The Role of Success and Failure in Fluid Teams—Evidence from the Motion Picture Industry

ABSTRACT

Many business settings involve *fluid teams*—wherein team members come together to work on a project after which the team is disbanded. It is well known that coordination can be challenging and affect performance outcomes of fluid teams. The literature has studied how several facets of experience can facilitate learning and improve outcomes for fluid teams. However, the role of experience with *success* and *failure* and its effect on improving outcomes for fluid teams has remained unexplored. In this study, we use data from the motion picture industry to examine how the experience with success and failure resident within key members of a movie production team affects profitability. Our analysis of the data on 1,941 movies released in the U.S. from 2000 to 2016 reveals that a movie's profitability depends on the production team's history with success and failure. Additionally, we find that teams with a history of success result in movies with higher profits, whereas teams with a history of failure result in movies with lower profits. We also find that increased relative dispersion in the team's experience does not affect the movie's profitability. Further analysis of the composition of movie teams indicates that financial performance can be significantly impacted when movie teams are predominantly composed of members with a history of success or of failure. We contribute by illustrating a new measure of team experience relevant for fluid teams, and by providing insights on how to compose teams based on members' experience with success and failure.

1. Introduction

Teams are used in several business activities such as quality management, new product development, and service delivery (see, e.g., Lawler et al. 2001). One reason why teams are commonly used, in business, is because they allow organizations to bring together different members with complementary skills to achieve desired organizational outcomes (Lazear 1999). Often, the success and failure of business endeavors depends on how well team members coordinate their efforts to deliver on business outcomes. At the same time, it is well known that organizing and managing the coordination effort across team members can be demanding (Lazear and Shaw 2007). The literature has recognized the importance of learning to coordinate within teams (see, e.g., Argote et al. 2021). When members work in teams that remain stable over time, it has been observed that experience—as measured by cumulative output—of key individuals, teams, and organizations can facilitate the development of knowledge (i.e., learning), which in turn contributes to improved outcomes. For example, Reagans et al. (2005) find that surgical teams lower their surgery completion times as they gain experience.

However, many business settings involve *fluid teams*—i.e., teams where members work on a project to deliver on business outcomes after which the team is dissolved, and members take on other projects (Arrow and McGrath 1995). Coordination tends to be more demanding in fluid teams because of the lack of repeated interactions amongst team members. For instance, Huckman et al. (2009, p. 85) point out that "simple measures of cumulative output may not accurately capture team experience, particularly when changes in team composition are substantial over time." As a result, several studies have focused on exploring how alternative facets of experience can facilitate improved learning in fluid teams. This literature has provided a rich understanding of how different aspects of experience can improve business outcomes. The evidence, so far, indicates that familiarity of team members (Huckman and Staats 2011), diversity in the task experiences of team members (Huckman et al. 2009), prior partner exposure (Aksin et al. 2021), and partner variety (Kim et al. 2022) can contribute to improved business outcomes. In the context of fluid teams, one facet of experience that has hardly received any attention relates to how team members' experience with *success* (e.g., successful satellite launch, under budget project completion) and *failure* (e.g., failed satellite launch, over budget project completion) affects business outcomes.

At the same time, it must be noted that a large stream of work has explored how the experience with success and failure affects business outcomes. In this literature, the predominant focus has been to explore how success and failure at the organizational level influence business outcomes. This aligns with the fact that in several settings business outcomes are shaped by the collective organizational effort (e.g., satellite launches as in Madsen and Desai 2010, reducing airline accidents as in Haunschild and Sullivan 2002). An emerging stream of work has probed deeper to examine the role of the experience with success and failure at the individual level. This is because in many settings key individuals play a vital role in influencing outcomes (e.g., cardiac surgeons in cardiac surgery as in KC et al. 2013, racing drivers in formula one racing as in Lapré and Cravey 2022). But Argote and Miron-Spektor (2011) point out that learning can also occur at a team level and that the drivers for team learning could differ from those for individuals or organizations. However, to the best of our knowledge, hardly any work has explored how experience with success and failure at the team level affects business outcomes. Therefore, in this study, we seek to bridge these gaps—in the literature on fluid teams and the literature on success and failure—by examining how the experience with success and failure within a fluid team affects business outcomes.

The reason for the paucity of research on the impact of the experience with success and failure in fluid teams can be traced to the difficulties involved in tracking individuals across different teams and in measuring whether each team delivered successful business outcomes or not. Obtaining such information, in most business settings, remains elusive. This study overcomes these difficulties by using data from the motion picture industry. We focus on this industry for three broad reasons. First, the motion picture industry predominantly uses fluid teams. This is because each movie constitutes a project wherein different sets of members such as executive producers, producers, directors, screenwriters, and leading actors are brought together for the development and production of each movie. Moreover, the processes of creating, writing, organizing, planning, and producing a movie often involves significant interaction and coordination between different team members. This means that teamwork is a critical ingredient which drives successful outcomes in the movie industry. Second, the data from the motion picture industry allows us to track key individuals over time as they work on the development and production of different movie teams. Third, we can measure success and failure clearly in the motion picture industry. When individual members work on movies that make profits, they gain experience with success, whereas when individuals work on movies that make losses, they gain experience with failure. Thus, we can identify the experience with success and failure resident within each movie production team. Importantly, using profits and losses allows for a fine-grained continuous measure of success and failure in monetary terms. By contrast, prior work mainly uses binary constructs to measure success and failure—favorable events are identified as success (e.g., patient survival after cardiac surgery as in KC et al. 2013) and unfavorable events are identified as failure (e.g., patient mortality after cardiac surgery as in KC et al. 2013). In particular, the data from the motion picture industry enables us to measure the extent of the experience with success and failure resident within each team, which in turn allows for a more nuanced examination of the impact of experience with success and failure.

Our analysis is based on the data for 1,941 movies that were released in the U.S. from 2000 to 2016. Our data includes information on 6,809 executive producers, 5,790 producers, 2,070 directors, 3,418 screenwriters, and 5,583 lead actors that were involved in the development and production of these 1,941 movies. Our empirical analysis starts by examining how a movie team's overall history with success and failure affects the profitability of a movie. Then, we decompose a team's overall experience into the experience with success and experience with failure to examine how the history with success and failure affects profits. Next, we evaluate whether the relative dispersion in a movie team's overall history has a bearing on a movie's profitability. Finally, we examine how the composition of success and failure embedded within a team affects the movie's profitability.

This paper makes several contributions. First, we explicitly measure the extent of experience with success and failure that is resident within a team, which allows us to establish that a team's prior experience has a direct effect on business outcomes. Thus, we identify a new measure of team experience relevant for fluid teams. Second, consistent with literature, we find that a team's prior experience with success has a positive impact on business outcomes. By contrast, we find that a team's prior experience with failure has a negative impact on business outcomes. In this way, our results differ from several studies in the literature, which find that organizations learn from their experience with failure. Specifically, we show that this may not be true in fluid teams. Third, we find that increased relative dispersion in the team's experience does not have significant effect in the movie industry. Fourth, we delve deeper into the composition of teams and find that teams which are predominantly composed of members with a history of success or of failure can significantly impact financial performance. Thus, we add to the literature by providing guidance on how to compose teams based on the members experience with success and failure. Additionally, our results are also relevant for managers in the motion picture industry because they provide insights on how the composition of teams could affect profitability.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 presents our hypotheses. Section 4 describes the data and the measures used in our analysis. In Section 5, we discuss our methodology. Section 6 presents our results. Section 7 describes the robustness checks to validate our results. We also present further analysis on the impact of team composition on financial performance. Section 8 discusses the implications of our findings and the limitations of our analysis.

2. Related Literature

Our work draws on and contributes to the literatures on organizational learning, fluid teams and the motion picture industry. We provide a broad overview of the relevant literature in these areas and discuss the key differences in our study.

Organizational learning refers to the idea that as organizations gain experience by performing activities repeatedly, they develop knowledge which helps them to improve performance (Argote 2013). Several studies in the organizational learning literature have sought to develop a deeper understanding of how different facets of experience contribute to improved operational performance (e.g., Darr et al. 1995, Benkard 2000, Banker et al. 2001). One key facet of experience that has garnered much attention is whether organizations learn from their experience with success and failure (e.g., Madsen and Desai 2010, KC et al. 2013). Across several settings, studies have found that the experience with success (e.g., Baum and Dahlin 2007, Kim et al. 2009) as well as the experience with failure (e.g., Haunschild and Sullivan 2002, Thirumalai and Sinha 2011) contribute to the development of organizational knowledge. However, findings are mixed on whether success or failure contributes more to the development of organizational knowledge. Studies show that in some instances learning from success dominates (e.g., Baum and Dahlin 2007) while in other instances learning from failure dominates (e.g., Madsen and Desai 2010). Our study differs from this vast literature in two ways. First, most prior studies use the cumulative count of past instances with success and failure as the measure of experience (e.g., KC et al. 2013, Madsen and Desai 2010). By contrast, we use financial performance (i.e., cumulative profits and losses, and returns) to measure the impact of experience with success and failure, which is a granular and continuous measure of success and failure. An added advantage of our approach is that it overcomes the recent criticism of Bennett and Snyder (2017), who maintain that using the cumulative count of past instances with success and failure as the measure of experience could lead to biased results. Second, the literature has largely explored settings where success plays the dominant role. For instance, Madsen and Desai (2010) explore the satellite launch industry where successful launches account for over 93% of all launches, Haunschild and Sullivan (2002) examine the airline industry where successful (i.e., incident free) flights account for over 99% of all flights, KC et al. (2013) study cardiac surgeries where successful surgeries account for over 96% of all surgeries, to mention a few. A notable exception is Lapré and Cravey (2022) who explore formula one racing—a setting where success is rare and observed for less than 4.5% of their observations, because in each formula one race there is only one winner. In these settings, because failure (or success) is infrequent, such events can garner attention and initiate root cause analysis, which in turn facilitates learning. However, it remains to be seen whether the learning effects observed in these settings carries over to situations where neither success nor failure are dominant. We focus on the movie industry where success and failure are more intermingled, and nearly 41% of the movies in our data make losses. This adds another dimension to the literature that investigates learning from experience with success and failure.

