HALENUR ÖZTEKİN POPULARITY OF A MOVIE AND FINANCIAL SUCCESS Bilkent University 2021

POPULARITY OF A MOVIE AND FINANCIAL SUCCESS

Master's Thesis

by
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Department of
Management
İhsan Doğramacı Bilkent University
Ankara
August 2021

To my Family

POPULARITY OF A MOVIE AND FINANCIAL SUCCESS

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

HALENUR ÖZTEKİN

In Partial Fulfillment of the Requirements for the Degree
of
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August 2021

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Business Administration.

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ABSTRACT

POPULARITY OF A MOVIE AND FINANCIAL SUCCESS

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This thesis focuses on how the popularity of a movie and related factors such as director and casting worth affect the financial success of a movie and the market value of the distribution company when there is an unexpected loss or gain. Also, the thesis attempts to examine the determinants of the stock price of a movie on the virtual stock market, the Hollywood Stock Exchange. Cross sectional analysis is exercised using data from 450 films released in 2019. The findings show that popularity is a positive and significant factor in predicting box office revenue. Director's previous success makes a significant positive impact on the financial success. Casting worth, determined by the previous financial success of the actor/actress, derives movie success financially. Unexpected revenue gained/lost is found to make no effect on cumulative abnormal returns. The stock price of a movie on the Hollywood Stock Exchange highly depends on revenue and public awareness (number of news, theaters, popularity of a movie and number of weeks).

Keywords: Box-office, Cumulative abnormal return, the Hollywood Stock Exchange, Popularity, Casting, Director

ÖZET

FİLM POPÜLERLİĞİ VE FİNANSAL BAŞARI

Öztekin, Halenur

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Tez Danışmanı: Doç. Dr. Süheyla Özyıldırım

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Bu makale, bir filmin finansal başarısında popülerliğin, yönetmenin ve oyuncu seçiminin etkisine ve beklenmedik bir kayıp veya kazanç olduğunda dağıtım şirketlerinin hisse senedi fiyatlarındaki değişikliklere odaklanmaktadır. Ayrıca, makale Hollywood Borsası'ndaki bir filmin hisse senedi fiyatını belirleyen özellikleri ortaya çıkarmaya çalışmaktadır. Etkiyi anlamak için Sıradan En Küçük Kareler yöntemi kullanılmıştır. Veri, 2019'da vizyona giren 450 filmi içermektedir. Bulgular, popülerliğin gişe gelirini tahmin etmede pozitif olarak önemli bir faktör olduğunu göstermektedir. Yönetmenin daha önceki başarısı, finansal başarı üzerinde önemli ölçüde olumlu etki yapmaktadır. Filmin kadrosunun değeri, aktör ve aktrislerin önceki finansal başarılarına göre hesaplanmış olup filmin finansal başarısına katkı sağladığı görülmektedir. Beklenmeyen gelir/ kayıp, kümülatif anormal getiri üzerinde herhangi bir etkisi bulunmamaktadır . Hollywood Borsası'ndaki bir filmin hisse senedi fiyatı, büyük ölçüde filmin gelirine ve seyirci tarafından bilinirliğine (film hakkındaki haber sayısı, sinema salonu sayısı, filmin popülerliği ve hafta sayısı) bağlıdır.

Anahtar Kelimeler: Gişe geliri, Kümülatif anormal getiri, Hollywood borsası,

Popülerlik, Oyuncu Seçimi, Yönetmen

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CHAPTER 1

INTRODUCTION

The media and entertainment industry are a big market, and it touches almost everyone's life. In the United States, 80 percent of people watch television daily (Krantz-Kent, 2018). Stoll (2021) reports that as of 2019, 14 percent of adults in the U.S. go to a movie more than once a month, 40 percent of adults go to a film less than once a month, and the rest of them go to a film once a year or less. Escandon (2020) highlights that box-office revenues increased significantly in 2019 and reached more than $100 billion for the first time. In this thesis, I aim to inquire about factors that affected opening weekend revenues in 2019, which is known as “normal” (before the covid pandemic hit) but also an extreme year for the movie industry in the U.S.

Movie companies earn money not only from the box office but also from product placement, selling to online platforms and television, etc. In today's entertainment sector, an online platform such as Netflix, Hulu, Amazon Prime, and others, has become a threat to the movie industry. Each of them has millions of users. Nevertheless, the box office revenue is still an essential part of the movie company’s profits. Some movies have earned tremendous money through theater streaming, such as

Avengers (IMDb). These revenues can determine the selling price of a movie to other platforms. Gunter (2018, p.3) says, "*The theatrical performance window remains important not just because it can still deliver profits, but also because success at cinemas can drive performance on secondary platforms.*"

In the literature, there are many studies to predict the factors affecting financial success. In the next section, I present the literature in more detail. However, in the introduction, I also mention some of them to position my work and explain my contribution. Many early works find that star power is an essential aspect of predicting revenue (Ravid, 2009; Lash and Zhao, 2016; Prag and Casavant, 1994). In the literature, no relation is found for critical reviews and revenue (see, e.g. Addis and Holbrook, 2018 and 2007). There are papers that emphasize genre is a crucial determinant to predict box office revenue (see, (Gazley, Clark and Sinha, 2010; Prag and Casavant 1994). Budget (Ravid, 2009; Joshi and Hanssens, 2009) and advertising expenses (Joshi and Hanssens, 2009) are also found the most significant factors explaining the financial success of the movies.

One can expect the budget to derive success since with big-budget, better pieces of equipment can be bought, or the well-known stars can be cast. As mentioned by Gunther (2018, p.14) "*If you can afford the best, then you might expect the results to be profitable as well. This does not always happen."* Budget is a factor that has been a highly cited factor to achieve financial success. Especially, distribution companies and their big budgets seem to play a vital role in the success of a movie. Largest companies like Disney, Paramount, Warner Bros., and MGM can access higher budgets and promote movies with better sources. In the literature, there are papers on how a movie's financing decision matters. The question is to test whether outsourcing or private financing is better for movie success (Fee, 2002). As also highlighted by Gunther (2018, p.38), *"When it comes to film production and distribution, the Majors dominate the movie marketplace. The big studios tend to have the biggest and best facilities for making and distributing movies.*"

Walls (2005) emphasizes the existence of extreme uncertainty ("nobody knows demand") surrounding the movie returns. His regression model includes classical attributes that are correlated with movie success and factors that permit the variance of movie success at the box office. He finds that star and production costs are significant determinants of box-office revenues, although nobody knows the demand for a movie, still it can be predicted through stars and production costs.

