Tackling the 'Galácticos' Effect:
Team Familiarity and the Performance of Star-Studded Project

Gino Cattani
Stern School of Business – NYU
gcattani@stern.nyu.edu

Simone Ferriani[*]
University of Bologna
simone.ferriani@unibo.it
&
City University London

Marcello Mariani
University of Bologna
marcello.mariani@unibo.it

Stefano Mengoli
University of Bologna
stefano.mengoli@unibo.it

Forthcoming in

Industrial and Corporate Change

[*] Corresponding author

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ABSTRACT

Findings on the performance implications of assembling star-studded teams have remained rather mixed. We elaborate on the theoretical reasons for current inconclusive findings and delineate more precise boundary conditions for studying the relationship between stars and project level performance. Specifically, we argue that lack of scholarly attention to team familiarity may account for empirical results' observed inconsistency. Our findings show that a history of past collaboration reduces the downsides of having too many stars within the same team. Previous interactions enhance coordination efforts by reducing conflicts among team members. We situate the analysis within the context of the Hollywood film industry over the period 1992-2004. The theoretical implications of the results are discussed.

Key Words: Stars; Familiarity; Project Performance; Hollywood Film Industry.

1. INTRODUCTION

Staffing a project team with the right combination of individual talents is one of the most challenging tasks facing a manager or team leader. As people enter a new team, they carry with them status and expectations about the roles that they will occupy and their influence within the team. But these prior expectations may sometimes prove problematic, especially when they clash with those of others (e.g., Overbeck, Correll and Park, 2005). Specifically, what does it happen when several team members display high status?

This situation is epitomized by what – using a metaphor – we call the 'Galácticos' effect, namely, the case in which the arrival of too many star professionals results in very disappointing team performance. When Florentino Perez was elected president of Real Madrid in 2000, he introduced the famous Galáctico (Superstar) recruitment policy wherein the club would sign a star player every year. Yet, despite the club's star-studded line-up of some of the world's finest football players, Real Madrid did not win a single trophy in the 2003-04, 2004-05 and 2005-06 seasons, resulting in one of the worst series of results in the club's illustrious history: not since 1954, when Real Madrid ended a seven-year run without silverware, had the club ever suffered such a poor spell. In spite of stars' talents and achievements, their prima donnas aspirations may take precedence over team goals and jeopardize project performance.[1]

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[1] This quote from Miguel Angel Arroyo, director of the Real Madrid soccer team President's cabinet, is instructive of what happened during Perez's mandate: "The true art of managing a football club is knowing how to strike the balance between business and sports. In the Florentino Perez years, we were too focused on marketing, and not enough on sports. Perez's idea of bringing in the most talented players and emphasizing the 'show business' aspect of soccer was very innovative. It made it a true spectacle. However, it was extremely difficult to manage: the accumulation of stars produced excesses that we could not correct. It led to big egos, commitments we had to make to our stars, and jalousie among players who were not ready to share the spotlight. So we try to balance that more now. Our new model is to focus less on individualism, and more on the team" (Source, Elberse and Quelch, HBS Case 9-508-060, 2008: 2).

Two competing camps, however, seem to characterize the existing literature on the performance implications of recruiting stars. While some scholars highlight the benefits resulting from hiring stars (e.g., Elberse, 2007; Zucker and Darby, 1996, 2007), others emphasize the dysfunctional dynamics often plaguing star-studded teams (e.g., De Vany and Walls, 2004; Groysberg, Lee and Nanda, 2008; Groysberg and Lee, 2009; Overbeck *et al.*, 2005). Which of these two views best describes the actual performance of star-studded project teams? Can these views be reconciled?

The present paper seeks to shed light on the theoretical foundations for current mixed findings on hiring stars and delineate more precise boundary conditions for understanding when the presence of stars is likely to have a positive or negative effect on project team performance. First, we argue that a correct evaluation of the role of stars should account for their impact on both the revenues and the costs – and, by implication, the profits. Not only are stars enormously expensive, but star-studded project teams face significant coordination challenges, as stars' hubris and overconfidence may easily disrupt collective efforts. Second, we suggest that lack of scholarly attention to prior experience working together (i.e., team familiarity) might help explain empirical results' observed inconsistency. Focusing on talent alone could be misleading if one remains oblivious to the growing body of literature that shows how team performance crucially depends on having people (both stars and non-stars) with prior joint experience (e.g., Huckman, Staats and Upton, 2009; Reagans, Argote and Brooks, 2005). Our findings show how team familiarity is an important boundary condition for establishing when the presence of stars is beneficial or detrimental as it moderates the relationship between stars and project performance.

The empirical setting is the Hollywood motion picture industry, which we traced over the period 1992-2004. The feature film industry is an ideal setting to study the interplay among stars, other team members and project (movie) performance. Given the project-based character of the industry, professionals usually work on several projects at the same time and over a relatively short time period (Whitley, 2006). While projects are typically terminated upon completing a movie, ties to other professionals tend to last much longer as they are reactivated when the very same professionals work on a new movie. It is indeed rather customary that individuals end up working together in more than one movie, which makes past collaboration a distinctive feature of this industry (Ferriani, Corrado and Boschetti, 2005; Schwab and Miner, 2008; Ferriani, Cattani and Baden-Fuller, 2009). As noted by Manning and Sydow (2011, 1370): "Project researchers […] have increasingly studied the embeddedness of temporary projects in long-term organizational, relational and institutional structures." While in fact projects are temporary, ties among the parties (individuals or organizations) involved may survive them: the same project-members often cooperate repeatedly, even routinely. In addition, Hollywood is the birth place of the star system and the industry still places an enormous importance on star power. As Walker (1970: 13) explains, "Wherever films are made, stars are made too. Stardom is a characteristic of film industries the world over. But it has always dominated American movies more than those of any other country. Stars laid the basis of the Hollywood film industry." Third, and more pragmatically, due to the great demand for information about the feature-film industry, rich data are available on all movies distributed by Hollywood every year and on the professionals who have ever worked in one of these feature-length films.

The paper is organized as follows. In the next section (2), we present the theory and the main hypothesis. We then describe the empirical setting, the data and the variables (3). Next, we discuss the model and methods we used in the analysis (4). After summarizing the findings and check the robustness of the results (5), we conclude (6) with the contributions, limitations and possible extensions of the present study.

2. THEORY

2.1. Number of *stars* and project team performance

Is the recruitment of stars an appropriate solution for improving project performance? A growing body of academic research seeks to address this question. For instance, studies on scientists involved in R&D have found that scientists at the very top of the talent distribution are far more productive than less 'stellar' colleagues and enjoy reputational advantages which provide them with greater access to the resources (e.g., funds, grants) they need to conduct their research, which fosters even greater accomplishments (Zucker and Darby, 1996). Similarly, research on top managers suggests that being anointed as a star can enable CEOs to translate their credibility into power as they deal with internal and external constituencies (Wade *et al.*, 2006). By having greater market visibility, stars usually garner a disproportionate amount of media attention. This visibility in turn helps the team of which stars are members to secure material and symbolic resources, elicit market attention and, by implication, perform better. For example, Stinchcombe (1990) suggested that hiring a Nobel Prize winner brings ceremonial benefits to a university. Similarly, as Pfeffer (1981: 22) noted, "one of the important ways of generating external support … [is] through identification of the organization with socially valued and accepted individuals."

By contrast, research on group dynamics and social-psychology highlights coordination costs that may arise from the overconfidence and hubris in professionals anointed as stars, despite their productivity and signalling effects (Hayward and Hambrick, 1997; Wade *et al.*, 2006). In a star-studded team, individuals may care more about their personal performance relative to the other team members, rather than their team performance relative to that of other teams (Overbeck *et al.*, 2005). As a result, too many group members might feel entitled to give directives, while too few might be willing to take suggestions from others—thus jeopardizing the smooth functioning of the team. Similarly, recent research on status emphasizes that the competitiveness that may stem from status conflict is likely to restrict information sharing among group members. Because sharing information is needed to "achieve optimal joint outcomes its restriction is likely detrimental to group performance" (Bendersky and Hays, 2012: 326).

Another argument against the practice of assembling star-studded teams is the 'winner-take-all' compensation effect, that is, the ability of stars to reap most (if not all) of the value they create by commanding high salaries or rewards (De Vany and Walls, 1999; Ravid, 1999). Performers who are publicly recognized as stars often receive compensation premiums that are higher than their marginal contributions would justify (Frank and Cook, 1995). With respect to our empirical setting stars may capture the excess of expected revenues over what the film would earn with ordinary talent in the same role (Elberse 2007); or, put it another way, star performers do well for themselves and their agents, but quite often fail to deliver for the producer/studio that employ them. Several alternative lines of research, therefore, indicate that star-studded teams are prone to dysfunctional dynamics that may depress group performance. This brings us to the question of which of the two views on star assembly and project performance is more accurate. In a recent attempt to pit these views against each other empirically, Groysberg, Polzer and Elfenbein (2011) have pointed out the possibility of an inverted U-shaped effect. Using evidence on Wall Street research analysts, they show how groups benefit from star analysts up to a point after which group effectiveness declines as the proportion of stars increases. The authors suggest that stars initially add to the visibility of the group and its ability to secure critical resources; however, too many stars "may become a breeding ground for dysfunctional, counterproductive and even vindictive behaviour, the antithesis of the behavioural integration necessary for achieving high group effectiveness" (Groysberg *et al.*, 2011: 726).

