Title Page (WITH author details)

An Empirical Investigation of Director Selection in Movie Preproduction: A Two-Sided Matching Approach

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Abstract

This paper examines how movie producers recruit directors in the preproduction phase as mutual choices in a two-sided matching model. It conceptualizes that movie attributes and filmmaker characteristics determine the matching outcomes ("who directed which movie") and in turn indirectly affect movie box office. We exploit a dataset of 4,807 feature films from 1990 to 2010 to examine empirically the complementarities between the movie/producer side and the director side in terms of movie budget, filmmaker track records and social relations. A series of simulations suggest that social relations facilitate positive assortative matching. Further simulation analyses are conducted to quantify the financial implications of movie–director mismatches, as well as the indirect effects of production budget and producer characteristics. The simulation results show that: a) the financial implications of having a mismatched director can be substantial; and b) the indirect effect of production budget and producer characteristics affect movie box office in an interactive manner. These findings can help filmmakers to better understand the financial impacts of movie–director choices and make more informed decisions at the early phase of preproduction.

Keywords: Movie producers; movie directors; network embeddedness; collaborations; two-sided matching; movie preproduction

1. Introduction

Motion pictures are indeed a "*Risky Business*".[1] For some movie production companies, one unsuccessful movie can sometimes put them in severe financial difficulty or even force them to shut down. This highlights the fact that the making of a movie is a "long succession of creative decisions with far-reaching economic implications for the different players involved" (Eliashberg, Elberse, & Leenders, 2006, p. 640). As Sorenson and Waguespack (2006) explain, "The production of a film begins with the mobilization of resources. In the modern motion picture era, this process has an archetypal sequence. A producer first purchases rights to a story (e.g., a popular novel), a script, or a screenplay. He or she then hires a director, who enjoys a non-binding contract until the actual start of production. Together, the producer and director, often with the assistance of a casting agent, select actors to fill the various roles" (p. 567).

While clearly the activities in the preproduction phase have significant implications for the success of movie projects, these preproduction phase decisions are underresearched in the literature. The well-researched driving factors of movie performance are mostly those that become available in the much later distribution/exhibition phase (Eliashberg et al., 2006; Hadida, 2009). Also, the role of the director is also surprisingly underresearched (Simonton, 2009). In this paper, we aim to fill these gaps and focus on the producers' problem of matching their new movie projects with directors that possess the right characteristics, and examine the financial implications that director choice may have on movie box office.

First, this paper conceptualizes the producers' director selection problem as a mutual, two-sided matching between the movie/producer side and the director side. At the preproduction phase, the producers and the directors must base their choices on scarce information about the

[1] *Risky Business* is a 1983 comedy movie starring Tom Cruise.

new movie projects and the filmmakers themselves, including their existing social relations in the industry and their individual track records at the box office and at major awards. A two-sided matching model was specified and estimated to show how the attributes and characteristics on the two sides complement or substitute each other to determine the matching outcomes (i.e., who directed which movie). The estimation results suggest positive assortative matching between movie production budget and director past box office records, between producer and director positional embeddedness, and between movie content attributes and director expertise, but negative assortative matching between producer and director junctional embeddedness. The impacts of all the social relation characteristics on the movie/producer–director matching at the preproduction stage is further investigated through counterfactual simulations. We find that social relations exacerbate the positive assortative matching between producers and directors but benefit smaller-budget movies to match with directors with stronger box office records and higher network embeddedness.

Second, we quantify the financial impacts of the factors at the preproduction phase on movie revenues through a series of simulations, using examples of movies from our dataset. The simulation results demonstrated in dollar amounts that these movie and filmmaker characteristics had indirect effects on the box office through the directors they match. When movies were not matched with their optimal directors, the economic losses could be enormous. Our findings extended the literature on the effects of movie production budget (Brewer, Kelley, & Jozefowicz, 2009; Prag & Casavant, 1994) and provided a clearer understanding of how it affects box office. Producers who secured more financial resources for their new movie projects could match with directors with stronger past box office performance and stronger positional embeddedness, and better director matches in turn lead to better box office. Also, we find that the indirect effect of producers' characteristics on movie box office is the highest for medium-high-budget movies.

Methodologically, to the best of our knowledge, this research is the first to use two-sided matching to examine the movie industry (Fox, 2010; Roth & Sotomayor, 1992). Two-sided matching is both conceptually more appropriate and empirically more advantageous compared to one-sided models. Conceptually, two-sided matching is suitable to capture the mutual nature of the director recruitment process (Sorenson & Waguespack, 2006). Although producers are usually the decision-makers about who to direct their movie, directors are free to choose for themselves which movies they would like to direct. Empirically, using one-sided choice models to study a two-sided matching problem yields biased estimation and cannot uncover the true complementarity or substitution patterns underlying the matching process (Mindruta, Moeen, & Agarwal, 2016). Also, the use of two-sided matching better addresses selection bias to present a more accurate understanding of the impact of prominent personnel on movie performance (Liu, Mazumdar, & Li, 2015; Hofmann, Clement, Völckner, & Hennig-Thurau, 2017).

Next, we discuss the industry problems in the preproduction phase and the relationships between movie/producer and director characteristics. We explain the dataset and variable operationalization and the empirical analyses, consisting of the two-sided matching model and several simulations. Finally, we discuss the managerial implications and research limitations.

2. Industry Problem and Conceptual Framework

We consider the problem movie producers face when they recruit a suitable director for a new movie project at hand at the preproduction phase, as described in Sorenson and Waguespack (2006). For producers with new movie projects, getting the right director has important implications for the movie's success financially and artistically. This is because the director is a film's creative manager; they make almost all creative decisions during production and postproduction and almost invariably have direct contact with the motley crew consisting of all the cast and crew (Hennig-Thurau & Houston, 2019; Simonton, 2009). We conceptualize this director selection problem as two-sided matching between the movie/producer side and the director side, and the factors that affect the matching outcomes[2] in turn indirectly generate far-reaching monetary impact on movie box office. Two kinds of factors are considered: those about the movie and those about the filmmakers. Figure 1 presents the framework.

[Insert Figure 1 here.]

The preproduction phase is characterized by the lack of information on many of the well-researched movie-related factors that determine movie success at the box office. These include critics' reviews (Basuroy, Chatterjee, & Ravid, 2003; Carrillat, Legoux, & Hadida, 2018; Chen, Liu, & Zhang, 2012; Dhar & Weinberg, 2016; Eliashberg & Shugan, 1997; Legoux et al., 2016), word-of-mouth (Karniouchina, 2011; Liu, 2006), competition in the exhibition market (Krider & Weinberg, 1998), and screen allocations (Clement, Wu, & Fischer, 2014). Prior studies have also consistently shown actor star power as one of the key determinants of movie success (Carrillat et al., 2018; Elberse, 2007; Hofmann et al., 2017); however, it is important to recognize that director recruitment often precedes casting decisions and that directors oversee casting since they are ultimately in charge of all creative aspects. Thus, in this research, we consider only the movie-related variables known before even director recruitment: the financial resources that the producers have secured (e.g., production budget) and a few content attributes.

Yet, much can be known about the producers and directors based on the movies they have worked on. We distinguish between filmmaker individual track records and their social relations.

[2] We will use the terms "matching outcome" and "matching equilibrium" interchangeably in the rest of the paper because conceptually they both refer to the same observations of "who directed which movie".

The measures of past performance emphasize individual-level track record characteristics, whereas the measures of social relations capture the filmmakers' strength in dyadic and network-based professional relationships, respectively. Next, we discuss how these factors may affect the matching outcomes and hence movie box office.

2.1. Movie Production Budget and Director Track Records on Matching Outcome and Box Office

A movie with a big production budget is a highly risky venture. Therefore, the producers of such movies are motivated to hire directors with proven track records. The big budget also allows producers to pay more to attract directors. Researchers have used many different measures as indicators of filmmaker past performance or "star power". These measures include industry star lists to define "stars" (De Vany & Walls, 1999, 2004; Hsu, 2006; Liu, Mazumdar, & Li, 2015; Liu, 2006; Walls, 2009), popularity index (Bagella & Becchetti, 1999), and past movie commercial success (Hennig-Thurau, Houston, & Sridhar, 2006) or awards won (Nelson, Donihue, Waldman, & Wheaton, 2001). In this paper, filmmaker track records consisting of both commercial success at the box office and artistic accolades such as wins and nominations at the Academy Awards (a.k.a. the Oscars). We expect to find that a new movie with a bigger budget is more likely to match with directors that have stronger track records.[3]

We further posit that such matches are inducive to better box office for the new movie because directors with stronger records understand audience tastes better and can control movie quality better. Moreover, established directors can increase the demand for the movie because of

[3] The planned production budget for a movie is usually known when movie producers sign a legal contract with the movie's director. For example, the Directors Guild of America (DGA) requires its members to submit a project information form with production budget in it before they can start to work for a movie project. The DGA defines low-budget movies as the "projects budgeted under $11 million" (DGA.org, 2021).

their reputation among moviegoers (Ainslie, Drèze, & Zufryden, 2005; Gazley, Clark, & Sinha, 2011). Meanwhile, directors with great performance records are sought after, so they can afford to be selective in choosing movie projects. Directing big-budget movies could lead to more successes in the future and enhance their track records, thus is an appealing choice for directors.

Director past box office success is more aligned with big-budget movies' focus on financial return (Hadida, 2010). Thus, bigger-budget movies are more likely to be matched with directors with strong past box office performance. Oscar nominations and wins reflect more on a director's artistry and creative talent than on their ability to produce a movie with high financial return. Nevertheless, awards can boost a director's star power among moviegoers, which will help the financial return of their future movies (Kim, 2013). Thus, bigger budgets are also more likely to be matched with directors with award accolades. To sum up, a movie with greater financial resources in the form of production budget is more likely to match with directors with stronger track records, and the greater movie budget and the stronger director track record complement each other to improve box office.

