How Long to Squeeze the Creative Juice? An Empirical Study of the Impact of Movie Production Timing on Financial Performance

Tom Fangyun Tan

Cox Business School, Southern Methodist University, Dallas, Texas 75275

ttan@cox.smu.edu

Jehoshua Eliashberg

Kartik Hosanagar

The Wharton School of Business, University of Pennsylvania, Philadelphia, Pennsylvania 19104

eliashberg@wharton.upenn.edu, kartikh@wharton.upenn.edu

Abstract

We empirically examine the financial impact of production duration in a multi-stage production process for creative products. In particular, we analyze a novel data set from the movie industry to shed light on how the total production time and duration of individual stages affects box office revenues. We find that total production time is negatively associated with box office revenues. In particular, 1% additional total production delay may lower box office revenues by approximately 0.94% on average. In terms of the individual production stages, the duration of the post-production and distribution phases are critical, since both are negatively associated with box office revenues. Our study can help studios better understand how to prioritize production planning and minimize the negative impacts of production delays.

Keywords: operations/marketing interface, the movie industry, creative industries, product development process.

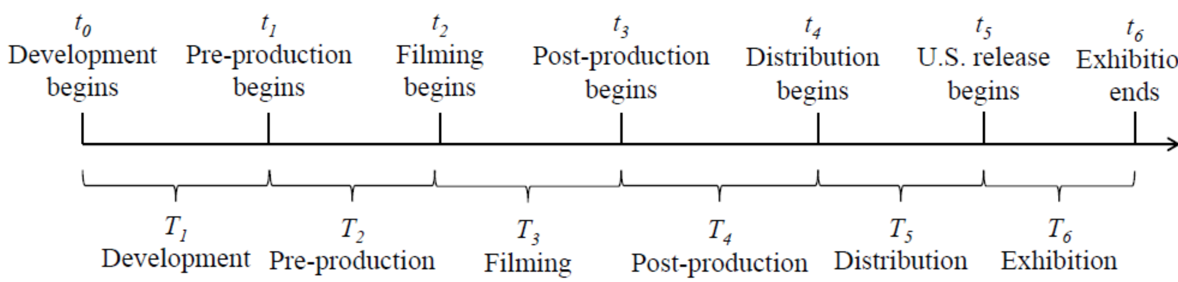
1 Introduction

New product innovation can be viewed as a stage-gate system (Cooper, 1990; Ulrich et al., 2011) analogous to a multi-stage manufacturing process. In this system, an idea proceeds though a series of "stages" and "gates" to market. The "stages" refer to production work, while the "gates" represent various quality checks. For example, the stages may include such activities as preliminary assessment, detailed investigation preparation, development, testing & validation, production and market launch, while the gates are the screening and reviewing activities between the stages.

Movie-making is representative of such a multi-stage production process, and is typically divided into a series of five stages – development, pre-production, filming, post-production, and distribution (Honthaner, 2010). The movie industry is itself a cornerstone of a large creative product industry and has a significant impact on the economy. In the U.S. alone, according to MPAA (2010), the movie/television industry provided 2.4 million jobs and $140 billion in total wages in 2008. Annual box office revenues reached $10.6 billion in the United States/Canada in 2010, when approximately 67% of the entire U.S./Canada population went to the movies at least once. The industry created trade surplus of $11.7 billion, which was larger than the surpluses of the management and consulting, legal, and insurance services sectors.

Figure 1 illustrates the production process of a typical movie (see Section 3 for a detailed description of the movie production process).

Figure 1: Movie Production Process



Each production phase adds value to the movie quality, which in turn drives financial success. Although additional time and resources spent in each stage can help enhance movie quality, longer development time may shorten the length of the sales window and thus limit sales potential. Further, with social media and instantaneous access to information on websites such as HSX.com, information on production delays can spread quickly and threaten a movie's future sales potential. Hence, time-to-market is extremely critical in the film industry. Anecdotal evidence suggests that a delayed movie release may cause box-office failure. For example, a science fiction movie *A Sound of Thunder (2005)* suffered from a long release delay and incurred a loss of $68.3 million (Dirks, 2005). Moreover, consumers who have been disappointed by delayed movies in the past may be more suspicious when a new film is delayed, even if the new film is of higher quality. For example, in 2005, consumers were disappointed by delayed flops such as Terry Gilliam's *Brothers Grim (2005)* and Jennifer Aniston's *Rumor Has It (2005)*. Some industry analysts have argued that when the higher quality movie *Proof (2005)* incurred delays, audiences doubted its quality and were reluctant to watch it, thus harming its box office performance (James, 2006).

There exists little to no research on the impact of movie production process on its financial success. While the movie industry itself has been the subject of numerous academic studies, much of this research relates to forecasting demand, which tends to be highly uncertain because of the experiential product nature (Caves, 2000). Understanding how the product development process relates to market success can help studios and filmmakers better plan their production process (Tatikonda and Montoya-Weiss, 2001).

Our objective in this study is to empirically examine the effects of the duration of the production stages on box office success. We choose to study the box-office revenue impact because theatrical performance is a central driver of a movie's overall success (Daniels et al., 1998). A high box-office performance figure creates buzz in the media and is known to influence other channel performance (Eliashberg, 2005). We investigate how the duration of total production time and each individual stage affects box office revenues, and how these effects change for movies having varying degrees of box office success. Among our findings, we highlight that total production time is negatively associated with box office revenues, controlling for other factors. In particular, 1% additional total production time may lower cumulative box office revenues by on average 0.94%. In addition, the post-production and distribution phases are critical - the durations of these two stages are also negatively associated with box office revenues. A 1% extra delay during post-production is associated with a drop of approximately 0.27% in cumulative box office revenues, while a 1% additional delay during distribution is associated with a drop of approximately 0.38%.

2 Literature Review

There are two streams of work closely related to our study. The first is the literature on new product development, with an emphasis on studies focusing on the impact of time-to-market. The second is the literature studying the drivers of box-office success of movies. We discuss both these streams below.

Time-to-market is a critical operational decision that directly affects product success and has thus been a topic of widespread interest in the new product development literature (see Krishnan and Ulrich, 2001; Shane and Ulrich, 2004 for a detailed literature review). Research tends to focus on the trade-offs of time-to-market, product quality, and development cost. Many papers use analytical modeling approaches to generate managerial insights into how to make these trade-offs. Cohen et al. (1996) introduce a multi-stage new product development model to explicitly analyze the trade-offs between time-to-market and product quality performance. Among their findings, they show that if product improvements are additive (over stages), it is optimal to allocate maximal time to the most productive development stage. Extending this work by Cohen et al. (1996), Morgan et al. (2001) analyze the time-to-market versus quality trade-off for multiple product generations. Unlike the single-generation case, they find that faster quality improvement rates lead to shorter time-to-market. Souza et al. (2004) examine more industry and firm factors in their analytical models and find that low industry clockspeed is associated with longer product development time. Other related analytical studies include work on development process design. For example, Loch et al. (2001) develop an optimal testing strategy in terms of a mix of parallel and serial testing activities to minimize testing time during new product design. Arora et al. (2006) discover that software companies have incentives to release a less robust product earlier and to release patches later to exploit the market potential demand.

Although considerable research has been devoted to analytical modeling, very few studies have empirically examined the impact of product development time on market outcomes. The handful of empirical papers generally examines the production process in its entirety rather than in a more granular multi-stage model (e.g., Hendricks and Singhal, 1997; 2008, Tatikonda and Montoya-Weiss, 2001). Some studies have analyzed the individual new product development stages as antecedents of total development time. For example, Eisenhardt and Tabrizi (1995) collected survey data from the electronics industry and found that the percentage time allocated to planning, an individual development stage, is positively associated with total development time. Using the same survey data, Terwiesch and Loch (1999) find that the percentage of time allocated to testing, another individual development stage, is negatively associated with total development time for projects with slow uncertainty resolution. Also in the electronics industry, Datar et al. (1997) study the impact of product development structures on how long each of the two development stages (i.e., prototyping time and time-to-volume production) lasts and how these two stages affect each other's duration. These studies differ from ours in that they focus on the relationship between stage duration and overall development time rather than on the relationship between duration of individual stages and market outcomes. They also tend to focus on the electronics industry, which is quite different from creative industries. In addition, the issue of how delays impact product success is more salient today because consumers are more aware of product release timing through the Internet and social media. In this study, we investigate the impact of duration of each stage of a movie's production process on its box-office success. We provide new empirical evidence of the importance of carefully managing and monitoring production timing in the movie industry.

