with "good" behavior. Their careers and successes are interdependent, and given changing consumer tastes and the large number of financially unsuccessful movies, involuntary career exits are a real possibility. This might be especially true of agents given the producer's key role in obtaining financing and distribution for movies and for organizing the entire production process. Note that the incentive for a team member to signal with one's own "good" behavior is heightened when he or she encounters a successful producer with "good" behavior because these producers are most likely to continue to thrive in their future careers.

Movie production might also involve investment in relationship-specific human capital assets. Given the complexity of movie production process and the temporal sequencing mentioned above, as well as the uncertainty in producing heterogeneous movies, team members might need to invest time and effort to ensure smooth production processes. They might especially need time and effort to understand team members' working styles and adapt their own style to others'. There might be a greater incentive to do this if repeated interactions are likely. In the course of repeated interactions, greater productivity will result from these investments in building relationship-specific human capital.

Movie production is also a good laboratory to study learning by doing. Bechky (2006) investigates how lower-ranked production assistants ("gaffers, gofers and grips") learn their roles. She discusses how lower-ranked roles have less latitude in defining their role structure compared to the higher-ranked roles. There is likely to be a greater heterogeneity of roles (i.e., less repetition) across movies for actors than for camera grips, electricians, etc. Therefore, learning by doing might not be as applicable in a pure production sense. Additionally, note that as mentioned earlier, the producer's role is mainly financing and the director is more the team leader for the artistic production process. This implies that the producer is less likely to be part of any production learning by doing routines. Therefore, the most likely place to find learning by doing is between team members other than the producer. However, this view of learning by doing might be too constrained by existing evidence on learning by doing in homogeneous tasks. Learning by doing might additionally occur in even nonhomogeneous tasks. For example, a producer and director might learn to choose more efficiently the rest of the production team over repeated interactions. A producer and leading actress might learn to write better contracts over repeated interactions.

3.2. Measures of (Team- and Individual-Level) Output, Experience and Success

Agency, transaction costs, and learning by doing are all unobservable in our data. The number of repeated interactions is a proxy for the three mechanisms of productivity improvement. However, as discussed in the introduction, there are various possible confounds in using the number of repeated interactions as a measure of productivity improvements. For example, repeated interaction might be correlated with, and caused by, past team output, with individual tenure/productivity and success in the industry, etc. (Further details are in §4.) Also, given double-sided agency and free-riding issues among agents, and different paths of learning by doing or asset specificity, it is not evident what types of repeated interactions are most helpful to improve team output. We employ various controls/proxies and control for endogeneity of repeated interactions and of various other endogenous variables. We describe robustness analyses in §5.2.

Our primary variables are team- and individual-level output and experience variables, especially repeated interactions among team members. Since we do not observe production inputs, we use measures of individual and team output. Consider first team output, which as mentioned before is measured by box office revenues. Our data set comprises 1,123 widely released movies over a sampling period of seven years: 366 weeks from January 1, 1999, to December 29, 2005. We collect weekly data for each of these movies up to the point that they are screening in at least 300 theaters (of about 5,900 total theaters in the United States in 2005); revenues for movies in our data are trivial below this level of theater screening.[4] This leads to a set of 8,350 movie-week observations. Our measure of team output, theatrical revenue data, is from www.Boxofficemojo.com (BM) and www.imdb.com (IMDB). For each movie, based on the order in which actors appear in the movie credits, we classify the first actor (actress) on this list as the lead actor (actress). For movies with multiple producers, we select two persons who are classified as "executive producers." The executive producer is responsible for all business and legal issues of the movie, and other producers (associate producers, co-producers, and line producers) work under her supervision. Our data comprises of 4,117 unique team members, which include 1,071 actors, 1,158 producers, 710 directors, and 1,178 screenwriters.

Individual output or performance cannot be measured by the researcher in the same way as team output can from market revenues. Therefore, following Elberse (2007), we measure any member's past performance (and success) by first measuring their "star power." *STAR POWER* is the total number of Academy Awards and Golden Globe awards for which the member was nominated for or which the member won in the five-year period preceding the release of the movie. Additionally, for each team member i ($i = 1, \ldots, 5$) in movie j ($j = 1, \ldots, 1{,}123$), we recorded the titles and U.S. box office revenues of all movies in which member i had worked (as actor, director, producer or screenwriter) and were released in an eight-year period prior to the release of movie j in the United States. Let this be set A. We measure (a) the number of movies member i has worked in the eight-year period preceding the release of movie j, $NMOV_{ij}$ ($i = 1, \ldots, 5$), and (b) the logarithm of the mean revenue of all movies member i has worked in the eight-year period, added to one. Star power is an important variable to include since it might signal high individual productivity (and that might be correlated with ability to appropriate rents, too). Number of movies finished prior to current production could also systematically signal low agency, greater willingness to invest in transaction costs, and high ability to learn by doing. Yet not all successful actors win awards. The mean revenues of movies finished prior to current production serves as a control for star power and success not captured by awards.

Consider next measures of team experience. Let the set of movies in which member i' worked in and were released in the same eight-year period be set B. We computed the number of movies that team members i and i' ($i' = 1, \ldots, 5$; $i' \neq i$) from movie j had both been a part of in this eight-year period, or $NREP_{ii'j}$. $NREP_{ii'j}$ is the number of movies common to set A and set B. For each of the 1,123 movies in our data, $NREP_{ii'j}$ is measured in an eight-year window before the release of the movie. Thus if movie j was released on January 1, 1999, the relevant eight-year period is January 1, 1991, to December 31, 1998. Our choice of an eight-year window is driven by the slow movie development process from script identification to theatrical distribution. Measuring repeated interactions over a longer duration also allows differences in the number of repeated interactions to manifest more clearly in the data.

To measure the productivity (or success) of repeated interaction, the mean revenue of all movies that team members i and i' ($i' = 1, \ldots, 5$; $i' \neq i$) from movie j had both been a part of in this eight-year period is labeled $REVREP_{ii'j}$. For example, the lead actor of the movie *Jersey Girl* is Ben Affleck and its executive producers are Jonathan Gordon and Bob Weinstein. In the eight years preceding the release of this movie in March 2004, Ben Affleck worked in seven movies that were produced by at least one of these producers. These movies are *Bounce*, *Daddy and Them*, *Dogma*, *Good Will Hunting*, *Jay and Silent Bob Strike Back*, *Phantoms*, and *Shakespeare in Love*. The value of $NREP_{ii'j}$ for the lead actor–producer pair is seven for this movie. With five team members per

[4] To investigate whether there might be a selection bias from ignoring movies exhibited in fewer than 300 theaters, we collected data on the daily box office revenue and number of theaters for all movies showing in theaters in the United States for the four-week period starting May 6, 2011. We found that 98.9% of all box office revenues are from movies exhibited in at least 300 theaters. Therefore, it appears unlikely that movies released in less than 300 theaters would materially bias our results.

movie, we construct 10 ($^5C_2$) variables for the number of past pairwise interactions and another 10 variables for the mean revenue from repeated interactions. Note that $NREP_{ii'j}$ for any pair of team members is symmetric and nondirectional; i.e., $NREP_{ii'j} = NREP_{i'ij}$. Three of these 10 pairwise interactions do not involve an actor or actress. As mentioned, audiences are likely to have weak preferences for these three pairs since they do not appear onscreen.