This work represents a first important step towards the reconciliation of competing views on the performance implications of star-studded project teams. Yet a more precise test of the proposed mechanisms for their findings would require including "a direct measure of behaviour in terms of the amount and quality of time spent working together" (Groysberg *et al.*, 2011: 743). In what follows, we seek to elaborate on this intuition and illustrate how a history of past collaboration among project team members is a critical boundary condition for understanding whether the presence of stars is going to have a positive or negative effect on project performance.

2.2. The moderating effect of ***team familiarity***

While we remain agnostic about the intuition that more stars are better when it comes to performance, the question we wish to explore here is whether specific combinations of very talented individuals might alleviate some of the drawbacks usually associated to star-studded teams and hence yield higher performance. Why should a given combination of stars be better than others, even after accounting for individual differences in prior performance that might affect the overall group effort? Why would the performance of two star-studded teams vary dramatically despite a substantial similarity in terms of overall talents at play?

Previous research has shown how individual workers' performance can be influenced by their level of familiarity with organizational assets (e.g., capital equipment, technology, culture, management, etc.), so suggesting that individual performance tends to be firm-specific and therefore only limitedly portable. Explanations for firm-specific performance typically revolve around “the potential complementarity between a worker and the human, physical, or organizational assets held by a given firm” (Huckman and Pisano, 2006: 475). In their study of cardiac surgeons’ performance across multiple hospitals, for instance, Huckman and Pisano (2006) found the quality of a surgeon’s performance at a particular hospital to improve significantly with the number of surgeries undertaken at that hospital. But in those cases where the organization of work relies on independent contractors or freelancers, who are free to move from project to project without being employed by a stable organization, the context in which individuals skills are learned and deployed does not necessarily coincide with the conventional notion of the ‘firm’ or the ‘organization.’ The context embraces instead the broader web of relationships the individuals involved in a project formed in previous collaborations (i.e., projects they worked on together). If reactivated, these relationships “promote trust among the parties involved and function as critical repositories of shared learned experiences and knowledge that can be retrieved as the same actors work together on a new project” (Cattani, Ferriani, Fredriksen and Täube, 2010: xviii; see also Jones, 1996). According to Starkey, Barnatt and Tempest (2000), who derive their insights from research interviews in the UK television industry, continuity of relationships among project members provides a context within which to develop the individual cognitive schemata required to seamlessly integrate each other’s capabilities and adjust individual contributions accordingly (Ferriani *et al.*, 2005). As acclaimed director Sydney Pollack pointed out, working with other professionals who are on the same wavelength is perceived as “an emotional pleasure” (quoted in Jones and DeFillippi, 1996: 97), to the point that “when you find people you can work with you never want to give them up” (quoted in Jones *et al.*, 1997: 12).

These considerations, we argue, hold important implications for the case in which multiple stars end up working on a project with other team members with whom they had already worked in the past. As we noted earlier, when stars enter a new group they also carry high expectations about their roles and status. Differences in these expectations may prove problematic to reconcile, especially when new members expect to have higher status than other group members. In fact, for a group to succeed, individual members must be able to subjugate their own personal needs and desires to maximize the collective good. A history of prior interactions helps resolve such differences by sustaining social integration. Accordingly, we expect familiarity among star-studded team members to mitigate disputes over people's relative status position in their team's social hierarchy and so broadening information sharing (Bendersky and Hays, 2012). By sorting status aspirations, star-studded project team members will also attain "greater satisfaction on average, due to their similarity on affiliative dimensions, and perceived similarity as a result of complementarity on dominance dimensions" (Overbeck *et al.*, 2005: 193). In this sense team familiarity is distinct from the cumulative experience of its members in performing a certain task. Experience working together is valuable because it facilitates the diffusion and recombination of distinct but complementary skills and knowledge, hence fostering a more accurate and shared sense of who knows what on the team (Reagans *et al.*, 2005; Huckman *et al.*, 2009). Indeed, as experimental research has shown (Moreland and Myaskovsky, 2000), individuals involved in stable collaborations "develop transactive memory systems, in which members understand one another's capabilities and can more easily coordinate their actions" (Edmondson, Bohmer and Pisano, 2001: 689).

Taken together, these arguments suggest that the impact of stars on project team performance will vary with the level of team familiarity. In newly formed project teams, when stars work with other team members with whom they have no familiarity, status sorting and information sharing are very problematic. It is in fact under these conditions that interaction uncertainty is highest, resulting in low propensity towards speaking up and discussing openly. However, as team familiarity increases team members become more positively disposed towards one another and interaction uncertainty diminishes. By reducing the pitfalls of power and status conflict, and facilitating information and knowledge exchange, as well as fostering social integration through the creation of mutual trust, we expect past collaboration to temper the downsides of assembling star-studded projects and lower coordination costs. Indeed, distinguishing between high and low levels of team familiarity provides a more nuanced understanding of when assembling star-studded teams is going to have a positive or negative impact on project team performance. Accordingly, we hypothesize:

> *Team familiarity moderates the relationship between number of star professionals and project performance; the number of star professionals in a team is positively (negatively) related to project performance for high (low) levels of team familiarity.*

3. EMPIRICAL SETTING AND METHODOLOGY

3.1. Research setting

The Hollywood motion picture industry is an instructive setting in which to analyze the impact of having stars on project performance. First, *stars* have always played a critical role in the movie industry which, not surprisingly, is regarded by many observers as the epitome of the star system (Elberse, 2007).[2] Second, every year top talent is identified and celebrated by

[2] Writer/director Michael Cimino' conduct during the making of Heaven's Gate provides an effective illustration of the huge influence that stars can exert over the production process and the negative consequences that may stem from overconfidence and hubris. Following the phenomenal financial and artistic

the industry through ritualized and highly visible events promoted by influential organizations that bestow awards on those seen as having made significant contributions to the field (Cattani and Ferriani, 2008). Detailed movie revenue data are also available, so allowing one to rank professionals' star-status not only against the awards they received, but also the commercial success of the projects in which they were involved over their career. Finally, like in other contexts (e.g., consulting, advertising, construction, etc.) where the organization of work relies extensively on project teams that employ the services of specialized professionals, completing a project involves at the same time a high degree of experimentation, and the complex task of combining professionals and coordinating their efforts. As Baker and Faulkner (1991: 287) pointed out, "there must be a great deal of mutual coordination between those who supervise the transformation of 'raw materials' and those who provide the expertise and talent for this process. Thus coordination of role players is a pressing problem." Film professionals may respond to these coordination problems by establishing enduring collaborations with trusted partners (Ferriani *et al.*, 2005, 2009; Zuckerman, 2004). Indeed, this is an industry that allows one to study the "dual matching of projects, economic returns to projects and their participants, and subsequent rehiring and renewal of ties on new project organizations" (Faulkner and Anderson, 1987: 881). For all these reasons, Hollywood star professionals appear to be an ideal test case.

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success of The Deer Hunter, Michael Cimino was a rising star of the film industry and could dictate his own terms to the studios. Cimino's uncontrolled ambition and relentless perfectionism immediately caused problems, and within only five days the movie shooting had fallen behind schedule. He ordered an elaborate Western set, built to his exact specifications, to be demolished and rebuilt from scratch at a cost of $1.2m because the spacing of the buildings didn't look quite right. In all, he shot a staggering 1.3 million feet (or the equivalent of 100 feature-films) of footage, at a cost of around $200,000 a day. Although shooting began on April 16, 1979, and was due to finish by late summer (in time for a Christmas release), it did not finish until March 1980, costing an unprecedented $40m, or $120m in today's dollars (Bach, 1985). As explained by Prince (2002: 35): "The success of the Deer Hunter gave Cimino the clout to cow UA with outsized demands. Believing that Cimino, more than the picture was their star, UA acceded to his remarkable terms. The novice director had won the dangerous privilege of working without budgetary restraints." In the end, the director presented UA with a film five hours and 20 minutes long, which turned out to be one of the biggest flops in the movie industry, leading to the bankruptcy of United Artists (UA).