The movie industry, given its significant economic value and highly unpredictable demand, has been an industry of great interest within the marketing literature (see Eliashberg et al. (2006) for a comprehensive overview of current research and future research opportunities). So far, the marketing literature on movie economics has tended to focus on demand-side issues such as the impact of advertising and the number of theaters rather than on supply-side factors such as production duration. For example, Eliashberg et al. (2000) designed a decision-support system called MOVIEMOD and used questionnaires to predict pre-launch box-office success. Krider and Weinberg (1998) study strategic release timing decisions that influence the demand for a movie and suggest that weak movies should wait to avoid competition. In respect to exhibition, Swami et al. (1999) and Eliashberg et al. (2001) developed an integer programming-based model known as SILVERSCREENER to improve revenues generated by weekly exhibition schedules. Swami et al. (2001) use a Markovian decision process to model an exhibitor's movie replacement problem. Furthermore, Elberse and Eliashberg (2003) find that the delay between U.S. and international release reduces the performance correlation between domestic and overseas markets. Some attention has been paid to estimating the demand for a new movie at the development stage, i.e., decisions made at t_0 in Figure 1. In particular, Eliashberg et al. (2007) developed a model to evaluate scripts that are associated with more profitable "green-lighting" decisions.

The discussion reveals two themes. First, the literature on new product development has acknowledged the impact of time-to-market on product success. However, much of that literature has been analytical rather than empirical in nature. Furthermore, none of the studies have looked at how the timing of individual production stages impacts product success and no studies have investigated creative industries, which are characterized by an interesting multi-stage product development process. Second, several studies in Marketing have looked at determinants of product success in creative industries such as movie-making. However, much of the emphasis has been on demand-side factors such as advertising with little to no focus on supply-side factors. Our study bridges this gap by empirically examining the relationship between the box-office success of a movie and overall as well as stage-specific production timing. The contributions of this paper are three-fold. First, we provide new empirical evidence of the impact of timing of a multi-stage production process on product success. Second, our study can help studio executives better understand how to prioritize production planning and minimize the negative impact of production delays. Finally, it is one of the first attempts to link marketing and operations management in the movie industry.

3 Movie Production Process and Hypotheses

3.1 Movie Production Process

The movie production process turns an idea into a released movie. The entire process can be further divided into a series of five stages – development, pre-production, filming, post-production, and distribution (Honthaner, 2010).

During development, a producer is in charge of searching for the story and securing the financing. She oversees screenwriters to develop a story that needs to satisfy both creative demands and business feasibility. Then the producer prepares the investment documents and pitches the story to the studio's executive committee and other potential investors to start the "greenlight" process (Eliashberg et al., 2007). During this process, the studio assesses the financial returns based on rough estimates of factors, such as the total production budget, the target audience, historical success of comparable movies, and the directors/actors to be hired. Depending on the likelihood of success, the studio will decide whether to support the project, i.e., greenlight the project.

The main pre-production activities include hiring and preparing for physical shooting. In other words, decisions about the cast and the crew, the shooting schedule and budget breakdowns, the shooting locations and logistics have to be made before the principal shooting starts. In particular, the producer hires ("attaches") a director from a list of candidates after consulting the advisory/management team and the distributors about their experiences with the candidates and their preferences (Lee Jr and Gillen, 2011). Following the same process as director attachment, the producer then attaches the lead cast. During pre-production, the marketing team starts to plan the advertising and promotional budget and to create consumer perception (Pisano and Wagonfeld, 2009). Sometimes the producer continues to secure product placement and brand tie-ins with advertisers.

In the next stage, filming, the director leads the team in shooting the movie. He needs to strike a balance between scheduling constraints and quality targets. On one hand, he may demand various reshoots to ensure quality, which can prolong the filming stage. On the other hand, the work tempo is generally fast for various reasons. First, filming is usually the most expensive stage of the entire production process. Anecdotal examples suggest that filming costs can range from 40% to 80% of the total production budget. The director therefore needs to shoot efficiently to stay on budget. Second, the actors, especially sought-after celebrities, tend to have other films scheduled immediately after a current project. During the principal shooting, the producer reviews all the picture's dailies.

All the remaining tasks to complete the film are passed onto the post-production stage, which tends to be lengthy. During this stage, the movie is usually cut from the negatives, edited digitally and transferred back to film for distribution. There is also a growing trend in digitally shooting, editing and distributing movies, which normally accelerates this process. A post-production supervisor is responsible for leading a small team in editing the picture, sound and special effects. The team also conducts quality control and may request reshoots in case of defect (Patz, 2002). The producer also reviews audience testing, which is a preview screening to gauge audience reaction. Testing results may prompt the filmmakers to revise the movie. For example, test screenings showed negative audience reaction to the kissing scene between Denzel Washington and Julia Roberts in *The Pelican Brief* (1993), causing this scene to be cut (Maher, 2010). In parallel, from the audience testing results, the producer and the marketing team create several versions of trailers to highlight the most attractive aspects of the movie.

The final stage of the movie-making process is distribution. The producer may distribute the movie alone or sell the distribution rights to standalone distributors. The producer invites exhibitors to pre-theater previews and signs exhibition contracts specifying revenue-sharing agreements and screen allocation decisions. Then decisions are made about how many movie prints need to be duplicated and how they should be delivered to cinemas for theater release. Advertising activities usually happen during this time period to stimulate market demand for the movie before its release. For example, the film's posters are displayed and commercials for brand tie-in partners begin airing in the media. Meanwhile, the final product is guarded in an attempt to avoid leaks and piracy.

Note that the duration of the first production stage, development, can be very long and also hard to clearly define. Some producers may define the start of development from greenlighting whereas others may consider it to begin with the conceptualization of the original idea. For example, Jim Cameron said that his blockbuster movie *Avatar* was in the development stage for close to 20 years because the 3D technology was not ready (Jensen, 2007). Since the effective duration of development lacks an accurate measurement and an exact definition, we do not consider development in this study and define instead total production time as running from the start of pre-production to the end of distribution, i.e., $t_5 - t_1$ in Figure 1. Further, note that some of the post-production activities may occasionally overlap with filming. Since such overlap is rare, and tends to be minimal, we ignore such parallelism and model movie production as a serial process.

3.2 Effects of Total Production Time

In this section, we develop our hypotheses about the impact of the duration of production activities on box-office success.

Conventional wisdom holds that total production time, i.e., cycle time, is traded off against product quality because increased investment in process improvement takes additional time (Putnam and Myers, 1991). As a result, improved product quality may rely on longer production times. However, faster cycle time and quality improvement may be simultaneously achieved by defect and rework reduction (Harter et al., 2000). More importantly, longer production time can negatively impact the financial performance of a movie in several ways.

First, a longer time-to-market may reduce a movie theme's timeliness. For example, holiday movies and movies about fashionable ideas or current affairs need to be released before consumers lose interest in the theme. Therefore, a longer time-to-market can imply a shorter selling period, thus harming box-office revenues (Cohen et al., 1996).

In addition, movie release delays after their announced release dates, i.e., excessively prolonged time-to-market, may induce impatient consumers to watch available movies instead (Hendricks and Singhal, 2008), thus causing a loss in box-office revenues. Such a delay may even generate negative publicity about the movie, which often hurts box-office revenues. For example, Columbia's *All the King's Men (2006)* starring Jude Law and Kate Winslet announced a delay two months before its planned Christmas release date, and generated widespread negative buzz (James, 2006). Most consumers interpreted that the movie was in trouble and started to doubt its quality, partly contributing to its box-office loss of approximately $45 million.

Furthermore, such delays can become self-perpetuating. The movie production process is sequential, similar to a tandem queue. A delay in one stage delays the start of later stages, which can additionally cause studios or distributors to allocate resources away from delayed projects, and towards on-time projects, thereby causing further delays (Adler et al., 1995).

Finally, a shorter time-to-market is a key source of strategic early-entry advantages when multiple firms are developing related products and consumers are aware of and waiting for these products to become available. Schmalensee (1982) and Carpenter and Nakamoto (1989) provide theoretical and behavioral support that in many markets, including experience goods such as movies, early entrants can set quality standards and make consumers reluctant to invest in learning about subsequent products. In addition, early entrants can have a longer sales cycle, which also increases profitability (Smith and Reinertsen, 1991).

Based on these arguments, we test the following main hypothesis:

HYPOTHESIS 1: *Total production time is negatively associated with box-office revenues.*

3.3 Effects of Individual Stage Duration

Although a delay at any stage will increase the total production time for a movie, the effects of the different production stages may vary depending on stage-specific characteristics. We provide three such characteristics that may differentiate the impacts of each stage duration on box-office revenues: labor intensity, decision power centralization and piracy risk.

Characteristic I: Labor Intensity

Differences in stage-specific productivity may result in differences in the way a delay in these stages affects movie success. Similar to Cohen et al. (1996), productivity in this paper is viewed as the quality improvement (output) rate per unit time (input). Cohen et al. suggest that it is optimal to allocate more time to the more productive product development stage, because the quality improvement in each stage is cumulative. Since we cannot directly measure stage-specific productivity, we proxy it by a primary production input, labor, which is positively associated with productivity (Cobb and Douglas, 1928) [1]. Hence, a stage with high labor intensity is considered to possess higher quality improvement rate, thus benefiting from additional time.