With few degrees of separation between people working in the movie industry, information about agency, ease of investing in relationship-specific assets, or ease of learning by doing might transmit easily. We measure $NREPOUT_{ij}$, the total number of repeated interactions (in the eight years preceding the release of movie j) of team member i with all other members of the universe of 4,117 unique individuals in our data set.[5] From this measure, we exclude the measure of within-team repeated interactions to only include outside-team repeated interactions with all other members of all producing teams of the 1,123 movies in our data (i.e., with $4{,}117 - 5 = 4{,}112$ members). This serves as a measure of outside-team interactions of member i.

Summary statistics of all our measures of repeated interactions and individual performance and success data are presented in Tables 1 and 2. The producer has the most pairwise interactions with members. Repeated interactions between the director and the producer generated higher revenues than those between other pairs of team members. The lead male actor has the most outside-team repeated interactions, and the director the least.[6] Further analysis reveals that correlations in number of repeated interactions between pairs is quite low (mean of absolute value of correlations = 0.19), which provides evidence against potential multicollinearity in our model.

3.3. Other Drivers of Movie Revenue

Although there is a vast literature in marketing on this industry (see Eliashberg et al. 2006 for a review), our focus is only on papers directly relevant to our research problem. There is a thriving research stream documenting the various drivers of (post-release) movie success. We borrow from this literature various drivers of movie revenue, including seasonality (Krider and Weinberg 1998), genre and Motion Picture Association of America (MPAA) rating (see Eliashberg et al. 2006), actors' star power and awards won (Elberse 2007), the importance of competitor movies, etc. Data on the production studio, the production budget, the release date, and the weekly box office revenue are from BM. We use IMDB to collect data on star power, movie genres, and MPAA ratings. Advertising expenditure is from Paul Kagan and Associates.

We measure competition based on the following established measures (Basuroy et al. 2006): $COMP\_NEW_{jt}$ stands for competition from new releases. For movie j in week t ($t = 1 \ldots T_j$), it is measured as the logarithm of the sum of the production budgets of all new releases in week t. $COMP\_ONG_{jt}$ stands for competition from ongoing movies; it is measured as the average age (weeks since release) of all movies in week $(t-1)$, excluding movie j. $COMP\_REV_{jt}$ denotes competition for various audiences' attention; it is measured as the number of movies in week t that have the same genre or MPAA rating as movie j, divided by the average age of all such movies.[7] The variable $SEQUEL$ is defined as 1 if the focal movie is a sequel and 0 otherwise. Note that for our research purpose, it is important to distinguish sequels from nonsequels, given sequels are compelled to use (most of) the team from the previous joint production and therefore might have systematically different agency issues.

Finally, to capture the release timing, we define 12 variables as follows: dummy variables for the season of release (March–May as spring, June–August as summer, September–November as fall, and December–February as winter); dummy variables for high-demand weekends (Christmas, Thanksgiving, and Independence Day), based on whether the focal movie was released on the Friday closest to the respective date; and yearly dummy variables to control for year-specific shocks (such as the September 11 attacks in 2001).

[5] This is roughly equivalent to degree centrality measure used in the social network literature. Note that there are several papers on demand-side social networks effects in marketing. In contrast, we examine supply-side repeat-interaction networks of the production team.

[6] Our initial sample included repeated interactions between supporting male and supporting female actors as well. However, supporting actors/actresses have the fewest past pairwise interactions with other current team members. More importantly, the effect of interactions of team members with supporting actors is not significant across all model specifications. Therefore, we do not include measures of interactions involving supporting actors in our analysis.

[7] Bornstein et al. (2002) discuss how intergroup competition reduces intra-group competition. In our context, if production teams face stiff competition in the movie business, there is likely to be greater productivity inside the team. We do not have information on production dates of various movies and therefore we cannot control for competition during production; controlling for competition during exhibition might be seen as a rough proxy if movies being exhibited are produced roughly at the same time. Additionally, if unaccounted for competition is systematically correlated with repeat interactions (using reduced agency to get around competition), then the endogeneity correction should control for this. We thank the associate editor for prompting this discussion.

Table 1 **Summary Statistics of Measures of Within-Team Interactions** ($N = 1{,}123$)

	$NREP_{ii'j}$: Number of movies common with other team members of focal movie in eight years prior to movie release		$REVREP_{ii'j}$: Mean revenue (in \$M) of movies common with other team members of focal movie in eight years prior to release	
	Mean	SD	Mean	SD
Lead male–Lead female	0.91	0.68	51.07	93.65
Lead male–Director	0.96	0.75	50.90	83.16
Lead male–Producer	1.22	1.20	65.40	121.13
Lead male–Screenwriter	0.97	1.05	52.43	95.72
Lead female–Director	0.80	0.58	43.56	82.10
Lead female–Producer	1.05	1.06	59.35	123.69
Lead female–Screenwriter	0.84	0.92	46.73	73.92
Director–Producer	1.29	1.24	72.33	125.08
Director–Screenwriter	2.79	1.75	43.75	82.41
Producer–Screenwriter	1.83	1.83	46.53	77.05

Table 2 **Summary Statistics of Member-Specific Characteristics** ($N = 1{,}123$)

	Number of repeated interactions with team members of all movies in eight years preceding release of focal movie[a]		Number of Academy Awards and Golden Globe awards nominated for in five years preceding release of focal movie		Mean revenue of all movies (in \$M) the member has worked in eight years preceding release of focal movie		Number of movies the member has worked in eight years preceding release of focal movie	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Lead male	72.18	46.39	1.08	0.82	56.81	92.43	11.26	6.47
Lead female	58.18	41.99	1.01	1.07	52.05	108.77	10.91	5.96
Director	18.69	13.52	0.33	0.48	60.48	109.36	3.97	2.71
Producer	69.19	98.56	0.46	0.43	63.24	90.75	15.48	21.22
Screenwriter	47.92	35.49	0.29	0.35	45.80	81.61	5.81	3.90

[a]Two members working in a movie is counted as one interaction, so the same movie could account for multiple interactions.

As discussed earlier, data include the season of movie release, its genre, its MPAA rating, competition, the studio, the production budget of the movie, etc. Correlations between our measures of repeated interactions and other factors that affect movie performance are very low. From a methodological perspective, this allays concerns of multicollinearity. Substantively, this suggests that the level of repeated interactions among team members in a movie (which is decided by the producer based on the team members he/she casts) is largely unaffected by the commonly understood determinants of movie performance.

4. Model Setup

To measure what types of team and individual measures of experience and productivity matter for box office success, we specify a revenue model. Let y_{jt} be the logarithm of the box office revenue of movie j in week t. We model y_{jt} as a function of revenue in previous weeks; time-varying measures of competition faced by movie j; a rich set of control variables; and, most importantly, measures of movie-specific team experience and interaction.

$$y_{jt} = \alpha + \mu_j + \lambda_t + \gamma y_{jt-1} + \beta Z_j + \delta C_{jt} + \varepsilon_{jt} \tag{1}$$

Following Yoganarasimhan (2012), we make the standard assumptions that $E(\varepsilon_{jt}) = 0$, $E(\mu_j) = 0$, and $E(\varepsilon_{jt} \cdot \mu_j) = 0$. Further, the errors ε_{jt} are assumed serially uncorrelated, i.e., $E(\varepsilon_{jt} \cdot \varepsilon_{js}) = 0$ if $s \neq t$, but heteroskedastic across movies, i.e., $E(\varepsilon_{jt} \cdot \varepsilon_{js}) = \sigma_j^2$ if $s = t$. We test the assumption of no serial correlation using an Arellano-Bond test reported later.