Our work relates to the body of work that explores the performance of fluid teams. This literature identifies a variety of factors that can affect the effectiveness of fluid teams including: the familiarity of team members (e.g., Huckman and Staats 2011), the experience of team members in specific roles (e.g., Huckman et al. 2009), the exposure of team members with other members on prior projects (Aksin et al. 2021), the team's experience with partner variety (Kim et al. 2022), and the presence of top performers within the teams (Tan and Netessine 2019). Our work contributes to this literature by exploring how the experience with success and failure resident within a team affects business outcomes. In contrast to the literature, we show that organizations do not necessarily learn and improve with failure experience in fluid teams. Furthermore, we examine how the composition of the experience with success and failure within the team affects business outcomes. In this way, we add to the literature by providing insights on how teams can be constituted to realize successful outcomes.

A large body of work has analyzed the motion picture industry. Several themes have been explored in this literature, and some of the key areas explored include how profitability is impacted by movie release strategy (e.g., Cabral and Natividad 2020), the role of prior relationships between producers and distributors (Sorenson and Waguespack 2006), the consequences of financial slack created by surprise hits (Natividad 2013), and repeated interactions between key roles in a movie production team (Narayan and Kadiyali 2016). We add to this literature by exploring how the experience with success and failure resident within key members in a production team affects the movie's profitability.

Next, we discuss the literature in further detail as we develop our hypotheses.

3. Hypotheses

We leverage the literatures on organizational learning and on learning from success and failure to explore how the experience of members of a movie's team contributes to the financial performance.

3.1 Learning from the Experience within a Movie Production Team

Wright (1936) found the initial evidence for the idea that organizations develop knowledge as they gain experience, which helps them to improve their performance. He documented that the unit cost of production declined at a constant rate with cumulative production (i.e., production experience) in aircraft production. Ever since, the literature has explored whether experience affects different dimensions of organizational performance. It has been shown that firms lower costs as they gain production experience (e.g., Argote et al. 1990, Darr et al. 1995), improve quality performance as they gain experience with quality improvement projects (e.g., Lapré et al. 2000, Agrawal and Muthulingam 2015), enhance patient health outcomes as they gain experience with learning activities (e.g., Nembhard and Tucker 2011), to mention a few. The evidence so far indicates that experience supports the development of knowledge, which in turn drives improvement across various dimensions of organizational performance.

Along similar lines, the experience resident within members of a movie production team can contribute to a movie's financial performance. This is because movie production involves significant coordination and creative collaboration across key team members. When members within a movie production team have experience of working in movies that were profitable, then such members are likely to have developed knowledge of the factors that can facilitate the box office performance of a movie. Conversely, when such members have experience of working in movies that were not profitable, then they are likely to have developed knowledge of the factors that can harm the box office performance of a movie. Thus, with increased experience, a movie production team can coordinate efforts to augment the factors that facilitate box office performance and simultaneously mitigate the factors that could harm box office performance.

The literature, so far, has mainly relied on the cumulative number of task performances as a measure of experience. In our setting, every opportunity of working in a movie provides more nuanced information. This is because the movie's box office performance and budget can be measured in dollar terms, which allows members to observe the movie's profitability. As a result, we expect that members of a production team would develop knowledge based on a movie's financial performance. They will learn more about the extent to which factors facilitate (harm) box office performance when the movie makes more profits (losses). Therefore, we hypothesize:

Hypothesis 1 (H1): *The financial performance of a movie will increase with the cumulative experience that is resident within the key members involved in the production team.*

3.2 Learning from the Facets of Experience within a Movie Production Team

H1 serves to establish the relation between the cumulative experience resident within team members and the movie's profitability. In the next pair of hypotheses, we delve deeper to unpack the experience resident within the movie production team.

The organization learning literature has recognized that there are different facets of experience, which have differing effects on the way in which knowledge is developed and leveraged to improve organizational performance (Argote et al. 2003). One facet of experience that is important relates to whether past events resulted in success or failure. This is because success and failure induce differing reactions within organizations (Cyert and March 1963). When an organization experiences success it obtains evidence on the factors that are effective in achieving organizational goals. Naturally, the focus of organizations after success will be to consolidate and build on the factors that led to success. As an organization gains experience with multiple successes, it gains a better understanding of how various factors can be leveraged to produce continued success. Several studies have found evidence supporting the notion that organizations learn from their experience with success (e.g., KC et al. 2013, Baum and Dahlin 2007).

Conversely, when an organization experiences failure it obtains evidence that the current ways of working are not effective in achieving organizational goals. Thus, failure could motivate organizations to search for improved ways of working to achieve organizational goals. Additionally, failure often provides clues on the specific factors that negatively affect organizational performance. Thereby, failure can focus organizational efforts on the critical areas to mitigate the factors that cause poor performance (Levinthal and March 1981). Finally, failure imparts a sense of urgency because repeated failure can threaten organizational survival. As a result, organizations will react quickly to fix the causes of failure. Studies also have found evidence that organizations learn from their experience with failure (e.g., Haunschild and Sullivan 2002, Kim and Miner 2007). Furthermore, studies have shown that failure has a larger learning effect than success (e.g., Li and Rajagoplan 1997, Madsen and Desai 2010).

The notion of success and failure is also relevant for the experience of the members of a movie production team. This is because each movie can result in profits (i.e., success) or makes losses (i.e., failure). Thus, when members of a production team have had experience with profitable movies, they will have better understanding of factors that lead to success, and they could leverage this knowledge to augment the factors that could contribute to the box office success of the focal movie. Conversely, when members have had experience with movies that made losses, they will have better understanding of factors that cause failure and they could leverage this knowledge to mitigate such factors, which should in turn contribute to the box office success of the focal movie. Success and failure have been primarily measured as binary constructs in the prior literature. However, in the movie setting, the notion of profits and losses allows for the measurement of the extent of success and failure in dollar terms. This would augment the learning effects as it would enable members to identify the degree to which specific factors contribute to the extent of success or failure. Based on the above discussion, we hypothesize:

Hypothesis 2a (H2a): *The profits of a focal movie will increase with the success experience of the members of its production team.*

Hypothesis 2b (H2b): *The profits of a focal movie will increase with the failure experience of the members of its production team.*

3.3 Learning from Dispersion of Experience within a Movie Production Team

Our hypotheses, so far, have sought to examine the impact of different facets of experience on a focal movie's profitability. Now, we turn to examine the impact of the dispersion of experience resident within the movie's production team.

When there is little dispersion in the experience that is resident within the different members of a production team, it is likely that the members have limited knowledge of the variety of factors that facilitate or harm box office performance. With the limited knowledge, it is possible that such production teams may overlook some factors that are critical for the success of the focal movie. Conversely, when the dispersion in experience is high, the members are likely to have varied knowledge about the factors that facilitate or harm box office performance. Such team may be able to synthesize the impact of a wider cross section of factors that would be essential to ensure box office success. There is limited research that has examined the impact of dispersion in experience on learning. A notable exception is Desai (2015) who finds in the context of cardiac surgery procedures that concentration of failures leads to higher future failure, whereas dispersion of failures lowers future failure. Based on the above discussion, we hypothesize:

Hypothesis 3 (H3): *The profits of a focal movie will increase with the dispersion in experience of the members of its production team.*

4. Data

4.1. Data Sources

The data for our analysis draws on the population of feature films released in the U.S. theaters from 2000 to 2016. We purchased the data from Nash Information Services who host the website 'www.the-numbers.com.' Nash Information Services owns one of the largest databases of movie industry information. The data includes information on each film such as box office revenues, acting credits, technical credits, production companies, movie ratings, and movie genre, to mention a few. We use the data to construct the variables required for our analysis. We describe these variables next.

4.2. Dependent Variables

Our dependent variables seek to measure the financial performance of a movie. Accordingly, for our first dependent variable, we define $Movie\text{-}Profit_{it} = (R_{it} - C_{it})$, where R_{it} represents the total domestic box office revenues (i.e., the dollar value of ticket sales in the U.S.) and C_{it} represents the production budget for movie i released at time t (viz, the weekend in which the movie was released theatrically). The production budget encompasses all the costs associated with producing a film. These include the costs for producers, directors, production cast (that includes the lead actors and other members of the cast), story rights, screenplay, production costs, visual effects, and music. It is important to note that the dependent variable can take both positive and negative values. Our measure is aligned with the approach adopted in prior work. For instance, Natividad (2013) uses positive values of box office revenues less production budget to measure the financial slack for each movie. Thus, positive values of *Movie-Profit* (i.e., when box office revenues exceed production budget) would be aligned with Natividad (2013) and indicate instances when a movie is a success. On the other hand, negative values of *Movie-Profit* mean that box office revenues are less than the production budget and indicate instances when a movie is a failure. While success and failure have been often conceptualized and evaluated as a binary event (e.g., Madsen and Desai 2010, KC et al. 2013), our measure is a continuous construct that quantifies success and failure in dollars. One advantage of our measure is that it enables us to evaluate how the extent of the experience with success and failure affects business outcomes.

One potential drawback of just using profits is that it does not account for the budget associated with a movie. Therefore, for the second dependent variable in our analysis, we normalize the profits with the costs and define *Percent Movie-Profit/Budget*$_{it}$ $= \frac{(R_{it} - C_{it})}{C_{it}} \times 100$.

In our data, 1,144 movies made a profit, and 797 movies made a loss. On average the movies that made a profit had revenue that were 252.15% greater than the production budget, while movies that made a loss failed to recoup 43.11% of the production budget.

4.3. Independent Variables

Our independent variables are measures of a movie team's history with success and failure. We consider the team's history because movie production typically involves significant organizational and artistic coordination across key team members. We leverage Narayan and Kadiyali (2016)—they identify producers, directors, screenwriters, and actors as the key roles involved in a production team that work jointly to deliver the final product (i.e., the movie). We expand on this approach and define the key roles of a movie production team to include the executive producers, producers, directors, screenwriters, and leading actors. Our definition of a movie's team differs from Narayan and Kadiyali (2016) in two ways. First, we include both executive producers and producers in our definition as opposed to Narayan and Kadiyali (2016) who only consider executive producers. This is because Finney (2008) points out that executive producers and producers play distinct but crucial roles in the production of a movie. While producers are often involved in the coordination of activities required for the development and production of the movie, executive producers are typically involved in coordinating the financing requirements of the movie. Second, Narayan and Kadiyali (2016) consider only the lead actor and the lead actress, which they define as the actor and the actress with the highest billing in the movie. Unlike them, our definition of leading actors includes all actors that appear in a movie's theatrical poster. For instance, in the movie "The Prestige" the approach of Naryanan and Kadiyali (2016) identifies Hugh Jackman as the lead actor and Scarlett Johansson as the lead actress. By contrast, our approach identifies Hugh Jackman, Scarlett Johansson, and Christian Bale as the lead actors. Thus, our definition considers all actors and actresses included in the promotional activities associated with the movie and, therefore, these actors and actresses can be considered key for the success or failure of the movie. Similarly, we observe from the data that any given movie could have multiple screen writers, producers, executive producers, and directors. We will use the above definitions of a movie team's key roles to define the relevant independent variables for our analysis.