3.2. Data

Our data consist of the entire population of crewmembers who worked in at least one of the 2,297 movies distributed in the United States by Hollywood major studios – i.e., the seven historical majors (Universal, Paramount, Warner Bros, Columbia-Tristar, Disney, 20th Century Fox and Metro-Goldwyn-Mayer) and Dreamworks – and their subsidiaries over the period 1992-2004. We focused on these studios because they dominate the industry either directly, through their financial power, or indirectly, through distribution control. Over the last decade, movies released by these companies have consistently accounted for an average 90% of total US box-office income. Since our interest is in feature films made and distributed by Hollywood, we did not include documentaries, foreign-made films, short films, and compilation screen classics. Using the Internet Movie Database (www.imdb.com), for each movie in the sample we collected information on the following crewmembers: producer, director, lead actor/actress, and cinematographer. We selected these roles because they are all simultaneously engaged in the production phase ("principal photography")—i.e., the phase in which, explains Clevè (1994: 11), "the film is actually shot."[3] The producer is at the core of "the film's financial, managerial and commercial networks: as such it supervises all its financial and administrative aspects" (Hadida, 2010: 48), and he is usually involved throuought the making of a movie form inception to distribution (Delmestri *et al.*, 2005; Ferriani *et al.*, 2009). The director is also responsible for the artistic quality of a movie and typically works closely with the producer (e.g., movie outline, casting, etc.). Specifically, s/he plays a critical role in coordinating the efforts of other crewmembers, solving possible

[3] For instance, the cinematographer typically works closely with both the director and the actors/actresses. Indeed, it is important for the cinematographer "to be in tune with the actor's performance ... the cinematographer is seeing through the lens what the actor is giving the director and that can be very helpful in making the final decision as to whether or not they 'got it.' Most cinematographers will agree that they see their role as the gatekeeper of the image" (Frost, 2009: 15).

conflicts and facilitating internal cohesion and communication. Lead actors/actresses "embody and enact the vision of the director" (Hadida, 2010: 48) and historically have been the most visible exponents of the Hollywood star system (Walker, 1970). Finally, the cinematographer is responsible for creating much of the visual look of the film and to some extent "has possibly the most important role in a film shoot after the director" (Caldwell, 2011: 43). Do to their crucial role, industry commentators have indeed sometimes described top cinematographers as a "new kind of star" (Grover, 1975). Our selection resulted in a total of 35,825 crewmembers distributed across these roles.

3.3. Dependent variables

Our first dependent variable captures movie revenues, which we measured in terms of domestic (i.e., US-based) *box office receipts*. While the advent of new technologies – television, VCR, cable and DVD – has expanded the number of viable revenue sources, box office receipts remain "the most important benchmark when considering a film, as these ancillary revenues tend to correlate highly to the movie's performance during its theatrical exhibition period" (Sorenson and Waguespack, 2006: 14). Our second dependent variable is movie *budget*. Budget data only refer to the "negative costs," that is, the cost of a project through the production of a finished negative, without including the costs of prints, distribution and capitalized interests. We collected data on box office and budget from the Internet Movie Database (IMDB).[4] Our third dependent variable is domestic (US-based) *profitability*, which we measured as return on invested capital the ratio between movie box office receipts and budget. This is a measure of profitability with values above 1 indicating an increasingly profitable movie (the lower bound 0 corresponds to the 'theoretical' case in which the movie

[4] According to the IMDB budget numbers are based on media reports and are often supplied by sources close to the production.

failed to generate any box office receipts). Focusing on the return on investment rather than just revenues is important because most studies have found that "budgets are a main driver of revenues. Thus, it is easy to produce movies that gross a lot of money – just put in a lot of money. However, that may not be a profit-maximizing strategy" (Ravid, 2005: 37). Also, the involvement of star professionals calls for the investment of a large amount of financial resources in the form of production budgets (Hadida, 2010). This indicator has also important caveats that it is important to acknowledge. First, our profitability variable is not a measure of accounting profits. Rather, it tries to measure if the movie provides a good return on investment. The calculation of accounting profit is complex, even if all relevant costs and revenue sources were available, and may be of dubious value even if it were to be announced. Hollywood accounting practices have often been criticized for their lack of transparency (Ross and Ikawa, 1997).[5] Second, in addition to their salary, sometimes stars also receive a percentage of the movie revenues; as a result, there is practically no way to get information about compensation packages, which are "one of the best-kept secrets in Hollywood" (Gumbel *et al.*, 1998). Thus, true profits are extremely hard to identify. Third, budget data for all films are not available from this (IMDB) or any other source. Information on missing budgets is very hard to find as studios are usually reticent when it comes to discussing how much a film costs (especially when a movie fared poorly at the box-office). These limitations notwithstanding, we believe our rate of return measure represents a reasonable proxy for economic profits for various reasons. Industry publications indicate that domestic box office receipts should approximate the negative cost for a movie to break

[6] Due to Hollywood accounting, it has been estimated that only about 5% of movies officially show a net profit, and the "losers" include such blockbuster films as Rain Man, Forrest Gump, Who Framed Roger Rabbit, and Batman. An instance of this problem is the film My Big Fat Greek Wedding. The movie was considered hugely successful for an independent film (it cost $5 million US dollars to make and grossed about $370 million worldwide); yet, according to the studio (IFC Films), it lost money. As a result, the cast sued the studio for their share of the profits (Daniels, Leedy and Sills, 2006).

even. Second, the appropriateness of the metric is premised on two basic assumptions, both of which seem plausible: a) the revenues available to the producer/production company (after exhibitors' cut) are a constant proportion of gross revenues. Because agreements with theatres tend to be standardized (Vogel, 2007), this is not an unreasonable assumption; b) the costs, including advertising and distribution costs, are a constant proportion of the negative cost (Ravid and Basuroy, 2004). As distribution agreements tend to be standardized across movies, this is also a reasonable assumption. If these assumptions hold, then the metric we use is a proxy of the 'true' return on investment that can be obtained by multiplying the box office of any particular movie by an unknown (but common) constant. Given that the bias is the same for each movie, any cross-sectional comparison among movies should not be affected by a common cross-sectional bias. Third, to account for missing budget data (budget information is available for 1,158 out of 2,297 movies in our sample), we re-ran the models by applying multivariate imputation through chained equations (Van Buuren, Boshuizen and Knook, 1999).

We adjusted box office receipts and budget values using a price deflator based on the consumer price index (CPI) per year, with 2004 as the baseline year. Since movie box office, budget distributions, and the ratio between the two variables are highly skewed, in the analysis we expressed both values after applying a natural logarithmic transformation. We also estimated the full models where the dependent variable is movie box office, movie budget, and the profitability index, respectively, using a Box-Cox transformation. This transformation is a useful method to alleviate heteroscedasticity when the distribution of the dependent variable is not *a priori* known and it is based on the observed distribution (Draper and Sminth, 1981).[6] Figure 1 shows graphically the frequency distribution of the (log of the)

[6] We would like to thank one of the anonymous reviewers for recommending this additional transformation.

profitability index split by year. For each year, the distribution is depicted through a box-plot whose central line is the median value.[7] Note that in order to be profitable a movie must have a value of the index higher then 0 (as the ln(1) = 0), highlighted by a vertical line in Figure 1. The maximum and minimum in the boxes represent the 75th and the 25th percentile of the distribution, respectively. The median value changes significantly over time: it is positive in 1992, 1994, 1995, 1998, 2001-2004; in all of the aforementioned years more than half of the movies had a positive (ln) profitability index. If the box is wider on the left (right) hand side it means that the distribution is left (right) tailed like in the case of 1992 and 1993. The range of the (ln) profitability index fluctuates over time, 1996, 1997, and 2002 are the years when the profitability is most disperse.

3.4. Independent variable

In order to estimate the moderating effect of team familiarity (i.e., past collaborations) on the relationship between stars and project profitability, we first created the variable *Number of Star Professionals*. Movie professionals can be characterized as stars when they have critically acclaimed skills, possess personality traits that appeal to the movie-going audience, attract a lot of free publicity and have the ability to secure investment (Elberse, 2007). Several approaches have been used to measure stars ranging from stars' market value published by *Variety* trade magazine, to star power as reported in *The Hollywood Reporter*'s Star Power Survey, in which executives and other insiders rank talent. This paper builds on Ravid's (1999) approach where stars are classified based on their previous participation to top grossing movies. A star's historical box office record is a valued source of information for studio executives (Chisholm, 2004). Being associated "to commercially successful films

[7] Because the distribution is barely symmetric, the median is the preferred statistic.

defines one's status and role relationships within the industry" (Jones, 1996: 66). Following this criterion, we looked at each individual professional's commercial reputation based on his/her historical economic performance. Specifically, we computed the cumulative number of 'top 10 box office' movies in which each professional (producer, director, actor/actress and cinematographer) worked in the prior years to the focal one. In other words, after identifying the top 10 box office movies for any given year, we computed the cumulative number of top 10 movies in which each professional was involved. We identified as a star a professional who performed in at least 2 top grossing movies over the selected 4-year time window. The choice of the cutoff values (2 top-grossing movies over a 4-year window) was motivated by the need to have restrictive enough criteria to isolate truly outstanding performers, but without making them so extreme to almost eliminate variability in the data.