The vector Z_j comprises the following 69 variables measuring repeated interactions and experience of team members and control variables measuring movie characteristics known to affect revenues:

(a) Ten variables measuring within-team number of pairwise repeated interactions $NREP_{ii'j}$ for each pair of team members of movie j. These are the key variables of interest.

(b) Ten variables measuring the logarithm of the mean revenue of all movies that each pair of team members of movie j had both been a part of in the eight-year period ($REVREP_{ii'j}$), added to one. It is plausible that movie audiences have preferences for specific pairs of team members. Then movies with more (less) popular pairs of team members will have more (fewer) repeated interactions.

(c) Four variables for each of the five team members: number of outside-team repeated interactions $NREPOUT_{ij}$, $STAR\ POWER$ (defined earlier), $NMOV_{ij}$, and the logarithm of the mean revenue of all movies member i has worked in the eight-year period, added to one. Outside-team repeated interactions capture repeated interactions with nonfocal team members and, as mentioned previously, might signal low agency/high productivity for this current project.[8]

(d) Seventeen control variables comprising dummies for movie genre (comedy, animation, romance, drama, action, science fiction, and horror); MPAA rating (G, PG, PG13 and R) and distributing studios; logarithm of production budget; logarithm of advertising expenditure; and *SEQUEL*.

(e) Twelve variables capturing the effect of release timing of movie j. These include dummy variables for the season in which the movie was released, dummy variables for high-demand weekends, and yearly dummy variables to control for year-specific shocks.

The movie-specific effect μ_j allows three types of unobservable factors to affect revenues and controls for unobserved heterogeneity across movies: movie-specific unobservables (e.g., production quality, word of mouth); individual characteristics of team members (e.g., acting abilities); and features of repeated interactions that we do not observe (e.g., repeated interactions of members not in our data, social interactions between members in our data, etc.). All these unobservables are collapsed into a cumulative effect μ_j, which, following the literature, we refer to as the "fixed effect." As in Yoganarasimhan (2012), we allow for correlation between μ_j and Z_j as well as between μ_j and C_{jt} and assume these correlations to be linear.

The vector C_{jt} comprises the three measures of time-varying competition discussed earlier: $COMP\_NEW_{jt}$, $COMP\_ONG_{jt}$, and $COMP\_REV_{jt}$; λ_t captures systematic weekly variations in revenues across movies (box office revenues are typically greater in the first few weeks and then taper down). We include the lagged dependent variable as a covariate to account for time-varying movie-specific factors (e.g., greater word of mouth and publicity in earlier weeks). It also serves to control for serial correlation in the error terms ε_{jt}, a critical estimation requirement which we discuss later. The addition of this variable also significantly improves model fit.

The model specified by Equation (1) is known to potentially suffer from three kinds of endogeneity (Yoganarasimhan 2012). First, Z_j might be correlated with the unobserved fixed effect μ_j. Second, time-varying observed measures of competition C_{jt} might also be correlated with μ_j. Third, measures of competition C_{jt} might also be correlated with the error term ε_{jt}. We start by taking first differences of Equation (1). Lagged values of the dependent variable and lagged values of time-varying explanatory variables can provide valid instruments (Arellano and Bond 1991).

$$y_{jt} - y_{jt-1} = (\lambda_t - \lambda_{t-1}) + \gamma(y_{jt-1} - y_{jt-2}) + \delta(C_{jt} - C_{jt-1}) + (\varepsilon_{jt} - \varepsilon_{jt-1}) \quad (2)$$

Note that first differencing eliminated the time-invariant movie characteristics Z_j and the unobserved fixed effect μ_j, so the first two of the three endogeneity issues discussed above are no longer valid. However, first differencing introduces a new endogeneity problem: $(y_{jt-1} - y_{jt-2})$ is correlated with $(\varepsilon_{jt} - \varepsilon_{jt-1})$ since y_{jt-1} is correlated with ε_{jt-1} as per Equation (1). To deal with this, we take advantage of the panel data structure (we have an average of 7.4 weekly observations per movie). Consider Equation (2) for week 3.

$$y_{j3} - y_{j2} = (\lambda_3 - \lambda_2) + \gamma(y_{j2} - y_{j1}) + \delta(C_{j3} - C_{j2}) + (\varepsilon_{j3} - \varepsilon_{j2}) \quad (3)$$

Here y_{j1} serves as a valid instrument for $(y_{j2} - y_{j1})$ since it is correlated with $(y_{j2} - y_{j1})$ owing to the common term y_{j1}. However, with serially uncorrelated error terms, y_{j1} is not correlated with $(\varepsilon_{j3} - \varepsilon_{j2})$. Similarly, C_{j1} is a valid instrument for $(C_{j3} - C_{j2})$ since it is uncorrelated with $(\varepsilon_{j3} - \varepsilon_{j2})$ but correlated with $(C_{j3} - C_{j2})$.[9] More instruments are available for later time periods. For example, in week 4, y_{j1} and y_{j2} both serve as a valid instruments for $(y_{j3} - y_{j2})$ since neither is correlated with $(\varepsilon_{j4} - \varepsilon_{j3})$. More generally, levels of variables that are lagged two or more periods are valid instruments for the difference equation (Equation (2)). The resulting estimator is the "difference GMM." However, this estimator has the major drawback that it does not permit estimation of the coefficient of Z_j, the key effect of interest. Also, lagged levels are known to be poor instruments if the dynamic process is persistent over time (Blundell and Bond 1998). Thus we add back the level equation (Equation (1)) to the system (see, for example, Clark et al. 2009, Yoganarasimhan 2012).

The movie-specific fixed effect μ_j might be correlated with all three explanatory variables (y_{jt-1}, Z_j,

[8] Correlations between these four member-specific variables are quite low (most are less than 0.1). There is no systematic variation in these correlations across members. This suggests that they control for distinct elements of the effect of each member. More importantly, these measures capture all theoretical and industry-relevant constructs pertaining to member level characteristics that are known in the literature to affect product success. Thus our specification of controlling for individual-level effects by employing industry-relevant controls with low intervariable correlation seems reasonable.

[9] The underlying assumption is that measures of competition for movie j are correlated across weeks. Correlations between $COMP\_NEW_{jt}$ and $COMP\_NEW_{jt-1}$, $COMP\_ONG_{jt}$ and $COMP\_ONG_{jt-1}$, and $COMP\_REV_{jt-1}$ and $COMP\_REV_{jt-1}$ are 0.82, 0.69, and 0.58, respectively, in our data.