Team History$_{it}$. This variable represents the history with success or failure for the average team member involved in a movie *i* released at time *t*. For each member *m* belonging to one of the five key team roles (i.e., executive producers, producers, directors, screenwriters, and leading actors), we identify the movies $(j = 1 \; to \; J)$ the specific member worked on in periods before *t*, and compute the cumulative profits for the team member as $\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(R_{mjl} - C_{mjl})$. Then, we calculate the average history across the team members for movie *i* as $(\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(R_{mjl} - C_{mjl}))/M$, where *M* represents the total number of members in the movie team. Thus, *Team History$_{it}$* is a measure of the average cumulative experience with success and failure that is resident within the average member of the movie team.

The next two variables decompose *Team History$_{it}$* into two components that separate the history with success and the history with failure.

Team History–Positive$_{it}$. This variable measures the history with success of the average team member involved in a movie *i* produced in year *t*. This variable is calculated in a manner similar to *Team History$_{it}$* but we only use the history with success for each member. Thus, we compute *Team History–Positive$_{it}$* as $(\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(R_{mjl} - C_{mjl})^{+})/M$, where $(a)^{+} = max(0, a)$.

Team History–Negative$_{it}$. This variable measures the history with failure of the average team member involved in a movie *i* produced in year *t*. This variable is calculated just like *Team History–Positive$_{it}$* but we only use the history with failure for each member. Thus, we compute *Team History–Negative$_{it}$* as $(\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(R_{mjl} - C_{mjl})^{-})/M$, where $(a)^{-} = min(0, a)$. To facilitate interpretation, we reverse code the sign of the dollar amount (i.e., we multiply the values with negative one).

Team–CV$_{it}$. This variable measures the relative dispersion in the history with success or failure that is resident within the members belonging to one of the five key team roles involved in the production team of movie *i* released at time *t*. We start by calculating the average standard deviation of the histories across the team members. Then, we compute the variable (i.e., *Team–CV$_{it}$*) as the standard deviation divided by the *Team History$_{it}$*.

The four independent variables defined above use only profits and do not account for the budget associated with a movie. Therefore, we normalize these variables with costs and define:

Team History/Budget$_{it}$. This measures the average history normalized with costs that is resident within the average member of the movie team. It is calculated as $(\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(\frac{R_{mjl}-C_{mjl}}{C_{mjl}}))/M$.

Correspondingly, *Team History/Budget–Positive*$_{it}$ and *Team History/Budget–Negative*$_{it}$ are calculated as $(\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(\frac{R_{mjl}-C_{mjl}}{C_{mjl}})^{+})/M$ and $(\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(\frac{R_{mjl}-C_{mjl}}{C_{mjl}})^{-})/M$, respectively.

Team–CV/Budget$_{it}$. This variable is calculated as the average standard deviation of the normalized histories across the members belonging to one of the five key team roles involved in the production team of movie divided by *Team History/Budget*$_{it}$.

Our approach of measuring a movie team's history with success and failure in multiple ways provides two distinct advantages. First, we avoid the potential concern that the results are driven by a single or chosen measurement approach. This is especially relevant because there is no established precedent in the literature on how to measure a movie team's history with success and failure. Second, if our findings are consistent across multiple measures, then the results would provide persuasive evidence on how a team's experience with success and failure can affect a movie's financial performance.

4.4. Control Variables

We follow prior work on the movie industry (e.g., Sorenson and Waguespack 2006, Narayan and Kadiyali 2016) and include a vector of movie-level characteristics that may directly influence the success or failure of a movie. To this end, we construct the following control variables: *Opening Weekend Theaters*, *Running Time*, and *Sequel*. The variable *Opening Weekend Theaters*$_{it}$ represents the number of theaters in which movie *i* was screened in the opening weekend. This variable has been recognized and used as a proxy measure for the level of resources allocated to promoting a film (see, e.g., Sorensen and Waguespack 2006, Moretti 2011, Natividad 2013). This variable will also affect revenues, and thus directly affect the success or failure of a movie. The variable *Running Time*$_{it}$ represents the total running time in minutes of movie *i*. This variable is expected to have a bearing on production costs and hence also have a direct consequence on the success or failure of a movie (see, e.g., Sorensen and Waguespack 2006). The variable *Sequel*$_{it}$ takes a value of 1 if the movie was a sequel and is 0 otherwise. This variable controls for the reality that sequels often have similar teams from the previous production (e.g., Narayan and Kadiyali 2016) and the fact that sequels are often commissioned following the success of the previous production.

Research recognizes that familiarity of team members can influence performance outcomes (see, e.g., Huckman and Staats 2011, Reagans et al. 2005). Therefore, we use the variable *Team Familiarity*$_{it}$ to control for the familiarity between the team members in a movie *i* produced in year *t*. We use the approach adopted in Huckman and Staats (2011) to compute this variable. *Team Familiarity*$_{it}$ is calculated as the count of the number of times each unique pair of individuals on a team has worked on a prior movie over the past three years divided by the possible number of pairs in a movie team (i.e., $^{n}C_{2}=n(n-1)/2$, where n represents the number of members in the team).

4.5. Fixed Effects

Our study includes the following fixed effects:

a. *Genre (Genre$_i$)*. Our regression models use seven dummy variables that identify the genre of a movie (i.e., Adventure, Comedy, Drama, Horror, Musical, Thriller/ Suspense, Western). These control for any genre related factors that may affect the revenues for a movie.

b. *Rating (Rating$_j$)*. We use indicators to identify the rating (e.g., G, PG-13, R) provided by the Movie Picture Association of America (MPAA), which may affect ticket sales.

c. *Distributor (Dist$_i$)*. Indicator variables identify the film distribution company (e.g., Warner Brothers, Mirimax, Walt Disney) that handles the production and distribution of the movie. These indicators control for potential organizational factors that may affect the success or failure of a movie

d. *Production Year (YR$_i$)*. Indicator variables that identify the relevant year in which the movie was produced. These indicators control for potential factors that may change over time.

Tables 1 and 2 provide the summary statistics and correlations, respectively, for the variables used in our analysis.

Table 1: Summary Statistics

Variable	Mean	S.D	Min	Max	N
Movie-Profit (million USD)	20.535	66.309	-190.641	630.662	1,941
Movie-Profit/Budget (Percent)	130.91	832.23	-98.36	23,882.00	1,941
Team History (million USD)	123.563	133.273	-144.689	881.850	1,941
Team History–Positive (million USD)	167.775	151.758	0.000	1099.890	1,941
Team History–Negative (*-1 million USD)	44.212	39.426	0.000	288.302	1,941
Team–CV	1.57	16.02	-217.85	467.79	1,941
Team History/ Budget	123.56	133.27	-144.69	881.85	1,941
Team History/Budget–Positive	167.78	151.76	0.00	1099.89	1,941
Team History/Budget–Negative (*-1)	44.21	39.43	0.00	288.30	1,941
Team–CV/ Budget	1.57	16.02	-217.85	467.79	1,941
Running Time (minutes)	111	18	52	201	1,941
Sequel	0.14	0.35	0.00	1	1,941
Opening Weekend Theaters	2,464	1,242	0	4,575	1,941
Team Familiarity	0.831	2.505	0	25	1,941

Table 2: Correlations

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Movie-Profit (million USD)	1.000												
(2)	Movie-Profit/Budget (Percent)	0.163	1.000											
(3)	Team History (million USD)	0.272	-0.028	1.000										
(4)	Team History–Positive (million USD)	0.215	-0.048	0.970	1.000									
(5)	Team History–Negative (*-1 million USD)	-0.091	-0.089	0.354	0.570	1.000								
(6)	Team–CV	-0.013	-0.009	-0.008	-0.005	0.008	1.000							
(7)	Team History/ Budget	0.272	-0.028	1.000	0.970	0.354	-0.008	1.000						
(8)	Team History/Budget–Positive	0.215	-0.048	0.970	1.000	0.570	-0.005	0.970	1.000					
(9)	Team History/Budget–Negative (*-1)	-0.091	-0.089	0.354	0.570	1.000	0.008	0.354	0.570	1.000				
(10)	Team–CV/ Budget	-0.013	-0.009	-0.008	-0.005	0.008	1.000	-0.008	-0.005	0.008	1.000			
(11)	Running Time (minutes)	0.085	-0.078	0.146	0.163	0.134	-0.021	0.146	0.163	0.134	-0.021	1.000		
(12)	Sequel	0.200	-0.012	0.285	0.284	0.129	-0.010	0.285	0.284	0.129	-0.010	0.082	1.000	
(13)	Opening Weekend Theaters	0.208	-0.057	0.279	0.278	0.128	0.003	0.279	0.278	0.128	0.003	0.000	0.340	1.000
(14)	Team Familiarity	0.128	-0.003	0.221	0.203	0.034	-0.006	0.221	0.203	0.034	-0.006	0.102	0.277	0.106

5. Methodology

5.1. Empirical Approach

Our empirical approach to evaluate the hypotheses encompasses two sets of interrelated analyses. First, we examine the relation between the profits generated by a movie and the team members' experience with success and failure. Then, we account for the potential endogeneity involved in the formation of movie teams. Accordingly, we use models with instrumental variables to examine how the movie team members' history influences the profits generated by the movie. All our analyses were done using STATA (version 18.0).