2.2. Filmmaker Social Relations on Matching Outcome and Box Office

Social relations can be dyadic collaboration ties (Narayan & Kadiyali, 2016) and network-based social embeddedness (Packard, Aribarg, Eliashberg, & Foutz, 2016). *Past collaborations* build trust between collaborators and learning-by-doing and reduce transaction cost and agency problems, thus leading to higher productivity in future collaborations (Gulati, 1995; Narayan & Kadiyali, 2016). Such benefits of past collaborations can prompt directors and producers to work with acquaintances in their future projects, increasing the likelihood of them teaming up again in a new project. Therefore, we expect a positive effect of past collaborations on matching outcomes.

Network embeddedness indicates an individual's position in the entire industry network and is valuable when working with any person. Economic sociology posits that the economic relations between individuals or firms are embedded in actual social networks (Granovetter, 1985). In the film industry, filmmakers interact with each other mainly through collaborating on movie projects (Rossman, Esparza, & Bonacich, 2010). The extent to which they are embedded (i.e., associated with well-connected others, serving as a bridge to connect others) in this network is an important indicator of their professional value, which can be leveraged when selecting movie projects in the future (Stuart, 1998; Uzzi, 1996).

Following Packard et al. (2016), this research also distinguishes between two embeddedness measures: positional embeddedness (henceforth PE) and junctional embeddedness (henceforth JE). PE captures how a filmmaker is tied to well-connected others in their professional network and is a good indicator of social status and professional prestige among their peers in the industry (Newman, 2006). High PE is associated with better information diffusion and information inference in social networks (Kamal et al., 2021). A director with high PE may attract better cast for the new movie and mitigate the financial risks associated with big-budget movie productions, thus are matched with bigger budgets (Elberse, 2007). Hence, high production budget and high director social status, once matched, can lead to better box office. Moreover, filmmakers with high PE seek to match with each other to maximize the complementarity of their respective social status. Such matches between high-PE producers and directors also pave the path to greater box office.

JE, on the other hand, indicates the extent to which an individual bridges two nonadjacent others (Freeman, 1977). If an individual with high JE is removed from the network, the network can fall apart into disconnected subnetworks. Although structurally important for the filmmaker network to remain connected, directors with high JE may not be valuable financially and are less appealing for big-budget movies in the matching process and less important for the box office outcome. In addition, it takes only one high-JE filmmaker to bridge otherwise non-connected subnetworks; there is little complementarity in a match between two high-JE filmmakers. Thus, high-JE directors and high-JE producers are not likely to match or have positive financial benefits for the movie.

2.3. Producer Track Records and Director Track Records on Matching Outcome and Box Office

Producers and directors that mutually choose to collaborate on a new movie project are often motivated by common goals, either financial success or artistic achievements, because shared goals make working together much easier during the collaboration (Kozlowski & Ilgen, 2006). Past performance measures such as box office and awards of producers and directors can suggest their focuses and ambitions. Many movies that are nominated for or win an Academy Award perform poorly at the box office (Galloway, 2015). This could be caused by how moviegoers' popular taste is at odds with the quality judgment of industry experts (Holbrook, 1999; Holbrook & Addis, 2007). A producer focusing on box office would find it easier to work with a director with strong box office record, rather than an artistically-focused director. Further, great directors are associated with great films because they play the single most important role in cinematic creativity (Allen & Lincoln, 2004; Simonton, 2004). This partially explains the empirical finding that the Academy Awards in the directing category often coincide with those in the Best Movie category (Wanderer, 2015). This implies that producers focusing on awards would seek to hire directors with a strong awards record. In summary, producers should prefer to match with directors with similar track records, and vice versa.

2.4. Movie Content Attributes and Director Expertise on Matching Outcome and Box Office

Directors accumulate experience through directing movies, and their past projects are indicators of their value in cumulative knowledge and capabilities. The knowledge and capabilities in directing, for example, a comedy might not be easily transferrable to directing an action thriller. We define this specialized knowledge and skills as director expertise, which is more valuable for directing a similar rather than a different type of movie in the future. In selecting directors, producers may prefer someone whose expertise matches the movie's content attributes. Highly specialized directors are well differentiated horizontally in the movie labor market (Christopherson & Storper, 1989), and may be willing to take on more directing work aligned with their expertise. Their direction adds legitimacy and appeal to the movies among moviegoers and investors. At the preproduction phase, the available information on movie content attributes includes genre, subgenre, theme, MPAA rating, and script type.

Movies are complicated cultural products and are typically hard to describe. The use of *genres* only has received criticism from scholars, as they are insufficient to describe the true characteristics of the movies (Eliashberg & Sawhney, 1994; Roos & Shachar, 2014). Thus, besides genres, we also incorporate *subgenres* and *themes* to ensure a more precise classification. For example, under the genre "comedy", a subgenre may be "comedy of manners" and the theme "culture clash". *MPAA ratings* are determined by the Classification and Ratings Administration (CARA) (Motion Picture Association, 2021). Although the ratings are assigned *after* the movie production ends, producers and directors can form an educated guess based on the movie script and the MPAA rating guide during preproduction. MPAA ratings might affect the participation decisions of creative talents including the directors. For example, because R-rated films tend to be edgy and complex, directors might prefer directing such movies for the artistic prestige (De

Vany & Walls, 2002). Lastly, *script types* may attract directors with specialized directing expertise. Original and adapted screenplays are often considered rather different (Joshi & Mao, 2012); for example, they are different categories in the Academy Awards. In summary, directors are more likely to match with movies that are consistent with their expertise, and such alignment between content attributes and directing expertise would create higher quality movies and thus better box office. Previous research has examined the effects of storyline on box office (Eliashberg, Hui, & Zhang, 2007; Hung & Guan, 2020). The movie content attributes considered here can advance our understanding of these effects.

The main constructs are summarized in Table 1, as well as their variable names, which will be explained in the next section.

[Insert Table 1 here.]

3. Data Description and Variable Operationalization

Our data are compiled through a number of publicly available online databases, including imdb.com, allmovie.com, boxofficemojo.com, the-numbers.com, and rottentomatoes.com, and the official websites of the Academy Awards (www.oscars.org) and the Motion Picture Association of America (MPAA: www.mpaa.org). We have crosschecked multiple databases to ensure data accuracy. After excluding foreign-language movies and documentaries, our final dataset contains 4,807 English-language feature films released in the U.S. theatrical market between 1990 and 2010 (Figure 2). This is equivalent to 229 movies released each year on average and covers nearly all major productions as well as theatrically released independent movies in the U.S. during the 21-year period.[4] For each movie, we have collected the following

[4] To put the size of data in perspective, the six MPAA member studios and their subsidiaries released an annual average of 177 movies from 2003 to 2010 (available at http://www.mpaa.org/wp-content/uploads/2014/03/2012-Theatrical-Market-Statistics-Report.pdf, accessed on August 2, 2020).

information: personnel, production budget, U.S. domestic box office, Oscar nominations and wins in the Best Picture and Best Director categories, and movie content attributes. Table 2a presents the summary statistics.

[Insert Table 2a Here]

The movies that a filmmaker had worked on in the most recent 10-year period were used to reliably operationalize their characteristics. Namely, the characteristics of a filmmaker working on movie a released in year t are constructed with their past movies during a 10-year moving window from $t-10$ to $t-1$. This requires the use of the first 10 years of data in our dataset (2,015 movies released in the initial period, 1990–1999) as the basis for constructing filmmaker characteristics; we used the other 2,792 movies released in 2000–2010 as observed matches in the matching model estimation. The majority (80%) of the movies in our dataset have more than one producer. It is reasonable to assume that the producer team have been formed *before* the director selection decision, and thus we treat them as one producer set for that movie. Moreover, the vast majority (96%) are directed by one director only. Even when there is more than one director, they are usually brothers, sisters, or long-established directing teams (e.g., Joel and Ethan Coen, Lilly and Lana Wachowski). In such cases, we treat the multiple directors in a movie as a director set as well. Next, we discuss how the variables are operationalized.[5]

3.1. Filmmaker Social Relations: Past Collaboration and Social Embeddedness

A movie project involves many people working together carrying out their different roles (Hennig-Thurau & Houston, 2019). Any role in a filmmaker's past projects could contribute to his/her social relations, albeit to different extents (Ferriani, Cattani, & Baden-Fuller, 2009). Therefore, we collected comprehensive personnel data listed in four major filmmaker roles

[5] Web Appendix 1 provides the detailed calculation procedures for some of the covariates.

(producer, director, writer, and cast) in each movie.[6] In addition, among the many producer titles, such as producer, co-producer, executive producer, line producer and so on, only those with "producer" credits are ultimately responsible for such key managerial decisions as selecting directors for their movies. Hence, only those individuals with the "producer" credits in a movie are examined in the movie/producer–director matching.

We use the number of movies that the filmmakers worked on together in the recent 10-year period to construct the past collaboration measures between a producer set and a director set. A filmmaker's role might change from one movie project to another; therefore, past collaborations are not all the same. Past collaborations as a producer–director pair may have stronger influence on their future producer–director choices than past collaborations performed in other roles. For example, the collaboration between Bill Unger and Tony Scott in *True Romance* (1993) as the producer–director duo may contribute strongly to their later mutual choice to collaborate again as producer–director match in *Crimson Tide* (1995), whereas Meir Teper and Quentin Tarantino were in a producer–actor collaboration in *From Dusk Till Dawn* (1996), but they did not work as a producer–director team since then. Therefore, we separated past collaborations into two types: producer–director collaborations and other collaborations (e.g., producer–cast, etc.). It is possible that an individual might work as both a director and a producer on a movie. In this situation, we excluded the director's name from the producer set when calculating the past collaborations.[7]

We performed social network analysis to construct filmmaker social embeddedness measures based on their filmmaking work in the most recent 10 years. A filmmaker's social embeddedness is time-variant for two reasons. First, filmmakers create new connections or

[6] For the movies with the exceedingly long list of cast members, we included the most important 20 cast members.
[7] There are very few cases (12 movies) in which one person is the sole director and producer of a movie. Also, these are all small-budget, independent movies, thus we excluded them from the two-sided matching model.

strengthen existing connections with others in the network each time they work on a new movie project. For example, a newbie filmmaker would have essentially no embeddedness, whereas a veteran and prolific filmmaker will have high social embeddedness. Second, the total number of individuals in the filmmaker network also changes over time due to new filmmakers joining in and existing ones becoming inactive.