and C_{jt}) in Equation (1). Therefore, we instrument all three of them. We first make the assumption that deviations of log revenues in the first week (y_{j1}) from the long term mean of y_{jt} are uncorrelated with the long term mean itself. Blundell and Bond (1998, p. 124) show how this condition is clearly satisfied for stationary models and that stationarity is not necessary for this condition to be satisfied. To enable identification of the effect of time-invariant endogenous variables Z_j, Yoganarasimhan (2012) makes two assumptions: (a) the relationship between the fixed effect μ_j and y_{jt} does not vary with time, and (b) there is a nonlinear relationship between the observed covariates Z_j and y_{jt}, (i.e., Δy_{jt} and Z_j are correlated). This enables the author to express y_{jt} in the form $y_{jt} = \mu_0 \mu_j + f_t(Z_j, C_{jt})$. She proves algebraically that the effect of μ_j on y_{jt} is constant for all time periods (i.e., μ_0 is a constant). This ensures that Δy_{jt} is independent of μ_j, which is a necessary condition for Δy_{jt} to be used as an instrument. Also, if there is no serial correlation (we test for this), $(y_{jt-1} - y_{jt-2})$ is uncorrelated with ε_{jt}. Combining the two, $(y_{jt-1} - y_{jt-2})$ is uncorrelated with $(\mu_j + \varepsilon_{jt})$. Further, since $y_{jt-1} - y_{jt-2} = f_t(Z_j, C_{jt-1}) - f_{t-1}(Z_j, C_{jt-2})$, and given the assumption of nonlinear relationship of Z_j on y_{jt}, differences in log revenues are correlated with Z_j and C_{jt}. This renders differences in log revenues as appropriate instruments for endogenous covariates in the levels equation. The resulting estimator is based on both the level equation and the difference equation and is referred to as the "system GMM."[10]

Although we use estimators with mathematically general properties, we note that the underlying assumptions are quite plausible in our substantive context. μ_j is composed of residual movie characteristics and/or member characteristics after controlling for 69 movie-specific variables; such an effect is likely to be minor and might not vary on a week-by-week basis. On the other hand, differences in audience characteristics across weeks might be sufficient for a correlation between Δy_{jt} and Z_j. Consumers choosing to view a movie around its release date might have stronger preferences for pairs of members and/or greater ability to discern improved product quality (due to supply-side factors) than consumers viewing the movie toward the end of the theatrical release window.

To test for the validity of the proposed instruments, we follow Arellano and Bond (1991) and Clark et al. (2009) and report (a) the Hansen J-test to examine whether our instruments are jointly exogenous and (b) the difference-in-Hansen J-test to examine whether instruments used for the level equation (but not for the difference equation) are valid. To test for the absence of serial correlation, we use the Arellano-Bond (2) test, which is a test for second order serial correlation in the first difference of error terms. By construction, $(\varepsilon_{jt} - \varepsilon_{jt-1})$ and $(\varepsilon_{jt-1} - \varepsilon_{jt-2})$ are correlated through the common term ε_{jt-1}. However, in the absence of serial correlation, $(\varepsilon_{jt} - \varepsilon_{jt-1})$ and $(\varepsilon_{jt-2} - \varepsilon_{jt-3})$ should be uncorrelated. This test examines whether that is indeed the case. We find that including y_{jt-1} and other time-varying covariates is sufficient to ensure absence of serial correlation of error terms. Estimation of both difference GMM and system GMM was carried out in STATA using the xtabond2 routine (Roodman 2009a). Using this routine, we incorporate third and fourth lags of log movie revenues and competition measures as "GMM-style" instruments for the difference equation and $(y_{jt-1} - y_{jt-2})$ and $(y_{jt-2} - y_{jt-3})$ as "IV-style" instruments for the level equation. The final model is estimated on data from movies with at least three observations (i.e., movies that have run in theaters for three or more weeks). This represents 941 out of 1,123 movies in our data. To allay concerns of any selection problem because of this, we compared summary statistics of all 10 variables of interest ($NREP_{ii'j}$) across the two samples and found that them to be virtually identical.

The tests described above and the preceding theoretical discussion are aimed at ascertaining the validity of instruments in terms of their being (a) correlated with the endogenous variables and (b) uncorrelated with the relevant error terms. Although these are necessary conditions for estimating unbiased causal effects, they are not sufficient. In particular, weak instruments (i.e., those that are insufficiently correlated with endogenous variables) may lead to biased coefficient estimates. The bias holds even for large samples (Bound et al. 1995, Staiger and Stock 1997, Park and Gupta 2012). In finite samples, this bias is in the same direction as ordinary least squares (OLS). As a consequence, standard hypothesis tests and confidence intervals might be unreliable. Bound et al. (1995) and Hahn and Hausman (2003) show that the bias is inversely related to the F-statistic of the regression of the endogenous variable on the instruments. Stock et al. (2002) propose that this F-statistic should exceed 10 for statistical inference to be reliable. To test for the strength of the instruments proposed above, we regressed each of the endogenous variables against the instruments described above. Specifically, we ran the following sets of OLS regressions and inspected the associated F-statistics: (a) $(y_{jt-1} - y_{jt-2})$ on y_{jt-3} (and y_{jt-4} for $t > 4$); (b) $(C_{jt-1} - C_{jt-2})$ on C_{jt-3} (and C_{jt-4} for $t > 4$); (c) y_{jt-1} on $(y_{jt-1} - y_{jt-2})$ and

[10] To test the robustness of our results to these assumptions, we specified and estimated a model which does not rely on them but instead employs latent instruments (Ebbes et al. 2005, Zhang et al. 2009). Our substantive results remain unchanged across both methods of endogeneity control, suggesting that our results are not sensitive to the assumptions specific to the proposed estimation method.

$(y_{jt-2} - y_{jt-3})$; (d) each element of Z_j on $(y_{jt-1} - y_{jt-2})$ and $(y_{jt-2} - y_{jt-3})$; and (e) C_{jt} on $(y_{jt-1} - y_{jt-2})$ and $(y_{jt-2} - y_{jt-3})$.

Other than the regressions of some elements of Z_j on $(y_{jt-1} - y_{jt-2})$ and $(y_{jt-2} - y_{jt-3})$, all regressions have F-statistics in excess of 10. Therefore, we augment the set of instruments for the level equation by computing the mean (across movies) of the number of repeated interactions between members in the same roles as i and i' in all other movies that are released at the same time as movie j. For example, for a movie j released on December 2, 2005, this instrument for number of repeated interactions between producer and director is the mean number of repeated interactions between producers and directors of all other movies released on this date. Inclusion of this instrument ensures that the F-statistics for all regressions described above exceed 10, allaying concerns of biases due to weak instruments.[11] Conceptually, the process of team formation is likely to be similar for movies released at the same time, resulting in correlation between this instrument and Z_j. Identification hinges on the assumption that after controlling for several time-varying measures of competition, this instrument is uncorrelated with the error term $(\mu_j + \varepsilon_{jt})$. As mentioned earlier, we conduct the difference-in-Hansen J-test to examine whether this and other instruments used for the level equation (but not for the difference equation) are valid. We do not add further instruments since a very large instrument collection might overfit the endogenous variables and weaken the Hansen J-test and the difference-in-Hansen J-test (Roodman 2009b). We use two-step GMM for model estimation, which is more efficient and leads to standard errors that are robust to heteroskedasticity. However, this might also lead to biased standard error estimates. We follow the method proposed by Windmeijer (2005) to correct for this bias. Before we present the results, we discuss an alternative model specification.