Unfortunately, in the empirical analysis, I do not use production cost and/or budget information due to data unavailability. Although both are important factors to study movie financial success, I only have limited data about the planned budget information for 2019. In the publicly available dataset from IMDB Pro, 183 out of 450 movies released in 2019 have estimates but not actual budget information. As De Vany (2003) emphasizes, the planned budget of a movie may underestimate the true budget of a movie. The production cost figures remain uncertain most of the time in the movie industry.

I also exclude well-studied indicator, industry recognition indicator of a movie in my empirical models. Agnani and Array (2010) argue that awards help future movie production. According to them, awards affect the sector's productivity as they allow for an increase in output, which is not explained by an increase in inputs. It is shown that award announcements and/or future movie production announcements affect investor's opinions positively. For example, Deuchert, Adjamah, and Pauly (2005) show that Oscar nominations positively and significantly impact the weekly returns and movies' survival time. In this thesis, I will ignore the impact of awards and/or nominations because my main dependent variable is opening weekend returns and abnormal returns following an opening weekend shock. I believe industry recognition of a movie cannot be related to the movie’s financial success in the week of release and the following week. Although awards and nominations create prior recognition, I will compensate recognition with popularity index and public awareness rather than applying awards and nominations.

Nevertheless, I try to contribute to the existing literature by focusing on the popularity of movies. Bhave et al. (2015) argue that classical attributes like casting, director, genre, and budget are not enough to predict financial success. They believe that classical determinants should be reinforced with feedback from social media like YouTube upvotes, IMDb rating, etc., to increase prediction accuracy.

I will not use social media indicators as popularity measures in my thesis but concentrate on casting/stars and director worth. Many actors draw large attention and help box-office success, although they have no Oscars or Oscar nominations. I use a financial proxy for the cast’s popularity and the director’s popularity by applying previous financial success. In particular, I will introduce a measure from the prior financial success of the movies that a star plays a part in. Moreover, financial proxy of directors is measured with their prior financial success of movies. In the list of famous directors in IMDB, the wealth of directors is mentioned, but it is well-known that their wealth is accumulated with their financially successful movie projects. For example, according to IMDB, "Steven Spielberg is Hollywood's best-known director and one of the wealthiest filmmakers in the world." Thus, by introducing both the IMDB popularity index and financial proxy of popularity indicator for cast and directors, I aim to contribute to understanding the financial success of the movies in 2019.

How human capital and management choice influence financial success of movies? Han and Ravid (2020) investigate the relationship between value of human capital and sales of Broadway Shows. Their finding indicates that value of human capital positively affects sales. In the literature, there are pieces of evidence that show human capital is important factor for business success. (see e.g. Honig, 1998)

I also study the effect of gain or loss (opening weekend box-office shock or open shock) on the stock price of a distribution company using both actual stock prices and virtual (Hollywood Stock Exchange, HSX) stock market data. Although previous findings show that the HSX acts like a real market, the evidence seems to be still limited. In this thesis, I would like to fill the gap. I analyze the relationship between open shock, which is the difference between real and estimated return, and the stock prices of a movie in HSX. Also, I attempt to understand how public awareness, which is measured by the number of news about the movie, popularity when the movie was released, whether the movie was anticipated by the audience before the release, number of theaters, and number of weeks, affect the stock price of a movie. The paper closest to my study is the work by Joshi and Hanssens (2009). In that paper, however, the main focus is how advertising may affect financial success and how this success is related to cumulative abnormal return (CAR). My thesis' focus is the popularity of a movie and the financial proxy for the director and the cast. I choose to study the year 2019 because it was the last year people can go to the cinemas, and it was an extreme year for box-office successes.

My findings show that popularity and financial proxy of directors and cast are significant for financial success. However, I could not find any significant relationship between CAR and unexpected gain or loss. Nevertheless, my results show that public awareness of a movie and unexpected gain affect stock prices of a movie positively.

CHAPTER 2

LITERATURE REVIEW

In this section, I present the literature on the financial success of a movie. I start summarizing the literature that emphasizes the importance of consumer preferences, the role of a star, genre and budget, critics, seasonal factors, and being #1. Second, I present literature about Hollywood Stock Exchange. Finally, I discuss the article by Joshi and Hanssens (2019) which I have a similar empirical methodology to inquire about the financial success of a movie in 2019.

Using a unique database of 349 U.S. films distributed in 1992 and 1993, Fee (2002) aims to identify which financing method is better for a movie. His findings indicate there are trade-offs between studio and independent financing. The financing choice directly affects the distribution method. In terms of financial success, studio financing has better pay-offs.

Gazley, Clark, and Sinha (2010) focus on the consumer preferences to purchase a movie ticket. They apply primary data, which they gather through surveys. Their results show that genre is a significant factor in the movie decision process. The audience popularly prefers comedies, but horror movies get less attention from consumers. Their findings indicate that people tend to go to the movie based on real-life events than the movies based on books. A movie's country of origin is an essential determinant for people's choice of going to a movie. Hollywood movies are preferable compared to other countries. Also, a movie in English is superior to the one with subtitles. The survey findings show that friends are higher influencers than critics. They find no evidence on the consumer's purchase of movie tickets and the sequel movies. In terms of promotion tools, posters and trailers are more appealing than interviews with stars. Well-known stars and directors make a positive impact on their taste for a movie. Based on the survey results, Gazley, Clark, and Sinha (2010) claim that a movie with broad (all around the country) or narrow distribution does not influence the respondent.

To understand the signaling power of stars and other variables on revenue, Ravid (1999) hypothesizes that casting a star (and perhaps big budgets) signals high returns or (at least) high box office. However, he could not find any evidence which shows that including star signals the increased revenue for a movie. In his empirical analysis using 200 movies, he finds that budget has signaling power on income, which means that big-budget movies have higher revenue. His sample consists of only successful films with unknown actors and actresses but not unsuccessful movies with unfamiliar people.

Lash and Zhao (2016) use social network analysis and text mining techniques to identify critical determinants for the profitability of movies. They define success based on budget and revenue. Lash and Zhao (2016) focus on whether star power has an impact on profitability. Their result shows that previous profitability records of the movies that the director and/or the cast played a part in are significant features to predict the success of a film. They find that quantifying star power gives better results for prediction.