Following Packard et al. (2016), we distinguished positional and junctional embeddedness, where PE is measured by eigenvalue centrality and JE by betweenness centrality. We used the *netsis* package for *Stata* to calculate the eigenvalue centrality and betweenness centrality and normalized them to a scale of 0~1 to make them comparable across years[8]. When there is more than one producer (director) in a producer (director) set, we use the average across all individual producers (directors) in that set.[9] Table 2b shows the summary statistics of these social embeddedness measures.

[Insert Table 2b here.]

3.2. Filmmakers' Individual Track Records: Performance and Expertise

All filmmakers' individual track records are constructed based on the performance of the movies they have worked as a producer or director role during the recent 10-year period. Movie performance measures include both financial performance and artistic excellence. A movie's financial performance is measured by its domestic box office revenues. To make the box office revenues more comparable across years and movies, we first adjusted the numbers with inflation,

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[8] Web Appendix 2 lists the top five individual directors and top five individual producers, respectively, ranked by positional and junctional embeddedness in 2010.

[9] We have also used the maximum of network embeddedness measures among producers (directors) in the situation that there is more than one producer (director) in a movie in the estimation. The estimation results are qualitatively consistent with the results using the average, showing robustness. But the model with average measures had a slightly better goodness-of-fit. Thus, we focus on the results from the average filmmaker embeddedness and present the results from the maximum measures in Web Appendix 3.

log-transformed them, then rescaled them to a 0~1 scale. The rescaling smooths the variables and makes the matching model estimation and result interpretation easier (Yang, Shi, & Goldfarb, 2009).

The *financial* performance of a director (producer) set is the average financial performance of the unique movies directed (produced) by the directors (producers) in the set in the recent 10 years. If a director (or producer) set had not directed (produced) any movie in the recent 10 years, their past box office measure was assigned 0. A movie's *artistic* excellence is evaluated by its wins and nominations at the Academy Awards, which have been found to exhibit the best single indicator of the consensus regarding cinematic creativity among similar major awards (Simonton, 2004). Thus, a producer set's artistic track record is measured by dummy variables to indicate whether producers in the set have won or been nominated in the Best Picture category in the recent 10 years. For a director set, the artistic performance is similarly defined as whether they have won or been nominated in the Best Director category. Table 2b shows the summary statistics of these filmmaker track records measures. Finally, director expertise is examined along the five movie content attributes: genre, subgenre, theme, MPAA rating, and script type, constructed from the director set's directing records in the recent 10 years (Web Appendix 1).

3.3. Movie Production Budget

Production budgets are the financial resources secured by the producers but expended by the directors in making the movie. Admittedly, the final production expenses in our dataset might not be the same as the financing secured by the producers before production begins, but they could still be a reasonable proxy for the planned budgets. Using the budgets reported on IMDb.com, the-numbers.com, and boxofficemojo.com, we collected production budget information on 3,787 of the movies 4,807 in our dataset. The production budgets are adjusted for inflation, and then log-transformed, and rescaled to a 0~1 scale similar to what we did with the box office. We excluded movies without a production budget from our estimation, but still used their other information in operationalizing filmmaker characteristics. We discuss our models and empirical analysis in the next two sections.

4. Two-sided Matching Model and Estimation Results

4.1. Two-sided Matching Model

Two-sided matching as a mechanism for resource allocation has received much scholarly attention in economics in both theory and empirical tests (Gale & Shapley, 1962; Roth & Sotomayor, 1992). Compared with one-sided choice models, two-sided models are more appropriate for studying two-sided choices because they can incorporate all the market participants' preferences at the same time by utilizing the equilibrium conditions. In our empirical setting, the observed decisions regarding "who directed which movie" are the outcomes of the mutual choices between movie producers and directors. Also, the preferences of all the movie producers and all the directors in the same market determine the final outcomes. Therefore, a two-sided matching model is an appropriate empirical approach.

We employ a one-to-one two-sided matching model to study the movie/producer–director matching for the following reasons. First, unlike actors, who can work on multiple projects in a given period (typically a year), directing needs a director's full-time commitment for the entire production period, including the preproduction, production, and postproduction stages. Therefore, it is very unlikely that one director would work on multiple movies simultaneously.

Second, a one-to-one matching model is not only more appropriate but also computationally simpler than other two-sided matching models.[10]

We apply Fox's (2010) maximum score estimation method for two-sided matching models with endogenous transfers. This method has been applied to study relationships such as contracts between athletes and teams (Yang et al., 2009) and legal firms and clients (Chatain & Mindruta, 2017), with shirt sponsorships of English football clubs (Yang & Goldfarb, 2015), advertisers' choices of online advertising networks (Wu, 2015), the sourcing market (Ni & Srinivasan, 2015), and research collaborations (Mindruta, 2013; Mindruta et al., 2016).[11] The method in Fox (2010) is particularly suitable for studying the producer–director matching market, where directors negotiate their contracts with movie producers and the amount and format of these payments are usually unavailable to the public, because Fox's (2010) maximum score estimation method can accommodate such unobservable endogenous transfer between the two sides. Another advantage of Fox's method is that it does not suffer from the computational curse of dimensionality. Given the large number of observations and explanatory variables in this study, Fox's (2010) estimation method is computationally feasible.

In matching models, researchers must define the market in which the two sides make mutual choices. In prior research on two-sided matching models, the exact dates of partnership formation are usually known (Yang & Goldfarb, 2015; Yang et al., 2009). However, in the context of filmmaking, it is nearly impossible to track the exact time when producers and directors decided to collaborate on a movie. Therefore, we treated the movies released in the

[10] We do not investigate why directors (or producers) decide to work together in the observed director (or producer) sets here, as it is beyond the scope of this paper and needs a different matching model (e.g., a one-sided matching model without transfer) to examine the matching among directors (or producers).

[11] When estimating matching problems without endogenous transfers, some researchers have used other methods, such as the Markov-Chain Monte Carlo method (Ni & Srinivasan, 2015; Rao, Yu, & Umashankar, 2016; Sorensen, 2007) and the moment method (Uetake & Watanabe, 2020).

same calendar year as a market in which movies and directors make their choices, termed a *year-market*. As the time between hiring a director and releasing the movie theatrically varies from movie to movie, this assumption is not always valid. However, our empirical estimation method —maximum score estimation—allows for consistent estimates, even if only a subset of the true market is used in the estimation. Our confidence interval was constructed by using only 80% of the movies in each year-market, suggesting good robustness of the point estimates.

4.1.1. Joint Valuation Function and Matching Equilibrium Concept

We used the joint valuation function and matching maximum score inequality developed by Fox (2010) to define the equilibrium used to solve the two-sided matching problem. The joint valuation function of a match between movie a and director set i is the total value that is generated for both sides. Suppose that we observe two matches: movie a is directed by director set i and movie b is directed by director set j. Let r_{ait} be the transfer from movie a to director set i, the function $\Delta V(a, i, t)$ be the value that director set i adds to movie a through their partnership (e.g., an increase in expected box office revenues), and the function $\Delta U(a, i, t)$ be the value that movie a adds to director set i (e.g., better track records and greater social relations with other filmmakers through directing the movie) because of their partnership in year-market t. Then, the payoff functions for movie a (denoted by π^M) and director set i (denoted by π^D) are:

$$\pi^M(a, i, t) = \Delta V(a, i, t) - r_{ait} \qquad (1)$$

$$\pi^D(a, i, t) = r_{ait} + \Delta U(a, i, t). \qquad (2)$$

The sum of payoffs to movie a and director set i from their match is the total value that the partnership (a, i, t) generates for both sides involved. Thus, the joint valuation function is:

$$f(a, i, t) = \Delta V(a, i, t) + \Delta U(a, i, t). \qquad (3)$$

Joint valuations for other matches are defined similarly. Then, the matching maximum score inequality condition can be written as:

$$f(a,i,t) + f(b,j,t) \geq f(a,j,t) + f(b,i,t). \qquad (4)$$

The inequality in Eq. (4) states that the sum of the joint valuations from two observed matches must be greater than the sum of the joint valuations if they exchange partners. In other words, the observed matches are socially optimal for year-market t. This maximum score inequality equilibrium concept is closely related to pairwise stability in cooperative game theory (Roth & Sotomayor, 1992). A match is stable if no coalition of agents prefers to deviate and form a new match. Eq. (4) formulates the inequality condition when the market has two movies and two director sets; similar matching maximum score inequality conditions can be formulated for a market with many movies and many director sets where the total joint valuations of any two observed matches exceeds the total joint valuations from an exchange of partners. However, the matching maximum score inequality condition is a necessary but not a sufficient condition for the equilibrium. A more robust condition is a core stability concept in which no coalitions of agents deviate from the equilibrium. Yet, because the computational cost of core stability is much higher than the benefit for estimation (Fox, 2010), we adopted the matching maximum score inequality as the equilibrium concept.

From the inequality conditions in Eq. (4), we derived a system of inequalities that defines the joint valuations as the interactions between the two sides of the market. The objective function is:

$$\max_{f} Q_H(f) = \frac{1}{H}\sum_{t\in H}\left\{\sum_{\{a,b,i,j\}\in A_t} 1[f(a,i,t) + f(b,j,t) \geq f(a,j,t) + f(b,i,t)]\right\}, \qquad (5)$$

where H is the number of observed markets and A_t is a realized quartet $\{a,b,i,j\}$ in the observed market t; and $1[\cdot]$ is an indicator function that is 1 when the inequality in the bracket holds. The maximum score estimator will be any valuation function f that maximizes the score function $Q_H(f)$. It is a consistent semiparametric estimator that makes no assumptions about the distribution of the error terms.