Since repeated interactions between team members are measured at a movie level, a movie-level revenue model is an alternative worth considering. That is, let y_j be the logarithm of the box office revenues of movie j across all T_j weeks, where $y_j = \alpha + \beta Z_j + \varepsilon_j$ with $\varepsilon_j \sim N(0, \sigma_j^2)$. Z_j has been defined earlier, and ε_j is an IID error term. Despite offering fewer degrees of freedom (just 1,123 observations), this model enables us, in principle, to estimate the effect of repeated interactions on movie revenues. Yet we prefer the movie-week-level to the movie-level model. First, product revenues are affected by competition, which might vary over the time the product is available for purchase. Competition has been known to substantially affect box office movie revenues (Basuroy et al. 2006). Time-varying measures of competition cannot be incorporated in a movie-level model. Not accounting for competition might lead to biases in coefficient estimates if covariates are affected by competition. Second, by specifying a fixed effect μ_j in the movie-week-level model, we control for movie-specific unobservables; individual characteristics of team members (e.g., acting abilities); and features of repeated interactions we do not observe. Not controlling for these unobservables could lead to biased parameter estimates if they are correlated with Z_j. Models with fixed effects require multiple observations for each unit of analysis (i.e., for each movie), which is not possible with the movie-level model that has one observation per movie. Finally, to control for endogeneity in the movie-week-level model, we make use of lags and lagged differences of explanatory variables as instruments. Econometric tests establish the validity of these instruments in our application. These are not available in a movie-level model. We are not aware of appropriate instruments to control for endogeneity in a movie-level model. For these reasons, the movie-week model is more appropriate for our context. We now present the results of this model.

5. Results

We present parameter estimates of two models (Tables 3–5). Model 1 is an OLS regression model specified at the movie-week level. It mirrors the proposed model except that it does not account for endogeneity and assumes $\mu_j = 0$ (i.e., ignores unobserved heterogeneity). Model 2 is the proposed model estimated using the "system GMM" approach described above.[12] We find that accounting for endogeneity and heterogeneity yields coefficients of typically smaller magnitudes. Three coefficient estimates are statistically significant ($p < 0.05$) as per Model 1, but not as per Model 2.

Table 6 reports various specification tests, goodness-of-fit measures, and number of observations employed for both models. For Model 2, the Hansen J-test indicates that our instruments taken together as a group are valid. The null hypothesis that the instruments as a group are uncorrelated with the error is not rejected. However, this is insufficient for the system GMM estimator to be appropriate. The difference-in-Hansen J-test confirms that the additional instruments for the level equation (and not for the difference equation) are valid. As mentioned, to

[11] Details of the coefficient estimates of all regressions are available from the authors.

[12] We do not report parameter estimates based on the "difference GMM" estimator since it does not permit identification of the coefficient of Z_j, the key effect of interest. These estimates are available upon request.

Table 3 Effects of Within-Team Interactions on Revenue

	Model 1: No endogen./ heterog. correction		Model 2: System GMM	
	Mean	Std. error	Mean	Std. error
Number of within-team interactions ($NREP_{ii'j}$)				
Lead male–Lead female	**0.012**	**0.001**	**0.009**	**0.002**
Lead male–Director	−0.002	0.015	−0.012	0.013
Lead male–Producer	0.001	0.004	0.005	0.011
Lead male–Screenwriter	0.003	0.008	0.005	0.010
Lead female–Director	−0.009	0.012	0.010	0.025
Lead female–Producer	**0.029**	**0.007**	**0.017**	**0.007**
Lead female–Screenwriter	0.011	0.018	0.004	0.020
Director–Producer	**0.019**	**0.004**	**0.012**	**0.004**
Director–Screenwriter	0.004	0.006	0.003	0.010
Producer–Screenwriter	0.007	0.006	0.009	0.027
Revenue from within-team interactions $\log(REVREP_{ii'j}+1)$				
Lead male–Lead female	0.003	0.024	0.004	0.031
Lead male–Director	0.007	0.009	0.009	0.013
Lead male–Producer	0.004	0.006	0.005	0.009
Lead male–Screenwriter	0.008	0.011	0.007	0.015
Lead female–Director	0.004	0.008	0.005	0.011
Lead female–Producer	0.008	0.021	0.009	0.029
Lead female–Screenwriter	0.001	0.010	0.000	0.011
Director–Producer	0.015	0.046	0.007	0.057
Director–Screenwriter	0.011	0.007	0.010	0.021
Producer–Screenwriter	0.005	0.009	0.003	0.016

Note. $p < 0.05$ for all coefficient estimates in bold.

Table 4 Effects of Team Member Characteristics and Movie Characteristics on Revenue

	Model 1: No endogen./ heterog. correction		Model 2: System GMM	
	Mean	Std. error	Mean	Std. error
Number of other interactions				
Lead male	0.008	0.111	0.006	0.138
Lead female	−0.003	0.004	0.001	0.005
Director	0.005	0.013	0.003	0.017
Producer	0.002	0.002	0.000	0.003
Screenwriter	0.003	0.005	0.001	0.006
Number of award nominations				
Lead male	**0.015**	**0.006**	**0.018**	**0.009**
Lead female	0.003	0.001	0.003	0.001
Director	0.004	0.010	0.006	0.016
Producer	0.015	0.009	0.015	0.009
Screenwriter	0.001	0.004	0.001	0.004
Number of past movies				
Lead male	0.001	0.001	0.003	0.002
Lead female	0.002	0.001	−0.002	0.002
Director	0.004	0.003	0.006	0.006
Producer	−0.002	0.002	0.003	0.004
Screenwriter	0.000	0.002	0.000	0.003
Mean revenue of past movies				
Lead male	0.000	0.003	0.001	0.004
Lead female	0.003	0.003	0.002	0.007
Director	0.006	0.010	0.002	0.013
Producer	0.001	0.011	0.000	0.015
Screenwriter	0.007	0.008	0.004	0.011
Movie characteristics				
Comedy	**0.072**	**0.017**	**0.080**	**0.038**
Animation	0.043	0.026	**0.118**	**0.054**
Romance	**0.112**	**0.022**	**0.130**	**0.044**
Drama	**0.139**	**0.017**	**0.209**	**0.037**
Action	**0.035**	**0.017**	**0.080**	**0.038**
Science fiction	0.010	0.007	0.022	0.065
PG-rated	**−0.051**	**0.025**	−0.027	0.048
PG13-rated	**−0.104**	**0.027**	**−0.066**	**0.032**
R-rated	**−0.105**	**0.028**	**−0.071**	**0.035**
Log(prodn. budget)	0.0003	0.0002	0.033	0.022
Log(ad. expense)	0.0007	0.0005	**0.005**	**0.001**
SEQUEL	0.005	0.004	0.007	0.008

Notes. $p < 0.05$ for all coefficient estimates in bold. Baseline genre and MPAA rating are horror and G, respectively.

test for the absence of serial correlation, we use the Arellano-Bond (2) test, which is a test for second order serial correlation in the first difference of error terms. This test provides evidence against serial correlation, which is a critical identification assumption. The null hypothesis of no serial correlation is not rejected. Next we discuss those substantive results that are validated by both models. Discussion of specific coefficient estimates pertain to the system GMM estimates (Model 2).

5.1. The Role of Repeated Interactions

Which repeated interactions affect team output? We find that three within-team interactions positively affect movie revenues. In decreasing order of effect size, these are the interactions between the following pairs: producer–lead female, producer–director and lead male–lead female. These interactions impact both overall box office revenues as well as weekly revenues after controlling for the previous week's revenue. Importantly, interactions involving the producer are more revenue-enhancing than are other interactions (Table 3). Of all seven interactions in our data involving members of the team who are visible to the audience, only two (producer–lead female and lead male–lead female) affect movie performance. This is consistent with the explanation that revenue enhancement due to repeated interactions is driven by supply-side considerations such as agency mitigation, investment in relationship-specific assets, and learning by doing. If revenue enhancement was driven by greater consumer preference for specific pairs of members, we would expect more interactions involving audience-facing members (such as director–lead male) to affect revenue.