Prag and Casavant (1994) find that budget, whether the movie is a sequel movie, having a star in the cast, winning an Oscar Award, and quality based on critics' review, positively affect financial success. When they include the advertising cost, their findings indicate that advertising cost is another significant factor for the box office. However, variables such as Academy Award, star power, and production cost became insignificant when advertising cost is in the model. They find that genre matters for only drama movies, which negatively influences the revenue. Moreover, it is shown that advertising expenses depend on the movie budget, the star in the cast, and the genre.

Ahmad et al. (2017) apply data mining processes to predict movie success in Bollywood. In particular, they inquire about the interrelationship between star and genre and find movie's genre and stars determine the success of a movie. More specifically, the paper indicates that some stars appeared in specific genre movies but not in others. For example, some actors or actresses prefer to take a role in action movies, some of them prefer romantic ones. So, genre and star variables can be correlated.

Karniouchina (2011) show that star can attract an audience and create a movie buzz. Her results suggest that attribution of a star is, directly and indirectly, makes a positive impact on the opening weekend revenue. However, if the audience does not appreciate the movie, including a star, the revenue of posterior weeks is found to be negatively affected. The results of Kim, Jung and Hyun (2016) show that star power has a significantly positive effect on revenue. Whether the star is nominated to Oscar or wins an Oscar award is also a significant determinant for box office revenue. Moreover, they find that number of screens, which the movie has been played, makes a significant positive impact on financial success.

Wallace, Seigerman, and Holbrook (1993) focus on the star worth in the movie industry. Their findings show that after subtracting the fee paid to the star, there is a significant relationship between the star and the movie's financial success. However, they find a negative impact of the salary paid to the star on financial success. Moreover, their findings reveal that star worth is alterable over time. In his/her career, the value of actor and actress may change by the performance. In some movies, they can be overpaid or underpaid based on their prior performances.

De Vany and Walls (2004) suggest a stable Paretian distribution model that characterizes the relationship between the profit in the movie industry and casting decisions. Their results indicate that including a star is right-skewed distribution. Moreover, they show that including a star has a higher expected value than the actual outcome, which causes a loss in profit. Therefore, they call the star effect as “curse of the superstar."

Walls (2009) applies nonparametric analysis for movie profitability. His findings suggest that big budgets contribute to movie profitability. The number of opening screens and being a sequel movie have a positive correlation to profitability. His findings show that including a star has a positive effect on profit. Still, the result is similar to De Vany and Walls (2004) findings, i.e., mean profitability of a movie is negative when there is a star in a movie.

Gaikar et al. (2019) examine the popularity factor to predict the movie successes in Hollywood and Bollywood. They use IMDb rating as a measure of success rather than using revenue or profit. They calculate popularity based on social media interactions. They collect the number of followers for an actor, an actress, a writer, and a director from social media sites like Facebook, Twitter, Instagram, etc. Their findings show that popularity makes a significant impact on predicting movie success.

Einav and Ravid (2009) investigate the market reaction to the change in movie dates. They apply an event study methodology of Brown and Warner (1985) to understand the market reaction. Their result shows a significant and negative impact of release date change on stock returns. The market takes date change as bad news. Also, their finding indicates that the magnitude of the market reaction is related to the budget since a piece of budget information is known in a given time process, but one can only predict revenue.

Addis and Holbrook (2018) study the factors affecting the ordinary evaluation of the consumers (quality judgments of the consumers). They focus on three main factors: reviewers ratings made by critics, opening box office, and Oscar nominations. Their result shows that there is only a significant relationship between reviewers' ratings and ordinary evaluation. They find that Oscar nominations and opening box office are not determinants of the ordinary assessment. They claim that "*Advertising that claims a high level of RR is expected to be much more effective in shaping consumers' attitudes than advertising claiming success in terms of ON or BO.*" [1]

Holbrook and Addis (2007) inquire the relevance between artistic quality assessment such as awards and industry recognition, audience attention (level of buzz), and financial success. Their results suggest that artistic quality and financial success are negatively correlated. Movies with quality assessments like Oscar nominations or awards increase industry recognition. However, audience attention ascends financial success. They claim they have different consumers.

Wallentin (2016) investigates the demand of critics and audiences demand in the motion picture industry in Sweeden. His findings show that the preferences of critics and audiences are different, yet there is a positive relationship between ticket sales and reviews. However, he does not provide evidence that reviews influence sales. In his findings, demand among critics is high for documentaries. Nevertheless, it has a negative effect on the general audience. Both groups demand animated movies. Interestingly, audiences prefer Swedish and U.S. movies, and critics prefer Asian movies. The family feature is demandable among a broad audience. He suggests that family features and animated movies have a chance to attract consumers and increase revenue. Genre is a vital aspect of revenue and demand.

[1] RR stands for Reviewers' Rating, ON for Oscar Nominations, and BO for Box Office

Lee (2009) examines whether the academy award impacts revenue in East Asia. His finding shows that drama-based awards do not influence box office revenue, but non-drama awards have a positive effect. He concludes that there is a vast cultural difference in terms of perceiving drama. He states that: "*...cultural differences tend to discount the values of the cinematic qualities and achievement indicated by the drama awards.*" He claims that although blockbuster movies can earn revenue in the East Asian market, quality can be perceived differently in different cultures.

Boatwright, Basuroy, and Kamakura (2007) focus on the relationship between film critics and box office revenue. Their data includes the critics who are influential for movie quality assessment. Their findings indicate that critics are significant at attracting movie-goers by creating positive advertising. Also, their findings show that big studios can attract movie-goers without critics' evaluation. It is related to movies' release. For independent movies, critics' reviews are essential to raising awareness for consumers, but big studios can do it without critical evaluations.

Legoux et al. (2016) explore the relationship between critical review and the decision of exhibitors, the owner of a movie theater. Their results show that excellent reviews have a significantly positive relationship with survival time, which exhibitors decide. Although excellent reviews increase the survival time, their findings show that negative thoughts about the movie do not shorten the survival time.

Einav (2007) investigates the seasonal effect on sales of the movie. His findings show that one can employ the seasonal effect for demand, but the market gives an endogenous reaction to the seasonal impact. The release date becomes an important aspect depending on the quality and the quantity of the movie. Einav (2010) develops a game design to understand the competition parameters among movie distributor companies. Since the price of tickets for movie theaters is identical for different movies, demand is related to release time (Orbach and Einav, 2007). His findings demonstrate that movie release date is clustered around big holidays like 4th of July. When he formed a pay-off matrix for a release date at holidays and non-holidays, streaming at holidays becomes the best decision for both parties. Therefore, he claims that studios decide to release movies around holidays. However, he also states that companies have started non-traditional releasing schedules to benefit from the non-competitive weekend. He says that "*Any deviation from the "predicted" seasonal pattern (for example, successful movies in October) is typically interpreted by industry observers as an extremely good movie in the wrong season rather than as a decent movie in a mediocre season. In other words, there is very little bad feedback after a bad release decision.*"

Cabral and Natividad (2016) analyze the effect of "being #1" on box office revenues. Their research includes pre-media attributes, star power, and movie quality (critical reviews). They claim that interaction between those attributes helps the movie become number 1 on the opening weekend and attracts movie-goers. Their findings show that being #1 at the box office during the opening weekend has an economically and statistically significant impact on a movie's performance.