Across the four movie production stages, pre-production and filming are most labor-intensive. For example, the pre-production task of hiring a crew and casting the film is highly labor-intensive(Bowen et al., 1991). During the casting process, many potential hires are called in to be auditioned by many interviewers (Patz, 2002). As a result, the hiring process is time-consuming (Bowen et al., 1991; Lomi et al., 2010). During filming, almost the entire crew and the cast work together on shooting the principal footage. For example, the number of crew in *The Matrix Revolution (2003)* exceeded 700 people (Filmreference, 2011). In contrast, post-production and distribution are less labor-intensive because they involve few cast or crew.

Characteristic II: Decision Power Centralization

Another key difference between the production stages is the degree of centralization in decision-making in each stage. Low centralization implies the presence of multiple decision-makers and the need for consensus (Eisenhardt and Bourgeois III, 1988). In the presence of multiple decision-makers who usually represent their own functional units, delays in clearing a production stage may signal ineffective coordination of different teams and problematic conflict resolution. Loch and Terwiesch (1998) suggest that ineffective coordination between teams may create errors, which require rework. Mending these mistakes can delay production schedules (Hoegl et al., 2004). In addition, Eisenhardt (1989) finds that conflict resolution, which is the extent to which disagreements are replaced by consensus, is poor for teams that make slow decisions because they tend to delay until external events force a decision. Ineffective coordination and conflict resolution among multiple decision-makers may cause movies to fail. For example, Paramount's action movie *Sahara (2005)* suffered from ineffective coordination. The production team, which included 20 producers and four credited screenwriters, created coordination complexity and changed the director's original vision of a light tone. Consequently the movie turned out to lack suspense and tension, contributing to a box-office loss of approximately $144.9 million (Dirks, 2005). Therefore, for those stages having low decision

[1] Ideally we would also use capital input as another proxy. Nevertheless, movie studios almost never publicize their budget breakdowns, leaving us to use only the labor proxy.

power centralization, i.e., multiple decision-makers, delays may indicate low movie quality and therefore box-office underperformance. For those stages having high decision power centralization, delays are not necessarily indicative of poor quality.

Pre-production and filming both have high decision power centralization. During pre-production, the producer mainly oversees the entire operation, ranging from budgeting and scheduling to hiring directors. During filming, the director is primarily responsible for ensuring footage quality. In contrast, post-production and distribution are generally associated with multiple decision-makers, i.e., low decision power centralization. During post-production, the post-production supervisor, the producer and the director jointly decide on the final movie print. In the case of disagreements in the final movie, reshoots may be demanded. During distribution, the producer and the distributor are both key decision makers.

Characteristic III: Piracy Risk

A key source of revenue loss for movies in the recent past has been loss to piracy. Delays in a movie's release date may contribute to higher levels of piracy, and hence to lower box-office receipts. However, the risk of piracy due to delays is different at different stages. A long delay during a stage with significant piracy risk allows pirates sufficient time to produce and distribute their illegal copies to the broader market. Further, the delay is likely to encourage consumers to seek the movie elsewhere especially if significant consumer interest has been generated through advertising and promotion. The detrimental consequence of piracy to box-office revenues is critical. For example, an illicit version of *X-Men Origins: Wolverine* was reported to have been shown on the Internet one month before the official theatrical release (Stelter, 2009). This leak in revenues to piracy reduces the revenues from legal exhibitors, who may in turn shorten the exhibition life of pirated movies because of low revenues. In addition, an illicit version of the pirated movie usually has a lower quality than the official version, thus creating bad word-of-mouth and reducing demand. This double jeopardy of piracy is estimated to cause a $10 billion motion-picture industry to lose roughly $3 billion annually (Ma et al., 2009). Hence, those stages having high piracy risks should avoid excessive delays. Those stages having low piracy risks, however, are not necessarily harmed by long duration.

Among the four production stages, pre-production and filming tend to face low piracy risk, while post-production and especially distribution are more prone to this risk.This is because the movie footage is incomplete during the first two stages. During the last two stages, however, the movie footage is almost or fully complete. Further, during the first two stages, advertising and promotion are generally limited, thus lowering the risk of consumers' strong desire for illegal copies. However, during the later two stages, advertising and promotional activity tend to stimulate consumer awareness and demand for the movie, including for pirated copies.

Applying the three characteristics to the individual production stages below, we propose the following research hypotheses.

3.3.1 Pre-production

Pre-production is characterized by relatively high labor intensity, high decision power centralization and low piracy risk. All these factors suggest that delays are less costly. In addition, Honthaner (2010) suggests that producers should spend adequate time thoroughly planning ahead during the pre-production stage to anticipate and avoid emergencies that can cause delay in production. In other words, pre-production uniquely functions as the strategic planning phase and secures supply of important resources, such as labor, for later development stages (Anderson, 1982). Such strategic planning has been widely shown to have positive influence on performance (Armstrong, 1982; Miller and Cardinal, 1994) Hence,

HYPOTHESIS 2a: *Pre-production time is positively associated with box-office revenues.*

3.3.2 Filming

Like pre-production, filming is characterized by high labor intensity, high decision power centralization and low piracy risk. In addition, sufficient filming time can help ensure that the director has obtained high-quality footage, which can help reduce errors and reshoots, thus shortening and benefiting the later production stages. Therefore,

HYPOTHESIS 2b: *Filming time is positively associated with box-office revenues.*

3.3.3 Post-production

In contrast, post-production has low labor intensity, low decision power centralization and relatively high piracy risk. Furthermore, post-production delays incur extra costs. Delays can therefore be costly in many ways. These higher costs raise revenue expectations and can consequently pressure the production firm to spend even more time tweaking the film. This vicious cycle, also known as "post-production hell" may further delay the movie release, which may miss the optimal selling window, hurting market reception and box-office revenues. A commonly cited example is *A Scanner Darkly (2006)*, which suffered from this "post-production hell" and encountered an increase in budget from $6.7 to $8.7 Million and almost 10 months delay in the theatrical release. Therefore,

HYPOTHESIS 2c: *Post-production time is negatively associated with box-office revenues.*

3.3.4 Distribution

Distribution is also characterized by low labor intensity, low decision power centralization and high piracy risk. In addition, during the distribution period, distributors invite potential buyers to pre-release previews and negotiate deals on the exhibition schedule. Longer distribution time might also signal that fewer exhibitors are interested in the film. Hence,

HYPOTHESIS 2d: *Distribution time is negatively associated with box-office revenues.*

4 Data

4.1 Research Setting and Data Collection

To examine our research hypotheses, we gathered data on production and advertising activities from the Internet Movie Database (IMDb Pro), the Numbers and Ad$pender. IMDb Pro is an online database with extensive movie characteristics information such as box-office revenues, production budget, genre and MPAA ratings. In addition, it compiles and records the dates of production status updates, which are reported by Hollywood studios. IMDb Pro assigns multiple genres to a movie, creating hundreds of genre possibilities. To standardize and simplify genre categorization, we collect genre data from the-Numbers.com, which assigns one major genre to each movie. Similar to IMDb, the-Numbers.com is also a popular data source website for business information on movies. Ad$pender provides data about aggregate advertising expenditure and the timing of each ad impression for over three million brands across eighteen media types, such as television, radio, magazines, newspapers and outdoor signage. Our data consist of Hollywood movies released in the U.S. market from January 2005 to December 2009. We selected this range because both production and advertising data are available from both IMDb Pro and Ad$pender collectively from 2005. Ideally we wanted to include all the movies that were released in this time period. We excluded those movies that have missing data and formed a final data sample that includes 315 movies.

Our sample represents a unique dataset from the field to study the impact of production timing decisions on movie success for several reasons. First, the dataset is among the largest in the existing literature on movie box-office performance (Eliashberg et al., 2000; Elberse and Eliashberg, 2003; Neelamegham and Chintagunta, 1999). Further, our dataset provides comprehensive production data, which allows us to systematically quantify the performance impact of production duration.

4.2 Measures and Controls

We use cumulative U.S. domestic box office revenues *USBOX* as the main performance measure. This domestic gross is an important measurement of a movie's financial success metric in the U.S. market because it is not only a major revenue resource but also an influential factor for a movie's other revenue resources, such as worldwide releases and rental markets. We use opening weekend box-office revenues as an alternative financial performance metric for a robustness check. The opening weekend box-office revenue is a critical measurement of the financial success of a movie because it affects the exhibition life time and the screen allocation in later weeks (Pisano and Wagonfeld, 2009).

We define the total movie production time *PRODTIME* as the number of days from the beginning of pre-production to the beginning of U.S. theatrical release. In addition, we use the production stage duration measured in days to construct variables *PREPROD, FILMING, POSTPROD* and *DISTR,* respectively. Our measures of individual production stage duration are in whole days, as opposed to a fraction of total production time. We choose to use whole days because 1) studios plan their production schedules in days and 2) it is more managerially meaningful to interpret the financial impact of an additional day in production.