Figure 2 gives some insights into our choice showing the cumulative percentage of movies as a function of the number of star professionals participating in the movie depending on the event window from 1 to 4 years. Each graph also discriminates results depending on the cutoff of top-grossing movies (BO) used to classify a crewmember as a star (from 1 to 4 for each graph). So, for example, considering the thick line (which describes the cumulative percentage of movies in which star professionals are defined as those having participated in at least one top grossing movie over a 4 year time window), approximately only 15% of movies did not include star professionals. The cumulative frequency distribution goes up to more than 50% when considering movies with at least one professional classified as star and to more than 65% when considering also movies with at least two stars, etc. Table 1 gives statistics split by role about the participation of crewmembers on top grossing movies in the previous rolling window. For instance, the last two columns emphasize that the stars in our sample are mainly producers (23%) but that star directors tend to be involved in movies for which the average top box office (BO) is higher (1.77). As explained later in the paper, (see the robustness checks section) we performed various sensitivity analyses to test the robustness of our findings against these alternative criteria. In addition, we emphasize that the choice of relatively short time-windows (from 1 to 4 years) is consistent with the tendency of film industry decision-makers to overly rely on recent performance, a practice well epitomized by Hollywood's oft-quoted maxim: "You're only as good as your last credit" (Faulkner and Anderson, 1987: 906). Data on top grossing movies came from the IMDB online database.

We created the *Familiarity* variable using the measure developed by Reagans *et al.* (2005). Familiarity among project team members is a function of the number of times they worked together in the past. Considering a movie is released at time t, we took into account past collaborations in movies released in the previous four years, i.e., from t-4 to t-1 included. We also used a 2-year and a 3-year time window but the results did not change appreciably. For each pair of professionals (whether stars or non-stars) on the same project team, we calculated the number of times the pair worked together in previous movies during the chosen time window. We then summed this value, RK_{ij}, across pairs on the team and divided the sum by all possible number of pairs to capture professional-specific experience working together as follows:

$$Familiarity = \sum_{i=1}^{N} \sum_{j=1}^{N} RK_{ij} \Big/ [N \cdot (N-1)/2]$$

where N is team size and RK_{ij} is the number of times that professional i worked with professional j. The variable measures the average number of times project team members worked together in the last 4 years—e.g., if professionals collaborated in the 4 years before the current movie the index is equal to 1; if the average per pair is 2 then the familiarity index increases to 2.[8] Finally, to estimate the hypothesized moderating influence of familiarity we created the two-way interaction between *Number of Star Professionals* and *Familiarity* (Familiarity*Number of Star Professionals).

3.5. Controls

We included several control variables at the individual, team and project (movie) levels in the final model specification to rule out competing result interpretations. Previous research (e.g., Eliashberg and Shugan, 1997; Basuroy, Chatterjee and Ravid, 2003; Zuckerman and Tai-Young, 2003) has shown how critics' reviews affect a movie's yearly box office returns and profitability: moviegoers might be more inclined to watch movies based on the critical acclaim they receive. Accordingly, we included a measure of critical reception in the model. We created this variable using data from a well-known online public source "www.rottentomatoes.com," which rates all movies distributed in the US. The meta-score is a weighted average of reviews from national critics and publications for each movie. For each movie review, the critic's score is converted to a 0-10 point scale. In those cases when a critic does not provide a numeric score the internal staff converts the reviewer's general impression into a score based on that critic's word choice, tone, and authoritativeness. The individual scores are then averaged to produce an overall critical acceptance rating. Because

[8] We checked the robustness of our results by re-estimating the model with an alternative measure for collaboration. Following Borgatti and Jones (1996), we created a measure of collaboration from a measure of non-collaboration. Formally, the adjusted collaboration index ξ' is computed as:

$$\zeta' = 1 - \eta' = 1 - \frac{\sum dummy_{notworking} - \text{size of the largest vitae}}{\sum dummy_{working} - \text{size of the largest vitae}}$$

where η' is the adjusted non-collaboration index, $dummy_{working}$ ($dummy_{notworking}$) is a dummy that is equal to 1 if a professional worked (did not work) in a movie with somebody s/he worked with in the past, otherwise 0. Both numerator and denominator of the non-collaboration index are adjusted for the size of the project team members' largest vitae. Although not reported, the results are consistent with those presented here.

the same list of critics is used to evaluate each movie, the scores are consistent and the risk of bias mitigated. We thus created the variable *Critical Reception* by using the meta-score value.

Although sequels tend to be more expensive and sometimes generate lower revenues than original films, they may still outperform the average film especially when they capitalize on a successful formula. Following previous studies (e.g., Ravid, 1999), we therefore created a dummy variable *Sequel* that takes on the value 1 if a movie is a sequel and 0 otherwise. The distribution and marketing strategy adopted for a particular movie might have a significant impact on commercial success (De Vany and Walls, 2004; Eliashberg, Elberse and Leenders, 2006). We thus created the variable *Opening Theatres* measuring the logarithm of the number of theatres on which each movie was initially released. Movies that are adaptations of a previous story (e.g., books, novels, comic strips, or TV shows) may be more likely to appeal to the audience than movies that rely on entirely new scripts because the public is already familiar with the story (Litman and Kohl, 1989)—though they may also prove more expensive because of the need to secure copyrights. We thus created the dummy variable *Adapted Script* that takes on the value 1 if a movie is based on prior material and 0 otherwise. The release date of a motion picture provides some indication of its box-office potential. The summer season (*Memorial Day* to *Labor Day*) and several holidays (*New Year's Day*, *Memorial Day*, *Independence Day*, *Thanksgiving*, and *Christmas*) are widely regarded to be the best periods to release a new high-caliber movie because consumers have more free time and, therefore, are more likely to attend movies (Radas and Shugan, 1998; Moul and Shugan, 2005). We thus created a dummy – *Release Date* – which takes on the value 1 if a movie was released during the summer or the weeks including holydays, otherwise 0.

Another important factor is the rating assigned by the Motion Picture Association of America (MPAA) (e.g., Moon, Bergey, and Iacobucci, 2010). Ratings signal the degree of graphic sequences, violence, and harsh language in a movie. While we have no reasons to expect differently rated movies to cost differently, prior research suggests that features produced for mature audiences (R and NC-17) perform worse at the box office (Ravid 1999). Since movies rated G, PG, and PG-13 have greater audience potential, and mall owners sometimes contractually prohibit theatres from showing NC-17 films, studios often exert pressure on producers and directors to ensure their films receive a rating aligned with their market aspirations. Accordingly, we created the dummy variable *Rating* that takes on the value 1 if a movie falls in the *P, G,* or *PG-13* category and 0 otherwise. The likelihood of a movie faring well at the box office might also depend on its genre. Family or action movies for example are more likely to appeal to a broader audience and generate more box office than horror or war movies. Also, certain special effects laden genres such science fiction, fantasy, adventure or action tend to absorb more financial resources. We controlled for this possibility by entering dummies for movie genre (*Genre*). We identified 17 genres (action, adventure, animation, comedy, crime, documentary, drama, family, fantasy, foreign, horror, musical, mystery, romance, sci-fi, thriller, and western). When a film was classified into more than one genre, we used the leading categorization. Since we had no a priori expectations about the existence of a time trend over the study period, we included year dummies into the model to control for the effect of all unobserved factors (e.g., macro-economic trends, changes in taste or fashion, and other factors that might affect the movie industry).

4. MODEL AND ESTIMATION

We followed two estimation strategies for modeling the data. First, we estimated a robust (to outliers) log-linear regression model. The equation takes the form:

$$Y_i = \theta + \alpha FS_i + \Sigma\gamma_x x_i + \varepsilon_i$$

where Y is the logarithm transform of movie Box Office, Budget, and Profitability Index, respectively; FS represents the interaction effect between familiarity and stars, and *X* refers to a vector of control variables γs are the coefficients of control variables. In these models, standard errors are computed using Huber-White sandwich correct estimators robust to outliers. We use the logarithmic transformations to reduce the significant (right) skewness of the response variables. In the robustness analysis, we also use the Box-Cox procedure to remove any ex-ante imposed logarithmic transformation of the endogenous variables by relaxing the linear regression model assumptions and letting the transformation be chosen according to the observed data (e.g., Draper and Smith, 1981; Delmestri *et al.*, 2005). The Box-Cox model is defined as:

$$\frac{r_i^{\lambda} - 1}{\lambda} \equiv N(\beta^T x_i; \sigma^2) \qquad \lambda \neq 0$$

$$\log(r_i) \equiv N(\beta^T x_i; \sigma^2) \qquad \lambda = 0$$

The model includes the lognormal distribution ($\lambda = 0$) and the normal distribution ($\lambda = 1$) as particular cases, respectively.