Elberse and Anand (2007) investigate the relationship between advertising expense and stock prices of movies on the Hollywood Stock Exchange (HSX). Their finding shows that there is a positive and significant relationship between them. The magnitude of the coefficient is smaller for poor-quality movies. Their result indicates that the return from advertising is negative for movies with inferior quality.

Elberse (2007) study the relevance between casting choice announcements and changes in stock prices of movies traded in the Hollywood Stock Exchange. She uses an event study methodology of Brown and Warner (1985). Her finding discloses that there is a significant relationship between them. When casting is favorable (unfavorable), cumulative abnormal return is positive (negative). The magnitude of the relation is highly dependent on the worth of the star. The star’s worth is proxied by the revenues' generated in the past projects and artistic quality (awards/nominations).

McKenzie (2013) compares the prediction made in an online game, the Derby, and in a simulated market, the Hollywood Stock Exchange (HSX). In the game, participants make predictions about box-office. However, in the HSX, people choose to make investments in a movie stock. He shows that investors overpredict (underpredict) the low-earning (high-earning) movies. However, the Derby game is more biased compared to market trading. He concludes that in HSX, people prefer to buy or sell stock, and they are well-informed. However, in the Derby game, they are asked to make predictions about movies. Also, the results show that predictions in HSX are correlated with box office revenue. His study also reveals that the accuracy of predictions increases when the movie is a big-budget movie, sequel, or the movie includes a star.

Joshi and Hanssens (2009) investigate the relationship between advertising and stock market reaction in a new product release, a movie. They analyze the change in postlaunch stock price and predict the direction and magnitude of excess returns based on the revenue expectation built for a movie release. Their finding shows that pre-release advertising attracts consumers and informs investors about the product. They hypothesize that media spending by studios for audience development drives up the expectation, and the stock market reacts based on media. Their findings show that highly advertised movies are associated with smaller post-launch excess returns. Moreover, they find that when a small (big) advertising budget movie has a good opening weekend box office, its excess return turns out to be positive (negative). In the case of an unsuccessful opening weekend box office, excess returns are negative whatever the advertising spendings of the movie.

CHAPTER 3

HYPOTHESES

In the thesis, the financial success of a movie is measured either by opening box office or gross earnings from ticket sales. Previous studies show that classical attributes such as genre, budget, star-power (including actor, actress, and director), seasons, number of screens, number of weeks, critical reviews affect ticket sales (or demand for a movie). In this study, I also control some the classical attributes but my main aim to highlight how the quality of the film director as the CEO of the movie may have an influence on the financial success of the movie. Moreover, I focus on star power as financial success. How previous financial success of stars affects movie's box-office revenue. Finally, I hypothesize that different popularity measures matter in financial success.

In the finance and strategy literature, several papers focus on how CEO matters on a firm's performance. For example, Mackey (2008) shows that the CEO of a firm is an essential determinant of performance, controlling for the nesting of the CEO effect in the firm and the industry effect. Using data from 1500 US firms, Hambrick and Quigley (2014) provide evidence that 10-20% of firm performance depends on the

CEO’s performance. Bloom, Sadun, and Van Reenen (2016) highlight that management practice can be considered a technology that raises total factor productivity. They show that especially leader CEOs are appointed to be in more productive and profitable firms. In a very recent paper by Bandiera et al. (2020), comprehensive literature is given about CEO behavior and firm performance. In the movie business, I adapt the findings by Bloom, Sadun, and Van Reenen (2016) as good film directors to be more probably leading the high-profit movies. I consider the director as the CEO of a movie and aim to study the director's effect on movie performance. In particular, I use the previous financial success of the director into account, i.e., the average revenue of previous movies of the director, and test its effect on the financial success of a movie in 2019. My aim is to measure quality of CEO (director) with financial proxy, and I claim that quality of CEO (director) affects financial success of firm (movie).

Hypothesis 1a: The quality of the director has no impact on the current box office (financial success).

In the literature, the evidence on the effect of a star or stars is mixed. For example, Karniouchina (2011) shows that star power has a positive influence on revenue. De Vany and Walls (1994) provide a contradicting evidence, i.e., stars negatively affect profit. In this thesis, I use two different success variables (popularity and previous average income of the stars of the movie) to measure the effectiveness of the star-power. Also, star power is related to the effect of human capital. The study of Ran and Ravid (2020) shows that value of human capital is important in Broadway shows. When there is a change in actor and actress, it affects ticket sales. (Ran and Ravid, 2020).

Hypothesis 1b: The previous success of the actor or actress does not affect the current box-office (financial success).

The study of Hossein and Miller (2008) shows that it is possible to predict the opening night success by the number of social media interactions, especially the number of tweets that started many days before the movie's release date. The paper documents that movies that get many tweets have high opening night revenue suggesting that movie companies may use Twitter as marketing tools. Tweet pattern is related to popularity level. I claim that popularity matters more and more, and an increase in popularity induces higher revenue of a movie in 2019. IMDb Pro measures the popularity level for each movie when it is added to the website. Popularity level is calculated based on the number of website visits, the number of searches for a movie made by the audience, and/or whether people talk about the movie.

Gaikar et al. (2019) examine popularity to predict success, but their success measure is ratings. They are not interested in the relationship between revenue and popularity.

Cabral and Natividad (2016) employ #1 in the box office (the movie with the highest revenue) in the opening weekend to predict financial success. In this study, I examine the relationship between popularity and revenue and claim that popularity can effectively predict movie revenue.

Hypothesis 1c: The popularity measure of the movie has no impact on the revenue.

In addition to the above hypotheses, I have two sets of hypotheses to examine the association between movie revenues and stock price using (1) real stock market prices and (2) virtual stock prices. In the US, there is a simulated market, Hollywood Stock Exchange (HSX), acting as a real stock market (Elberse, 2007). The gross revenue of a movie makes a positive impact on the stock prices of movie distribution companies. In the United States, major movie studios are also production and distribution companies such as Walt Disney, Warner Bros., Sony, etc. When a movie is released, I expect that the stock price will be higher.