In addition to these main variables, we consider the following control variables. Variable *BUDGET* is the production budget, which can affect the technology sophistication and the quality of the production team. Variable *ADEXP* is the total advertising expenditures for movies released from 2005 to the first half of 2010. Advertising expenditures can boost box-office revenues by creating awareness among prospective audience members. We delay our data extraction of advertising expenditures until June of 2010 in order to include the advertising expenditures of those movies released in late 2009. We further construct a group of dummy variables to control for movie genre, MPAA rating and production studio. For example, each genre is a combination of zero-one dummies except for the chosen baseline genre (Action). We categorize production studios into six "Big Six" studios including Fox, NBC Universal, Paramount, Sony, Walt Disney, and Warner Brothers, and five "Mini Majors" including Dreamworks, Lions Gate, MGM, Summit, and Weinstein. All other studios are coded as "Other". We also control for variable *OPNTHTR*, the number of theaters showing the movie during the opening weekend. These opening weekend theaters reflect the movie release strategy and this variable is shown to significantly affect box-office revenues, particularly opening weekend revenues (Elberse and Eliashberg, 2003). To control for unobserved movie quality and word-of-mouth effects, we create our last control variable, *AVGRATING*, and compile the average consumer ratings on a scale from 1 to 10 from IMDb before our data extraction in June 2010. We choose IMDb consumer ratings because this is one of the most popular websites for movie consumers to rate and review movies. Although consumers can continue rating movies after our data extraction, which could potentially change the average ratings that we collected, this change should be negligible because IMDb generally attracts large quantities of ratings in a short amount of time. This large number of consumer ratings by our data extraction should ensure that our average rating approaches the long-term average ratings.

To summarize, Table 1 shows a complete list of main variable definitions. These data allow us to empirically test our hypotheses while controlling for movie characteristics and other factors that can affect a movie's financial performance.

Table 1: Main Variable Definitions

Variable	Definition
USBOX	Cumulative U.S. domestic box-office revenues in million U.S. dollars
OPNBOX	U.S. market opening weekend box-office revenues in million U.S. dollars
PRODTIME	Total production time in days from the beginning of pre-production to the beginning of U.S. theatrical release
PREPROD	Pre-production stage duration in days
FILMING	Filming stage duration in days
POSTPROD	Post-production stage duration in days
DISTR	Distribution stage duration in days
BUDGET	Production budget in million U.S. dollars
ADEXP	Advertising expenditures in million U.S. dollars from 2005 to the June of 2010
GENRE	A group of 0-1 binary variables for each major genre, with Action treated as the baseline
MPAA	A group of 0-1 binary variables for each MPAA rating, with G treated as the baseline
STUDIO	A group of 0-1 binary variables for each major studio, with Dreamworks treated as the baseline
OPNTHTR	Number of theaters showing the movie during its opening weekend
AVGRATING	Average consumers ratings on a scale from 1 to 10 from IMDb by June 2010

4.3 Descriptive Statistics

Table 2 presents the descriptive statistics of movie financials. The average U.S. Domestic Box Office revenues, i.e., domestic gross revenues, is about \$47.78 million. The opening weekend box-office revenues are \$13.5 million on average, contributing to approximately 28% of total domestic gross revenues. On the cost side, it costs on average \$41.04 million to produce and \$17.16 million to advertise a movie. At the same time, there is significant variation in box-office performance and budgets across movies in our sample. In addition, all these financial metrics are positively skewed, suggesting that a small number of movies comprise the majority of revenues and costs.

Table 2: Descriptive Statistics of Movie Financial

	U.S. Domestic Box Office (in $thousands)	Opening Weekend Box Office (in $thousands)	Production Budget (in $thousands)	Advertisement Expenditure (in $thousands)
N	315	315	315	315
mean	47,778.91	13,496.99	41,041.08	17,158.20
sd	60,983.34	20,149.11	40,968.70	12,336.78
skewness	2,626.88	3,302.33	2,117.72	346.52
min	4.72	0.23	500	0.70
p1	14.50	4.72	1,500	3.80
p5	126	19.49	4,000	107.90
p25	7,770	477.84	15,000	7,009.90
p50	28,700	7,570.37	25,000	16,525.10
p75	62,600	18,623.17	54,000	26,452.50
p95	173,000	50,927.08	140,000	39,830.80
p99	319,000	102,750.70	200,000	44,030.60
max	423,000	151,116.50	258,000	50,748.30

Table 3 shows the descriptive statistics of movie production time. The average total production time is about 633 days. Of the four production stages, post-production tends to be the longest, with an average duration of about 205 days, which suggests that post-production seems to be the bottleneck of the entire production process. Distribution is the second longest stage with an average duration of 161 days, followed by pre-production (mean $\approx$ 158days) and filming (mean $\approx$ 111 days).

Table 3: Descriptive Statistics of Movie Production Time (in Days)

	Total Production Time	Pre-production	Filming	Post-production	Distribution
N	315	315	315	315	315
mean	633.33	157.55	110.64	204.60	160.55
sd	252.28	167.65	75.96	107.28	133.10
skewness	1.53	2.73	3.57	1.34	1.51
min	202	6	12	11	14
p1	248	8	23	27	23
p5	311	20	40	62	32
p25	463	59	70	132	65
p50	582	100	94	189	112
p75	751	194	128	258	238
p95	1,100	520	246	405	430
p99	1,460	783	471	460	612
max	1,961	1,333	744	857	812

Before testing our hypotheses, we transform several of our variables including *USBOX, OPN-*

BOX, PRODTIME, PREPROD, FILMING, POSTPROD, DISTR, *BUDGET,* and *ADEXP* into their natural log and rename them, respectively, *LN_USBOX, LN_OPNBOX, LN_PRODTIME, LN_PREPROD, LN_FILMING, LN_POSTPROD, LN_DISTR*, *LN_BUDGET,* and *LN_ADEXP*. The main purpose for transforming our variables is to linearize the multiplicative regression model (Kleinbaum et al., 2007). Analysis of the original data shows a non-linear relationship between *USBOX* and those variables that need transformation except *BUDGET.* We find that the log transformation increases linearity most effectively. Such transformations are commonly used when evaluating the drivers of movies' financial performance (see, for example, Neelamegham and Chintagunta, 1999; Elberse and Eliashberg, 2003; Chintagunta et al., 2010). In addition, several variables including *BUDGET* have large standard deviation relative to their means. Transforming such variables is recommended to increase normality prior to model estimation (Afifi et al., 2004). Finally, transforming monetary variables, such as *USBOX* and *BUDGET,* normalizes the scale of units to a percentage for easier interpretation.

Table 4 presents the correlations of box-office revenues, production time, production budgets, advertising expenditures, opening theaters and average rating. None of the correlations is high except for the correlation between *LN_OPNBOX* and *OPNTHTR.* The correlations among the predictors are low, suggesting that the predictors should not cause the multicollinearity issue in the model estimation.

Table 4: Key Variable Correlations

	LN_USBOX	*LN_OPNBOX*	*LN_PRODTIME*	*LN_PREPROD*	*LN_FILMING*
LN_USBOX	1.0000				
LN_OPNBOX	0.8366*	1.0000			
LN_PRODTIME	-0.2040*	-0.2124*	1.0000		
LN_PREPROD	0.2579*	0.2209*	0.5408*	1.0000	
LN_FILMING	0.3319*	0.2639*	0.1955*	0.1243*	1.0000
LN_POSTPROD	-0.1853*	-0.1662*	0.5028*	0.1518*	-0.1928*
LN_DISTR	-0.5262*	-0.4789*	0.4272*	-0.1706*	-0.2206*
LN_BUDGET	0.6804*	0.6426*	0.1176*	0.3974*	0.4822*
LN_ADEXP	0.7981*	0.6767*	-0.1495*	0.2594*	0.2798*
OPNTHTR	0.6737*	0.9010*	-0.1194*	0.2256*	0.2725*
AVGRATING	0.1249*	-0.1107*	0.1510*	0.1177*	0.1943*

	LN_POSTPROD	*LN_DISTR*	*LN_BUDGET*	*LN_ADEXP*	*OPNTHTR*	*AVGRATING*
LN_POSTPROD	1.0000					
LN_DIST	0.0789	1.0000				
LN_BUDGET	0.0021	-0.3998*	1.0000			
LN_ADEXP	-0.1342*	-0.4138*	0.5640*	1.0000		
OPNTHTR	-0.1359*	-0.4234*	0.6011*	0.5243*	1.0000	
AVGRATING	-0.0207	0.0237	0.0918	0.0964	-0.1992*	1.0000

* Significant at 0.05 level.

5 Analyses and Results

5.1 Multivariate Regression with Basic Control and Advanced Control

We employ the following multivariate regression model as a base model to examine the relationship between production time and box-office revenues:

$$
\begin{aligned}
LN\_USBOX_i &= \alpha_0 + \alpha_1 LN\_PRODTIME_i + \alpha_2 \text{Basic Control}_i + \varepsilon_i && (1)\\
LN\_USBOX_i &= \beta_0 + \beta_1 LN\_PREPROD_i + \beta_2 LN\_FILMING_i + \beta_3 LN\_POSTPROD_i && (2)\\
&\quad + \beta_4 LN\_DISTR_i + \beta_5 \text{Basic Control}_i + \theta_i,
\end{aligned}
$$

where Basic Control includes *GENRE, MPAA,* and *STUDIO.* In these two models, we use a Huber-White estimator to correct for heteroskedasticity.