5. RESULTS

Table 2 shows summary statistics for the variables of interest. The sample includes the 1,158 movies for which we had all relevant information (i.e., data on both revenues and budget) to run the regression analysis. As far as the dependent variables are concerned, the deflated box office ranges from a minimum of 5.032 million dollars (Duets) to a maximum of 670 million dollars (Titanic); the deflated budget ranges from a minimum of 8.022 thousand dollars (Blood, Guts, Bullets and Octane) to a maximum of 220 million dollars (Titanic). A quick comparison of the median and mean values for the dependent variables (deflated box office and profitability index) also reveals that the frequency distributions are asymmetric and right tailed. These numbers indicate that, on average, movie's box-office receipts are twice the budget. Yet this result seems to be strongly driven by the presence of left outliers as the appreciably lower profitability at the median (1.06) suggests. With respect to the independent variables, the number of star professionals in a given movie ranges from 0 to 9 in absolute value – i.e., 0 to 1 (all crew members in the selected roles are stars) as a percentage of the crew.[9] On average, 1 out 24 movies has a crewmember classified as star. The number of star professionals with previous collaborations ranges from a minimum of 0 to a maximum of 12 (with at least 75 percent of the movies displaying no collaborations). As to the familiarity index, the average value is 0.144 with a maximum value of 0.95. The critics' score and number of screens range from 1.70 to 9.50 and from 1 to 4,163, respectively. A comparison of the mean and median values suggests that the frequency distribution is right tailed. Finally, the dummies *Sequel* and *Original Script* indicate that only a relatively small proportion of the movies are sequels (10 percent of the sample), while about 36 percent of the sample movies are based upon adapted material.

Table 3 presents the Spearman's rank correlation values, which are highly significant in several cases. We opted for a non–parametric correlation statistics instead of the most common Pearson correlation coefficients due to the uncertain assumption about the particular nature of the underlying relationship (linear correlation) among variables. We

[9] Note that the number of crewmembers may be larger than the sheer number of roles as in any given movie the same role is sometimes jointly occupied by two or more professionals.

checked all models for the existence of multicollinearity by computing the variance inflation factors (VIFs) and found multicollinearity not to be a severe problem (highest VIF values are around 2). The results from the regression models are reported in Tables 4 to 9, respectively. Although the coefficients are not displayed because of space limitations, all models include dummies for movie rating, movie genre and year.

5.1. OLS regression estimates

Table 4 presents the OLS results for the baseline models with the controls only. Models 1 and 2 present the estimates of the correlates of movie box office and movie profitability, respectively. They include the same variables. Model 3 estimates the correlates of Movie Budget and differs from the previous models because it lacks controls for critical reception, number of theatres and release and. Critical reception is temporally subsequent to budgetary decisions and endogenously affected by it (Simonton 2004). The number of theatres is also decided after (or near to) movie completion (note that our budgetary information refers to the negative costs). Finally, while release dates are sometimes decided many months before filming, we found it difficult to imagine why it might influence the negative costs.

Starting from Model 1, as the number of star professionals working on the same movie increases, the very same movie is more likely to fare well at the box office, as indicated by the positive and statistically significant coefficient of the variable *Number of Star Professionals*. This result is consistent with the Hollywood industry concept of 'bankable stars' – i.e., stars that can make money for the studio. On the other hand, the negative and statistically significant coefficient of the variable in the model estimating movie profitability (Model 2) suggests that stars might prove very costly, as confirmed by the positive and significant effect on the budget in Model 3, to the point that the overall cost of hiring stars can even outweigh their positive effect on box office. A director performing multiple roles in the same movie (*Dummy Director Other Roles*) reduces box office receipts but has also a negative effect on movie budge resulting in no effect on the profitability index. The number of professionals working in principal photography (*Crew Size*) has no impact on the response variables. Also, critics' favourable reviews (*Critical Reception*) enhance movies' box office (Model 1) and profitability (Model 2). The dummy variable indicating whether a movie is a sequel (*Movie Sequel*) was statistically significant across all models, thus confirming the conventional wisdom according to which if a movie fared well, one should then invest more money and try to leverage the "winning formula" as much as possible. Similarly, the number of opening screens (*Opening Theatres*), which reflects the distribution and marketing effort for that particular movie, increases both movie box office and profitability. Movies that rely on adaptations of existing material (*Adapted Script*) have a positive impact on box office receipts (Model 1), but are less profitable (Model 2) than movies based on original scripts because they are more costly to make (Model 3). Finally, movies released during the Holidays and in the summer (*Release Date*) tend to fare better both in terms of box office and overall profitability.

Models 1, 2 and 3 in Table 5 present the regression results for the full model after including the interaction effect of theoretical interest *Familiarity*Number of Star Professionals*. Focusing first on the influence of familiarity alone, Model 1 suggests that a history of repeated interactions among key crew members enhances the revenues but has no effect on movie profitability (Model 2) due to its negative effect on budget (Model 3). This finding seems particularly intriguing as it suggests a possibility that Sorenson and Waguespack (2006) already hinted at, i.e., the extra costs production companies are willing to incur in order to retain teams who performed well in the past (significant and positive effect of familiarity on movie budget) more than offset the revenues generated by such teams (significant and positive effect of familiarity on movie revenues), thus resulting in no impact on the bottom line (lack of significant effect on movie profitability). These are the effects of team familiarity when there are no stars in the team. The situation looks very different when familiarity works in tandem with the presence of stars. For illustration purposes, Figure 3 depicts the profitability index as a function of familiarity and number of star professionals in percentage based on the results in Table 5 (Model 2). Taking as an example one of the most recurrent movies (i.e., a comedy rated PG-13) in year 2004, an increase in the familiarity index from 0 (minimum) to 50% does not significantly enhance the profitability index when there are no stars in the team. But for a movie with five stars the same increase in familiarity boosts movie profitability from approximately -2% (-0.0208) to 15% (0.146). This multiplier effect of familiarity increases with the number of star professionals. Stated differently, as familiarity increases the negative effect of the number of star professionals gets smaller and eventually becomes positive at a high familiarity level, thus corroborating our hypothesis.

5.2. Robustness checks

To test the robustness of the analyses, we estimated additional models. First, we checked whether the results were sensitive to the time-window chosen to identify a star by re-running the analyses using a time-window of 1, 2 and 3 years, respectively. We found the coefficient estimates of the key variables (i.e., *Number of Star Professionals*, *Familiarity* and the interaction term between them) to be consistent with those presented earlier (with a 4-year time window), the only major difference being that the interaction terms is still positive but no longer significant with a very short 1-year window. Second, we re-estimated the final model using an award-based measure of artistic reputation as a criterion to establish whether a professional can be seen as a star. A high number of awards/nominations in a professional's career may indeed indicate an exceptional talent and the ability to deliver outstanding performance. Unlike Ravid's (1999) measure that looks only at Academy Awards, which tend to be highly correlated to movie box office, we collected data on awards and nominations from the following professional societies: Academy of Motion Picture Arts and Sciences, the various Guilds, the Independent Feature Project/West societies, the Hollywood Foreign Press Association, the National Board of Review, the National Society of Film Critics, the New York Film Critics Circle, the Los Angeles Film Critics Association, the Broadcast Film Critics Association, the Chicago Film Critics Association, and the Boston Society of Film Critics. The selected awards are widely recognized as highly prestigious and reflect the judgments of hundreds of experts from the worlds of film practice and critics whose task is to identify and reward exceptional achievements in film-making. Including a broader range of awards allows us to measure a professional's artistic reputation more precisely. The primary data sources were Tom O'Neil's (2003) Movie Awards and the official web sites of each award-granting organization. To ensure consistency with the other criterion, we chose a cutoff of at least 2 awards/nominations over the 4-year time window. As reported in Table 6, the results of this additional analysis are consistent with those we obtained using a professional's commercial success as a basis for measuring stardom.[10] Third, we split the sample by budget size to ascertain the consistency of the effect of the variables of theoretical interest in small and big budget movies. We thus re-run the analysis by including a dummy variable Big Budget that is equal to 1 if the movie budget was higher than the median movie

[10] In their study on the determinants of commercial success in the context of the Italian feature film industry Delmestri *et al.* (2005) use a somewhat similar awards-based approach to identify star crewmembers but find no relationship between the presence of stars and box office revenues. The authors suggest that this finding is likely to reflect the strong tendency of the cultural elites responsible for bestowing the *David di Donatello* (the award used by the authors to operationalize the presence of stars) "to differentiate themselves from popular culture… and distancing themselves from commercial considerations" (Delmestri *et al.*, 2005: 996).

budget for that particular year, 0 otherwise. Then, we interacted this dummy with the variables of interest, i.e., Number of Stars, Familiarity, and Familiarity x Number of Stars. Finally, using movie box office (Box Office) and profitability (Pi) as dependent variables, we estimated the main models. Interestingly enough, the analysis revealed that all the main effects (including the interaction term) are stronger for big budget movies than small budget movies. Thus, while this extra evidence does not alter the fundamental interpretation of our findings it does suggest that big budget movies are particularly important in driving our previous results, thus further clarifying the relationship between familiarity and team performance in the presence of stars. These additional analyses are available upon request from the authors.