Hypothesis 2a: Unexpected gain in revenue does not affect the stock price of a movie.

Hypothesis 2b: Number of news, popularity, and number of screens negatively impact the stock price of a movie distributor company.

Finally, in line with the paper by Joshi and Hanssens (2009), I examine how unexpected opening weekend revenues in 2019 pass through the stock prices of distributor movie companies. Unexpected revenue is difference between actual revenue and predicted revenue.

Hypothesis 3: Unexpected revenue in opening weekend has no impact on the stock price of distributors' company following week of the release date.

DATA COLLECTION

The data covers 450 movies released in the United States in 2019. I exclude movies without revenue information. Documentaries are not included in the data collection process because they are not, in general, released at theaters (Lash and Zhao, 2016). I download data from IMDbPro. Information includes genre, IMDb point, numbers of ratings, whether it is based on book/comics, whether it is a sequel movie, distributor company, opening weekend revenue, USA revenue, Metascore, popularity during and before the release, season, how many theaters and how many weeks it was streamed, run time, whether it includes star or foreign language, director's average gross before the movie, change in popularity, and average gross revenue of actor and actress.

Among the available data, some of the variables need further explanation. For example, as Einav (2010) shows, beating rivals in the movie industry significantly depends on the decision of release date. I use the season as a dummy variable to capture the release date impact and include my empirical model to predict its impact on financial success. For genre, I have taken different categories as dummy variables. These categories are fantastic, adventure, crime, animation, biography, music, and horror. If a movie includes one of the features in the movie description given as genre, the dummy variable takes 1 for that category, and other genre dummies take 0.

I include the star variable as a dummy variable, taking value one if the actor or actress has high popularity in recent years. I gather the total gross revenue of each actor and actress mentioned in movie posters from movies and divide total revenue by the number of movies they had played in. It is calculated as an average for each star. It includes all movies the star plays in. Finally, I sum up all the average revenues and then divided them into a number of mentioned people in the movie poster to capture general star power as a group. Thus, I have the average revenue of actors and actresses as the star power financial value. To find the financial value of the director of the movie, I follow the same calculation. Movies generally have a director, but in rare cases, some movies have more than one director. I consider multiple directors as well.

The number of ratings, IMDb point, and Metascore are taken as reported. The literature shows that movie scores have a significant effect on movie revenue (see e.g., Boatwright, Basuroy, and Kamakura, 2007). Moreover, Ravid (1999) says that "*…attention by reviewers seems to be important to success - the more reviews a film receives, the higher the revenues. Film ratings are important as well, and sequels seem to do better, which is consistent with the view that insiders are not better informed than outsiders.*" Stock prices of distribution companies are collected from Bloomberg and WRDS. Distribution companies are included in the models as a categorical variable. On opening weekend and when the stock has been delisted, stock prices of movies are attained from Hollywood Stock Exchange (HSX), which is a virtual market, people can buy and sell stock of movies and bond of stars. Tables 1, 2 and 3 present detailed explanations of the variables in our data set and the descriptive statistics, respectively.

***Table 1*:** List of variables

Variable	Description	Source
Anticipated	Dummy variable takes value 1 if the movie is anticipated before the release	MentalFloss
Fantastic	Dummy variable, value 1 if genre includes fantasy	IMDb
Adventure	Dummy variable, value 1 if genre includes adventure	IMDb
Crime	Dummy variable, value 1 if genre includes crime	IMDb
Animation	Dummy variable, value 1 if genre includes animation	IMDb
Biography	Dummy variable, value 1 if genre includes biography	IMDb
Music	Dummy variable, value 1 if genre includes music	IMDb
Horror	Dummy variable, value 1 if genre includes horror	IMDb
Stock	Categorical variable, Distribution company's stock name	IMDb& Bloomberg& WRDS
Based on books/comics	Dummy variable, value 1 if the movie is based on books/comics	IMDb
Series	Dummy variable, value 1 if it is a sequel movie	IMDb
IMDb point	Value between 0-10 given by audience	IMDb
Rating	How many people rate for the movie	IMDb
Metascore	Critic review rate between 0-100	IMDb
User Review	How many user rate for metascore	IMDb
Critics	How many critics rate for metascore	IMDb
US Production	Dummy variable, value takes 1 if it is US production	IMDb Pro
Sales	Dummy variable, value takes 1 if the movie has sales representative	IMDb Pro
Before MM	Popularity in IMDb before movie release	IMDb Pro

Table 2 : List of Variables Continues

Variable	Description	Source
Moviemeter	Highest level of popularity in IMDb when it is released (starts with release, 4 weeks period)	IMDb Pro
Season	Dummy variables for the five main movie release seasons given in Joshi and Hanssens (2009) (January–March, April–May, Memorial Day–July, August–November, Thanksgiving–December)	IMDb& Joshi and Hanssens (2009)
Federal Holiday	Dummy variable, value takes 1 if it is federal holiday weekend	www.officeholidays.com
OW	Numerical variable, opening weekend gross, value includes First weekend revenue (Friday, Saturday, Sunday)	IMDb Pro
Gross USA	Numerical variable, USA gross, value includes all revenue when the movie is released in USA	IMDb Pro
Run time (min)	How many minutes the movie it takes time	IMDb Pro
News Article	Numerical variable, how many news article released about the movie	IMDb Pro
Week	How many weeks the movie released	IMDb Pro
Theaters	How many theaters the movie released	IMDb Pro
Foreign Language	Dummy variable, value takes 1 if the foreign language is spoken in movie	IMDb
HSX (OW)	Hollywood stock exchange price in opening weekend	Hollywood Stock Exchange
HSX (Close)	Hollywood stock exchange price when the stock is delisted	Hollywood Stock Exchange
DAV	Average gross of director from previous movies per a movie	IMDb Pro
logDAV	Logaritmic variable of DAV	IMDb Pro
AcAvGross	Average Gross of lead actor/actress from previous movies (average is taken for actors and actresses)	IMDb Pro
logAcAv	logarithmic variable of AcAvGross	IMDb Pro
STAR	Dummy variable takes value 1 if the actor/actress has high popularity	IMDb Pro
CAR(0,+5]	Cumulative abnormal return based on distributors companies stock between day 0 to day +5 (day 0 is release date)	Bloomberg& WRDS
CAR[-5,+5]	Cumulative abnormal return based on distributors companies stock between day -5 to day +5 (day 0 is release date)	Bloomberg& WRDS