5.1.1. Model Specification

We evaluate Hypothesis 1 that seeks to examine how the history of a movie team affects profits using the following specifications:

$$\textit{Movie-Profit}_{it} = \beta_0 + \beta_1 \textit{Team History}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \varepsilon_{it} \quad \ldots(1a)$$

$$\textit{Movie-Profit/Budget}_{it} = \beta_0 + \beta_1 \textit{Team History/ Budget}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \varepsilon_{it} \quad \ldots(1b)$$

In equations (1a) and (1b), the variables $\textit{Movie-Profit}_{it}$, $\textit{Movie-Profit/Budget}_{it}$, $\textit{Team History}_{it}$, and $\textit{Team History/ Budget}_{it}$ are as defined in § 4.2 and § 4.3. The vector $\boldsymbol{X}_{i(t-1)}$ includes the control variables—$\textit{Opening Weekend Theaters}_{it}$, $\textit{Running Time}_{it}$, $\textit{Sequel}_{it}$, and $\textit{Team-Familiarity}_{it}$—as described in § 4.4. FE_i includes the fixed effects—$\textit{Genre}_i$, $\textit{Rating}_i$, $\textit{Dist}_i$, and $\textit{YR}_i$—as described in in § 4.5. and ε_{it} represents the error terms.

Hypothesis 2 seeks to examines how the history with success or the history with failure of a movie team affects profits. We include the variables *Team History–Positive*$_{it}$ and *Team History–Negative*$_{it}$ in equation (1a) and the variables *Team History/Budget–Positive*$_{it}$ and *Team History/Budget–Negative*$_{it}$ in equation (1b) to obtain the following specifications to evaluate Hypotheses 2a and 2b:

$$\textit{Movie-Profit}_{it} = \beta_0 + \beta_2 \textit{Team History–Positive}_{it} + \beta_3 \textit{Team History–Negative}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \varepsilon_{it} \quad \ldots(2a)$$

$$\textit{Movie-Profit/Budget}_{it} = \beta_0 + \beta_2 \textit{Team History/Budget–Positive}_{it} + \beta_3 \textit{Team History/ Budget–Negative}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \varepsilon_{it} \quad \ldots(2b)$$

Hypothesis 3 seeks to examine how the relative dispersion in the history of a movie team affects profits. Therefore, we include the variable *Team–CV*$_{it}$ in equation (2a) and the variable *Team–CV/Budget*$_{it}$ in equation (2b) to obtain the following specifications to evaluate Hypothesis 3:

$$\textit{Movie-Profit}_{it} = \beta_0 + \beta_2 \textit{Team History–Positive}_{it} + \beta_3 \textit{Team History–Negative}_{it} + \beta_4 \textit{Team–CV}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \varepsilon_{it} \quad \ldots(3a)$$

$$\textit{Movie-Profit/Budget}_{it} = \beta_0 + \beta_2 \textit{Team History/Budget–Positive}_{it} + \beta_3 \textit{Team History/Budget–Negative}_{it} + \beta_4 \textit{Team–CV/Budget}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \varepsilon_{it} \quad \ldots(3b)$$

We estimate the above specifications with OLS regression and robust standard errors. These results are in Table 3. Columns (1), (2), and (3) show the estimation results for specifications (1a), 2(a), and (3a), respectively; while columns (4), (5), and (6) show the estimation results for specifications (1b), 2(b), and (3b), respectively.

5.1.2. Instrumental Variables Analysis

An underlying assumption in the analysis, so far, is that the movie team's history is exogenous to the success or failure of a movie. However, there are two broad reasons why the assumption may not be valid. First, several studies find that the previous box office performance of team members (e.g., actors, producers, directors) plays a role in driving the box office receipts of a focal movie (see, e.g., Hadida 2010, Carrillat et al. 2018). Furthermore, a common belief that prevails in the industry is that the cast and crew can have a significant impact on a movie's box office success (see, e.g., Anderson 2023). Thus, it is likely that movie makers will strive to create teams that have had a successful track record. Second, it is also possible that movies with a greater potential for success may attract team members with a history of success, which in turn could influence the collective experience of the members assembled to form a movie team. Therefore, it is likely that there is endogeneity between the profits of a movie and the *Team History* variable. Along similar lines, one could envisage that, at the extreme, movie makers focus solely on the past success of team members and create teams with members who have a history of working on profitable or successful projects. This would mean that there is potential endogeneity between the profits of a movie and the *Team History—Positive* variable.

To account for the potential endogeneity involved in the formation of movie teams, we leverage the "market-based instruments" framework (Nevo 2001, Nevo and Wolfram 2002)[1], which has also been used in several operations management (OM) studies (e.g., Kesavan et al. 2014, Cachon et al. 2018, Rawley et al. 2018). We use instruments that are related to the *Team History* variables but that are otherwise unrelated to the error terms in our model, in line with Wooldridge (2010). We instrument the *Team History* of the focal movie with the *Average Team History* of other movies in the same year. We reason that the *Average Team History* of other movies will be related to the *Team History* of the focal movie because all movies face similar challenges in generating box office revenues, thus satisfying the inclusion restriction. We also examine the F-statistics for the joint significance of the instruments in the first stage regression models and observe that the F-statistics are above 10 in all our first stage models. (The first stage results are shown in online appendix Table A1.) These results verify that our instruments satisfy the inclusion restriction and are not weak (Staiger and Stock 1997, Kesavan et al. 2014, Mani and Muthulingam 2019). While it is unlikely that *Average Team History* of other movies will be directly related to the box office revenues of the focal movie, these market-based instruments could be problematic when there exist unobserved shocks that make the errors correlated. Such potential shocks may occur across the distributors, genres, or similarly rated movies. Thus, following Nevo's (2001) suggestion, we include distributor-year, genre-year, and rating-year fixed effects in our instrumental variable regression models to absorb any unobservable group-specific shocks. While there is no generally accepted statistical approach for testing the exclusion restriction condition, especially when the number of endogenous variables and the number of instruments are the same as in our case, the presence of group-specific fixed effects plays the role of satisfying the exclusion restriction assumption. We use the instrumental variable approach to evaluate the models indicated in

[1] For example, Nevo and Wolfram (2002) investigate the effect of manufacturer coupons on the shelf price at retailers. Their instrument was the average of coupons at other cities within a region.

§ 5.1.1. The results of the instrumental variables regression are shown in columns (1) through (6) of Table 4.

6. Results

In this section, we present our results with the associated effects. We also discuss the robustness checks we did to validate our analysis. Aligned with recent suggestions in the literature (e.g., Amrhein et al. 2019, Haaf et al. 2019), we provide confidence intervals (CIs) and estimates of magnitude wherever applicable.

6.1. Results

We start by examining the estimation results for the control variables in our regression models. We observe that the coefficients for *Running Time (minutes)*, *Sequel*, and *Opening Weekend Theaters* are positive and significant in columns 1–3 in Tables 3 and 4 of the paper. Higher running time is often aligned with larger allocation of production budget and therefore such movies would have better creative inputs for production which would reflect in the improved quality of the final product (i.e., the movie). As a result, movies with higher running time are likely to be profitable. Movies with higher number of opening weekend theaters are likely to be movies that have higher resources allocated for promotion (see, e.g., Sorensen and Waguespack 2006, Moretti 2011, Natividad 2013) and therefore likely to garner profits. Sequels are typically commissioned after the success of the previous production (see, e.g., Narayan and Kadiyali 2016) and therefore likely to be profitable. In columns 4–6 of Tables 3 and 4, we note that the analysis involves normalization with production budget and correspondingly the coefficients of *Running Time (minutes)*, *Sequel*, and *Opening Weekend Theaters* are not significant. Overall, the results for these control variables are aligned with intuition.

H1 seeks to assess the impact of a team's history on the profits of a movie. To evaluate H1, we examine the coefficients of *Team History*$_{it}$ in column (1) of Tables 3 and 4. We observe that these coefficients are positive (0.105, 0.103) and significant ($p < 0.001$, $p < 0.001$), with CI [0.069, 0.142; 0.069, 0.136]. Next, we examine the coefficients of *Team History/Budget*$_{it}$ in column (4) of Tables 3 and 4 and observe that these coefficients are positive (0.051, 0.043) and significant ($p < 0.10$, $p < 0.10$). These results support H1 because they indicate that the team's history has a significant impact on the profitability of movie. Based on column (1) of Table 3, increasing the value of *Team History*$_{it}$ by a million dollars from the average value can increase the profits for an average movie by $105,470.

H2a and H2b seeks to assess the impact of a team's history with success or failure on the profits of a movie. To evaluate H2a, we examine the coefficients of *Team History–Positive*$_{it}$ in column (2) of Tables 3 and 4 and observe that these coefficients are positive (0.0129, 0.125) and significant ($p < 0.001$, $p < 0.001$), with a CI [0.093, 0.166; 0.089, 0.162]. Then, we examine the coefficients of *Team History /Budget–Positive*$_{it}$ in column (5) of Tables 3 and 4 and observe that these coefficients are positive (0.064, 0.058) and significant ($p < 0.05$, $p < 0.05$). These results support H2a because they indicate that the history with success of the team has a positive effect on the profitability of movie. Based on column (2) of Table 3, increasing the value of *Team History–Positive*$_{it}$ by a million dollars from the average value can increase the profits for an average movie by $129,440. Next, we evaluate H2b. We see that the coefficients of *Team History–Negative*$_{it}$ in column (2) of Tables 3 and 4 and observe that these coefficients are negative (-0.463, -0.456) and significant ($p < 0.001$, $p < 0.001$), with a CI [-0.574, -0.352; -0.565, -0.347]. Then, we examine the coefficients of *Team History /Budget–Negative*$_{it}$ in column (5) of Tables 3 and 4 and observe that these coefficients are negative (-0.995, -0.975) and significant ($p < 0.001$, $p < 0.001$). These results are counter to H2b because they indicate that the history with failure has a negative effect on the movie's profitability. Based on column (2) of Table 3, we calculate that increasing the value of *Team History–Negative*$_{it}$ by a million dollars (or in other words increasing the experience with failure resident within the team) can decrease the profits for an average movie by $463,250. Furthermore, a Wald test indicates that the coefficients of *Team History–Negative*$_{it}$ and *Team History–Positive*$_{it}$ are significantly different from each other (i.e., $\beta_3 < \beta_2$; $p < 0:001$). This suggests that failure has a bigger impact than success. Furthermore, since this result is counter to H2b, it suggests that when organizations have fluid teams they do not necessarily learn and improve as they gain experience with failure, as they do from the experience with success.