We further include another set of Advanced Control in the model to provide a robustness check:

$$
\begin{aligned}
LN\_USBOX_i &= \alpha_0 + \alpha_1 LN\_PRODTIME + \alpha_2 \text{Basic Control} + \alpha_3 \text{Advanced Control} + \varepsilon_i && (3)\\
LN\_USBOX_i &= \beta_0 + \beta_1 LN\_PREPROD_i + \beta_2 LN\_FILMING_i + \beta_3 LN\_POSTPROD_i + && (4)\\
&\quad \beta_4 LN\_DISTR_i + \beta_5 \text{Basic Control}_i + \beta_6 \text{Advanced Control}_i + \theta_i,
\end{aligned}
$$

where Advanced Control includes *LN_BUDGET, OPNTHTR, LN_ADEXP,* and *AVGRATING.* Similar to the null model, we also use a Huber-White estimator to correct for heteroskedasticy.

Although we use extensive control variables, we may face one potential issue in the OLS regression: studios may allocate resources to movies based on unobserved financial potentials, thus causing *LN_PRODTIME, LN_PREPROD, LN_FILMING, LN_POSTPROD, LN_DIST* to be endogenous variables. If such an unobserved priority exists, the OLS estimates are likely to be biased. In order to address this possible endogeneity issue, we use instrumental variables and conduct the Hausman Test of endogeneity detailed in Subsection 5.3.1.

5.2 Results

Table 5 shows the estimation results of Models 1 through 4. As can be seen, the estimates of total production time *LN_PRODTIME* are both significantly negative (-1.6924 and -0.9430), suggesting that total production time is negatively associated with the cumulative domestic box-office revenues and supporting our Hypothesis 1. Interpreting the coefficient from Model 3, we find that 1% delay in total production time is on average associated with a 0.94% decrease in box-office revenues. Given that the average total production time is 633 days and that the average gross box office revenues is 48 million dollars, we estimate that one week of production time delay is associated with approximately on average 4.88 million dollars of loss in box-office revenues.

For the individual production stages, the coefficients of *LN_POSTPROD* (-0.6153 and -0.2655) and *LN_DISTR* (-1.0073, -0.3796) are significantly negative across the two models, suggesting that both post-production time and distribution time are negatively associated with box-office revenues. Therefore, Hypotheses 2c and 2d are supported. In addition, the coefficient of *LN_PREPROD* is significant and positive in the model with basic controls (0.3212), which seems to support H2a, although its coefficient becomes insignificant after advanced controls are included. We find no support for H2b that filming time affects box-office revenues.

If these variables about production time are highly correlated with other predictors, their standard errors may be inflated, thus causing multicollinearity issue. The correlation table (Table 4) shows that none of these predictors have a correlation over 0.5. Second, we compute the variance inflation factors (VIF) and find that none of the VIFs of these variables exceed 10, a common rule-of-thumb for multicollinearity (Kennedy, 2003). Hence, we do not expect multicollinearity to affect the estimation of the movie's production stages time-related predictors.

The control variables, *LN_BUDGET, OPNTHR, AVGRATING* and *LN_ADEXP*, are all positively associated with domestic gross, which is not surprising because higher production, distribution and marketing inputs are widely known to improve the box office revenues (Elberse and Eliashberg, 2003). Due to space limitation, we do not report the estimated coefficients of the Basic Controls, which all have the expected signs.

Table 5: Results of Model 1 through Model 4 with DV = *LN_USBOX*

	Model 1 Basic Control	Model 3 Advanced Control	Model 2 Basic Control	Model 4 Advanced Control
LN_PRODTIME	-1.6924***	-0.9430***		
	(0.3126)	(0.1708)		
LN_PREPROD			0.3213**	-0.0836
			(0.1167)	(0.0735)
LN_FILMING			0.3969	-0.2152
			(0.2224)	(0.1280)
LN_POSTPROD			-0.6153***	-0.2655*
			(0.1770)	(0.1061)
LN_DISTR			-1.0073***	-0.3796***
			(0.1321)	(0.0747)
LN_BUDGET		0.4258**		0.3774*
		(0.1446)		(0.1520)
OPNTHTR		0.0004***		0.0004***
		(0.0001)		(0.0001)
AVGRATING		0.3126***		0.3004***
		(0.0627)		(0.0618)
LN_ADEXP		0.5338***		0.5368***
		(0.1192)		(0.1199)
Basic Control	Yes	Yes	Yes	Yes
Hypothesis Supported	H1	H1	H2a, H2c, H2d	H2c, H2d
Obs	315	315	315	315
Adjusted R^2	0.369	0.802	0.498	0.802
Prob $> F$	0.000	0.000	0.000	0.000

1. Standard errors are shown in parentheses.
2. *: p-value<=0.05, **: p-value<=0.01, ***: p-value<=0.001

5.3 Robustness Check

5.3.1 Instrumental Variable 2SLS Estimation

In order to address the aforementioned possible endogeneity issue, we adopt an instrumental variable 2SLS approach (Angrist and Krueger, 1994). The 2SLS estimator provides consistent estimates. It is quite robust in the presence of other estimating issues such as multicollinarity. In addition to its relatively low computation cost, the 2SLS instrumental variable approach has been widely used to address the endogeneity issue (Kennedy, 2003).

A valid instrumental variable should satisfy relevance and exclusion restriction assumptions (Wooldridge, 2002). In particular, it should be uncorrelated with the error (i.e., exclusion restriction) and correlated with the endogenous regressor (i.e., relevance).

We find such an exogenous shock in our study period to be the 2007–2008 Writers Guild of America strike. The Writers Guild of America, the labor union representing film, television, and radio writers working in the United States, started this strike in order to improve writers' compensation, which diminished in comparison with the profits of larger studios. This Writers' Strike started on November 5th, 2007, and ended on February 12th, 2008 with an agreement of 3 to 3.5% pay raises.

We expect that this strike may have delayed the production of the movies that were still in production during the strike for two reasons. First, a movie producer may still consult writers about script revisions and rewrites even in later production stages. Second, this writers' strike received wide support from actors and supporting staff, including even truck drivers who refused to cross the picket line. Anecdotal evidence also suggests that this strike caused Warner Brothers to delay the release of *Harry Potter and the Half-Blood Prince* to the summer of 2009. Warner Brother, therefore, unusually released no potential blockbusters in the summer of 2008. We further expect that the strike was an exogenous shock to the movie industry because it broke out only five days after the negotiation between the studios and the guild failed, which may have left studios little time to prepare.

Admittedly, studios may have anticipated this strike, prioritizing resource allocation in advance, which may invalidate the strike as an instrument. In order to address this possible issue, we construct another instrumental variable, *SUMPROD*, which sums the production time of *other* movies made by the same studio. In other words,

$$SUMPROD_i = \sum_{\forall j \neq i;\, j \in i'\text{s studio}} PRODTIME_j,$$

where j is any other movie made by the same studio that produced movie i.

We expect that *SUMPROD* satisfies both the relevance and the exclusion restriction assumptions of a valid instrument. For the relevance assumption, we anticipate that *SUMPROD* is negatively associated with the total production time of movie i. This is because a studio is constrained by its resources of production, marketing and exhibition. For example, a movie studio has only limited release slots in a year. In order for it to release certain movies on time, it may shift resources away from other movies, thus delaying their total production time. Second, analytical and empirical evidence have shown that increasing levels of load in a system is associated with increasing service rate (Crabill, 1972; George and Harrison, 2001; Kc and Terwiesch, 2009). A high *SUMPROD* is likely to suggest a high load on a studio's capacity, thus accelerating the studio's production rate and shortening its production time. For the exclusion restriction assumption, we assume that the production time of other movies in the same studio with movie i should not affect the unobserved factors for movie i's box-office revenues.

Following the same reasons and the same procedure as in constructing *SUMPROD*, we construct the following instruments for the duration of each individual production stage, *SUMPREPROD, SUMFILMING, SUMPOSTPROD* and *SUMDISTR.* For example, for movie i

$$SUMPREPROD_i = \sum_{\forall j \neq i;\, j \in i\text{'s studio}} PREPROD_j.$$

where j indexes movies made by the same studio that made movie i.

With both types of instruments, we employ the following 2SLS Instrument Variable estimation procedures to estimate the impact of total production time on box-office revenues:

$$\begin{aligned}
\text{Stage 1:}\quad LN_PRODTIME_i &= \alpha_0 + \alpha_1 STRIKE_i + \alpha_2 LN_SUMPROD_i + \alpha_3 \text{Basic Control}_i + \\
&\quad \alpha_4 \text{Advanced Control}_i + \varepsilon_i \\
\text{Stage 2:}\quad LN_USBOX_i &= \beta_0 + \beta_1 LN_\widehat{PRODTIME}_i + \beta_2 \text{Basic Control}_i + \\
&\quad \beta_3 \text{Advanced Control}_i + u_i,
\end{aligned} \tag{5}$$

where *STRIKE* is a dummy variable equal to one if the movie was in production during the strike period, and zero otherwise, and *LN_SUMPROD* is log transformed from *SUMPROD*.