Table 3**:** Descriptive Statistics

	Min	Max	Mean	Std Deviation	Median
Based on book/Con	0.00	1.00	0.15	0.36	0.00
Series	0.00	1.00	0.12	0.32	0.00
IMDb point	0.00	8.70	6.18	1.12	6.30
Rating	15.00	864525.00	31048.88	82172.46	4330.00
Metascore	0.00	96.00	42.11	30.32	51.00
User Review	0.00	10518.00	371.31	971.97	64.50
Critics	0.00	699.00	97.29	116.31	52.50
US Production	0.00	1.00	0.54	0.50	1.00
Sales	0.00	1.00	0.42	0.49	0.00
Before MM	1.00	1084303.00	14374.89	55350.70	3885.00
Moviemeter	1.00	124532.00	4271.33	9582.58	602.00
logMM	0.00	5.10	2.65	1.20	2.78
Season	1.00	5.00	2.72	1.36	3.00
OW	512.00	357115007.00	8375141.39	27510872.56	95255.50
Gross USA	220.00	858373000.00	24701000.35	77279677.49	421967.50
Run time (min)	63.00	230.00	110.02	20.37	106.00
News Article	0.00	7382.00	234.17	593.04	57.00
Week	0.00	82.00	8.26	6.80	7.00
Theaters	0.00	8588.00	1021.96	1490.64	127.50
Foreign Language	0.00	1.00	0.36	0.48	0.00
HSX (OW)	0.00	357.12	7.97	27.17	0.00
HSX (Close)	0.00	771.37	21.59	67.41	0.04
DAV	0.00	363070709.00	17421287.12	47217418.30	21726.50
logDAV	0.00	8.56	3.44	3.34	4.34
AcAverage	3919.00	283471874.60	29961549.52	34008615.77	20358267.50
STAR	0.00	1.00	0.34	0.47	0.00

I report the correlation matrix in the appendix (see Table A1). There are several highly correlated variables. Cabral and Natividad (2016) highlight that opening weekend revenue (OW) is highly correlated with total gross revenues (GUSA). In 2019, I find that the correlation between OW and GUSA is 75 percent. The correlation between the number of news articles about the movie and the opening weekend is about 74 percent, and the gross revenue is about 73 percent. The number of theaters is also highly correlated with the revenue figure. The correlation with the opening weekend is around 57 percent, and total revenue is around 61 percent. Director's average revenue from previous projects is also correlated with both revenue figures by around 62 percent. The average revenue of stars in the movie is correlated with an opening weekend by 47 percent and with USA gross revenue by about 50 percent.

I take the logarithm of my main dependent variables, OW and GUSA. This log transformation aims to reduce the potential impact of outliers on my analysis. I look look at the correlation between other variables with the log of opening weekend (logOW) and log of gross revenue in the USA (logGUSA). News articles released are correlated with logOW by around 40 percent and with logGUSA by around 50 percent. A number of theaters are also highly correlated with logOW (71 percent) and logGUSA (84 percent). How many weeks the movie streamed is correlated with both logGUSA (39 percent) and logOW (25 percent), but obviously, “weeks” cannot be an independent variable for opening weekend box-office success.

Revenue from the director's previous movies is correlated with logOW (around 40 percent) and logGUSA (around 50 percent). I also take the logarithm of the director's average revenue for a movie and report the correlation in the log-linear models. Similarly, it is highly correlated with logOW (around 44 percent) and logGUSA (around 49 percent). The average previous financial success of the movie star is correlated with logOW (around 45 percent) and logGUSA (around 51 percent) at almost the same level. As I use the logarithm of stars' average revenue in the empirical analysis, I also report the correlation between the logarithm of stars' average revenue and logOW (38 percent) and logGUSA (45 percent). Whether there is a star in the movie is correlated with logOW around 42 percent and logGUSA 46 percent.

The rating, which is how many people rates for a movie in IMDB, is correlated with opening weekend around 72 percent, logOW around 42 percent, gross revenue around 75 percent, and logGUSA around 52 percent. Whatever the correlation, a number of ratings are not included in the opening weekend estimations because the rating figures cover all durations such as before the release, during the release, and after the stream stops. Critics, which is how many critics rates for a movie in IMDb for Metascore, is highly correlated with rating. I keep critics as an independent variable in the empirical models, although it makes less sense. However, Boatwright, Basuroy and Kamakura (2007) provide a shred of evidence that critics play a role in the opening weekend revenues. Critics are correlated with opening weekend around 61 percent, logOW around 57 percent, gross revenue around 65 percent, and logGUSA around 69 percent. In the model, I include ratings and critics separately but not both at the same time. Nevertheless, it is important to note that critics are also highly correlated with news articles released about movie and number of theaters. A number of news articles and theaters are correlated around 53 percent. Therefore, I do not use both variables in the same model.

METHODOLOGY

I have two empirically testable questions in the thesis: (1) Is popularity a factor in 2019's box office numbers? (2) Does opening week shock (open shock), i.e., unexpected revenue of a movie, affect the stock prices of the distributing movie company in the following first week?

I start my analysis by forming a simple model to estimate the revenue of a movie. As a basic model, I enrich the model by in Joshi and Hanssens (2009) with several new variable. Joshi and Hanssens (2009) emphasize advertising expenditure on opening week shock. In the thesis, I emphasize the importance of managerial skills (director's performance) and the popularity of the cast at the box office. As mentioned in the introduction, 2019 is a year such that the success of the movies is challenged by the other platforms, especially by Netflix, Amazon, Hulu, etc. I hypothesize that due to competition, movie companies may prefer to recruit successful directors and casts to ensure the financial success of their new products.

In addition to the opening weekend successes, I study the overall financial success of a movie's gross revenue that is released in 2019. I use the ordinary least square method (OLS) to estimate the box office successes. I use R program to obtain regression coefficients. I have different model to study the effect of open shock. Open shock is calculated by taking the difference between the movie's actual and estimated opening weekend revenues. I calculate the cumulative abnormal return for distribution companies to understand whether the unexpected success or failure induces the distribution company's stock prices. I also have a linear model to study the association between cumulative abnormal return and open shock. Finally, I examine the relationship between the Hollywood Stock Exchange and open shock, and the relationship between the Hollywood Stock Exchange and public awareness of the movie.

I have three designs based on the data. The first design includes all the data without any restrictions. The second design has a constraint, excluding movies without distributor's stock. I run the model for the data including only the movies with the distributor's stock price. In the third design, I have two constraints. In the first constraint, I exclude movies that do not have an opening stock price in Hollywood Stock Exchange. In the second constraint, I omit movies that do not have a closing price.