Table 7 reports the results when we used the Box-Cox procedure to remove the ex-ante imposed logarithmic transformation of the endogenous variables and choose the best approximation to the normal distribution implied from the data (Draper and Smith, 1981; Delmestri *et al.*, 2005). Using maximum likelihood estimation, we find the parameter λ to be 0.23 in the model where the dependent variable is movie Box Office (Model 1), 0.08 in the model where the dependent variable is pi (Model 2), and 0.42 in the model where the dependent variable is budget (Model 3). This approach produces qualitatively similar results so confirming the previous conclusions.

For many of the movies in our sample budget data are missing. We thus used multivariate imputation by chained equations as described by van Buuren, Boshuizen and Knook (1999). In particular, we performed univariate imputation of missing data using multiple regression combined with random draws from the conditional distribution of the missing observations, given the observed data and covariates, and by prediction matching. The results of the analysis with multiple imputations are reported in Model 4 of Table 7 and are consistent in sign with those discussed earlier for the full model without correcting for missing data (Model 3 of Table 5). The number of star professionals continues to have a strongly significant negative impact on movie profitability, and the familiarity index too is negative, albeit only moderately significant. However, when interacted with the number of stars, the familiarity index becomes positive and highly significant. Finally, to test whether budget data were missing at random we also used a Heckman self-selection model. In model 5 (Table 7) we report results for the first step logit regression where the dependent variable is equal to 1 in case budget data were available and 0 otherwise. The significance of the lambda coefficient at the bottom of the model suggests that the selection bias is not at random. However, the fact that we have missing data does not seem to drive our previous conclusions because the coefficient of the variable of interest (*Familiarity*Number of Star Professionals*) remains significant in the second regression (Model 6). These additional analyses confirm that our earlier results are reliable despite the sample limitations.

6. Discussion and Conclusions

A recent front cover story of *The Economist* titled "The search for talent" displays a beautiful pearl, one that is fixed in its shining splendour (The Economist, October, 2006). This image nicely captures the assumption that seems to be often implicit in HR practices obsessed with the attraction of top talents and celebrated professionals. Certainly, having talented individuals is important. But focusing on individuals alone without ever questioning that assumption may also lead to unwanted consequences. Particularly when star players must interact regularly with other individuals, their performance may not be simply factored additively into an organizational setting. This case is epitomized by what we have metaphorically termed as the 'Galácticos effect', i.e., a situation in which the arrival of too many stars leads to very disappointing team performance.

Our study is an attempt to unpack the 'Galácticos' effect and thereby contribute to the organizational literature by delving more deeply into the performance implications of recruiting stars. Despite a growing body of research concerned with the impact of recruiting stars, findings have remained rather mixed due to the difficulty of deriving compelling theoretical arguments for adjudicating why and under what conditions the costs of hiring stars should be higher/lower than the revenues they are expected to generate. In addressing this puzzle we argued that the experience stars and other team members have working together is critical for clarifying some of the results' observed inconsistency. Using data on Hollywood feature films, we found that signing star professionals to a movie project has a positive impact on box office revenues but also a positive effect on budget resulting in a net negative effect on profitability. This suggests that as the number of stars in the team goes up, the increasing costs, including the costs of coordinating their work, more than offset the revenues they contribute to generating. Although this result seems consistent with previous studies finding negative (Ravid, 1999) or no impact (Delmestri *et al.*, 2005) of stars on commercial performance, it is hard to invoke compelling theoretical arguments explaining why we should *consistently* expect to observe such an outcome. On the basis of theory alone, benefits as well as downsides can be associated to star-studded project teams—which explains why empirical evidence supports both camps (Elberse, 2007). Different considerations hold when star-studded team members worked together in the past. Specifically, the results show how team familiarity tempers the negative implications of having stars within the same team, thus enhancing movie profitability. As the familiarity among stars and other team members increases, the negative effect of stars decreases up to a point when the effect becomes positive. Interestingly, the effect of familiarity on movie profitability by itself is not statistically significant, a result that echoes evidence provided in the context of the Italian feature film industry by Delmestri and colleagues (2005). It is instead the combined effect of stars and familiarity that really boosts profitability. For example, moving from a movie with no familiarity among crewmembers to a movie with an average familiarity (0.172, see Table 2) enhances the profitability of a comedy/PG-13/2004 movie, all things being equal, by 4%, 8% and 11% when 3, 6, and 9 star professionals work on it, respectively. Moreover, if one increases familiarity to the average plus one standard deviation (0.172+0.143=0.172), these figures go up by 8%, 15% and 21%, respectively. Our evidence suggest that star performance is not fully portable across project teams (Groysberg *et al.*, 2008) but is relation-specific: it depends on the level of familiarity that stars develop with other project team members. While received explanations tend to revolve around the idea of coordination benefits and routines for interaction (Alvarez and Svejenova, 2002), we offered more star-specific theoretical explanations for why this is the case by looking at how team familiarity helps deal with and possibly overcome status sorting issues common to star-studded teams (Overback *et al.*, 2005).

The study has several implications for organizational theory and project management research. Theoretically-grounded predictions about the performance implications of recruiting stars requires one to account for the stars' attitude towards working together with other stars and non-star team members. We suggest that lack of scholarly attention to prior joint experience working experience might explain the lack of decisive findings. Despite a large body of research discussing the costs and benefits accruing to teams whose members collaborated in the past (Katz, 1982; Gruenfeld *et al.*, 1996; Delmestri *et al.*, 2005), only a few studies have looked at whether similar effects also hold for stars who repeat a previous collaboration with other team members. By highlighting the importance of project teams' relational antecedents the study adds to the literature on team assembly mechanisms and performance (Guimerà *et al.*, 2005). Especially in contexts (e.g., filmmaking, consulting, advertising, etc.) where teams disband upon completing a project, the possibility of building and cultivating relationships among team members over an extended period of time is not an option: a star-studded project team, in fact, has to function smoothly immediately after being assembled. Hiring stars with prior experience working with other (stars and non-stars) team members is critical for attenuating coordination problems and enhance the functioning of the team. Overall, the results provide cautionary information for executives responsible for assembling project teams and human resource strategists more in general. Given that stars per se do not appear to have unequivocally beneficial effects on profitability, the argument that organizations should be willing to pay exorbitant levels of compensation to attract and retain stars that have performed well in the past may be somewhat misplaced. Organizations with many stars are not necessarily better than organizations with fewer stars if such stars have not developed some familiarity with other team members. Without sharing a common vision a collection of individuals evolves into a group where collective performance may remain an elusive dream. Before building a successful team that includes stars, project and human resources managers should therefore carry out a careful analysis of each stars' existing professional/personal linkages in order to select individuals who, besides their expertise and competence, display a genuine attitude to build long-term relationships with their peers (whether stars or not).

The study suffers from obvious limitations that however represent avenues for future research. First, due to the structure of many deals in the industry and the profit-sharing nature of several contracts, major distributors might have a vested interest in keeping some information asymmetry to be able to generate ad hoc figures for budget data. Thus, while profitability at the movie level is a more fine-grained performance measure than box-office receipts, we are aware that profit calculations are hard to make in the film industry and, admittedly, we have a crude proxy. Second, we measured past collaborations directly but without providing any in-depth characterization of them. Additional quantitative and qualitative data about familiarity within star-studded teams should therefore shed light on those particular features that might increase the likelihood that certain relationships among professionals will temper the negative impact of an increasing number of star professionals on team performance. Last, questions about the generalizability of our findings can only be answered by examining other contexts. The freelancers to whom our study is most relevant are those who must interact regularly with other people in an organization. As such, our findings might be especially relevant to freelance consultants and in general professionals in project-industries who, unlike professionals completing projects independently, typically work on subsequent projects with other team members.