In estimating the effects of individual stage duration, we drop the *STRIKE* variable. Ideally we would use four different instrumental variables indicating whether or not the Writers' Strike impacted the duration of each production stage. However, such instruments would be weak in our data sample because most of the movies in our sample started early production stages such as pre-production and filming before the 2007-2008 strike. Weak instruments are poor predictors of the endogenous individual stage variables and thus break the relevance assumption of a valid instrument (Wooldridge, 2002).

We employ the following 2SLS estimation procedure to estimate the effects of individual stages on box-office revenues:

$$\begin{aligned}
\text{Stage 1:}\quad LN_PREPROD_i &= \alpha_0 + \alpha_1 \text{Instruments} + \alpha_2 \text{Basic Control} + \alpha_3 \text{Advanced Control} \\
LN_FILMING_i &= \alpha_0 + \alpha_1 \text{Instruments} + \alpha_2 \text{Basic Control} + \alpha_3 \text{Advanced Control} \\
LN_POSTPROD_i &= \alpha_0 + \alpha_1 \text{Instruments} + \alpha_2 \text{Basic Control} + \alpha_3 \text{Advanced Control} \\
LN_DISTR_i &= \alpha_0 + \alpha_1 \text{Instruments} + \alpha_2 \text{Basic Control} + \alpha_3 \text{Advanced Control} \\
\text{Stage 2:}\quad LNUS_BOX_i &= \beta_0 + \beta_1 LN_\widehat{PREPROD}_i + \beta_2 LN_\widehat{FILMING}_i + \beta_3 LN_\widehat{POSTPROD}_i + \\
&\quad \beta_4 LN_\widehat{DISTR}_i + \beta_5 \text{Basic Control} + \beta_6 \text{Advanced Control} + \varepsilon_i.
\end{aligned} \tag{6}$$

In Stage 1, Instruments include a vector of *LN_SUMPREPROD, LN_SUMFILMING, LN_SUMPOSTPROD* and *LN_SUMDISTR,* which are log-transformed from *SUMPREPROD, SUMFILMING, SUMPOST-PROD* and *SUMDISTR,* respectively.

Table 6 shows the Instrumental Variable 2SLS estimation results. Supporting our main findings in Table 5, *LN_PRODTIME* is negatively associated with domestic box-office revenues (the coefficient is -0.7882). With respect to individual stages, *LN_DISTR* is also negatively associated with the domestic cumulative gross (the coefficient is -0.5932). Unlike in Table 5, *LN_POSTPROD* is not significant because of the reduced variation through first-stage instrumental estimation. Note that the 2SLS estimate of *LN_PRODTIME* -0.7882 is less negative than the OLS estimate -0.943, which is within our expectations; however, the 2SLS estimate of *LN_DISTR* -0.5932 is more negative than the OLS estimate -0.3796, which is outside our expectations. This difference seems to suggest that unobserved project priority does not necessarily cause or drive the biases. Furthermore, we notice that the OLS and 2SLS estimates are quite close to each other. Finally, we perform

Durbin-Wu-Hausman tests of endogeneity on both Models 5 and 6. We find that the p-values of the Wu-Hausman F statistics are over 0.5, which fails to reject the null hypotheses that the production time variables are exogenous. For these reasons, we suggest that our main results in Table 5 are robust from possible endogeneity issues.

Table 6: Instrumental Variable 2SLS Estimation Results

	Model 5	Model 6
LN_PRODTIME	-0.7882*	
	(0.3735)	
LN_PREPROD		0.0771
		(0.1820)
LN_FILMING		0.0160
		(0.3791)
LN_POSTPROD		-0.1489
		(0.2979)
LN_DISTR		-0.5932***
		(0.1677)
LN_BUDGET	0.4131***	0.2377
	(0.0849)	(0.1444)
OPNTHTR	0.0004***	0.0003***
	(0.0001)	(0.0001)
AVGRATING	0.3111***	0.2928***
	(0.0634)	(0.0679)
LN_ADEXP	0.5400***	0.5163***
	(0.0401)	(0.0434)
Basic Control	Yes	Yes
Hypothesis Supported	H1	H2d
Obs	315	315
Adjusted R^2	0.801	0.791
Prob $> F$	0.000	0.000

1. Standard errors are shown in parentheses.

2. *: p-value<=0.05, **: p-value<=0.01, ***: p-value<=0.001

5.3.2 Alternative Financial Performance Measures

In addition to the cumulative U.S. domestic gross, a movie's financial performance may also be reflected in its opening weekend box office revenues. This opening weekend revenue performance affects exhibition lifetime and screen allocation in later weeks (Pisano and Wagonfeld, 2009), thus receiving close attention from studios and the media. We substitute the dependent variable *LN_USBOX* from Models 1 to 4 with *LN_OPNBOX* as defined in Table 1.

Table 7 presents the results of the robustness check with opening weekend box-office revenues, which resemble the main results in Table 5. Estimates of total production time *LN_PRODTIME* are significantly negative in both models (the coefficients are -1.8263 and -0.6314), supporting Hypothesis 1 that total production time is negatively associated with box-office revenues. Interpreting the estimate from Model 3, we find that a 1% delay in total production time is associated with approximately 0.63% loss in opening weekend box-office revenues. For the individual stages, as in the main results in Table 5, we find that distribution time is consistently negatively associated with opening weekend box-office revenues (the coefficients are -1.0462 and -0.1733). In Model 2 (column 3), the *LN_PREPROD* and *LN_POSTPROD* estimates are significant (the coefficients are 0.3124 and -0.6268), which support H2a and H2c. Nevertheless, like the main results, the *LN_FILMING* estimates are insignificant in both models. The estimate for *LN_POSTPROD* becomes insignificant after advanced controls are included, which differs from that in Table 5. In general, the results of the opening weekend box-office revenues are comparable to those of the cumulative box-office revenues. The exception about the *LN_POSTPROD* estimate after including advanced controls is within expectation because cumulative box office revenues have a longer observation window and therefore reflect more production-related information than do opening weekend box office revenues.

Table 7: Robustness Check with DV = *LN_OPNBOX*

	Model 1 Basic Control	Model 3 Advanced Control	Model 2 Basic Control	Model 4 Advanced Control
LN_PRODTIME	-1.8263***	-0.6314***		
	(0.3599)	(0.1743)		
LN_PREPROD			0.3124*	-0.0912
			(0.1398)	(0.0595)
LN_FILMING			0.2821	-0.2480
			(0.2714)	(0.1479)
LN_POSTPROD			-0.6268**	-0.1366
			(0.2013)	(0.1049)
LN_DISTR			-1.0462***	-0.1733*
			(0.1568)	(0.0758)
LN_BUDGET		0.2177		0.2251
		(0.1292)		(0.1342)
OPNTHTR		0.0013***		0.0014***
		(0.0001)		(0.0001)
AVGRATING		0.0217		0.0230
		(0.0592)		(0.0601)
LN_ADEXP		0.2936***		0.3063***
		(0.0774)		(0.0791)
Basic Control	Yes	Yes	Yes	Yes
Hypothesis Supported	H1	H1	H2a, H2c, H2d	H2d
Obs	315	315	315	315
Adjusted R^2	0.360	0.888	0.448	0.886

1. Standard errors are shown in parentheses.

2. *: p-value<=0.05, **: p-value<=0.01, ***: p-value<=0.001

5.3.3 Quantile Regression

The movie industry tends to be a winner-take-all industry, with a small number of movies driving the majority of box-office revenues. For example, the domestic cumulative box-office revenues of *The Dark Knight (2008)* were approximately 531 million dollars, which comprises about 5.31% of that year's U.S. box-office revenues (approximately 10 billion dollars a year). Therefore, the conditional box-office revenue distributions tend to be skewed, even adjusting for both basic and advanced controls. In addition, unequal variance, i.e., heteroskedasticity in $Var(\text{errors}|\text{controls})$ is likely to be present because the movie industry is very segmented. For example, movies aiming for large box-office revenues, which tend to secure many exhibiting theaters, have different production and release strategies from those aimed for small revenues, which show at a limited number of theaters. For these reasons, the partial effects of production time vary among quantiles and OLS may yield biased estimates (Cade and Noon, 2003; Koenker, 2005).

Understanding how production time may differently affect movies having different box-office revenue levels may be of particular interest to studios, who constantly make resource allocation decisions to optimize their portfolio revenues. In order to address these issues, we employ a quantile regression (Koenker and Bassett Jr, 1978; Buchinsky, 1994). Unlike the OLS Models 1 and 3, which estimate the average effects of total production time, a quantitle regression estimates the effect of total production time on the conditional quantiles of box-office distribution. We employ the following quantile regression model:

$$LN\_USBOX_i = X_i'\beta_\theta + u_{\theta i} \quad \text{with } \text{Quant}_\theta(LN\_USBOX_i|X_i) = X_i'\beta_\theta, \tag{7}$$

where $\text{Quant}_\theta(LNUS\_BOX_i|X_i)$ is the θth conditional quantile of *LN_USBOX* distribution. Covariates X_i include an intercept, *LN_PRODTIME*, Basic Control and Advanced Control as specified in Models 1 and 3.