EMPIRICAL ANALYSIS

Opening Weekend Revenue as Dependent Variable

I start my empirical analysis with standard factors that explain the opening weekend revenue (revenue on Friday, Saturday and Sunday). I have the same right hand side variables for the regressions of both the level (OW) and the logarithm of the opening weekend revenue (logOW):

(1) $OW_i = a0 + a1\ Series_i + a2\ US_i + a3\ Sale_i + a4\ BBC_i + a5\ DAV_i + a6\ STAR_i + a7\ Metascore_i + a8\ MM1_i + a9\ Time_i + a10\ Theater_i + a11\ DIST_i + a12\ Season_i + a13\ ANT_i + a14\ AcAvGross_i + a15\ Change\ BMM_i + error$

where Series is dummy variable and takes a value of 1 if the movie is a sequel movie (e.g., Frozen 2, Avengers, Star Wars in 2019); 0 if otherwise. US is a dummy variable and takes a value of 1 if the movie is a US based production; 0 if otherwise. Sale is another dummy and takes a value of 1 if the movie has a sales representative; 0 if otherwise. Sales representatives are responsible for the marketing activities of the movies and the big movie companies mostly outsource instead of having their own sales representatives. BBC is a dummy variable and takes a value of 1 if the movie is from book or comics; 0 if otherwise. DAV is the director's previous box-office records (average gross revenue). STAR is the star's or stars' previous box-office records. Metascore is composed of reviews of critics and range between 0-100. The higher scores indicate the quality of the movie. MM1 is derived from movie-meter. (MM). Moviemeter shows the highest popularity level of a movie during the opening month (highest rank between the release day and one month period after the release). MM1 is calculated as 1/(Moviemeter) since the highest popularity level is expressed with 1. (When the movie has Moviemeter value 1, it has the highest popularity. When the value increases, the popularity level is decreasing. MM=1> MM=2). In this way, it is not in descending order anymore.

Time indicates the run time of a movie. The run time or the length of the movie typically 90-100 minutes. Legoux et al. (2016) show that run time affects exhibitors' decision to allocate room for a movie. Consumers may give up buying a ticket for a long run-time movie because they have to spend a longer time in the theater. Or they may prefer long run-time movies to spend more time in the theaters. Theater indicates the number of theaters the movie streamed in the opening weekend. DIST indicates distribution companies. I include distribution companies if they are listed in the stock market, and the impact of the rest of the distributor companies might be captured by the intercept. In my basic model, there are 20 distributor companies. It is hypothesized that distributor companies play an important role on box office success since the film industry is an oligopolistic market (McDonough and Winslow, 1949), and few of the companies seem to be strongly dominating the market (Joshi and

Hanssens, 2009). By including distributing companies into the model, I aim to see whether market dominance matters in the movie revenue.

Season is categorized as in Joshi and Hanssens (2009): Jan-Mar (1), Apr-May (2), Memorial Day-Jul (3), Aug-Nov (4), Thanksgiving-Dec (5). ANT shows whether the movie is anticipated before the launch. ANT variable is based on an article called "The Most Anticipated Movies of 2019" in MentalFloss. It is a dummy variable taking value 1 when the movie is among the list in Mental Floss, otherwise taking value 0. ChangeBMM is introduced to obtain the relationship between change in popularity with release and estimated revenue. In general, popularity is calculated with social media channels like Youtube, Twitter, and Instagram data. However, I use IMDb's popularity index, which depends on many variables like the number of clicks, how many people talk about the movie, the number of news released about the movie, etc. More specifically, changeBBM is calculated as:

$$(2)\ \text{changeBMM} = (-1) * \frac{(\text{MM} - \text{BMM})}{\text{BMM}}$$

Similar to the MM1 variable, changeBMM has a descending order, creating a negative impact on change. However, the multiplication of -1 solves the problem that when the popularity increases (higher changeBMM), one can expect revenues to increase. AvAcGross indicates the average financial success of stars in the movie.

***Table 4*:** Dependent variable is Opening weekend revenue (in millions)

	Estimate	t value
Intercept	-1.737	-0.365
Series	**10.21*** **	4.01
US	0.577	0.342
Sale	-2.014	-1.282
BBC	2.521	1.186
DAV	**0.000*** **	7.511
STAR	**-4.285***	-2.211
Metascore	0.045	1.621
MM1	**39.03*** **	5.112
Time	0.014	0.362
Theaters	0.001	1.583
DIST	0.000	
AMC	-0.944	-0.309
Amazon	0.509	0.125
Bona	3.867	0.28
CIDM	-0.504	-0.149
CJ ENM	1.999	0.34
Comcast	-0.523	-0.15
COHN	-0.922	-0.131
CSSE	-1.338	-0.116
Disney	**9.338****	3.025
EROS	2.195	0.482
Entertainment One	1.001	0.141
Lai Sun Development	4.039	0.292
Lionsgate	-0.964	-0.3
Maoyan Entertainment	2.795	0.202
MGM	-6.385	-1.109
Netflix	-5.069	-0.511
PBS	-19.520	-1.381
Paramount Pictures	**-13.72***	-2.546
Sony	-3.882	-1.334
Warner Bros	**-8.822***	-2.138
Season	-0.915.	-1.752
ANT	**59.7*** **	11.104
AcAvGross	**0.072****	2.634
ChangeBMM	-0.49	-0.328
R-square	78%	
Adjusted R- square	76%	
# of observations	378	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

All coefficients are divided by 10^6 for readibility

Table 4 presents the regression output for design 1. The determination coefficient value (Adjusted R^2) is 0.76, indicating that there is still 24 percent explained by other factors. Among standard factors, if the movie is a sequel movie, it positively affects revenue at a 0.001 significance level. This finding is consistent with Wall (2009). According to the regression results, I find no significant impact of whether the movie is produced by a US company on revenue. Yet, the coefficient of US production is positive. Unexpectedly, the coefficient of Sale (a movie with a sale representative) is negative but not significant at any level. The survey made by Gazley, Clark, and Sinha (2010) suggests that the audience prefer movies based on real-life event rather than based on books or comics. The finding shows that the movie based on books or comics (Sequel) has a positive impact on opening weekend revenue, but the coefficient is not significant. Similarly, Metascore influences revenue positively but insignificantly. These findings are consistent with the previous evidence. For example, Wallentin (2016) could not find a significant relationship between Opening Weekend revenue and critical reviews, sales representative. Addis and Holbrook (2018) argue that critical review is not a significant factor for ordinary evaluations made by consumers.