H3 seeks to examine how the relative dispersion in a team's history affects the profitability of a movie. To evaluate H3, we examine the coefficients of *Team–CV*$_{it}$ in column (3) of Tables 3 and 4. We observe that these coefficients are negative (-0.0710, -0.0710) but they are not significant. Then, we examine the coefficients of *Team–CV/Budget*$_{it}$ in column (6) of Tables 3 and 4. We observe that these coefficients are negative (-5.219, -5.243) and significant ($p < 0.10$, $p < 0.10$). The signs of the coefficients for the relative dispersion are not aligned with H3. Furthermore, the coefficients are not significant across all models. Therefore, our results do not support H3. In other words, we infer that the increased relative dispersion in the team's experience does not have a significant effect on the movie's profitability.

Table 3: Main Regression Results

Dependent Variable →	Movie Profit			Movie Profit/ Budget		
	(1)	(2)	(3)	(4)	(5)	(6)
Team History (β_1)	0.105***					
	(0.018)					
Team History—Positive (β_2)		0.129***	0.129***			
		(0.019)	(0.019)			
Team History—Negative (β_3)		-0.463***	-0.462***			
		(0.056)	(0.057)			
Team—CV (β_4)			-0.0710			
			(0.071)			
Team History/Budget (β_5)				0.051+		
				(0.030)		
Team History/Budget—Positive (β_6)					0.064*	0.064*
					(0.030)	(0.030)
Team History/Budget—Negative (β_7)					-0.995***	-0.985***
					(0.242)	(0.239)
Team—CV/ Budget (β_8)						-5.219+
						(2.918)
Controls						
Running Time (minutes)	0.256*	0.314**	0.314**	-2.038+	-1.6650	-1.6640
	(0.116)	(0.116)	(0.116)	(1.238)	(1.157)	(1.157)
Sequel	19.681**	19.822**	19.778**	-25.2740	-19.1690	-19.2100
	(6.383)	(6.260)	(6.262)	(31.302)	(30.402)	(30.459)
Opening Weekend Theaters	0.009***	0.009***	0.009***	-0.0490	-0.0460	-0.0460
	(0.002)	(0.002)	(0.002)	(0.046)	(0.046)	(0.046)
Team Familiarity	0.7060	0.5110	0.5130	1.3620	1.7910	1.7070
	(0.637)	(0.626)	(0.626)	(3.453)	(3.501)	(3.487)
Constant	-29.1060	-39.2090	-38.2910	327.289+	257.594	267.742+
	(25.748)	(25.708)	(25.662)	(171.165)	(158.100)	(161.850)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.129	0.155	0.155	0.043	0.049	0.049
Number	1,941	1,941	1,941	1,941	1,941	1,941

*+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; We report coefficient estimates with clustered standard errors in parentheses.*

Table 4: Regression Results with Instrumental Variables

Dependent Variable →	Movie Profit			Movie Profit/ Budget		
	(1)	(2)	(3)	(4)	(5)	(6)
Team History (β_1)[@]	0.103***					
	(0.017)					
Team History—Positive (β_2)[#]		0.125***	0.125***			
		(0.019)	(0.019)			
Team History—Negative (β_3)		-0.456***	-0.455***			
		(0.056)	(0.056)			
Team—CV (β_4)			-0.0710			
			(0.070)			
Team History/Budget (β_5)[@]				0.043+		
				(0.026)		
Team History/Budget—Positive (β_6)[#]					0.058*	0.058*
					(0.027)	(0.027)
Team History/Budget—Negative (β_7)					-0.975***	-0.967***
					(0.239)	(0.236)
Team—CV/ Budget (β_8)						-5.243+
						(2.855)
Controls						
Running Time (minutes)	0.298**	0.317**	0.317**	-2.739+	-1.6760	-1.6740
	(0.115)	(0.114)	(0.114)	(1.461)	(1.133)	(1.132)
Sequel	17.223**	20.032**	19.988**	-60.615+	-16.8900	-17.1330
	(5.802)	(6.129)	(6.129)	(35.802)	(29.804)	(29.862)
Opening Weekend Theaters	0.010***	0.010***	0.010***	-0.0300	-0.0460	-0.0460
	(0.002)	(0.002)	(0.002)	(0.033)	(0.045)	(0.045)
Team Familiarity	0.5850	0.5430	0.5440	-4.4790	1.9500	1.8520
	(0.607)	(0.608)	(0.608)	(8.027)	(3.392)	(3.377)
Constant	-125.9970	-46.572*	-45.726*	368.669+	404.681+	414.916+
	(126.925)	(21.651)	(21.623)	(212.392)	(211.164)	(214.925)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Distributor-Year	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Genre-Year	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Rating-Year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.152	0.155	0.155	0.030	0.049	0.049
Number	1,941	1,941	1,941	1,941	1,941	1,941

*+ $p< 0.10$, * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$; We report coefficient estimates with clustered standard errors in parentheses. @— 'Team History' and 'Team History/Budget' are instrumented with average 'Team History' and average 'Team History/Budget' of other movies in the same year as the focal movie, respectively; #— 'Team History—Positive' and 'Team History/Budget—Positive' are instrumented with average 'Team History—Positive' and average 'Team History/Budget—Positive' of other movies in the same year as the focal movie, respectively.*

7. Robustness Checks and Analysis

In this section, we conduct robustness checks to validate our results and present further analysis on the impact of team composition on financial performance.

7.1. Robustness Checks

7.1.1. Propensity Score Matching

Movies that make profits may be distinctly dissimilar to movies that fail to make profits. To ensure our results are not driven by systematic differences between movies with and without profits, we use a propensity score matching (PSM) approach with the nearest three neighbor (NN3) algorithm to minimize differences between such movies. The idea behind this matching approach is that movies with profits are matched with three similar movies that did not make profits (Heckman et al. 1997).

We generated a matched sample of movies that are similar with respect to their observed characteristics but differ in whether they made profits or not. For the PSM, we use Production Budget, Running Time, Sequel, and Opening Weekend Theaters as the matching variables. The reduction in bias across these covariates ranges between 38.1% to 99.8%. Figure 1 illustrates the standardized reduction in bias. We repeat the analysis conducted in Section 5.1.1. and Section 5.1.2. and these results are shown in Tables 5 and 6. These results are consistent with the main results in Tables 3 and 4, which provides additional validity to our findings.

Figure 1. Standardized Bias Reduction after PSM

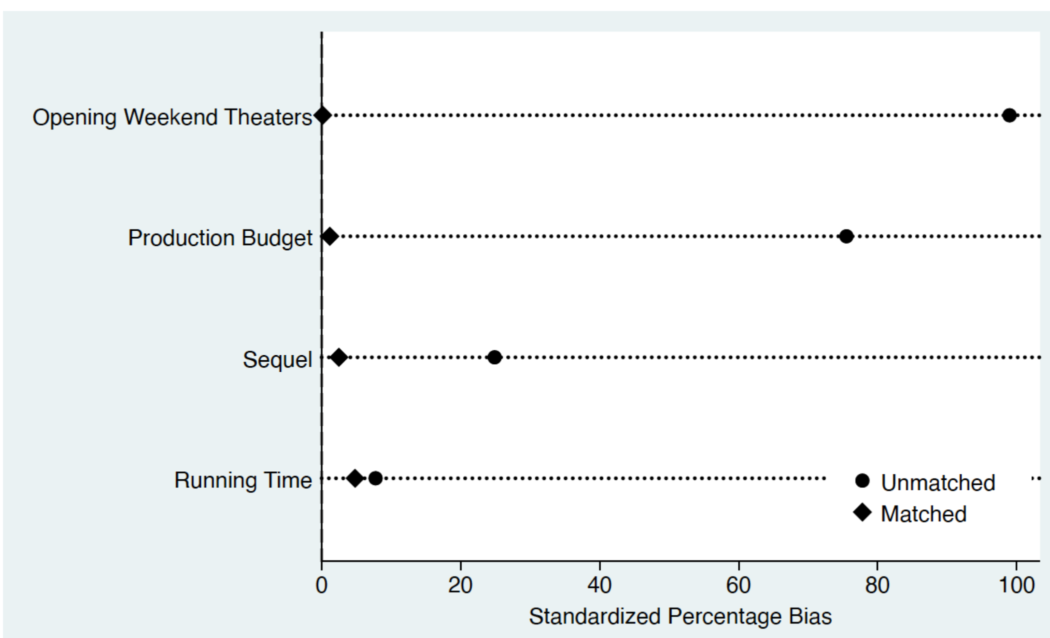

Table 5: Regression Results with PSM (NN3)

Dependent Variable →	Movie Profit			Movie Profit/ Budget		
	(1)	(2)	(3)	(4)	(5)	(6)
Team History (β_1)	0.090***					
	(0.025)					
Team History—Positive (β_2)		0.110***	0.110***			
		(0.024)	(0.024)			
Team History—Negative (β_3)		-0.440***	-0.441***			
		(0.065)	(0.065)			
Team—CV (β_4)			0.0100			
			(0.055)			
Team History/Budget (β_5)				0.098***		
				(0.026)		
Team History/Budget—Positive (β_6)					0.119***	0.121***
					(0.028)	(0.028)
Team History/Budget—Negative (β_7)					-1.167***	-1.137***
					(0.262)	(0.255)
Team—CV/ Budget (β_8)						-6.199*
						(2.738)
Controls						
Running Time (minutes)	0.3670	0.485+	0.484+	-2.0640	-1.4400	-1.4130
	(0.261)	(0.258)	(0.259)	(1.294)	(1.169)	(1.164)
Sequel	5.9110	7.9180	7.9090	-68.7150	-54.4200	-59.7050
	(9.042)	(8.631)	(8.633)	(46.497)	(44.227)	(45.143)
Opening Weekend Theaters	0.016**	0.017**	0.017**	-0.0080	-0.0040	-0.0060
	(0.006)	(0.006)	(0.006)	(0.037)	(0.036)	(0.036)
Team Familiarity	0.4400	0.2750	0.2760	-1.2080	-0.8460	-0.4420
	(0.963)	(0.875)	(0.875)	(4.553)	(4.571)	(4.526)
Constant	-82.132+	-100.727*	-100.692*	292.230	165.262	180.479
	(42.309)	(41.986)	(42.089)	(207.917)	(190.077)	(192.386)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.254	0.280	0.279	0.045	0.057	0.057
Number	1,439	1,439	1,439	1,439	1,439	1,439

*+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; We report coefficient estimates with clustered standard errors in parentheses.*

Table 6: Regression Results with Instrumental Variables and PSM (NN3)