4.1.2. Matching Value Specification

The joint valuation function $f(a, i, t)$ is specified as:

$$f(a, i, t) = \alpha \times X_{at} + \beta \times [X_{at} \times Y_{it}] + \gamma \times Y_{it} + \epsilon_{ait}. \quad (6)$$

where X_{at} and Y_{it} denote the characteristics of movie a and its producer set and the characteristics of director set i, respectively, in year-market t. Since the movie-specific term $\alpha \times X_{at}$ and the director-specific term $\gamma \times Y_{it}$ will be canceled out in the inequality condition in Eq. (4), the estimation focuses on the interaction term $\beta \times [X_{at} \times Y_{it}]$, denoted as the matching value MV_{ait} between movie a and director set i. Based on our conceptual framework (Table 1), we included the following interaction terms in the specification for the matching value MV_{ait}:

$$\begin{aligned}
&MV_{ait} = \beta \times [X_{at} \times Y_{it}] \\
&= \beta_1 \times M_BUGT_a \times D_BO_{it} + \beta_2 \times M_BUGT_a \times D_O_NOM_{it} \\
&+\beta_3 \times M_BUGT_a \times D_O_WIN_{it} \\
&+\beta_4 \times M_BUGT_a \times D_PE_{it} + \beta_5 \times M_BUGT_a \times D_JE_{it} \\
&+\beta_6 \times P_PE_{at} \times D_PE_{it} + \beta_7 \times P_JE_{at} \times D_JE_{it} \\
&+\beta_8 \times PD_COL_PD_{ait} + \beta_9 \times PD_COL_OTH_{ait} \\
&+\beta_{10} \times M_BIG_BU_a \times PD_COL_PD_{ait} + \beta_{11} \times M_BIG_BU_a \times PD_COL_OTH_{ait} \\
&+\beta_{12} \times P_BO_{at} \times D_BO_{it} \\
&+\beta_{13} \times P_O_NOM_{at} \times D_O_NOM_{it} + \beta_{14} \times P_O_WIN_{at} \times D_O_WIN_{it} \\
&+\beta_{15} \times M_CONT_a \times D_EXPT_{it}\,. \qquad (7)
\end{aligned}$$

In Eq. (7), the first three terms are the interactions between movie budget (M_BUGT_a) and director track record measures: box office D_BO_{it}, Oscar nomination $D\_O\_NOM_{it}$, and Oscar win $D\_O\_WIN_{it}$. The fourth and fifth terms capture the movie budget and director PE D_PE_{it}, and JE D_JE_{it}. The sixth and seventh terms are the interactions between filmmaker PE and JE, respectively. The eighth and ninth terms examine the number of past collaborations between movie producers and directors as producer–director ($PD\_COL\_PD_{ait}$) and as other roles ($PD\_COL\_OTH_{ait}$). The 10th and 11th terms are three-way interactions to investigate whether the effect of past collaborations varies for movies with different budgets, where $M\_BIG\_BU_a$ is a dummy to indicate whether movie a's budget is in the top 25% of the movies used in the estimation. The 12th to 14th terms are the covariates between filmmaker track record measures. The last term captures the relationship between movie content attributes (M_CONT_a) and director expertise (D_EXPT_{it}).

4.2. Two-sided Matching Model Results

After excluding 458 movies without production budget and 12 movies directed and produced by the same person, the estimation sample consisted of 2,313 movies released in the 11 year-markets between 2000 and 2010.[12] Table 3 presents the results. In the estimation, one coefficient needs to be normalized to ± 1 to obtain the point estimates of the parameters (Fox, 2010). We chose to normalize the coefficient for the relationship between movie budget and director PE ($\beta_4 = 1$) because these two variables are continuous and have more variations, thus making the objective function smoother, which in turn makes it easier to find the global optima in the estimation process.

[Insert Table 3 here.]

Fox (2018) points out that there is no literature to provide guidelines on the size of subsampling when constructing the 95% confidence intervals of the estimates. We subsampled 80% of the movies from each year-market 100 times to construct the confidence intervals of our parameter estimates at the 95% level. Given the 95% confidence interval calculated based on two

[12] Before running the estimation, we have checked the correlations between all the covariates (Web Appendix 4) to ensure that the covariates can be differentiated enough to capture their matching values.

sides of the distribution, we also reported a percentage of subsamples that had the same sign as the point estimates for a one-tailed test. For model goodness-of-fit, 85.27% of inequalities satisfied the inequality condition in Eq. (4), which is quite high. The last two columns in Table 3 present the results of a one-sided logit model to compare the model performance with the two-sided models using the maximum score estimation method. Overall, two-sided models perform better in capturing the complementarity in matching markets (Mindruta et al., 2016).[13] Thus, we will focus on the findings from the two-sided matching model next.

4.2.1. Movie Production Budget and Director Track Record on Matching Outcomes

The matching value between movie production budget and director past box office ($\beta_1 = 112.70$) is positive and statistically significant, suggesting that movies with more financial resources would be more likely to attract directors with better box office records. However, the matching value is insignificant between production budget and director Oscar nominations ($\beta_2 = -18.60$) and Oscar wins ($\beta_3 = 66.47$) with 95% confidence interval. Still, high percentages of the subsamples (87% and 90%, respectively) showed the same signs as the point estimates, suggesting that these relationships existed, albeit statistically insignificant. Because Oscar wins are more exclusive than nominations, and thus provide more meaningful information about the director's cinematic creativity than that provided by nominations alone (Simonton, 2004), the positive relationship between movie budget and director award wins was thus more prominent than that between budget and direct award nominations.

[13] Web Appendix 5 provides further details about the logit model and its comparison with the two-sided model.

4.2.2. Filmmaker Social Relations on Matching Outcome

Social relations: Network embeddedness. The matching value between movie production budget and director PE is significant and positive[14] (β_4 normalized to 1), suggesting that movies with more financial resources would be more likely to attract directors who are tied to well-connected others and have high social status in the industry. In contrast, the relationship between movie budget and director junctional embeddedness was insignificant ($\beta_5 = 1.65$), suggesting that movie financial resources are not important in attracting directors that bridge otherwise disconnected networks.

The matching model also revealed significant positive sorting between producer PE and director PE ($\beta_6 = 183.90$). In the filmmaker network, individuals who have attained a higher positional social status will make strategic choices to further strengthen their value by collaborating with well-connected others. Therefore, producers and directors with greater PE are attracted to each other to further strengthen their prominence in the social network by working with each other on new projects. In contrast, we found negative sorting for JE ($\beta_7 = -30.19$). Even though the 95% confidence interval for β_7 includes zero in the range, 98 out of 100 subsamples show a negative result for this parameter. Therefore, the sorting between producer JE and director JE is significantly negative with the one-tailed test at 95%. A filmmaker with greater JE is better at connecting subcommunities that are otherwise separated. Yet, one side (either producer or director) in a strong bridging position is enough to bridge the personnel needed; thus, the producer–director matching value of JE is negative.

Social relations: Past collaborations. The results show that the past collaborations either as a producer–director pair ($\beta_8 = 62.48$) or other collaboration types ($\beta_9 = 73.17$) matter in future

[14] In the estimation process, we compared the maximum scores between normalizing the coefficient as 1 and as -1, and the positive normalization showed better fit. Thus, the estimate for the coefficient is positive one.

collaborations. These findings are consistent with previous research in that revenue enhancement due to repeated interactions is driven by supply-side factors such as mitigated team agency, increased investment in relationship-specific assets, and learning-by-doing (Narayan & Kadiyali, 2016). Thus, past collaborations improve team productivity irrespective of the roles in which producers and directors have collaborated before. Moreover, large movie production budgets do not moderate these relationships in significant ways ($\beta_{10} = -7.23$, $\beta_{11} = 1.29$, *insig*.). These results suggest that the benefits of past collaborations between filmmakers would not diminish even for big-budget movie projects, which can sometimes be make-or-break risks for the producers.

4.2.3. Producer Track Records and Director Track Records on Matching Outcome

Movie producers and directors will prefer someone who shares the same goals as them because shared goals make working together much easier during the collaboration (Kozlowski & Ilgen, 2006). In particular for movies, *auteur* theory of film criticism suggests that great directors are associated with great films because they play the single most prominent role in cinematic creativity (Allen & Lincoln, 2004). This partially explains the empirical finding that the Oscars in the directing category often correspond with awards in the Best Movie category (Wanderer, 2015). Producers with award ambitions or goals would seek to collaborate with directors with award wins or nominations. The matching value between producer past box office and director past box office is significant and positive ($\beta_{12} = 3.23$) as well as that between producer Oscar nominations and director Oscar nominations ($\beta_{13} = 10.53$). However, the matching value between producer Oscar wins and director Oscar wins is insignificant ($\beta_{14} = 1.10$), suggesting that producers and directors who have been nominated for major awards are artistically driven. Therefore, as the results confirmed, such filmmakers are motivated to win and more likely to match with filmmakers with similar award ambitions. However, once they have won, their motivation to match with other Oscar winners diminishes.

*4.2.**4**. Movie Content Attributes and Director Expertise on Matching Outcome*

Among the matchings between director expertise and movie content attributes, the matching values are positive and statistically significant for genre ($\beta_{15}^{1} = 10.44$), subgenre ($\beta_{15}^{2} = 13.03$), theme ($\beta_{15}^{3} = 5.51$), and MPAA rating ($\beta_{15}^{4} = 6.50$), but not for script type ($\beta_{15}^{5} = 0.85$, *insig*.). These positive assortative matchings show that expertise matters for director choice. However, the positive assortative matchings in director expertise make it more difficult for directors to overcome genre or subgenre typecasting, a barrier previously found for actors (Zuckerman, Kim, Ukanwa, & von Rittmann, 2003).

4.3. Impacts of Social Relation Characteristics on the Movie/Producer–Director Matching

The two-sided matching results show that social relations (i.e., network embeddedness and past collaborations) play an important role in the movie/producer–director matching market. Still, some questions remain unanswered. Particularly, how would the matching outcome differ if social relations are not considered in the matching process? What types of movies would be benefited or disadvantaged, and in what ways? We used counterfactual simulation analyses to answer these questions.