According to Koenker and Bassett Jr (1978), the estimator for β_θ is a solution to the following minimization problem:

$$\min_\beta \left[\sum_{i:LN\_USBOX_i \geq X_i'\beta} \theta \,|LN\_USBOX_i - X_i'\beta_\theta| + \sum_{i:LN\_USBOX_i < X_i'\beta} (1-\theta)\,|LN\_USBOX_i - X_i'\beta_\theta| \right].$$

We then replace *LN_PRODTIME* with the individual production stage time variables in Model 7 to analyze the impact of individual stages on box-office revenues.

Table 8 presents the quantile regression results. The estimates for *LN_PRODTIME* are significantly negative in all three quantile models (the coefficients are -0.4135, -0.4326, -1.0103), suggesting a consistent negative association between total production time and box-office revenues. In particular, the coefficient of movies in the 90th percentile revenue distribution is as large as slightly over twice the coefficient of movies in the 10th and 50th percentile revenue distribution, which seems to imply that movies in the higher box-office-revenue distribution may be more sensitive to production delay than those in the lower and medium box-office-revenue distribution.

The rightmost three columns in Table 8 show the results of individual production stages. Distribution time is consistently negatively associated with box-office revenues (-0.2008, -0.2286, -0.2597), supporting H2d and the main results. These consistent results seem to suggest that distribution is probably the most critical stage in production time. Post-production time is also negatively associated with box office revenues for movies in the 90th revenue percentile. We do not find significant relationships between earlier production stages and box-office revenues, i.e., pre-production and filming.

Table 8: Quantile Regression Results with DV = *LN_USBOX*

	Model 3 for 10th Percentile	Model 3 for 50th Percentile	Model 3 for 90th Percentile	Model 4 for 10th Percentile	Model 4 for 50th Percentile	Model 4 for 90th Percentile
LN_PRODTIME	-0.4135*	-0.4326*	-1.0103***			
	(0.2081)	(0.1736)	(0.1595)			
LN_PREPROD				-0.1108	-0.0438	-0.1563
				(0.0598)	(0.0773)	(0.1086)
LN_FILMING				-0.1881	-0.1484	-0.2892
				(0.1751)	(0.1291)	(0.1649)
LN_POSTPROD				-0.1392	-0.1118	-0.3938***
				(0.1121)	(0.1004)	(0.1109)
LN_DISTR				-0.2008***	-0.2286**	-0.2597*
				(0.0598)	(0.0770)	(0.1188)
LN_BUDGET	-0.0589	0.2677**	0.5066***	0.0543	0.2327	0.4966**
	(0.1533)	(0.1014)	(0.1379)	(0.1261)	(0.1271)	(0.1775)
OPNTHTR	0.0002*	0.0003***	0.0002***	0.0003**	0.0003***	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVGRATING	0.1931*	0.2264***	0.1845*	0.1956**	0.2579***	0.2008*
	(0.0845)	(0.0586)	(0.0804)	(0.0731)	(0.0643)	(0.0935)
LN_ADEXP	1.1040***	0.7642***	0.3126	1.0793***	0.8010***	0.3277
	(0.0819)	(0.0775)	(0.2137)	(0.0779)	(0.0926)	(0.2041)
Basic Control	Yes	Yes	Yes	Yes		
Hypothesis Supported	H1	H1	H1	H2d	H2d	H2c, H2d
Obs	315	315	315	315	315	315
Adjusted R^2	0.772	0.5783	0.438	0.780	0.581	0.435
Prob $>$ F	0.000	0.000	0.000	0.000	0.000	0.000

1. Standard errors are shown in parentheses.

2. *: p-value<=0.05, **: p-value<=0.01, ***: p-value<=0.001

6 Managerial Insights and Concluding Remarks

6.1 Descriptive Insights

In our study, multiple analysis models have shown consistent results, underscoring a few key insights for managers who need to deliver the right product at the right time. First, streamlining total production time is critical to achieving higher box-office revenues, particularly for above-average performers. We find that total production time is likely to negatively impact domestic office revenues, in terms of both cumulative and opening weekend revenues. Particularly, a 1% additional total production delay may lower cumulative box-office revenues by approximately 0.94% on average. From quantile regressions, we also discover that total production duration has a larger negative impact for successful movies than for moderate and low-revenue movies. In order to reduce total production time, we suggest that studios should exert effort in the following: simplifying production procedures, eliminating unnecessary steps, and increasing parallel processing (Millson et al., 1992; Loch et al., 2001). Some studios have already started practicing parallel processing, such as performing post-production editing in parallel with filming (Honthaner, 2010). We also suggest that studios should simplify certain paperwork like talent releases, location agreements, and camera reports. Digitizing these forms and associated processes can also save time. In addition, we suggest that studios invest more resources in speeding up the post-production and distribution phases, which tend to be the critical stages delaying the entire production process.

The trade-off between distribution time and opening weekend theaters needs to be balanced. Focusing too much attention on reducing distribution time could be suboptimal because studios face trade-offs of other revenue-generating decisions, such as securing a sufficient number of opening weekend theaters. U.S. antitrust law regulates that a studio is required to negotiate with exhibitors one by one, which can be a time-consuming process (De Vany, 2004). In addition, making prints to support those exhibitors still takes time, despite the increasing popularity of faster digital distribution. Our results show that a 1% extra delay in distribution time is associated with 0.38% lower box-office revenues on average, controlling for everything else. Given that average distribution time in our sample is about 160 days and that average box-office revenues are $48 million, a 10% reduction in distribution time, 16 days on average, is associated with a 3.8% revenue lift on average, which is approximately $1.82 million. In addition, Models 3 and 4 consistently show that increasing opening weekend by 100 theaters is associated with approximately a 4% revenue lift on average. Hence, a preliminary estimation suggests that reducing distribution time by 16 days is approximately equivalent to securing an additional 95 theaters during opening weekend.

6.2 Concluding Remarks

We study the impact of a multi-phase process of film-making on financial performance. In particular, we examine the effects of the duration of production phases on box office success. We find that an increase in total production time and, in particular, in a movie's distribution time can adversely affect a movie's box-office prospects.

Our research makes three main contributions. First, it is a first attempt to link operations management, marketing and film-making. Second, it provides new empirical evidence of multi-phase production impacts in the movie industry, a typical creative industry. Finally, our study helps studios better understand how to prioritize production planning and minimize the negative impact of production delay.

We conclude by highlighting the limitations of our findings and outlining opportunities for future research. First, our performance metrics are restricted to box-office revenues and our sample excludes movies that have missing production information. An interesting future research area would be to incorporate other performance metrics, including competitive aspects such as market share in the analysis. Furthermore, our study does not directly examine the impact of other factors, such as direction and production approaches. For example, a director may write his own screenplays or collaborate with long-standing screenwriters. Some directors may also be the cinematographer or even appear in the movie as an actor. These factors are worth including in future research. Moreover, our advertising data are limited to monthly advertising expenditures and we are therefore unable to synchronize it with the production stages. A fruitful future venue for research would be to examine the interdependent impact of production and advertising decisions. In addition, data on budget allocation by production stage would be useful in understanding the impact of resource allocation in a multi-phase production process. Our hypotheses and findings apply to other industries with the following characteristics: 1) multi-stage production processes having distinguishing stage-specific labor intensity, decision power centralization and piracy risks, 2) products that consumers are aware of while still in the making, and 3) other creative industries that require a significant upfront investment and have extremely uncertain demand.

References

Adler, P.S., A. Mandelbaum, V. Nguyen, E. Schwerer. 1995. From project to process management: An empirically-based framework for analyzing product development time. *Management Science* **41**(3) 458–484.

Afifi, A.A., V. Clark, S. May. 2004. *Computer-aided multivariate analysis*. CRC Press.

Anderson, P.F. 1982. Marketing, strategic planning and the theory of the firm. *Journal of Marketing* **46**(2) 15–26.

Angrist, J., A.B. Krueger. 1994. Why do World War II veterans earn more than nonveterans? *Journal of Labor Economics* **12**(1) 74–97.

Armstrong, J.S. 1982. The value of formal planning for strategic decisions: Review of empirical research. *Strategic Management Journal* **3**(3) 197–211.

Arora, A., J. P Caulkins, R. Telang. 2006. Sell first, fix later: Impact of patching on software quality. *Management Science* **52**(3) 465–471.

Bowen, D.E., G.E. Ledford Jr., B.R. Nathan. 1991. Hiring for the organization, not the job. *The Executive* **5**(4) 35–51.