Dependent Variable →	Movie Profit			Movie Profit/ Budget		
	(1)	(2)	(3)	(4)	(5)	(6)
Team History (β_1)@	0.067***					
	(0.015)					
Team History—Positive (β_2)#		0.101***	0.101***			
		(0.017)	(0.017)			
Team History—Negative (β_3)		-0.371***	-0.371***			
		(0.050)	(0.050)			
Team—CV (β_4)			0.0320			
			(0.044)			
Team History/Budget (β_5)@				0.073*		
				(0.028)		
Team History/Budget—Positive (β_6)#					0.079*	0.080*
					(0.033)	(0.033)
Team History/Budget—Negative (β_7)					-1.146***	-1.125***
					(0.294)	(0.289)
Team—CV/ Budget (β_8)						-8.116+
						(4.410)
Controls						
Running Time (minutes)	0.291**	0.307**	0.307**	-2.6690	-2.3180	-2.3120
	(0.101)	(0.108)	(0.108)	(1.669)	(1.609)	(1.606)
Sequel	13.607*	14.204*	14.214*	-14.7820	-3.1300	-8.6710
	(5.316)	(5.570)	(5.571)	(42.428)	(39.451)	(39.510)
Opening Weekend Theaters	0.007***	0.007***	0.007***	-0.0250	-0.0730	-0.0730
	(0.002)	(0.002)	(0.002)	(0.027)	(0.058)	(0.058)
Team Familiarity	1.917**	1.692*	1.693*	-6.0740	-0.6070	-0.4490
	(0.689)	(0.691)	(0.691)	(6.812)	(3.710)	(3.715)
Constant	-170.023***	(21.196)	(21.144)	251.631	644.300*	654.592*
	(50.672)	(23.850)	(23.858)	(232.449)	(320.262)	(324.249)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Distributor-Year	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Genre-Year	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Rating-Year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.186	0.149	0.148	0.074	0.053	0.053
Number	1,439	1,439	1,439	1,439	1,439	1,439

*+ p< 0.10, * p< 0.05, ** p< 0.01, *** p< 0.001; We report coefficient estimates with clustered standard errors in parentheses. @— 'Team History' and 'Team History/Budget' are instrumented with average 'Team History' and average 'Team History/Budget' of other movies in the same year as the focal movie, respectively; #— 'Team History—Positive' and 'Team History/Budget—Positive' are instrumented with average 'Team History—Positive' and average 'Team History/Budget—Positive' of other movies in the same year as the focal movie, respectively.*

We also validated that our results are similar when we use the NN5 and NN1 matching algorithms. These results are in the online appendix Tables A2 and A3.

7.1.2. Alternative Definitions of Success

It is possible that executives in the film industry may assess whether the movie is a success or failure based on whether the movie crosses some threshold of financial return. To address this issue, we evaluated our findings with alternative definitions of success. We created four alternative measures of success based on four different thresholds (i.e., 5%, 10%, 15%, and 20%) of financial return. In the first measure, we record a film as a success when the film's financial return is greater than 5 % of the production budget. Similarly, in the second, third and fourth measures, we record a film as a success if the financial return is greater than 10 %, 15%, and 20%, respectively, of the production budget. We use these modified measures to create indicators that serve as the dependent variables for our analysis. The results for the estimation of the logit models are shown in Table 7 below and they are consistent with the main results presented in Table 3.

Table 7: Regression Results with Alternative Definitions of Success

Dependent Variable →	Success if Movie Profit/Budget > 5%			Success if Movie Profit/Budget > 10%			Success if Movie Profit/Budget > 15%			Success if Movie Profit/Budget > 20%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Team History/Budget (β_1)	0.00032***			0.00032***			0.00032***			0.00032***		
	(0.000)			(0.000)			(0.000)			(0.000)		
Team History/Budget—Positive (β_2)		0.00052***	0.00052***		0.00052***	0.00052***		0.00052***	0.00052***		0.00052***	0.00052***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Team History/Budget—Negative (β_3)		-0.0049***	-0.0049***		-0.0049***	-0.0049***		-0.0049***	-0.0049***		-0.0049***	-0.0049***
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Team—CV/ Budget (β_4)			-0.043*			-0.043*			-0.043*			-0.043*
			(0.020)			(0.020)			(0.020)			(0.020)
Controls												
Running Time (minutes)	0.0007	0.0022	0.0021	0.0007	0.0022	0.0021	0.0008	0.0023	0.0022	0.0008	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Sequel	0.2700	0.32+	0.31+	0.2700	0.32+	0.31+	0.27+	0.32+	0.31+	0.27+	0.32+	0.31+
	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)	(0.170)
Opening Weekend Theaters	0.00037***	0.00038***	0.00038***	0.00037***	0.00038***	0.00038***	0.00036***	0.00038***	0.00038***	0.00036***	0.00038***	0.00038***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Team Familiarity	0.080**	0.085**	0.085**	0.080**	0.085**	0.085**	0.080**	0.086**	0.085**	0.080**	0.086**	0.085**
	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)
Constant	-0.8000	-1.13+	(1.060)	(0.800)	-1.13+	(1.060)	(0.800)	-1.12+	(1.060)	(0.800)	-1.12+	(1.060)
	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)	(0.670)
Fixed Effects												
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log. Likelihood	-1185.7	-1166.7	-1163.6	-1185.7	-1166.7	-1163.6	-1186.4	-1167.5	-1164.3	-1186.4	-1167.5	-1164.3
Number	1,927	1,927	1,927	1,927	1,927	1,927	1,927	1,927	1,927	1,927	1,927	1,927

*+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; We report coefficient estimates with clustered standard errors in parentheses.*

7.1.3. Role Based Measures of Experience

One potential concern on our measures, so far, is that they may be influenced by the roles with more members. In other words, if a movie team has many members in the leading actor role but only one member each for the other roles then the resulting measures would be influenced more by the history of the leading actors. Therefore, we define another set of four independent variables as follows:

Team History (Role)$_{it}$. To calculate this variable, we compute the average history for each role. For instance, for a specific screenwriter *k* we compute the cumulative profits as $\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(R_{kjl} - C_{kjl})$, then we calculate the average history for the screenwriter role for movie i as $(\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(R_{kjl} - C_{kjl}))/K$ (where K represents the number of screen writers involved in the movie). Similarly, we calculate the average history for the other roles (i.e, executive producers, producers, directors, and lead actors). Then, we calculate *Team History (Role)$_{it}$* as the sum of the average histories of the executive producers, producers, directors, screenwriters, and lead actors.

Correspondingly, *Team History (Role)–Positive$_{it}$* and *Team History (Role)–Negative$_{it}$* are calculated using each member's history with success and history with failure, respectively.

Team (Role)–CV$_{it}$. We calculate the standard deviation of the average histories of the executive producers, producers, directors, screenwriters, and lead actors. Then, we compute the variable (i.e., *Team (Role)–CV$_{it}$*) as the standard deviation divided by the *Team History (Role)$_{it}$*.

We use the above defined role-based definitions of experience and evaluate the models indicated in § 5.2.1. Table 8 shows these results for the OLS models in columns (1) through (3) and for the instrumental variables models in columns (4) through (6). The results in Table 8 are aligned with the main results presented in Tables 3 and 4.

Table 8: Regression Results with Role-Based Definitions of Experience

Dependent Variable →		Movie Profit OLS			Movie Profit Instrumental Variable	
	(1)	(2)	(3)	(4)	(5)	(6)
Team History (Role) (β_1)	0.021***			0.016***		
	(0.005)			(0.004)		
Team History (Role)—Positive (β_2)		0.030***	0.030***		0.022***	0.022***
		(0.006)	(0.006)		(0.004)	(0.004)
Team History (Role)—Negative (β_3)		-0.105***	-0.105***		-0.089***	-0.089***
		(0.015)	(0.015)		(0.012)	(0.012)
Team (Role)—CV (β_4)			-0.0760			-0.0730
			(0.111)			(0.106)
Controls						
Running Time (minutes)	0.247*	0.313**	0.314**	0.296*	0.330**	0.330**
	(0.117)	(0.118)	(0.118)	(0.116)	(0.115)	(0.115)
Sequel	21.326***	20.645***	20.608**	19.847***	20.825***	20.790***
	(6.363)	(6.255)	(6.259)	(5.808)	(6.141)	(6.143)
Opening Weekend Theaters	0.009***	0.010***	0.010***	0.011***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Team Familiarity	0.7670	0.7800	0.7770	0.6910	0.6230	0.6210
	(0.639)	(0.624)	(0.624)	(0.613)	(0.618)	(0.618)
Constant	-30.7860	(40.598)	(40.550)	(128.008)	-47.563*	-47.435*
	(26.064)	(25.970)	(25.976)	(132.247)	(22.034)	(22.026)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Distributor-Year	-	-	-	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Genre-Year	-	-	-	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Rating-Year	-	-	-	Yes	Yes	Yes
Adjusted R-Square	0.124	0.150	0.150	0.141	0.147	0.147
Number	1,941	1,941	1,941	1,941	1,941	1,941

*+ p< 0.10, * p< 0.05, ** p< 0.01, *** p< 0.001; We report coefficient estimates with clustered standard errors in parentheses. In columns (4) through (6) 'Team History (Role)' and 'Team History (Role)—Positive' are instrumented with average 'Team History (Role)' and average 'Team History (Role)—Positive' of other movies in the same year as the focal movie, respectively.*