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Figure 1 – Distribution of the natural logarithmic transformation of the Box Office and Budget (each deflated, left graph) and profitability index (box office over budget, right graph) split by year

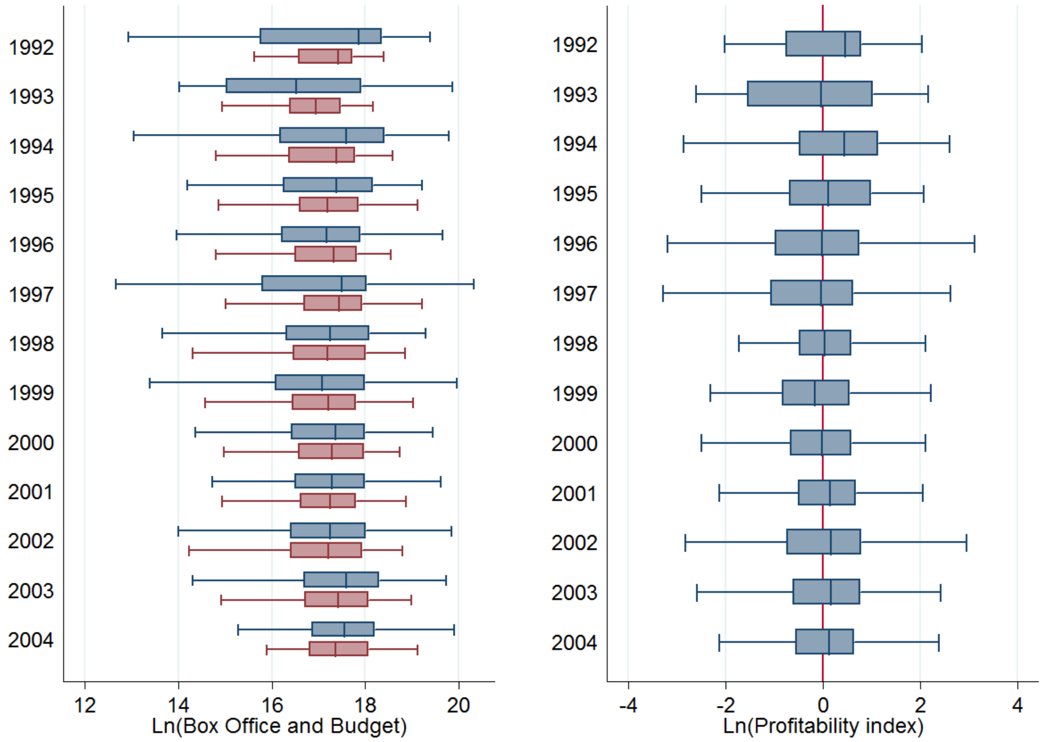


Figure 2 – Cumulative percentage of movies as a function of the number of star professionals participating in at least 1, 2, 3, or 4 top grossing movie (BO) in the previous time windows (4, 3, 2, 1 year)

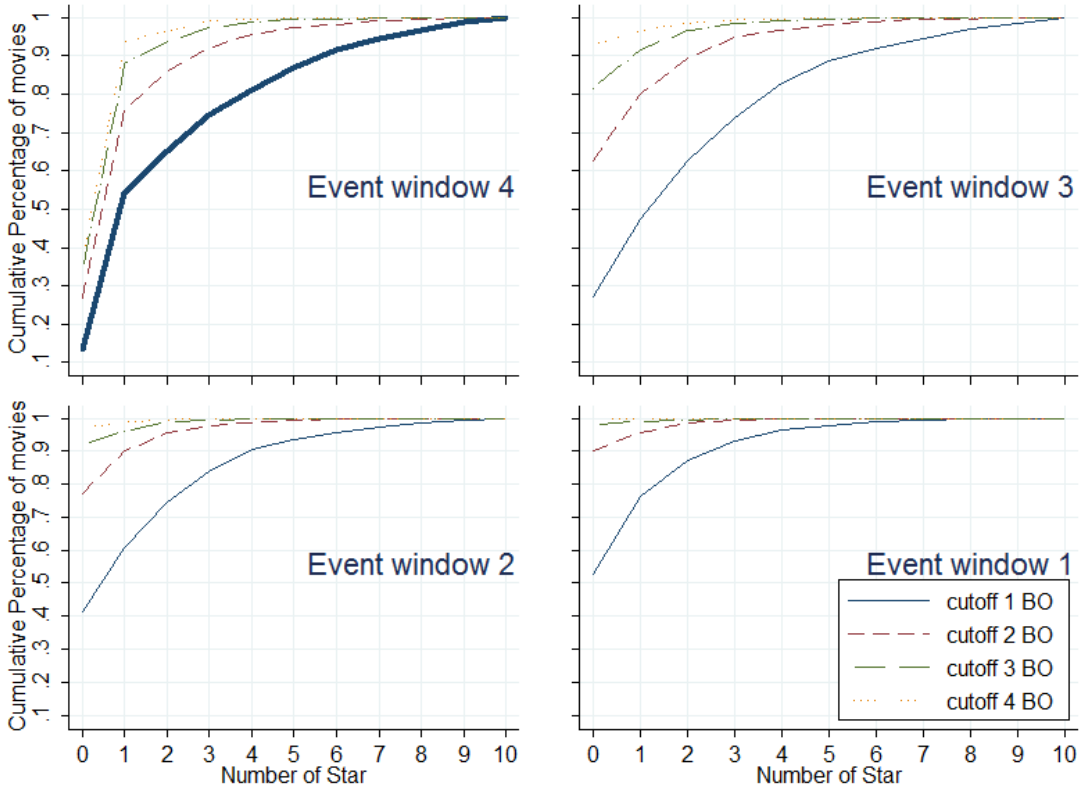


Table 1 – Participation of crew members on top grossing movies in the previous rolling window

Previous rolling window	1 year (>1993)		2 year (>1994)		3 year (>1995)		4 year (>1996)	
	%	Average Top BO participated	%	Average Top BO participated	%	Average Top BO participated	%	Average Top BO participated
Director	0.0322	1.3836	0.0742	1.5871	0.1165	1.6531	0.1514	1.7743
Producer	0.0695	1.2077	0.1336	1.3762	0.1864	1.5422	0.2291	1.6693
Cinematographer	0.0582	1.0786	0.1132	1.1858	0.1574	1.2500	0.1885	1.3400
Actor	0.0565	1.1211	0.1087	1.2352	0.1499	1.3438	0.1803	1.4897

Table 2 – Descriptive Statistics (in bold variables used in the multivariate analysis)

	Mean	sd	**Min**	**25th percentile**	**Median**	**75th percentile**	**Max**
deflated box office	53,892,097	64,227,988	5,032	13,191,489	33,700,000	70,555,552	670,000,000
deflated budget	41,462,942	33,944,305	8,022	15,957,447	31,914,894	61,015,326	220,000,000
Profitability index (pi)	1.99	8.03	0.000	0.500	1.06	1.95	234.62
Number of star professionals (specific roles)	1.89	1.83	0.000	0.000	1.000	3.000	9.000
… as a % of film crew (specific roles)	0.230	0.220	0.000	0.000	0.144	0.370	1.000
Number of previous collaborations	32.618	21.751	0.000	16	29.000	44.000	118.000
# of film crew (specific roles) with previous collaborations	5.653	1.988	0.000	4.000	6.000	7.000	11.000
Number of film crew (specific roles)	8.296	1.274	4.000	7.000	8.000	9.000	14.000
… as a % of film crew	0.023	0.061	0.000	0.000	0.000	0.000	0.571
Familiarity	0.172	0.143	0.000	0.050	0.110	0.190	0.95
Movie Critical Reception	5.619	1.442	1.700	4.600	5.700	6.700	9.500
Movie Sequel	0.105	0.306	0.000	0.000	0.000	0.000	1.000
Movie Opening Theatres	1,942	1,087	1	1,268	2,229	2,740	4,163
Movie Adapted Script	0.356	0.479	0.000	0.000	0.000	1.000	1.000
Release Date	0.090	0.291	0.000	0.000	0.000	0.000	1.000

Table 3 – Spearman's Rank (non-parametric) Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11
1. Ln(Box Office)	1										
2. Ln(Profitability index)	0.709***	1									
3. Number of star professionals (4 years)	0.443***	0.096***	1								
4. Familiarity (4 years)	0.208***	0.082***	0.372***	1							
5. Director Star (4 years)	0.232***	0.058**	0.621***	0.251***	1						
6. Crew size	0.061**	0.016	0.042	-0.103***	-0.059**	1					
7. Movie Critical Reception	0.217***	0.271***	0.091**	0.073**	0.064**	-0.059**	1				
8. Movie Sequel	0.200***	0.114***	0.224***	0.414***	0.134***	0.035	-0.049*	1			
9. Movie Opening Theatres	0.693***	0.305***	0.439***	0.204***	0.215***	0.121***	-0.192***	0.249***	1		
10. Movie Adapted Script	0.111***	-0.019	0.067**	0.007	0.037	-0.054*	0.126***	-0.008	0.048	1	
11. Release Date	0.089***	0.042	0.088***	0.027	0.028	0.018	0.142***	-0.012	-0.108***	0.055*	1

Table 4 – Baseline regression models

(ln of the dependent variable)	(1) Box Office	(2) Pi	(3) Budget
N of star Professionals	0.10***	-0.02**	0.14***
	(9.42)	(-1.98)	(16.76)
Director Other Roles	-0.21***	-0.11	-0.22***
	(-3.07)	(-1.46)	(-4.10)
Crew size	0.00	-0.01	0.01
	(0.38)	(-0.56)	(1.02)
Movie Adapted Script	0.16**	-0.13*	0.32***
	(2.40)	(-1.96)	(5.88)
Movie Sequel	0.27***	0.29***	0.03
	(3.24)	(2.93)	(0.32)
Movie Critical Reception	0.43***	0.37***	
	(17.17)	(12.68)	
Movie Opening Theatres	0.41***	0.20***	
	(12.95)	(6.86)	
Release Date	0.52***	0.19*	
	(4.37)	(1.78)	
Dummy Rating	YES	YES	YES
Dummy Genre	YES	YES	YES
Dummy Year	YES	YES	YES
Constant	12.70***	-2.56***	16.75***
	(20.81)	(-3.29)	(31.18)
Observations	1,158	1,158	1,158
R^2-adjusted	0.581	0.241	0.412
F-test	35.38	7.351	24.37