Of all team members involved in movie production, the role of actors and actresses has been deemed most critical for box office success in terms of their unparalleled ability to attract audiences to theaters (Wallace et al. 1993). Hollywood industry reports suggest that the lead male is usually the highest paid

Table 5 Effects of Release Timing and Time-Varying Covariates on Revenue

	Model 1: No endogen./ heterog. correction		Model 2: System GMM	
	Mean	Std. error	Mean	Std. error
	Release timing			
Christmas	**0.217**	**0.006**	**0.209**	**0.007**
Thanksgiving	0.009	0.055	0.008	0.059
Independence Day	**0.133**	**0.052**	**0.119**	**0.049**
Spring	−0.015	0.014	−0.022	0.017
Summer	**0.068**	**0.014**	**0.063**	**0.016**
Fall	**−0.039**	**0.015**	**−0.034**	**0.016**
Year of release—2000	0.005	0.005	0.004	0.006
Year of release—2001	0.007	0.005	0.006	0.006
Year of release—2002	−0.009	0.006	−0.005	0.011
Year of release—2003	0.010	0.024	0.008	0.023
Year of release—2004	0.016	0.011	0.011	0.017
Year of release—2005	0.028	0.017	0.023	0.035
	Competition			
$COMP\_NEW_{jt}$,	**−0.003**	**0.001**	**−0.002**	**0.001**
$COMP\_ONG_{jt}$	**−0.007**	**0.002**	−0.005	0.003
$COMP\_REV_{jt}$	**−0.014**	**0.003**	−0.006	0.004
Log(lagged weekly revenue)	**0.994**	**0.006**	**0.989**	**0.007**

Notes. $p < 0.05$ for all coefficient estimates in bold. Baseline season and year of release are winter and 1999, respectively. Dummies for studios were included in all models, but their coefficients are not presented for brevity. Estimates of λ_t are not presented for brevity. These are available from the authors.

member of a movie production team, followed by the lead female. Yet we find that repeated interactions of the producer and those of the lead female are more revenue enhancing than repeated interactions of the lead male. With the exception of his interactions with the lead female, repeated interactions of the lead male do not affect revenues.

There could be several reasons why producer-member repeated interactions have a larger empirical effect on production success compared to repeated interactions between members other than the producer. Consider first agency explanations. Producer-member relationships might be the more salient

Table 6 Specification Tests and Goodness-of-Fit Measures

	Model 1: No endogen./ heterog. correction	Model 2: System GMM
Hansen J-test of overidentifying restrictions (p-value of J-statistic)	n.a.	0.138
Difference-in-Hansen J-test (p-value of J-statistic)	n.a.	0.279
Arellano and Bond AR(2) test (p-value)	n.a.	0.323
R^2	0.906	n.a.
Adjusted R^2	0.905	n.a.
Root mean square error	0.421	0.435
Number of observations	7,227	6,104

Note. n.a., not applicable.

agency in teams. If members have observed a producer's good behavior from repeated interactions, for the sake of their own future careers, members have an incentive to want to not shirk/behave well in this current interaction so as to be invited by the producer for future movie productions; members can place a higher probability on this producer surviving into the future because of his or her good behavior. Consider next transaction costs and learning by doing. Recall the producer's role is predominantly financing (and obtaining marketing and distribution contracts) and selecting the team. It would appear that investing time and effort to develop working relationships seems less likely between the producer and the team, given the distinction between the producer's and director's role in production. However, this might be too simplistic a view. Given the producer's role in assembling teams, repeated interactions are likely to reduce costs of negotiating, writing, monitoring, and enforcing contracts. Therefore, transaction costs could be a major reason why producer-team member interactions are key for improved production success. For the same reason, learning by doing might apply to the contracting process. Alternatively, producers might learn about types of agents through repeated interactions. The numbers of repeated interactions of all members in our data (other than the screenwriter) are predictive of current revenues. However, the level of success (or failure) of these repeated interactions (to the extent that it is captured by box office revenues of common movies) does not contribute to revenue enhancement of the focal movie. Higher (or lower) box office demand for movies which pairs of members have been a part of has no bearing on demand for the current movie. Thus, agency mitigation, investment in relationship-specific assets, and learning by doing appear to not be limited to successful interactions.

Next we turn to the relative importance of members' repeated interactions and their individual-level factors. To comprehensively capture the effect of a team member's individual-specific characteristics on movie reviews, we incorporated four member-specific covariates: star power (as measured by award nominations), experience (number of past movies), success (revenue of past movies), and number of outside-team repeated interactions. Although the repeated interactions of most members in our data affect current revenues, the number of movies they have worked in the past does not. Surprisingly, after controlling for several factors, the success of past movies also does not affect current movie revenues. One possible explanation is that even unsuccessful past productions offer opportunities to learn. Although successful past productions make it easier to observe desirable behavior, unsuccessful past productions might offer opportunities to observe undesirable behavior. Undesirably behaving individuals might be better managed in, or even eliminated from, future productions. If both successful and unsuccessful past movies offer revenue-enhancing learning opportunities, then success of past movies is immaterial. Another explanation is that success of past movies positively affects current movie revenues solely because of factors we control for in the model. For example, successful past movies would increase member star power (a control variable) and affect future movies featuring those members.

The only individual-specific covariate that affects revenues in our data is star power, validating the common practice in the movies literature of measuring individual-specific effects solely in terms of star power. Consistent with previous research, lead male actors who were nominated for more awards are associated with greater current revenues. But award nominations of other members do not affect revenues. Directors, producers, and screenwriters do not appear on screen, and their identities might not be known to or noticed by many viewers. The number of awards these artists have won might not have a material effect on viewer behavior. Greater effect of the star power of the lead male than that of the lead female is consistent with prior research (Treme and Craig 2013) and with one industry view that male actors are more bankable than female actors. In a recent estimate by entertainment magazine *Vulture,* only 30 of the "100 most valuable stars" in Hollywood are female.[13]

From an econometric standpoint, our estimates of the effects of within-team interactions might be biased if we do not control for interactions of team members with those outside the focal team. We find that outside-team interactions of members do not impact the revenue of the focal movie. A plausible theoretical explanation is as follows: observing and mitigating agency, investing in relationship-specific assets, and learning by doing are all relationship specific and not portable across relationships. From a managerial perspective, our estimates indicate that choosing team members based on within-team interactions is more critical than the individual-level connectedness of each member with the overall movie-making fraternity. We find that the effect of producers, lead females and directors on movie revenues is not driven by their individual-specific characteristics (star power, past success, etc.) but by their repeated interactions with other team members. We show for the first time that team members' interactions with other members are a more important determinant of product success than are their personal characteristics.

The effects of the control variables are along expected lines. Horror and science fiction movies garner lower revenues than others. R-rated movies and PG-13 movies also systematically perform worse at the box office. Although advertising is positively associated with revenues, production budget is not. One explanation is that greater production budgets affect movie revenues by positively impacting revenues in the first week of release. This leads to greater revenues in subsequent weeks. However, there is no independent effect of production budget on revenues after controlling for previous weeks' revenues. Movies released around Christmas and Independence Day weekend do better than other movies do. Finally, greater competition in terms of more high-budget movies being released in a week negatively impacts revenue of the focal movie in that week.