7.2. Analyzing the Impact of Team Composition on Financial Performance

So far, we explored how a movie team's history with success and failure affects the financial performance of a movie. Now, we delve deeper to examine how the composition of the history with success and failure embedded in the five key roles affects financial performance. Specifically, we ask whether it is beneficial to compose movie teams where all the roles (i.e., executive producers, producers, directors, screenwriters, and lead actors) have a history of success, all the roles have history of failure, or the roles have a mix of history with success and failure. Towards this end, we calculate the average history for each role as $(\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=0}^{(t-1)}(R_{kjl}-C_{kjl}))/K$(as described in § 7.1.3.). We use this value to score the history for a role on a scale of 1, 0, -1. Where 1 indicates that the history for the role is positive (i.e., success), 0 indicates that there is no history (i.e., when the members in the role have not been involved in any movies before), and -1 indicates that the history for the role is negative (i.e., failure). Then, we compute a team's composition as the sum of scores for all the roles. Thus, a team's composition score of 5 indicates that all five roles (i.e., executive producers, producers, directors, screenwriters, and lead actors) have history with success. At the other extreme, a team's composition score of -5 indicates that all five roles have history with failure. Next, we use indicators to identify the different potential team compositions. For instance, '*Team Comp-All Roles Positive*' is 1 when the team's composition score is 5, '*Team Comp-Net Four Roles Positive*' is 1 when the team's composition score is 4, and so forth. This allows us to use the following specification to evaluate the impact of team composition on a movie's financial performance:

$$\begin{aligned}
&\textit{Movie-Profit}_{it} = \beta_0 + \beta_5 \textit{Team Comp-All Roles Positive}_{it} + \beta_6 \textit{Team Comp-Net Four Roles Positive}_{it} + \\
&\beta_7 \textit{Team Comp-Net Three Roles Positive}_{it} + \beta_8 \textit{Team Comp-Net Two Roles Positive}_{it} + \\
&\beta_9 \textit{Team Comp-Net One Role Positive}_{it} + \beta_{10} \textit{Team Comp-Net One Role Negative}_{it} + \\
&\beta_{11} \textit{Team Comp-Net Two Roles Negative}_{it} + \beta_{11} \textit{Team Comp-Net Three Roles Negative}_{it} + \\
&\beta_{11} \textit{Team Comp-Net Four Roles Negative}_{it} + \beta_{11} \textit{Team Comp-All Roles Negative}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \\
&\varepsilon_{it} \qquad \ldots(4)
\end{aligned}$$

We estimate equation (4) in a stepwise fashion with OLS and robust standard errors. These results are shown in columns (1) through (11) of Table 9, where column (1) has the results for only the control variables while column (11) has the results for the comprehensive model.

We examine column (11) of Table 9 and observe that the coefficients of *Team Comp-All Roles Positive*$_{it}$ are positive (13.036) and significant ($p < 0.05$). We also see that the coefficients of *Team Comp-Net Four Roles Positive*$_{it}$ are positive (12.727) and significant ($p < 0.05$). These results suggest that movie teams which predominantly have roles with a history of success will have higher profits. For instance, based on column (11) of Table 11, when an average movie has a team where all roles have a history of success then the profits will be higher by $13.04 million dollars. By contrast, in Column (11) of Table 9, we observe that the coefficients of *Team Comp-Net Three Roles Negative*$_{it}$, *Team Comp-Net Four Roles Negative*$_{it}$, and *Team Comp-All Roles Negative*$_{it}$ are all negative (-16.330, -23.172, -23.106) and significant ($p < 0.10, p < 0.10, p < 0.05$). These results suggest that movie teams which predominantly have roles with a history of failure will realize lower profits. For instance, based on column (11) of Table 9, when an average movie has a team where all roles have a history of failure then the profits will be lower by $23.106 million dollars. The coefficients for all other team compositions are not significant.

Table 9: Regression Results for the Net Positive or Net Negative History of Team Roles

Dependent Variable →	Movie Profit										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Team Comp–All Roles Positive (β_1)										13.213*	13.036*
										(6.087)	(6.101)
Team Comp–Net Four Roles Positive (β_2)								4.6290	4.0270	12.882*	12.727*
								(5.512)	(5.539)	(5.612)	(5.626)
Team Comp–Net Three Roles Positive (β_3)						(4.945)	(5.576)	(3.659)	(4.272)	4.289	4.130
						(4.225)	(4.254)	(4.845)	(4.885)	(4.729)	(4.744)
Team Comp–Net Two Roles Positive (β_4)					-1.2470	-3.0450	-3.7090	-1.8180	-2.4210	5.794	5.634
					(3.536)	(3.907)	(3.937)	(4.512)	(4.544)	(4.606)	(4.627)
Team Comp–Net One Role Positive (β_5)		-2.6750	-3.1710	-3.1710	-3.8020	-5.6180	-6.3600	-4.4930	-5.1640	2.985	2.833
		(3.685)	(3.716)	(3.716)	(3.874)	(4.229)	(4.269)	(4.746)	(4.786)	(4.821)	(4.838)
Team Comp–Net One Role Negative (β_6)			-6.6940	-6.6940	-7.3690	-9.1510	-9.954+	-8.0910	-8.8850	(0.944)	(1.096)
			(5.488)	(5.488)	(5.592)	(5.848)	(5.871)	(6.263)	(6.297)	(6.346)	(6.364)
Team Comp–Net Two Roles Negative (β_7)					-9.7770	-11.563+	-12.416+	-10.6000	-11.3080	(3.496)	(3.638)
					(6.629)	(6.813)	(6.847)	(7.125)	(7.137)	(7.268)	(7.278)
Team Comp–Net Three Roles Negative (β_8)							-24.829**	-23.141**	-23.869**	-16.197+	-16.330+
							(8.677)	(8.844)	(8.885)	(8.950)	(8.963)
Team Comp–Net Four Roles Negative (β_9)									-31.269*	-23.030+	-23.172+
									(12.168)	(12.066)	(12.082)
Team Comp–All Roles Negative (β_{10})											-23.106*
											(9.362)
Controls											
Running Time (minutes)	0.357**	0.357**	0.355**	0.355**	0.355**	0.351**	0.350**	0.356**	0.357**	0.340**	0.339**
	(0.118)	(0.117)	(0.118)	(0.118)	(0.118)	(0.118)	(0.118)	(0.119)	(0.119)	(0.120)	(0.120)
Sequel	25.645***	25.535***	25.391***	25.391***	25.292***	25.089***	24.951***	25.042***	24.738***	24.192***	24.285***
	(6.506)	(6.501)	(6.502)	(6.502)	(6.501)	(6.494)	(6.488)	(6.471)	(6.467)	(6.444)	(6.463)
Opening Weekend Theaters	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Team Familiarity	1.537*	1.515*	1.509*	1.509*	1.475*	1.386*	1.381*	1.420*	1.426*	1.233+	1.229+
	(0.643)	(0.644)	(0.645)	(0.645)	(0.652)	(0.654)	(0.655)	(0.658)	(0.656)	(0.673)	(0.674)
Constant	-47.698+	-47.126+	-45.977+	-45.977+	-45.540+	(42.747)	(41.727)	-44.908+	-43.390+	-47.480+	-47.274+
	(25.883)	(25.901)	(26.013)	(26.013)	(26.037)	(26.428)	(26.430)	(26.298)	(26.319)	(26.265)	(26.274)
Fixed Effects											
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.098	0.098	0.098	0.098	0.097	0.097	0.098	0.098	0.099	0.100	0.100
Number	1,941	1,941	1,941	1,941	1,941	1,941	1,941	1,941	1,941	1,941	1,941

*+ $p< 0.10$, * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$; We report coefficient estimates with clustered standard errors in parentheses.*

Overall, the results in Table 9 indicate that compared to the average, a movie can expect a boost in profits when it has a history of success for at least four of the five key roles in a movie's team, whereas a movie can anticipate lower profits when it has a history of failure for at least three of the five key roles. This suggests that when we compose teams, we should not have more than two roles that have a prior history of failure and try to have at least four roles with prior history of success.

Next, we seek to examine how the history of success or failure of a specific role affects the financial performance of a movie. To this end, we use indicators to identify whether a specific role has a history with success or not. For instance, '*Lead Actors—Positive*' is 1 when the movie's lead actors' average prior history is positive and is 0 otherwise. '*Executive Producers—Positive*', '*Producers—Positive*', '*Directors—Positive*', and '*Screenwriters—Positive*' are defined analogously. These indicators allow us to estimate the following specification:

$$\textit{Movie-Profit}_{it} = \beta_0 + \beta_{12}\textit{Lead Actors—Positive}_{it} + \beta_{13}\textit{Directors—Positive}_{it} + \beta_{14}\textit{Producers—Positive}_{it} + \beta_{15}\textit{Executive Producers—Positive}_{it} + \beta_{16}\textit{Screenwriters—Positive}_{it} + \gamma \boldsymbol{X}_{i(t-1)} + \delta_1 FE_i + \varepsilon_{it} \quad \ldots(5)$$

Table 10 shows the stepwise estimation results for equation (5).

Table 7: Regression Results for the Impact of Specific Roles on Movie Profits

Dependent Variable →	**Movie Profit**				
	(1)	(2)	(3)	(4)	(5)
Lead Actor—Positive (β_1)	4.0480	4.1130	3.8590	3.6650	3.6290
	(3.975)	(3.985)	(3.970)	(3.980)	(3.976)
Director—Positive (β_2)		-2.6230	-3.6280	-3.7410	-4.1300
		(2.846)	(2.885)	(2.883)	(2.936)
Producer—Positive (β_3)			5.967*	5.061+	4.822+
			(2.793)	(2.854)	(2.868)
Executive Producer—Positive (β_4)				8.901**	8.744**
				(3.268)	(3.275)
Screenwriter—Positive (β_5)					2.9610
					(2.881)
Controls					
Running Time (minutes)	0.360**	0.377**	0.378**	0.366**	0.362**
	(0.117)	(0.119)	(0.118)	(0.119)	(0.118)
Sequel	25.59***	25.60***	25.24***	25.09***	24.61***
	(6.500)	(6.504)	(6.512)	(6.490)	(6.493)
Opening Weekend Theaters	0.0109***	0.0110***	0.0108***	0.0105***	0.0104***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Team Familiarity	1.506*	1.556*	1.479*	1.435*	1.361*
	(0.644)	(0.652)	(0.652)	(0.647)	(0.658)
Constant	-50.84*	-52.14*	-53.19*	-53.64*	-53.47*
	(25.760)	(25.700)	(25.760)	(25.560)	(25.520)
Fixed Effects					
Year	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.098	0.098	0.099	0.102	0.102
Number	1,941	1,941	1,941	1,941	1,941

*+ $p< 0.10$, * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$; We report coefficient estimates with clustered standard errors in parentheses.*

We observe from column (5) for the full model that the coefficients for '*Producers—Positive*', and '*Executive Producers—Positive*', are positive (i.e., 4.822, 8.744) and significant ($p <0.10, p < 0.01$) whereas the coefficient for '*Lead Actors—Positive*', '*Directors—Positive*', and '*Screenwriters—Positive*' are not significant. These results indicate that the presence of Producers and Executive Producers with a history of success can provide a positive boost to the current movie's profits. Interestingly, the results suggest that the history of Lead Actors and Directors does not have a significant effect on a movie's profits. In this way, our results are counter to the conventional wisdom espoused in prior research that actors and directors play a disproportionate role in the success of a movie (see, e.g., Elberse 2007, McKenzie 2012)—probably, because prior work has mainly explored the impact of actors and directors without considering the influence that other team members can have on the success of a movie. Thus, our results suggest that studios should take greater care in ensuring that the movie team is composed with Producers and Executive Producers with a track record of success.