Buchinsky, M. 1994. Changes in the US wage structure 1963-1987: Application of quantile regression. *Econometrica* **62**(2) 405–458.

Cade, B. S., B. R. Noon. 2003. A gentle introduction to quantile regression for ecologists. *Frontiers in Ecology and the Environment* **1**(8) 412–420.

Carpenter, G.S., K. Nakamoto. 1989. Consumer preference formation and pioneering advantage. *Journal of Marketing Research* **26**(3) 285–298.

Caves, R.E. 2000. *Creative industries: Contracts between art and commerce*. Harvard Univ Pr.

Chintagunta, P.K., S. Gopinath, S. Venkataraman. 2010. The effects of online user reviews on movie box-office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science* **29**(5) 944–957.

Cobb, C.W., P.H. Douglas. 1928. A theory of production. *The American Economic Review* **18**(1) 139–165.

Cohen, M.A., J. Eliashberg, T.-H. Ho. 1996. New product development: The performance and time-to-market tradeoff. *Management Science* **42**(2) 173–186.

Cooper, R.G. 1990. Stage-gate systems: A new tool for managing new products. *Business Horizons* **33**(3) 44–54.

Crabill, T.B. 1972. Optimal control of a service facility with variable exponential service times and constant arrival rate. *Management Science* **18**(9) 560–566.

Daniels, B., D. Leedy, S.D. Sills. 1998. *Movie money: Understanding Hollywood's (creative) accounting practices*. Silman-James Press, Los Angeles.

Datar, S., C. Jordan, S. Kekre, S. Rajiv, K. Srinivasan. 1997. New product development structures and time-to-market. *Management Science* **43**(4) 452–464.

De Vany, A. 2004. *Hollywood Economics*. Routledge, New York.

Dirks, T. 2005. Greatest box-office bombs, disasters and film flops: The most notable examples. *Filmsite* .

Eisenhardt, K. M., B. N. Tabrizi. 1995. Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly* **40**(1) 84–110.

Eisenhardt, K.M. 1989. Making fast strategic decisions in high-velocity environments. *Academy of Management Journal* **32**(3) 543–576.

Eisenhardt, K.M., L.J. Bourgeois III. 1988. Politics of strategic decision making in high-velocity environments: Toward a midrange theory. *Academy of Management Journal* **31**(4) 737–770.

Elberse, A., J. Eliashberg. 2003. Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures. *Marketing Science* **22**(3) 329–354.

Eliashberg, J. 2005. The film exhibition business: Critical issues, practice, and research. *A Concise Handbook of Movie Indutry Economics* 138.

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

Eliashberg, J., S.K. Hui, Z.J. Zhang. 2007. From storyline to box office: A new approach for green-lighting movie scripts. *Management Science* **53**(6) 881–893.

Eliashberg, J., J.-J. Jonker, M. S. Sawhney, B. Wierenga. 2000. Moviemod: An implementable decision-support system for prerelease market evaluation of motion pictures. *Marketing Science* **19**(3) 226–243.

Eliashberg, J., S. Swami, C.B. Weinberg, B. Wierenga. 2001. Implementing and evaluating silverscreener: A marketing management support system for movie exhibitors. *Interfaces* **31**(3) 108–127.

Filmreference. 2011. Crew size and onscreen credits. URL `http://www.filmreference.com/encyclopedia/Academy-Awards-Crime-Films/Crew-CREW-SIZE-AND-ONSCREEN-CREDITS.html`.

George, J.M., J.M. Harrison. 2001. Dynamic control of a queue with adjustable service rate. *Operations Research* **49**(5) 720–731.

Harter, D.E., M.S. Krishnan, S.A. Slaughter. 2000. Effects of process maturity on quality, cycle time, and effort in software product development. *Management Science* **46**(4) 451–466.

Hendricks, K.B., V.R. Singhal. 1997. Delays in new product introductions and the market value of the firm: The consequences of being late to the market. *Management Science* **43**(4) 422–436.

Hendricks, K.B., V.R. Singhal. 2008. The effect of product introduction delays on operating performance. *Management Science* **54**(5) 878–892.

Hoegl, M., K. Weinkauf, H.G. Gemuenden. 2004. Interteam coordination, project commitment, and teamwork in multiteam R&D projects: A longitudinal study. *Organization Science* **15**(1) 38–55.

Honthaner, E.L. 2010. *The complete film production handbook*. Focal Press.

James, C. 2006. When the bad buzz arrives before the movie does. *The New York Times* September 26th.

Jensen, Jeff. 2007. Great expectations. *Entertainment Weekly* .

Kc, D.S., C. Terwiesch. 2009. Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science* **55**(9) 1486–1498.

Kennedy, P. 2003. *A guide to econometrics*. The MIT Press.

Kleinbaum, D.G., L.L. Kupper, K.E. Muller. 2007. *Applied regression analysis and other multivariable methods*. Duxbury Pr.

Koenker, R. 2005. *Quantile regression*, vol. 38. Cambridge university press.

Koenker, R., G. Bassett Jr. 1978. Regression quantiles. *Econometrica* **46**(1) 33–50.

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

Krishnan, V., K.T. Ulrich. 2001. Product development decisions: A review of the literature. *Management Science* **47**(1) 1–21.

Lee Jr, J.J., A.M. Gillen. 2011. *The Producer's Business Handbook: The Roadmap for the Balanced Film Producer*. Focal Press.

Loch, C.H., C. Terwiesch. 1998. Communication and uncertainty in concurrent engineering. *Management Science* **44**(8) 1032–1048.

Loch, C.H., C. Terwiesch, S. Thomke. 2001. Parallel and sequential testing of design alternatives. *Management Science* **47**(5) 663–678.

Lomi, A., E.R. Larsen, F.C. Wezel. 2010. Getting there: Exploring the role of expectations and preproduction delays in processes of organizational founding. *Organization Science* **21**(1) 132–149.

Ma, L., A. Montgomery, P.V. Singh, M.D. Smith. 2009. Pre-release movie piracy and box office sales: Estimates and policy implications. *NYU Stern Working Paper* .

Maher, Kevin. 2010. Denzel Washington is unstoppable. *The Times* (10).

Miller, C.C., L.B. Cardinal. 1994. Strategic planning and firm performance: A synthesis of more than two decades of research. *Academy of Management Journal* **37**(6) 1649–1665.

Millson, M.R., S.P. Raj, D. Wilemon. 1992. A survey of major approaches for accelerating new product development. *Journal of Product Innovation Management* **9**(1) 53–69.

Morgan, L.O., R.M. Morgan, W.L. Moore. 2001. Quality and time-to-market trade-offs when there are multiple product generations. *Manufacturing & Service Operations Management* **3**(2) 89–104.

MPAA. 2010. The motion picture & television industry contribution to the u.s. economy. *Motion Picture Association of America Reports* .

Neelamegham, R., P. Chintagunta. 1999. A Bayesian model to forecast new product performance in domestic and international markets. *Marketing Science* **18**(2) 115–136.

Patz, D.S. 2002. *Production Management 101: The Ultimate Guide to Film and Television Production Management and Coordination*. Michael Wiese.

Pisano, G., A. Wagonfeld. 2009. Warner bros. entertainment. *Harvard Business School Case* (November) 9–610–036.

Putnam, L.H., W. Myers. 1991. *Measures for excellence: Reliable software on time, within budget*. Prentice Hall Professional Technical Reference.

Schmalensee, R. 1982. Product differentiation advantages of pioneering brands. *American Economic Review* **72**(3) 349–365.

Shane, S.A., K.T. Ulrich. 2004. Technological innovation, product development, and entrepreneurship in Management Science. *Management Science* **50**(2) 133–144.

Smith, P.G., D.G. Reinertsen. 1991. *Developing products in half the time*. Van Nostrand Reinhold New York.

Souza, G. C., B. L. Bayus, H. M. Wagner. 2004. New-product strategy and industry clockspeed. *Management Science* **50**(4) 537–549.

Stelter, Brian. 2009. Piracy puts film online one month before open. *The New York Times* April 1st.

Swami, S., J. Eliashberg, C.B. Weinberg. 1999. Silverscreener: A modeling approach to movie screens management. *Marketing Science* **18**(3) 352–372.

Swami, S., M.L. Puterman, C.B. Weinberg. 2001. Play it again, Sam? Optimal replacement policies for a motion picture exhibitor. *Manufacturing & Service Operations Management* **3**(4) 369–386.

Tatikonda, M. V., M. M. Montoya-Weiss. 2001. Integrating operations and marketing perspectives of product innovation: The influence of organizational process factors and capabilities on development performance. *Management Science* **47**(1) 151–172.

Terwiesch, C., C.H. Loch. 1999. Managing the process of engineering change orders: The case of the climate control system in automobile development. *Journal of Product Innovation Management* **16**(2) 160–172.

Ulrich, K. T., S. D. Eppinger, A. Goyal. 2011. *Product design and development*. Irwin/McGraw-Hill.

Wooldridge, J.M. 2002. *Econometric analysis of cross section and panel data*. The MIT press.