5.2. Robustness Checks

We first perform a robustness check to determine if our relevant variables of interest-measures of repeated interaction are economically meaningful even if they are econometrically significant.[14] We measure predictive performance in terms of the mean absolute prediction error (MAPE) between the predicted and actual logarithms of weekly revenues. We compare the out-of-sample predictive performance of the proposed model with a nested model that excludes the following variables: 10 variables measuring within-team number of pairwise repeated interactions $NREP_{ii'j}$; 10 variables measuring the logarithm of the mean revenue of all movies that each pair of team members of movie j had both been a part of in the eight-year period ($REVREP_{ii'j}$), added to one; and 5 variables measuring the number of outside-team repeated interactions $NREPOUT_{ij}$. The MAPE estimates of the proposed model and nested model are 4.73% and 5.16%, respectively. Although the improvement in MAPE might not seem very high, the extent of prediction improvement is comparable to recent research in movies. For example, Eliashberg et al. (2007) report an improvement in mean absolute error associated with the prediction in the return on investment of movies from 0.72 to 0.67. Also, as Eliashberg et al. (2006, p. 641) note, even marginal improvements in forecasting revenues "could confer tremendous financial and reputation benefits for studios and other members involved." Therefore, our measures of repeated interaction and experience are economically and managerially meaningful.

[13] Source: http://www.vulture.com/2012/07/most-valuable-movie-stars.html, accessed September 2014.

[14] We employ a *K*-fold cross-validation procedure. We divide our sample of movies into 10 subsamples of approximately equal number of movies. Of these 10 subsamples, we use varying number of subsamples for estimation and holdout.

We conduct the following additional robustness analysis. Theory suggests the possibility of diminishing returns to increased repeated interaction among team members (Cattani and Ferriani 2008). That is, agency mitigation might only improve production success up to a point. Also, there might be diminishing returns to learning by doing and investing in relationship-specific assets. For example, relying excessively on previously used team members can result in team being shielded from market forces that might offer greater efficiency or newer/better talent, etc. (see also Uzzi 1997 for a discussion on "overembeddedness"). To test for this in our data, we incorporated quadratic and logarithmic transformations of $NREP_{ii'j}$ for all pairs as covariates in the revenue model. The effects of these transformations are not significant, and the effects of the linear variables remain unchanged in direction. Lack of evidence for nonmonotonic effects of pairwise repeated interactions could be driven by insufficient variation in our pairwise measures.[15]

5.3. Isolating Production Improvements from Repeated Interactions

The effects of repeated interactions on revenue are likely to be a combination of demand-side and supply-side effects. To better understand the role of supply-side effects, which are relatively understudied in the literature, we attempt to investigate which of the two effects is larger. This knowledge might be particularly relevant for contexts where demand-side effects might be irrelevant since team members are unknown to the consumer (e.g., consumers of a brand do not know the identity of members of the brand management team).

For this purpose, we first collected primary data to estimate which members in a movie affect consumer preferences for that movie. We conducted an online survey of a representative sample of U.S.-based viewers. Analysis of these data supported the following propositions: (a) knowledge of the name of the producer of a movie does not affect respondents' stated liking for that movie and (b) even when respondents are exposed to the name of the movie producer (in addition to those of other artists and the movie genre), their stated liking for the movie is not affected by this exposure. In light of this evidence that the producer's identity does not affect consumer preferences of the focal movie, we conclude that the effect of the producer's repeated interactions on revenue is not driven by consumer preferences but by supply-side factors.

Next we consider the following three pairs of repeated interactions that affect revenues in decreasing order of effect size: producer–lead female, producer–director and lead male–lead female. Coefficient estimates pertaining to these effects are 0.017, 0.012, and 0.009, respectively (Table 3). Two of the largest three effects involve the producer and are therefore supply-side effects. We make two observations about the interaction between the lead male and the lead female. First, this interaction has a substantially smaller effect than are the other two interactions. Second, to the extent that the identity of the lead pair of a movie affects consumer preferences for that movie, this is a demand side effect. Yet we cannot rule out the role of supply-side factors in how interactions between the lead pair affect movie revenues.

With the largest two effects being driven by supply-side factors, and the smallest effect being driven by both demand and supply, we conclude that revenue improvement due to repeated interactions is predominantly driven by supply-side considerations. This suggests that repeated interactions are likely to affect product success in contexts where consumers might have preferences for some team members (e.g., sports teams) and also in contexts where consumers do not know the identity of team members (e.g., brand management teams, software development teams).

6. Conclusions

The impact of team members' repeated interactions with each other on production success is unclear, especially in relation to their individual-level past experience. We examine movie production teams for 1,123 U.S. movies released during 1999 through 2005. We find that repeated interactions between the following pairs of team members in a focal team improve team output: producer–lead female, producer–director, and lead male–lead female. The interactions of the producer have the greatest revenue impact. Importantly, it is the number of repeated interactions that affects current productivity, not the success of these interactions (in terms of box office demand), suggesting that the mechanism that drives productivity improvements is driven by supply-side considerations. Repeated interactions with members outside a focal team have no impact on focal product success. Our results also show patterns consistent with agency mitigation, investing in relationship-specific capital, and learning by doing. Survey results show that productive repeated interactions do not come purely from consumer preferences for (repeated) team compositions, providing further

[15] We also estimated models of triadic repeated interactions; these interactions were not significant predictors of team productivity. Further, it is plausible that agency mitigation in the focal movie is due to an expectation of future interactions with other members. To investigate this possibility, we estimated the model after replacing measures of repeated interactions with measures of future interactions. All substantive results remain unchanged. Details are available from the authors.

evidence for supply-side factors driving improved production success. To our knowledge, this is the first study to empirically estimate the effect of team members' repeated interactions in the movies industry by making use of appropriate methods of controlling for endogeneity and unobserved heterogeneity in panel data on a wide range of movies released over seven years.

Our findings are relevant for team-based production in other industries. Several large creative industries (e.g., music, TV shows, theatre, etc.) have some members who are viewed and recognized by the consumer and others who are not. Our results suggest that members who are not viewed by the consumer can have an important role in enhancing product success due to their past interactions. More generally, for product development teams (e.g., software and advertising) and for other team oriented business activities (e.g., business consulting, investment banking), our result suggest that the past interactions of team members with each other are a larger determinant of success than is their individual experience. Given the better fit of our model compared to one without measures of interaction, our results have monetary implications for casting decisions in the movie industry. Bringing a less experienced person with a strong history of collaboration with other members to the team is perhaps more beneficial than recruiting a more experienced new-to-the-team player. It might be profitable to overlook a team member's few failures in repeated interactions in favor of seeking a team member with more within-group repeated interactions.

Our empirical research has the following limitations. We have not examined repeated interactions among the production team outside of the five members, e.g., costume designers, cinematographers, etc. Supply-side effects might exist in team networks other than those in our data (e.g., producers or directors repeatedly working with the same cinematographer), making our estimate of supply-side effects a conservative one. (Demand-side effects are less likely because of lower recognition of producers compared to that of lead actors.) Additionally, we have not been able to measure the process of selecting team members. It would be useful to consider the set of choices available to each member and the trade-offs associated with each choice. Modeling the "consideration set" of possible choices based on repeated interactions is beyond the scope of this study. Also, note that in our analysis, because of lack of data on wages and measures of individual input and output in teams, we have been unable to conclusively estimate the extent to which agency is reduced because of repeated interactions or the extent of learning by doing or investments in relationship-specific assets. Understanding the role of networks among consumers on marketing outcomes is an important and substantial domain of research in marketing science. Not as much research has been conducted on interactions between economic agents other than consumers. We hope that this research will serve to highlight the role of supply-side issues in how interactions among some such agents also positively affect marketing outcomes.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2139.