8. Discussion and Conclusion

Our study extends the literature by casting light on how the experience with success and failure resident within members of a team affects performance in the motion picture industry. We observe that the history of a team has a significant effect on the profitability of a movie. On examining the impact of experience with success and failure, we find that the team's history with success has a positive effect on the movie's profitability. By contrast, the team's history with failure has a negative effect on the movie's profitability. Furthermore, we examine how the composition of the history with success and failures embedded across the five key roles in a movie team affects profits. We find that movie teams composed with at least four key roles with a history of success realize higher profits, whereas teams composed with three or more key roles with a history of failure realize lower profits.

Our results raise the logical question, why does the history with failure not contribute to improved performance as has been observed across several studies in the literature? One explanation can be traced to the mechanisms by which failure contributes to the development of knowledge. Prior work suggests that failure reveals the inadequacies in current processes (e.g., the disintegration of foam insulation in orbital launch vehicle, as in Madsen and Desai 2010). Thus, failure can provide clues on what needs to be fixed or improved. Unfortunately, in the context of movie production, when a movie fails to make profits there is little information that can be gleaned on what was inadequate in the production process. Another explanation can be drawn from attribution theory. For instance, KC et al. (2013) find that individual surgeons do not learn from their own failure as they attribute such failures to other events out of their control. Similarly, individuals who work on movies that fail to make profits may attribute the failure to the inadequacies of other team members, which may prevent them from learning how to avoid failure.

Our results also raise the questions, why do teams realize higher profits only when they are predominantly composed of key roles with a history of success? Or, alternatively, why does increased relative dispersion in a movie team's experience not contribute to success? The answer can be traced to the context of movie production, where different roles perform distinct tasks in coordination with other roles. When teams are composed predominantly with members with a history of success, each role performs its task using the experience that led to success in the past. As a result, most of the distinct tasks in movie production tend to be executed with knowledge gleaned from prior success, which in turn drives the success of the current movie. By contrast, if a minority of the roles had a history with success, then some tasks may not be executed in a manner that are consistent to ensure success, which in turn could disrupt the profit potential of the movie.

Our study is not without limitations, but we hope these can be addressed in future research. First, we have restricted our study to the U.S. motion picture industry. It would be interesting to explore whether our results carry over to motion picture industries in other countries such as France, China, and India. Second, movie production is a creative endeavor which involves significant coordination of creative talent. It remains to be understood whether our results would apply to industries which use fluid teams but with lesser requirements for creativity such as software implementation, construction, and consulting services. Third, we do not observe the time spent by each member or the incentives for each member for a movie. It would be a fruitful avenue for future studies to examine whether these factors affect movie profits. Fourth, we could not obtain reliable information on the advertising expense for a movie, and we hope that future studies could obtain such information to augment our analysis. Fifth, we provide insights on the composition of teams that facilitate successful outcomes, but we were unable to pinpoint the exact mechanisms that drive success. We hope that future research can obtain detailed information not only on the decisions involved in movie production but also on the contribution of various team members in the decision-making processes. Analysis of such information could help illuminate the mechanisms that potentially contribute to success. We hope our research spurs further work on how the prior experiences of team members can shape business outcomes.

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Online Appendix

Here we present additional analysis that supplement the main analysis reported in the paper.

Table A1: First Stage Regression Results with Instrumental Variable

Dependent Variable →	Team History	Team History—Positive		Team History/Budget	Team History/Budget—Positive	
	(1)	(2)	(3)	(4)	(5)	(6)
Average Team History (β_1)	-147.174***					
	(0.104)					
Average Team History—Positive (β_2)		-133.951***	-133.943***			
		(3.527)	(3.528)			
Team History—Negative (β_3)		0.488***	-0.488***			
		(0.064)	(0.064)			
Team—CV (β_4)			-0.0193			
			(0.030)			
Average Team History/Budget (β_5)				-172.804***		
				(6.537)		
Average Team History/Budget—Positive (β_6)					-162.926***	-162.948***
					(5.055)	(5.049)
Team History/Budget—Negative (β_7)					0.1284	0.1371
					(0.239)	(0.239)
Team—CV/ Budget (β_8)						-5.294*
						(2.350)
Controls						
Running Time (minutes)	-0.0484	-0.1086	-0.1086	-0.6397	-1.103*	-1.101*
	(0.104)	(0.080)	(0.080)	(0.631)	(0.463)	(0.463)
Sequel	5.8625	9.992*	9.979*	39.5833	46.5984	46.3586
	(5.089)	(3.990)	(3.991)	(31.339)	(25.331)	(25.285)
Opening Weekend Theaters	0.004+	0.005***	0.0045***	-0.0064	-0.0054	-0.0055
	(0.002)	(0.001)	(0.001)	(0.011)	(0.008)	(0.008)
Team Familiarity	0.5432	0.7608	0.7612	-4.3150	-3.2588	-3.3584
	(0.705)	(0.566)	(0.566)	(4.605)	(4.049)	(4.047)
Constant	22218.03***	27841.64***	27840.24***	148005.90***	161077.70***	161109.10***
	(933.95)	(731.54)	(731.86)	(5612.99)	(4986.83)	(4981.18)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistic	2873.5	5418.3	335.3	15508.1	1951.6	352745.4
Adjusted R-Square	0.918	0.920	0.919	0.945	0.929	0.930
Number	1,941	1,941	1,941	1,941	1,941	1,941

*+ p< 0.10, * p< 0.05, ** p< 0.01, *** p< 0.001; We report coefficient estimates with clustered standard errors in parentheses. @— 'Team History' and 'Team History/Budget' are instrumented with average 'Team History' and average 'Team History/Budget' of other movies in the same year as the focal movie, respectively; #— 'Team History—Positive' and 'Team History/Budget—Positive' are instrumented with average 'Team History—Positive' and average 'Team History/Budget—Positive' of other movies in the same year as the focal movie, respectively.*

Table A2: Regression Results with PSM (NN5)

Dependent Variable →	Movie Profit			Movie Profit/ Budget		
	(1)	(2)	(3)	(4)	(5)	(6)
Team History (β_1)	0.092***					
	(0.025)					
Team History—Positive (β_2)		0.112***	0.112***			
		(0.024)	(0.024)			
Team History—Negative (β_3)		-0.446***	-0.446***			
		(0.065)	(0.066)			
Team—CV (β_4)			0.0060			
			(0.059)			
Team History/Budget (β_5)				0.092**		
				(0.029)		
Team History/Budget—Positive (β_6)					0.114***	0.117***
					(0.031)	(0.031)
Team History/Budget—Negative (β_7)					-1.232***	-1.197***
					(0.281)	(0.274)
Team—CV/ Budget (β_8)						-7.066*
						(3.131)
Controls						
Running Time (minutes)	0.3700	0.489+	0.488+	-2.303+	-1.6440	-1.6090
	(0.262)	(0.259)	(0.261)	(1.399)	(1.265)	(1.259)
Sequel	5.4870	7.5350	7.5300	-82.4290	-67.3610	-73.2870
	(9.079)	(8.669)	(8.671)	(53.110)	(50.570)	(51.655)
Opening Weekend Theaters	0.016**	0.017**	0.017**	-0.0290	-0.0240	-0.0270
	(0.006)	(0.006)	(0.006)	(0.056)	(0.055)	(0.056)
Team Familiarity	0.4700	0.3050	0.3060	-1.2400	-0.8530	-0.3570
	(0.950)	(0.862)	(0.863)	(4.778)	(4.846)	(4.793)
Constant	-78.199+	-97.733*	-97.714*	392.021	252.942	270.003
	(42.254)	(41.998)	(42.094)	(275.828)	(254.705)	(257.957)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.250	0.277	0.277	0.042	0.052	0.053
Number	1,439	1,439	1,439	1,439	1,439	1,439

*+ $p< 0.10$, * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$; We report coefficient estimates with clustered standard errors in parentheses.*

Table A3: Regression Results with PSM (NN1)

Dependent Variable →	Movie Profit			Movie Profit/ Budget		
	(1)	(2)	(3)	(4)	(5)	(6)
Team History (β_1)	0.086***					
	(0.025)					
Team History—Positive (β_2)		0.102***	0.102***			
		(0.025)	(0.025)			
Team History—Negative (β_3)		-0.411***	-0.411***			
		(0.067)	(0.067)			
Team—CV (β_4)			0.0060			
			(0.047)			
Team History/Budget (β_5)				0.108***		
				(0.025)		
Team History/Budget—Positive (β_6)					0.128***	0.130***
					(0.027)	(0.027)
Team History/Budget—Negative (β_7)					-1.163***	-1.138***
					(0.267)	(0.261)
Team—CV/ Budget (β_8)						-5.546+
						(2.856)
Controls						
Running Time (minutes)	0.469+	0.571*	0.571*	-1.6740	-1.1090	-1.1020
	(0.261)	(0.260)	(0.263)	(1.282)	(1.166)	(1.165)
Sequel	5.2000	8.0790	8.0710	-71.4240	-55.1670	-59.7240
	(9.045)	(8.853)	(8.857)	(45.117)	(43.421)	(44.398)
Opening Weekend Theaters	0.016**	0.018**	0.018**	0.0260	0.0310	0.0290
	(0.006)	(0.006)	(0.006)	(0.022)	(0.021)	(0.021)
Team Familiarity	1.2200	0.8380	0.8390	-1.6010	-2.2430	-1.9970
	(0.809)	(0.797)	(0.798)	(4.839)	(4.855)	(4.797)
Constant	-93.465*	-111.704**	-111.675**	141.854	13.566	26.278
	(42.699)	(42.775)	(42.901)	(162.331)	(145.054)	(147.519)
Fixed Effects						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Distributor	Yes	Yes	Yes	Yes	Yes	Yes
Genre	Yes	Yes	Yes	Yes	Yes	Yes
Rating	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.266	0.289	0.288	0.083	0.099	0.100
Number	1,439	1,439	1,439	1,439	1,439	1,439

*+ $p< 0.10$, * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$; We report coefficient estimates with clustered standard errors in parentheses.*