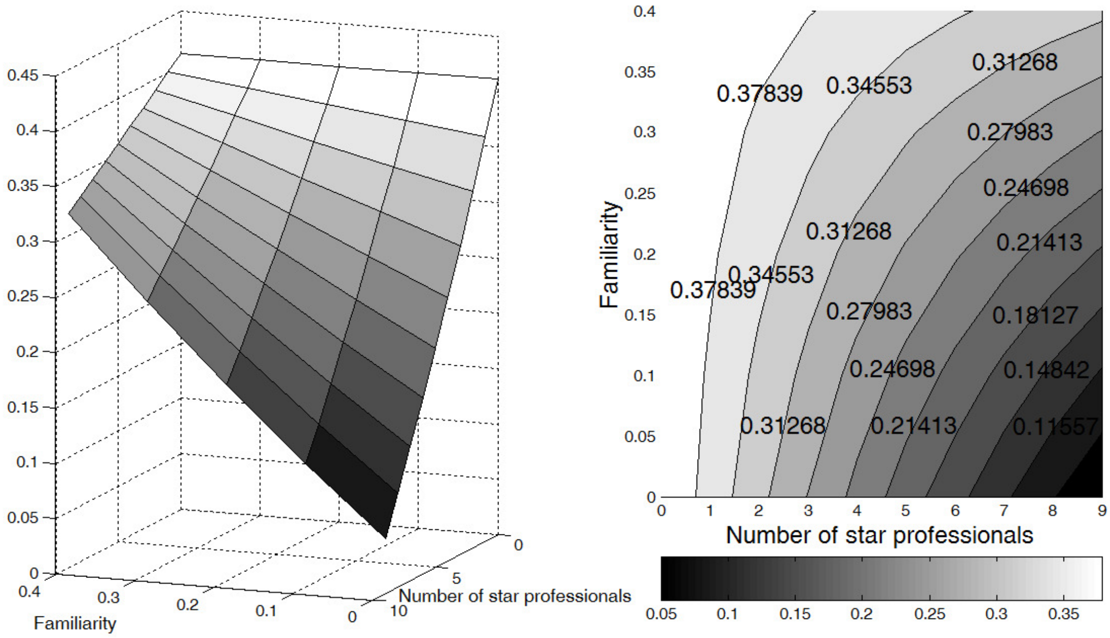
Robust value of t-statistics in parentheses -- * significant at 10%; ** significant at 5%; *** significant at 1%.
Apart from some dummy variables, stepwise regressions (cutoff p<0.05) omitted Movie Sequel only

Table 5 – Team Familiarity and Movie Performance (4-year time window)

(ln of the dependent variable)	(1) Box Office	(2) Pi	(3) Budget
N of star Professionals	0.11***	-0.03**	0.18***
	(8.91)	(-2.52)	(16.44)
Familiarity	0.73***	-0.41	1.28***
	(2.72)	(-1.48)	(4.43)
Familiarity x N of stars	-0.07	0.06**	-0.15***
	(-1.34)	(2.12)	(-5.98)
Director Other Roles	-0.21***	-0.11	-0.22***
	(-3.11)	(-1.46)	(-4.18)
Crew size	0.00	-0.01	0.01
	(0.45)	(-0.55)	(1.14)
Movie Adapted Script	0.14**	-0.12*	0.28***
	(2.12)	(-1.75)	(5.31)
Movie Sequel	0.26***	0.28***	0.03
	(2.80)	(2.65)	(0.32)
Movie Critical Reception	0.43***	0.37***	
	(17.07)	(12.76)	
Movie Opening Theatres	0.41***	0.20***	
	(12.95)	(6.91)	
Release Date	0.51***	0.19*	
	(4.38)	(1.81)	
Dummy Rating	YES	YES	YES
Dummy Genre	YES	YES	YES
Dummy Year	YES	YES	YES
Constant	12.62***	-2.51***	16.52***
	(20.73)	(-3.22)	(31.06)
Observations	1,158	1,158	1,158
R^2-adjusted	0.585	0.244	0.435
F-test	37.06	8.329	26.36

Robust value of t-statistics in parentheses -- * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 3 – Estimated profit of a film as a function of Familiarity and Number of Star Professionals*



* 3D and 2D surfaces are built conditioned to mean value of variables used in Model (2) of Table 5 for a comedy/PG-13/2004 year film

Table 6 – Team Familiarity and Movie Performance Using an Awards-Based Measure of Stardom (4-year time window)

(ln of the dependent variable)	(1) Box Office	(2) Pi	(3) Budget
N of star Professionals	0.08***	-0.11***	0.22***
	(3.61)	(-4.62)	(11.19)
Familiarity	0.70***	-0.19	1.00***
	(4.01)	(-1.05)	(4.72)
Familiarity x N of star	-0.11	0.12**	-0.25***
	(-1.22)	(1.98)	(-3.87)
Director Other Roles	-0.22***	-0.09	-0.28***
	(-3.11)	(-1.21)	(-4.92)
Crew size	0.01	-0.01	0.02**
	(0.84)	(-0.76)	(1.96)
Movie Adapted Script	0.15**	-0.09	0.26***
	(2.25)	(-1.35)	(4.78)
Movie Sequel	0.33***	0.24**	0.17*
	(3.38)	(2.26)	(1.94)
Movie Critical Reception	0.44***	0.40***	
	(15.96)	(13.21)	
Movie Opening Theatres	0.43***	0.20***	
	(13.57)	(7.11)	
Release Date	0.56***	0.24**	
	(4.58)	(2.23)	
Dummy Rating	YES	YES	YES
Dummy Genre	YES	YES	YES
Dummy Year	YES	YES	YES
Constant	12.55***	-2.49***	16.40***
	(16.58)	(-3.71)	(35.62)
Observations	1,158	1,158	1,158
R^2-adjusted	0.560	0.258	0.387
F-test	127.7	7.753	21.69

Robust value of t-statistics in parentheses -- * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7 – Robustness models

	Box-cox			Full imputation	Heckman correction model	
	(1) Box Office	(2) Pi	(3) Budget	(4) Pi	(5) d_budget=1	(6) lpi
N of star Professionals	6.80***	-0.04***	24.54***	-0.03***	0.07***	-0.05***
	(10.90)	(-2.79)	(20.73)	(-2.89)	(3.53)	(-3.29)
Familiarity	23.05**	-0.48*	115.35***	-0.40*		-0.48
	(1.98)	(-1.67)	(4.00)	(-1.67)		(-1.55)
Familiarity x N of stars	-2.58	0.06**	-16.92***	0.06***		0.07**
	(-1.07)	(2.37)	(-6.31)	(2.81)		(2.22)
Director Other Roles	-9.24***	-0.10	-9.12	-0.03	0.20**	-0.15*
	(-2.93)	(-1.43)	(-1.53)	(-0.51)	(2.22)	(-1.90)
Crew size	0.31	-0.01	1.54	-0.00	0.00	-0.01
	(0.65)	(-0.65)	(1.35)	(-0.07)	(0.28)	(-0.54)
Movie Adapted Script	4.01	-0.13**	31.63***	-0.16***	0.03	-0.13*
	(1.27)	(-1.99)	(4.94)	(-2.65)	(0.33)	(-1.67)
Movie Sequel	19.36***	0.28***	9.34	0.25**	0.01	0.29**
	(3.98)	(2.72)	(0.91)	(2.46)	(0.06)	(2.13)
Movie Critical Reception	21.47***	0.35***		0.35***	0.25***	0.28***
	(20.17)	(12.82)		(14.82)	(7.19)	(7.23)
Movie Opening Theatres	16.47***	0.17***		0.18***	0.19***	0.12***
	(15.00)	(6.62)		(9.56)	(9.02)	(3.66)
Release Date	20.20***	0.17		0.10	0.19	0.11
	(3.78)	(1.56)		(1.04)	(1.18)	(0.86)
TopBoxOffice					0.72***	
					(2.81)	
λ					-0.98***	
					(-3.39)	
Dummy Rating	YES	YES	YES	YES	YES	YES
Dummy Genre	YES	YES	YES	YES	YES	YES
Dummy Year	YES	YES	YES	YES	YES	YES
Constant	25.71	-2.22***	28.90***	-2.41***	-2.57**	-0.26
	(1.13)	(-2.91)	(3.98)	(-3.30)	(-2.27)	(-0.22)
θ	0.2345	0.0758	0.4242			
Observations	1,158	1,158	1,158	1,416	1,416	1,416
R^2-adjusted	0.610	0.230	0.538	0.241		
F-test (Wald-χ^2)	120.0	8.709	101.1	11.06		(210.12)

Robust value of t-statistics in parentheses -- * significant at 10%; ** significant at 5%; *** significant at 1%