Acknowledgments

The authors thank the associate editor and two reviewers for their constructive suggestions. The authors also thank Dinesh Puranam for helpful comments, Libby Mattern and Leah Plante for excellent research assistance, and seminar participants at the Marketing Science Conference for their feedback.

References

Alchian A, Demsetz H (1972) Production costs, information and economic organization. *Amer. Econom. Rev.* 62(5):777–795.
Anderson E, Schmittlein D (1984) Integration of the sales force: An empirical examination. *RAND J. Econom.* 15(3):385–395.
Anderson TW, Hsiao C (1982) Formulation and estimation of dynamic models using panel data. *J. Econometrics* 18(1):47–82.
Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econom. Stud.* 58(2):277–297.
Baker G, Gibbons R, Murphy K (1997) Subjective performance measures in optimal incentive contracts. *Quart. J. Econom.* 109(4): 1125–1156.
Baker WE, Faulkner RE (1991) Role as resource in the Hollywood film industry. *Amer. J. Sociol.* 97(2):279–309.
Basu A, Lal R, Srinivasan V, Staelin R (1985) Salesforce compensation plans: An agency theoretic perspective. *Marketing Sci.* 4(4):267–291.
Basuroy S, Desai KK, Talukdar D (2006) An empirical investigation of signaling in the motion picture industry. *J. Marketing Res.* 43(2):287–295.
Bechky BA (2006) Gaffers, gofers, and grips: Role-based coordination in temporary organizations. *Organ. Sci.* 17(1):3–21.
Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. *J. Econometrics* 87(1):115–143.
Bornstein G, Gneezy U, Nagel R (2002) The effect of intergroup competition on group coordination: An experimental study. *Games Econom. Behav.* 41(1):1–25.
Bound J, Jaeger D, Baker R (1995) Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *J. Amer. Statist. Assoc.* 90(430):443–450.
Cattani G, Ferriani S (2008) A core/periphery perspective on individual creative performance: Social networks and cinematic achievements in the Hollywood film industry. *Organ. Sci.* 19(6):824–844.
Cheatham C, Davis D, Cheatham L (1996) Hollywood profits: Gone with the wind? *CPA J.* 66(2):32–34.
Chisholm DC (1993) Asset specificity and long term contracts: The case of the motion pictures industry. *Eastern Econom. J.* 19(2):143–155.
Clark CR, Doraszelski U, Draganska M (2009) The effect of advertising on brand awareness and perceived quality: An empirical investigation using panel data. *Quant. Marketing Econom.* 7(2):207–236.

Ebbes P, Wedel M, Bockenholt U, Steerneman T (2005) Solving and testing for regressor-error (in)dependence when no instrumental variables are available: With new evidence for the effect of education on income. *Quant. Marketing Econom.* 3(4):365–392.

Edmondson AC, Nembhard IM (2009) Product development and learning in project teams: The challenges are the benefits. *J. Product Innovation Management* 26(2):123–138.

Elberse A (2007) The power of stars: Do star actors drive the success of movies? *J. Marketing* 71(4):102–120.

Eliashberg J, Elberse A, Leenders M (2006) The motion picture industry: Critical issues in practice, current research, and new research directions. *Marketing Sci.* 25(6):638–661.

Eliashberg J, Hui SK, Zhang ZJ (2007) From story line to box office: A new approach for green-lighting movie scripts. *Management Sci.* 53(6):881–893.

Hahn J, Hausman J (2003) Weak instruments: Diagnosis and cures in empirical econometrics. *Amer. Econom. Rev.* 93(2):118–125.

Hamilton B, Nickerson J, Owan H (2003) Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation. *J. Political Econom.* 111(3):465–497.

Heywood J, Jirjahn U (2009) Profit sharing and firm size: The role of team production. *J. Econom. Behav. Organ.* 71(2):246–258.

Holmstrom B (1982) Moral hazard in teams. *Bell J. Econom.* 13(2): 324–340.

Huckman R, Pisano G (2006) The firm specificity of individual performance: Evidence from cardiac surgery. *Management Sci.* 52(4):473–488.

Huckman R, Staats B, Upton D (2009) Team familiarity, role experience, and performance: Evidence from Indian software services. *Management Sci.* 55(1):85–100.

Joskow P (1985) Vertical integration and long-term contracts: The case of coal-burning electric generation plants. *J. Law, Econom., Organ.* 1(1):33–80.

Kellogg R (2011) Learning by drilling: Inter-firm learning and relationship persistence in the Texas oil patch. *Quart. J. Econom.* 126(4):1965–2004.

Knez M, Simester D (2001) Firm-wide incentives and mutual monitoring at continental airlines. *J. Labor Econom.* 19(4):743–772.

Kremer M (1993) The O-ring theory of economic development. *Quart. J. Econom.* 108(3):551–575.

Krider R, Weinberg C (1998) Competitive dynamics and the introduction of new products: The motion picture timing game. *J. Marketing Res.* 35(1):1–15.

Lal R, Staelin R (1986) Salesforce compensation plans in environments with asymmetric information. *Marketing Sci.* 5(3): 179–198.

Lal R, Outland D, Staelin R (1994) Salesforce compensation plans: An individual level analysis. *Marketing Lett.* 5(2):117–130.

Lazear E, Shaw K (2007) Personnel economics: The economist's view of human resources. *J. Econom. Perspect.* 21(4):91–114.

Levin J (2003) Relational incentive contracts. *Amer. Econom. Rev.* 93(3):835–847.

MacLeod B (2003) Optimal contracting with subjective evaluation. *Amer. Econom. Rev.* 93(1):216–240.

Masten S (1984) The organization of production: Evidence from the aerospace industry. *J. Law Econom.* 27(2):403–417.

Monteverde K, Teece D (1982) Supplier switching costs and vertical integration in the automobile industry. *Bell J. Econom.* 13(1): 206–212.

Park S, Gupta S (2012) Handling endogenous regressors by joint estimation using copulas. *Marketing Sci.* 31(4):567–586.

Roodman D (2009a) How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata J.* 9(1):86–136.

Roodman D (2009b) A note on the theme of too many instruments. *Oxford Bull. Econom. Statist.* 71(1):135–158.

Schwartz S (2010) Investing in the big screen can be a profitable story. *CNBC* (October 18), http://www.cnbc.com/id/39342145.

Staiger D, Stock JH (1997) Instrumental variables regression with weak instruments. *Econometrica* 65(3):557–586.

Stock JH, Wright JH, Yogo M (2002) A survey of weak instruments and weak identification in generalized method of moments. *J. Bus. Econom. Statist.* 20(4):518–529.

Treme J, Craig LA (2013) Celebrity star power: Do age and gender effects influence box office performance? *Appl. Econom. Lett.* 20(5):440–445.

Uzzi B (1997) Social structure and competition in interfirm networks: The paradox of embededness. *Admin. Sci. Quart.* 41(1):35–67.

Wallace WT, Seigerman A, Holbrook MB (1993) The role of actors and actresses in the success of films: How much is a movie star worth? *J. Cultural Econom.* 17(1):1–27.

Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. *J. Econometrics* 126(1):25–51.

Yoganarasimhan H (2012) Impact of social network structure on content propagation: A study using YouTube data. *Quant. Marketing Econom.* 10(1):111–150.

Zhang J, Wedel M, Pieters R (2009) Sales effects of visual attention to feature ads: A Bayesian mediation analysis. *J. Marketing Res.* 46(5):669–681.