Following similar processes in matching simulation studies done in previous research (Yang & Goldfarb, 2015; Yang et al., 2009), we used a linear program (Shapley & Shubik, 1971) to simulate the matching outcomes in two scenarios: (1) the optimal matches when considering all the covariates in our matching model; and (2) the counterfactual matches when omitting all the social relation covariates from the two-sided matching model. Web Appendix 6 describes the details of the above simulation process. After simulating the matching outcomes, we calculated the total matching values of the three matching outcomes: observed matches, optimal matches, and counterfactual matches[15]. The total matching value of the actual observed matches is 92.6% of the total matching value of the optimal matches. This high percentage shows that our simulation fits well with the original data. In contrast, the total matching value of the counterfactual matches *without* the social relation covariates is only 81.5% of the total matching value of the optimal matches. This 18.5% reduction from the optimal matches shows that social relation characteristics have important implications in determining the matching outcomes.

To study how movies are affected differently by social relation characteristics, we first calculated the differences between the matched directors of the counterfactual and optimal scenarios for each movie along five director characteristics. We then regressed each of the five director-side differences on movie/producer side attributes including production budget and producer characteristics, while controlling movie content attributes. Table 4 presents the results from these five regressions.

[Insert Table 4 here.]

The coefficients for movie budget are positive in the dimensions of director past box office (0.930), PE (0.009), and JE (0.007). These results suggest that, if the movie/producer–director matches were made without considering filmmaker social relation characteristics, movies with higher budgets would be more likely to match with directors with better box office records and greater embeddedness. In other words, when social relation variables are considered in making movie–director matches, such consideration would disadvantage larger-budget movies in the sense that they are matched with directors with poorer box office records and lower

[15] To make the measures comparable, the matching value including all the covariates between a movie and a director set is used to calculate the total matching value of all the observed, optimal, and counterfactual matches.

embeddedness but more past dyadic collaborations with the producers. However, with social relation variables, movies with relatively fewer financial resources but more connected producers are more likely to attract directors with better box office records and greater embeddedness, which in turn can influence movie box office.

Meanwhile, the regression results show that, interestingly, when social relation variables are omitted from the matching process, the coefficients for the producer characteristics—box office records, Oscar wins, and positional and junctional embeddedness—are significantly negative in the director's corresponding characteristics (-0.132, -0.102, -0.021, -0.079, respectively). In other words, positive assortative matching between filmmakers' characteristics would be mitigated if social relations were absent in the matching. These findings imply that social relation characteristics facilitate positive sorting among producers and directors, which may make it more difficult for newbie filmmakers to break through in the industry. The important role of social relation characteristics in the movie/producer–director matching process might be a contributor to the "small-world" social network in the movie industry (Packard et al., 2016).

5. Financial Implications Analysis of Two-Matching Results

5.1. Quantifying the Financial Impacts of Movie–Director Mismatches

In this subsection, we will use regressions to demonstrate the process that utilizes our two-sided matching model to quantify the financial impact of a mismatch between a movie and its director. We keep the movie/producer side unchanged and quantify the financial effects of matching with the observed actual director and the counterfactual optimal director.

First, we identify the impacts of director characteristics on movie financial success through a log-linear regression of movie box office on director characteristics and production budget. In the regression, we controlled movie content attributes such as genre, MPAA rating, script type, and director expertise in movie content attributes which are known at the preproduction phase when the director is being matched with the movie. Table 5 presents the regression results from two model specifications. Model 1 included director network embeddedness and individual track records[16], and Model 2 had a better adjusted R^2 as it removed the two variables which Model 1 found as insignificant (i.e., director junctional embeddedness and Oscar nominations). Thus, we will focus on Model 2 estimation results where director PE, past box office performance, and past Oscar wins showed statistically significant effects on movie box office.[17]

[Insert Table 5 here.]

Second, we apply our two-sided matching estimates to find the optimal matches for the movies in the 2010 year-market using the same simulation process discussed in Section 4.3. Even though the total matching value of the actual observed matches is 92.6% of the total matching value of the optimal matches, some movies were mismatched with their observed directors. We examine some mismatched ones to demonstrate how matching with the right director could improve box office. To examine the financial implication of such mismatches, we combine the regression results and optimal matches together. We first use the regression Model 2 estimates (Table 5) to predict a movie's box office with its observed director and simulated optimal director and examine the difference between the predicted box office outcomes attributed to the different directors.

[16] Unlike network embeddedness, past collaborations are not individual filmmaker specific but involving both the producer and the director sides simultaneously in its construction. Therefore, in the analyses focusing on director side alone, past collaborations were not incorporated as director-side covariates.
[17] Other factors such as cast star power, word of mouth, critic reviews, or the number of release screens are not used in the estimation or the box office prediction because these variables are known often after the director choice is made or even later at the post-production or exhibition phases.

Table 6 illustrates the financial implications using as examples two movies from the 2010 year-market. Take *The Tourist* (2010) for an example, which had a production budget of US$100 million and was directed by Florian Henckel von Donnersmarck. Based on the estimation results from Model 2 above, the actual director von Donnersmarck would have generated a predicted box office of US$43.3 million (Table 6, row 1). Based on the two-sided matching results, we identified the counterfactual optimal director as someone with stronger characteristics than von Donnersmarck in past box office (0.717 vs. 0) and PE (0.058 vs. 0). Lasse Hallström had the characteristics of such a counterfactual, optimal director in the 2010 year-market and was rumored to have been approached for this directing job but did not direct it in the end due to scheduling conflict (IMDb.com, 2021). Had Hallström directed *The Tourist*, the predicted box office would have been US$96.1 million (Table 6, row 2). Such a financial outcome would have been not only double the predicted box office with von Donnersmarck (US$43.3 million), but also higher than the actual box office (US$67.6 million) and closer to recovering its production budget (US$100 million). In other words, this movie was undermatched with a weaker director and the mismatch was shown in its financial performance.

[Insert Table 6 here.]

Similarly, for *Marmaduke* (2010), with a US$50 million production budget, Model 2 predicted its domestic box office with the actual director Tom Dey to be US$54.2 million (Table 6, row 3). With the counterfactual optimal director (e.g., Ben Affleck, who had the optimal director's characteristics in the 2010 year-market), the box office would have been US$83.2 million (Table 6, row 4), and the movie would have turned in a profit rather than a deficit. It is noteworthy that, unlike *The Tourist*, for *Marmaduke*, the counterfactual optimal director Affleck was not an undermatch, but a mismatch. In the 2010 year-market, Affleck was better than Dey in PE only (0.110 vs. 0.009) but weaker in past box office (0.736 vs. 0.820).

To sum up, these simulated results showed how matching with the optimal director can substantially improve movie financial success. The two examples illustrated that those mismatched directors might not always be weaker in every aspect than the optimal directors, yet still could lead to severe negative financial outcomes. The same procedure can be easily applied to all other movies to identify the financial implications of movie–director mismatches.

5.2. Quantifying the Indirect Monetary Effects of Production Budget on Box Office

The two-sided matching model has shown that the movie/producer side attributes affect the matching outcomes, that is, which director directs that movie project (Section 4), and, in turn, the matched director affects the box office (Section 5.1). Here, we focus on the movie budget and its indirect effects on the box office through the matched directors. To do so, first we simulate the matching process with different production budgets and examine what director characteristics these budget levels would be matched with, then we predict the resulting box office based on Model 2 estimates (Table 5). We selected three movies from the 2010 year-market with different actual budgets and different producer PE[18] to illustrate the simulation results, shown in Table 7.

[Insert Table 7 here.]

Take *From Paris with Love* (2010) as an example, which had a budget of US$52 million and producers with low embeddedness. In the simulated matching process, all the variables were kept unchanged except production budget. The 10 simulated budget levels were the 10 deciles in

[18] We defined three levels of PE based on producer set PE distribution in the 2010 year-market: Low (PE=0, ranked at the bottom), Medium (PE=0.012, in the 60th percentile), and high (PE=0.096, in the 99th percentile).

the production budget distribution of all the movies in the 2010 year-market when it was released. The lowest decile was US$2.5 million and the highest US$260 million. The simulations identified 10 different optimal directors that these 10 budget levels would have matched with, leading to 10 different predicted box office outcomes (Table 7, rows 1 to 10).[19] We term a baseline or newbie director as one with their characteristics set as 0. Thus, the estimated monetary impact at each budget level is the difference between the optimal director the budget would have matched and the baseline director. The first seven rows (from the 1st to the 7th decile) showed that the low budgets would have matched *From Paris with Love* with a director with the lowest characteristics only, thus the estimated indirect financial impact on box office would be 0. Had the movie had a higher budget (in the 8th decile at US$69 million or above), however, it would have matched with a director better than the baseline one, leading to US$17.3 million more at the box office. The higher the budget, the more pronounced the monetary effect (Table 7, rows 8 to 10). We repeated the same procedure for two other movies with greater actual budgets and greater producer PE, where *The A-Team* had a budget of US$110 million and producers with medium PE and *Prince of Persia* a budget of US$200 million and producers with high PE. They both replicated the pattern found with *From Paris with Love*. The indirect monetary impact could be huge: for example, *The A-Team* could make as much as US$109.3 million more in domestic box office revenues.

A comparison across the three movies revealed that when producers had greater PE, the threshold for the optimal director to generate a positive box office effect over the baseline director became lower (the 8th, 7th, and 1st deciles for the producers with low, medium, and high PE, respectively). For instance, with a budget in the 1st decile (or US$2.5 million), the producers

[19] Web Appendix 6 provides the details about the simulation.

of *Prince of Persia*, who had high PE, would match with a better-than-baseline director and in turn have positive effects on box office (US$19,664), and the monetary gain would be remarkably greater (US$13.9 million) when the budget was in the 6th decile (or US$30 million). But for producers with low embeddedness, the same positive monetary effect would require a production budget in the 8th decile (or US$69 million) or more. In summary, production budget has significant indirect monetary implications for box office through its match with a better director. The magnitude of such indirect effects varies due to producer characteristics.

5.3. Quantifying the Indirect Monetary Effects of Producer Characteristics on Box Office

Section 5.2 has quantified the indirect monetary effects of movie production budgets. Now we turn to the indirect monetary effects of other factors on the movie/producer side but focus on producer characteristics. To what extent do producer characteristics affect the matched directors and in turn affect the box office? To answer this question, we ran simulations and chose six movies released in 2010 to illustrate these effects (Table 8). We term a baseline or newbie producer set as one with 0 track records and 0 network embeddedness. In the simulations, for each movie, its producer characteristics (i.e., box office records, Oscar wins, and PE) were replaced with those of the baseline one, while all other factors were kept unchanged. Next, we identified the optimally matched director set for the actual producer set and that for the baseline producer set. Then we calculated the predicted box offices based on Model 2 estimates (Table 5). The difference between them would indicate the indirect monetary effects that the producer characteristics have on the box office through their matchings with directors.[20] For example, the actual producer set on *The Losers* could match with a better director set than the baseline newbie producer set could in terms of greater director PE (0.001 vs. 0) (Table 8, rows 1 and 2). This is

[20] Web Appendix 6 provides the details about the simulation.

not surprising because our two-sided matching model found statistically significant positive sorting in terms of past box office and PE (Table 3). The better match would lead to an increased box office of US$121,182. The same pattern was largely replicated in all the six movies, and among them, *Marmaduke* gained the most at the box office (US$53.3million).

[Insert Table 8 here.]

The six movie examples were selected because they had similar producer characteristics but different production budgets. A comparison across them revealed that the indirect monetary effects of producers were moderated by production budget. Producer characteristics have the greatest monetary effects when the movie had a moderately high budget (e.g., *Marmaduke*'s US$50 million, approximately in the 75th percentile). Compared with a newbie producer, an established producer would benefit hugely from matching with better directors (0.736 vs. 0 in director box office records, 0.110 vs. 0 in director PE). In contrast, an extremely high budget (e.g., *Harry Potter and the Deathly Hallows*' US$200 million, approximately in the 95th percentile) would eliminate the advantage that an established producer has over a newbie producer in terms of attracting directors, and there is nearly no gain at the box office from having better producers (US$0). In addition, when the movie budget is relatively low (e.g., *The Losers*) producer characteristics have small effects on the matched director, especially in term of director box office records, and hence small eventual box office effects.

In summary, the results from Sections 5.2 and 5.3 combined suggest that the two factors on the movie/producer side—movie budget and producer characteristics—can have significant monetary effects on box office performance, indirectly through the directors they can match with. Also, they interact in affecting the matched directors and the resulting box office.

6. Managerial Implications and Conclusion

Set in the U.S. movie industry, this empirical research illustrates a new approach to understanding the effects of various movie attributes and filmmaker characteristics on box office, indirectly through the matching outcomes between movies/producers and directors. It contributes to the literature on box office determinants by focusing on the producer’s problem to optimize director selection at the preproduction phase and demonstrates empirically how far-reaching economic implications the optimal matches have. The use of the two-sided matching model captured the complementarity between the movie/producer side and the director side, and the simulations explicitly demonstrated the monetary values of optimal matches.

6.1. Managerial Implications

The results from the two-sided matching estimation and counterfactual simulations provide a rich set of interesting and useful insights for film producers in recruiting directors for their movie projects. Several noteworthy findings, we believe, are of interest to movie producers as well as entrepreneurial start-ups. First, matching with an optimal director leads to sizable gains at the box office, everything else being equal. Examples such as *The Tourist* (2010) and *Marmaduke* (2010) both testified to such gains worth millions more dollars in box office revenues. Director mismatches, not necessarily undermatches, on the other hand, could be costly in millions of dollars (Table 6).

Second, our results illuminated how movie budget affects box office, indirectly through matching with directors of stronger characteristics, such as better director box office records and greater PE in the filmmaker network. For producers, these results point out the characteristics they should look for in an optimal director, given the production budget they have secured for their movie project. Especially when producers themselves do not possess strong characteristics such as PE, securing more financial resources would be worthwhile since the bigger budget might match with a better director, and the bigger budget combined with these improved director characteristics can lead to sizable gains at the box office (Table 7, e.g., *From Paris with Love*).

Understanding the indirect impact of production budget on movie financial performance by attracting a better director can help producers to make better financing decisions. For example, to convince investors, producers can show the direct and indirect impacts of their money on the predicted movie box office. Our results showed a clearer link from project funding and project financial outcome, which can be useful for funding decisions in other high-risk projects such as innovations and R&D, a sentiment shared in Lo and Pisano (2016).

Third, for producers without huge production budgets, the good news is that their own characteristics such as PE and box office records can help their movie projects to match with directors with strong characteristics. In other words, producers' own strengths sometimes substitute movie budget in attracting strong directors (Table 8). Such matching outcomes also boost the box office revenues for the new movie project. For entrepreneurial start-ups beyond filmmaking, this suggests that the lack of financial backing can be offset by the entrepreneur's social status and experience.

Lastly, the matching model estimation results revealed the importance of social relations on matching outcomes. Producers are more likely to match with directors they have collaborated with before, and such preferences to work with familiar partners are not dented by the high financial risk, as in the case of big-budget movies. We found that when social relations were considered in making two-sided matchings, positive assortative matching between producers and directors was strengthened; for example, producers with strong box office records and directors also with strong box office records tend to match, making it difficult for newbie filmmakers to break through in the industry. However, with social relations in the matching process, interestingly, movies with a bigger budget tend to match with less strong directors, which again suggests the substitutability between movie budget and producer characteristics in attracting directors.

6.2. Limitations and Future Directions

The present research has several limitations. First, the social relation characteristics of filmmakers (either network embeddedness or past collaborations) are restricted to recorded professional collaborations. Although the professional network is impactful on the matching outcomes, a more accurate and more complete measure should include interactions outside filmmaking (e.g., in TV or theater production) or even outside the professional domain. Friendship and kinship might also matter in matching decisions. For example, Baccara et al. (2012) have shown that the interaction between co-authorship and friendship has a sizeable effect on faculty members' office-matching preferences. Second, the data do not record the exact time when movie–director mutual choices were made, making it difficult to precisely construct the matching markets. To alleviate this issue, we used only 80% of movies to construct the confidence interval for robustness. Such a problem will not be eliminated unless we have detailed documentation on the dates when contracts were signed by directors and producers. Third, our analysis of the matching terms on movie success is not embedded in the structural model. Future research might integrate two stages—movie–director matching and movie performance determination—in a structural model using the approach described by Sorensen (2007) to quantify the effect of the endogeneity from the matching process on movie success.

Future research can extend the empirical methods we employed here to other industries wherever a two-sided matching process takes place and complementarities from both sides determine the economic outcome. For example, studying acquisitions and their CEOs, Chen et al. (2021) find that the fit between the nature of CEOs' human capital and the type of acquisitions they engage in is associated with stronger performance. Studying buyer–seller two-sided matching in foal-sharing alliances in the thoroughbred industry, Kamal et al. (2021) suggest that buyer centrality has a larger marginal effect on alliance performance than supplier centrality. Scholars can examine similar contexts such as consulting projects, architecture projects, and software development to understand the matching between project attributes and team leader characteristics and how the project success is affected by the matching outcomes.

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Figure 1. **Conceptual framework**

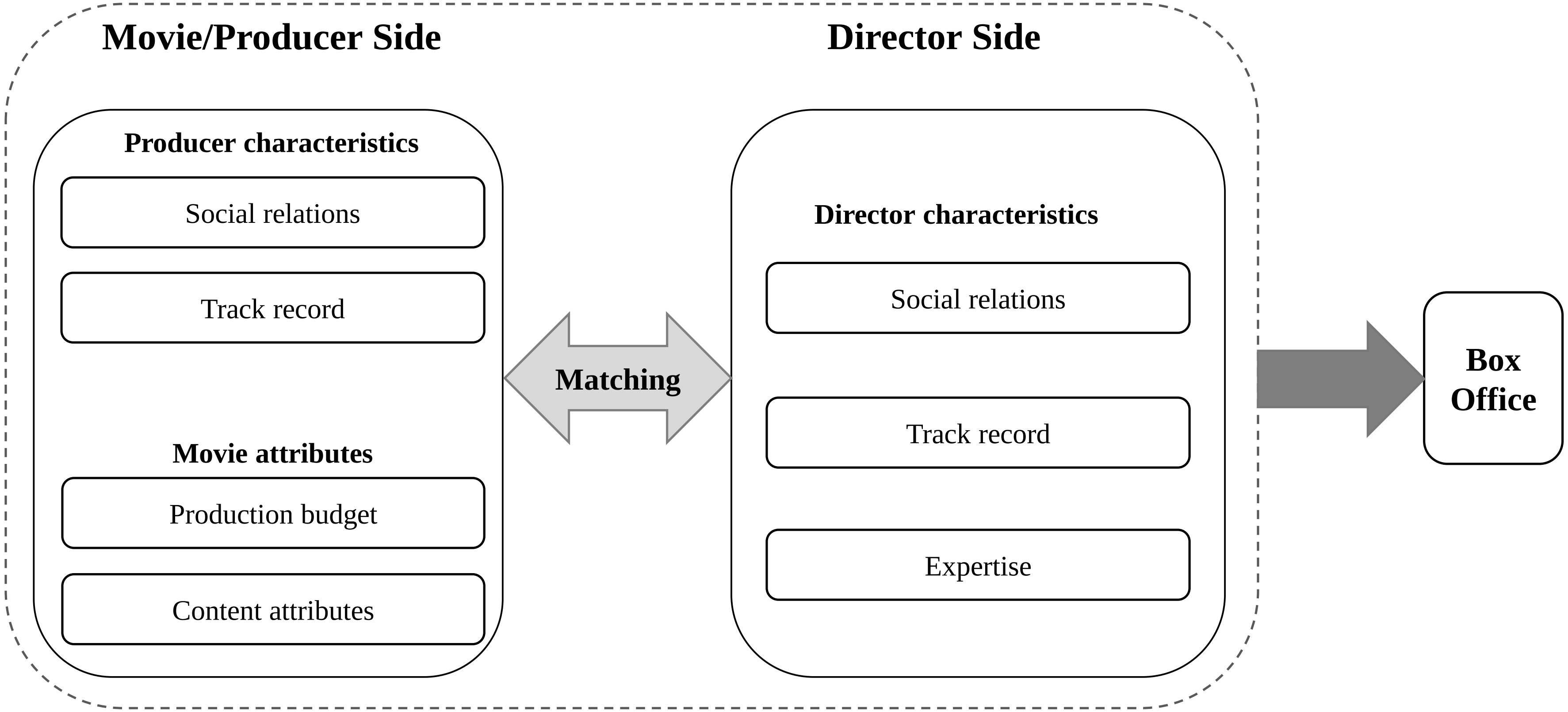

Figure 2. Numbers of movies year by year in the dataset (1990–2010)

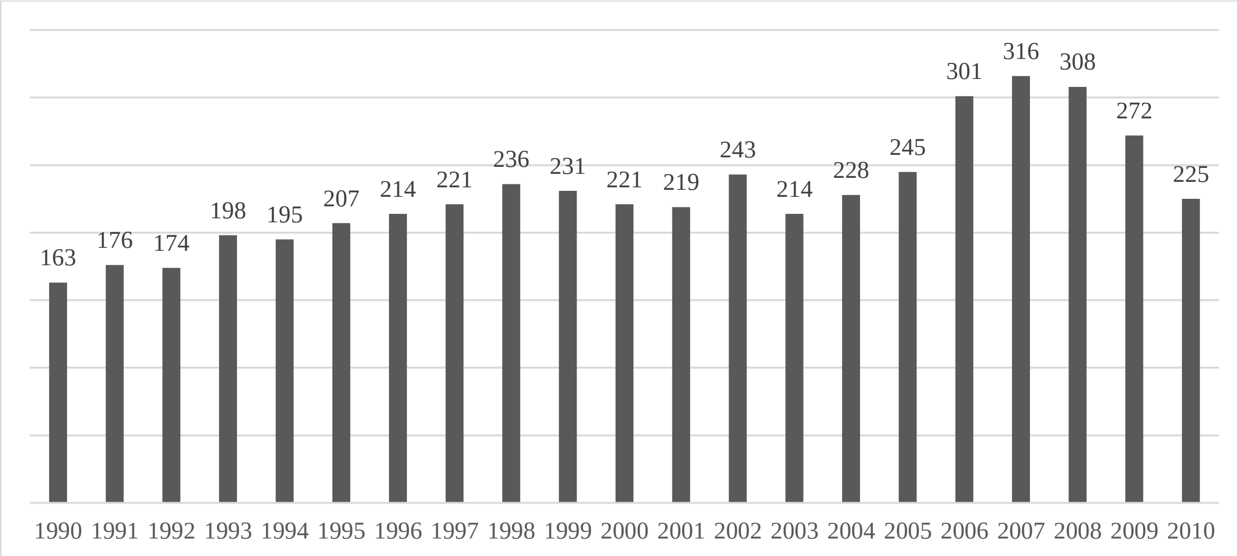

Table 1. Main variables

<table>
<tr><th colspan="2"></th><th>Movie/Producer side</th><th>Director side</th></tr>
<tr><td rowspan="3">Filmmaker characteristics</td><td rowspan="2">Social relations</td><td colspan="2">Past collaborations
• Collaborations as Producer–Director team (PD_COL_PD)
• Collaborations in other roles (PD_COL_OTH)</td></tr>
<tr><td>Network embeddedness
• Positional embeddedness (P_PE)
• Junctional embeddedness (P_JE)</td><td>Network embeddedness
• Positional embeddedness (D_PE)
• Junctional embeddedness (D_JE)</td></tr>
<tr><td>Individual track record</td><td>Past performance
• Box office (P_BO)
• Oscar wins (P_O_WIN)
• Oscar nominations (P_O_NOM)</td><td>Past performance
• Box office (D_BO)
• Oscar wins (D_O_WIN)
• Oscar nominations (D_O_NOM)
Expertise in content attributes (D_EXPT)</td></tr>
<tr><td colspan="2">New movie project attributes</td><td>Production budget
• Budget (M_BUGT)
• Big budget dummy (M_BIG_BU)
Content attributes (M_CONT)
• Genre, subgenre, theme, MPAA rating, script type</td><td></td></tr>
</table>

Table 2a. Summary statistics of raw movie data

Variable Name	Sample Size	Mean	Std. Dev.	Minimum	Maximum
Initial Period 1990–1999	**2,015**				
Movie box office*		2.265E+07	3.621E+07	1124.800	4.890E+08
Movie nominated in Best Director category		0.023	0.151	0	1
Movie winning in Best Director category		0.005	0.070	0	1
Movie nominated in Best Picture category		0.024	0.153	0	1
Movie winning in Best Picture category		0.005	0.070	0	1
Movie production budget*	1,462	2.160E+07	1.930E+07	4706.288	1.628E+08
Number of genres per movie		1.338	0.519	1	5
Number of subgenres per movie		2.121	0.848	1	6
Number of themes per movie		2.891	1.452	0	8
MPAA rating					
Not Rated		0.017	0.129	0	1
G		0.027	0.163	0	1
PG		0.156	0.363	0	1
PG-13		0.254	0.435	0	1
R		0.541	0.498	0	1
NC-17		0.005	0.074	0	1
Script type: adapted dummy		0.425	0.495	0	1
Estimation Period 2000-2010	**2,792**				
Movie box office*		2.347E+07	3.971E+07	496.136	4.632E+09
Movie nominated in Best Director category		0.019	0.136	0	1
Movie winning in Best Director category		0.004	0.063	0	1
Movie nominated in Best Picture category		0.023	0.151	0	1
Movie winning in Best Picture category		0.004	0.063	0	1
Movie production budget*	2,325	2.304E+07	2.555E+07	1575.393	1.890E+08
Number of genres per movie		1.188	0.408	1	4
Number of subgenres per movie		1.973	0.776	1	5
Number of themes per movie		3.016	1.426	0	9
MPAA rating					
Not Rated		0.05	0.21	0	1
G		0.019	0.135	0	1
PG		0.125	0.331	0	1
PG-13		0.340	0.474	0	1
R		0.467	0.499	0	1
NC-17		0.002	0.042	0	1
Script type: adapted dummy		0.441	0.497	0	1

* All the box office and budget figures are the inflation-adjusted numbers with 1990 as the base year.

Table 2b: Summary statistics of producer set and director set characteristics

Variable	Sample size#	Mean	Std. Dev.	Min	Max
Producer set characteristics	**2313**				
Producer BO		0.595	0.284	0	0.958
Producer Oscar nominations		0.145	0.352	0	1
Producer Oscar wins		0.049	0.217	0	1
Producer PE		0.016	0.024	0	0.5
Producer JE		0.015	0.028	0	0.5
Director set characteristics					
Director past BO		0.449	0.367	0	0.973
Director past Oscar nominations		0.058	0.233	0	1
Director past Oscar wins		0.020	0.141	0	1
Director PE		0.008	0.015	0	0.129
Director JE		0.005	0.012	0	0.164

These statistics are based on the number of movies that are used as the estimation sample in the two-sided matching model.

Table 3. Estimation Results of Two-sided Matching Model and One-sided Logit Model

Interaction Variables	Parameters	Two-sided Model: Point Estimates	Two-sided Model: 95% Confidence Interval++		% of Subsamples with the Same Sign as Point Estimates	Logit Model: Estimates	Logit Model: Std. dev
Sample size		2313	1849			495,019	
Movie Production Budget and Director Track Record							
Movie budget × Director past BO	β_1	**112.7+**	(107.39,	132.06)	**100%**	**-1.14**	0.17
Movie budget × Director past Oscar nominations	β_2	-18.6	(-57.91,	10.37)	87%	**-1.19**	0.27
Movie budget × Director past Oscar wins	β_3	66.47	(-18.05,	146.41)	90%	**-2.3**	0.49
Filmmaker Social Relations							
Movie budget × Director PE	β_4	**1***				**-31.81**	4.63
Movie budget × Director JE	β_5	1.65	(-2.21,	6.44)	54%	**-16.04**	6.23
Producer PE × Director PE	β_6	**183.9**	(146.32,	270.74)	**100%**	43.55	53.83
Producer JE × Director JE	β_7	**-30.19**	(-113.81,	14.09)	**98%**	-47.17	100.23
Past producer–director collaborations	β_8	**62.48**	(52.78,	74.44)	**100%**	**7.9**	0.25
Past other collaborations	β_9	**73.17**	(64.68,	85.92)	**100%**	**10.3**	0.28
Past producer–director collaborations × Big-budget movie dummy	β_{10}	-7.23	(-15.10,	21.19)	63%	**0.9**	0.36
Past other collaborations × Big-budget movie dummy	β_{11}	1.29	(-25.67,	14.35)	43%	**-2**	0.47
Producer Track Records and Director Track Records							
Producer past BO × Director past BO	β_{12}	**3.23**	(1.16,	7.01)	**100%**	0.33	0.19
Producer past Oscar nominations × Director past Oscar nominations	β_{13}	**10.53**	(6.79,	15.76)	**100%**	**1.44**	0.3
Producer past Oscar wins × Director past Oscar wins	β_{14}	1.1	(-24.04,	12.34)	75%	**-1.3**	0.56
Movie Content Attributes and Director Expertise							
Director expertise in movie genres	β_{15}^1	**10.44**	(9.65,	13.97)	**100%**	**1.47**	0.15
Director expertise in movie subgenres	β_{15}^2	**13.03**	(10.18,	17.84)	**100%**	**1.77**	0.2
Director expertise in movie themes	β_{15}^3	**5.51**	(1.11,	7.51)	**100%**	**1.01**	0.2
Director expertise in movie MPAA rating	β_{15}^4	**6.5**	(5.60,	9.36)	**100%**	-0.07	0.12
Director expertise in movie script type	β_{15}^5	0.85	(-0.84,	2.75)	80%	**-0.3**	0.13
Model fitness: % of strong inequalities satisfied		85.27%	(84.56%,	85.96%)			
Constant for the logit model						**-5.39**	0.03
Total number of inequalities		246,353	157,277				

Notes: BO = Box Office; PE = Positional Embeddedness; JE = Junctional Embeddedness.
* The *Movie budget × Director PE* relationship serves to normalize the scale and its coefficient is set to +1; the parameter estimate is superconsistent and there is no need to calculate a confidence interval for this covariate.
+Bold numbers are significantly different from zero if zero is not in the 95% confidence level or percentages of subsamples with the point estimate sign is higher than 95%.
++ 95% confidence interval. Please note the confidence intervals are not symmetric around the estimates because subsampling method is used to calculate the confidence interval.

Table 4. The Impacts of Filmmaker Social Relation Characteristics in the Movie–Director Matching Outcomes+

Independent variables	Dependent variables: Differences in director characteristics between the counterfactual and the optimal scenarios (2-1)				
	BO	Oscar nominations	Oscar wins	PE	JE
Movie budget	**0.930*** **	-0.139	0.048	**0.009** **	**0.007** **
	(0.133)++	(0.142)	(0.070)	(0.004)	(0.003)
Producer characteristics					
Producer BO	**-0.132*** **	-0.028	-0.012	**-0.002** **	**-0.001***
	(0.031)	(0.033)	(0.016)	(0.001)	(0.001)
Producer Oscar nominations	-0.013	**0.179*** **	**0.054*** **	**0.002*** **	**0.002*** **
	(0.025)	(0.027)	(0.013)	(0.001)	(0.001)
Producer Oscar wins	0.032	**-0.119*** **	**-0.102*** **	0.001	0.001
	(0.039)	(0.041)	(0.020)	(0.001)	(0.001)
Producer PE	0.160	0.320	0.011	**-0.021*** **	0.003
	(0.190)	(0.205)	(0.101)	(0.005)	(0.005)
Producer JE	-0.585	-0.333	-0.028	-0.015	**-0.079*** **
	(0.452)	(0.483)	(0.238)	(0.012)	(0.011)
Constant	**-0.759*** **	0.164	-0.011	**-0.006** **	**-0.005***
	(0.110)	(0.117)	(0.058)	(0.002)	(0.003)
R-square	0.050	0.040	0.020	0.050	0.060

Notes: BO = Box Office; noms = nominations; PE = Positional Embeddedness; JE = Junctional Embeddedness.
+ The regressions included the following control variables: genre dummies, MPAA rating dummies, and script dummy. To save The space, we omitted their coefficients from the table.
+ + standard deviations are in the brackets.
***, **, and * indicate significance at 0.01, 0.05, 0.1 levels, respectively.

Table 5. The Impacts of Director Characteristics on Movie Box-office#

Independent Variables##	**Model 1**	**Model 2**
Movie production budget	**0.910***** (0.034)	**0.910***** (0.034)
Director past BO	**0.289***** (0.053)	**0.291***** (0.052)
Director past Oscar nominations	0.013 (0.087)	
Director past Oscar wins	0.210 (0.140)	**0.216*** (0.116)
Director PE	2.417* (1.466)	**2.196*** (1.155)
Director JE	-0.500 (1.747)	
Adjusted R-square	0.5343	0.5347
Sample size	2313	2313

Notes: BO = Box Office; PE = Positional Embeddedness; JE = Junctional Embeddedness.
*, **, *** denote significance level at 0.1, 0.05, 0.01 respectively.
Box office and production budget variables used in the regression are inflation-adjusted first and then log-transformed.
##The regressions included genres, MPAA ratings, script type and director expertise in movie content attributes as the control variables. Script type and director expertise are insignificant and removed to improve the adjusted R-square. The following genres: Adventure, Avantgarde/Experimental, Crime, Epic, Fantasy, Musical, Romance, ScienceFiction, SpyFilm, and Thriller are also removed to improve the adjusted R-square. To save the space, we omitted the estimates for the controlled variables.

Table 6. Financial Implications of Movie–director Mismatching: Examples

Movie Title	Release Year	Production Budget (US$ mil) #	Domestic BO (US$) #	Director Characteristics ##					Predicted BO (US$) #	Differences in Predicted BO (US$)
				Director Type	Director Name	BO	Oscar Wins	PE		
The Tourist	2010	100	67,631,157	Actual	Florian Henckel von Donnersmarck	0	0	0	43,342,596	
				Optimal	Lasse Hallström	0.717	0	0.058	96,147,041	52,804,445
Marmaduke	2010	50	33,341,633	Actual	Tom Dey	0.820	0	0.009	54,194,339	
				Optimal	Ben Affleck	0.736	0	0.110	83,172,149	28,977,810

Notes: BO = Box Office; PE = Positional Embeddedness

Production budget and actual box-office numbers are the original numbers before adjustments and rescaling. The predicted box-office numbers are adjusted back to make the results easy for comparison and interpretation.

Director characteristics are the same rescaled values used in the two-sided matching model and the regression model.

Table 7. Indirect Impact of Movie Production Budget on Financial Performance: Examples

Movie Title	Release Year	Movie/Producer side Characteristics		Director Characteristics##			Predicted BO (US$) #	Estimated Indirect Impact (US$) #
		Simulated Production Budget (US$ mil) #	Producer PE	BO	Oscar Wins	PE		
From Paris with Love (Budget: US$52 mil)	2010	2.5 (10%)	Low	0	0	0	1,009,938	0
		6 (20%)		0	0	0	2,239,994	0
		10 (30%)		0	0	0	3,565,381	0
		15.5 (40%)		0	0	0	5,312,365	0
		20 (50%)		0	0	0	6,699,030	0
		30 (60%)		0	0	0	9,688,040	0
		40 (70%)		0	0	0	12,586,875	0
		69 (80%)		0.860	0	0.006	37,953,159	17,295,108
		110 (90%)		0.860	0	0.006	58,015,084	26,437,250
		260 (100%)		0.860	0	0.006	126,899,796	57,827,748
The A-Team (Budget: US$110 mil)	2010	2.5 (10%)	Medium	0	0	0	1,965,228	0
		6 (20%)		0	0	0	4,358,780	0
		10 (30%)		0	0	0	6,937,834	0
		15.5 (40%)		0	0	0	10,337,272	0
		20 (50%)		0	0	0	13,035,567	0
		30 (60%)		0	0	0	18,851,891	0
		40 (70%)		0.800	0	0.030	48,478,249	24,120,158
		69 (80%)		0.820	0	0.009	72,959,345	32,697,414
		110 (90%)		0.820	0	0.009	111,525,691	49,981,284
		260 (100%)		0.820	0	0.009	243,946,125	109,326,743
Prince of Persia: The Sands of Time (Budget: US$200 mil)	2010	**2.5 (10%)**	High	0	0	0.003	1,530,322	19,664
		6 (20%)		0	0	0.003	3,394,180	43,614
		10 (30%)		0	0	0.003	5,402,502	69,420
		15.5 (40%)		0	0	0.003	8,049,630	103,435
		20 (50%)		0	0	0.003	10,150,792	130,434
		30 (60%)		0.882	0	0.015	28,410,634	13,851,252
		40 (70%)		0.882	0	0.015	36,911,520	17,995,754
		69 (80%)		0.868	0	0.003	56,124,298	25,254,281
		110 (90%)		0.868	0	0.003	85,791,433	38,603,619
		260 (100%)		0.868	0	0.003	187,656,203	84,439,765

Notes: BO = Box Office; PE = Positional Embeddedness.
Production budget and actual box-office numbers are the original numbers before adjustments and rescaling. The predicted box-office numbers are adjusted back to make easy comparisons and interpretations.
Director characteristics are the rescaled numbers used in the two-sided model and the regression model.
Bold represents the production budget threshold to attract a better match (80% for the low PE, 70% for the medium PE, 60% for the high PE).

Table 8. Indirect Impact of Producer Characteristics on Financial Performance: Examples

Movie Title	Release year	Production budget (US$ mil) #	Producer Characteristics##				Matched Director Characteristics##			Predicted BO (US$) #	Estimated Indirect Impact (US$) #
			Actual / Baseline	BO	Oscar wins	PE	BO	Oscar Wins	PE		
The Losers	2010	25	Actual	0.807	0	0.034	0	0	0.001	16,091,292	
			Baseline	0	0	0	0	0	0	15,970,111	121,182
Jonah Hex	2010	47	Actual	0.820	0	0.032	0	0	0.019	14,084,127	
			Baseline	0	0	0	0	0	0	12,675,612	1,408,515
Marmaduke	2010	50	Actual	0.800	0	0.035	0.736	0	0.110	83,172,149	
			Baseline	0	0	0	0	0	0	29,878,647	53,293,502
Due Date	2010	65	Actual	0.809	0	0.032	0.836	0	0.035	37,246,024	
			Baseline	0	0	0	0.776	0	0.008	31,023,152	6,222,872
The Other Guys	2010	100	Actual	0.836	0	0.030	0.859	0	0.012	96,873,708	
			Baseline	0	0	0	0.705	0	0.016	89,314,079	7,559,629
Harry Potter and the Deathly Hallows	2010	200	Actual	0.822	0	0.032	0.929	0	0.009	196,149,825	
			Baseline	0	0	0	0.929	0	0.009	196,149,825	0

Notes: BO = Box Office; PE = Positional Embeddedness.
Production budgets are the original numbers before adjustments and rescaling. The predicted box-office numbers are adjusted back to make easy comparisons and interpretations.
Producer and director characteristics are the rescaled numbers used in the two-sided matching model and the regression model.

An Empirical Investigation of Director Selection in Movie Preproduction: A Two-Sided Matching Approach

Highlights

- Filmmaker characteristics affect box office through movie–director matching
- Production budget and producer characteristics interactively affect box office
- Social relations facilitate positive assortative producer–director matching
- Financial implications of movie–director mismatch can be staggering
- Director selection conceptualized and empirically examined as two-sided matching