As seen from the coefficient of MM1, the popularity of a movie has a positive impact on revenue at a 0.001 significance level. In 2019, there were box office blockbusters (extremely high box-office movies) such as Avengers, Star Wars, and IT: Chapter Two. These movies last long run-times (the mean run time is 110 and the median is 106); however, I could not find any significant relation between the run-time of a movie and its opening box office in 2019.

In line with the literature (see e.g., Elliot and Simmons, 2008; Walls, 2009), I find that the number of theaters the movie streamed has a positive impact on revenue, but the coefficient is not significant. Whether the movie has at least one star in the cast, opening week revenue is significantly low at 0.05. In the literature, it has been argued that star power impacts the decision of exhibitors to allocate screen for a movie and the decision of the audience to see the movie or not in the first weeks. For example, Karniouchina (2011) find that stars may affect negatively in following weeks after performance revealed. In literature, there are also evidence (see e.g. Prag and Casavant, 1994 and Ahmad et al., 2017) that star is a significant determinant to predict box office success. Ravid (1999) find no significant relationship between star worth and box office revenue. De Vany and Walls (2004) document that including a star has negative mean distribution overall. Although I find that STAR has a negative impact on opening weekend, when I look at the effect of the average revenue of actors and actresses per movie, I find a positive relationship at a 0.01 significance level. This finding is consistent with the study of Lash and Zhao (2016). As Gunter (2018, p2) mentions, *"..the hiring of star actors can also trigger greater interest in a movie both among movie-goers and investors. However, stars cannot provide cast-iron guarantees of a movie's success…"* In general, starbuzz is vital to attract an audience.

Disney is significant at 0.01 level among distribution companies, Paramount Pictures and Warner Bros are significant at 0.05 level. When I examine the sign of the coefficient of Disney versus Paramount and Warner Bros., in 2019, Disney movies had positive and significant opening weekend revenue as compared to other companies, whereas Paramount and Warner Bros. had significantly less. However, when I smooth the dependent variable by taking the logarithm, I observe that distributor Company matters in revenue generation. (see Table 6).

Similar to the findings of Joshi and Hanssens (2009), I have a significant relevance between estimated revenue and season dummy at a 0.1 level. ANT is found to be positive and significant. ChangeBMM has no significant relevance in the first model. The average revenue for a movie of a director's previous project (DAV) has a small but positive coefficient; also, it is highly significant at 0.001. According to the initial findings, DAV good indicator to estimate opening weekend revenue.

The coefficients for some of the variables, including intercept, are extremely high, suggesting that I have to work on the logarithm of opening weekend (logOW). However before presenting the logOW estimations, I explain how the relationship between the distributor company's cumulative abnormal return (CAR) and open shock is studied. As mentioned before, models with CAR are aimed to examine how the unexpected revenue is related to the stock price of a distributor company. β_i and α_i are calculated based on Sharpe (1964) and CAR is calculated as follows:

$$CAR_{i,t} = R_{i,t} - \alpha_i - \beta_i * R_{m,t} \qquad (3)$$

$$\beta_i = \frac{Cov(R_{i,t}, R_{m,t})}{Var(R_{m,t})} \qquad (4)$$

$$\alpha_i = R_i - (r_f + \beta_i * (R_m - R_f)) \qquad (5)$$

Openshock=OW-OW_e *(6)*

where OW_e is the estimated opening weekend revenue from the regression model.

The following model is used to examine the relationship between CAR and Openshock:

$$CAR_i = \beta_0 + \beta_1 * Openshock_i + \boldsymbol{\varepsilon}_i \qquad (7)$$

Table 5**:** Dependent variable is Cumulative Abnormal Return (CAR)

	Estimate	t-value
Intercept	57060	0.6
open shock	0.0004	0.164
R-square	0.00007	
Adjusted R- square	-0.002	
# of observations	416	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

Values are multiplied with 10^7 for readibility

CAR is calculated for five days after the movie is released. As seen in Table 4, there is no significant relevance between open shock and CAR.

In Table 6, I report a similar model with the logarithm of opening weekend (logOW), the logarithm of director's previous revenue, and actor/actress average revenue. Now we have a better model in terms of explanatory power, i.e., the adjusted R-squared increased to 82 percent.

A sequel movie has a positive but insignificant coefficient. In one of the early papers by Prag and Casavant (1994), a sequel movie is found to have a significant impact on box-office revenues. A movie produced by a U.S. company with a sales representative and/or based on books or comics (BBC) has no explanatory power on opening weekend revenue. However, including a star (STAR) negatively affects estimated revenue at a 0.05 significance level as in Holbrook and Addis (2007). Meta-score has a significant and negative impact on revenue, suggesting that award or critical assessment and consumer attention are different concepts. Financial success in the box office does not depend on reviews or awards. I could not find any significant relationship between MM1 and logOW in this model. Nevertheless, the change in popularity (changeBMM) when the movie was released has a significantly positive relationship with financial success at the box office.

***Table 6*: **Dependent Variable is Opening weekend revenue (in logarithm)

	Estimate	t value
Intercept	**6.104 *** **	8.052
Series	0.339	1.351
US	0.155	0.894
Sale	-0.199	-1.272
BBC	-0.055	-0.258
logDAV	0.02125 .	1.939
STAR	**-0.4714 ***	-2.469
Metascore	**-0.006977 ***	-2.528
MM1	0.3862	0.52
Time	**0.01665 *** **	4.341
Theaters	**0.001323 *** **	15.043
DIST		
AMC	-0.2289	-0.740
Amazon	**1.006 ***	2.473
Bona	1.183	0.854
CIDM	**0.9794 ****	2.897
CJ ENM	0.09662	0.164
Comcast	**1.842 *** **	5.242
COHN	-0.2105	-0.297
CSSE	-1.482 .	-1.757
Disney	**1.421 *** **	4.600
EROS	**1.644 *** **	3.606
Entertainment One	1.179 .	1.656
Lai Sun Development	0.09668	0.070
Lionsgate	**1.754 *** **	5.446
Maoyan Entertainment	-0.3219	-0.232
MGM	**1.516 ****	2.631
Netflix	**3.208 ****	3.235
PBS	-1.127	-0.800
Paramount Pictures	**1.664 ****	3.152
Sony	**0.9185 ****	3.125
Warner Bros	**1.432 *** **	3.466
Season	0.019	0.366
ANT	0.267	0.501
logAcAv	**0.1231 ****	3.015
ChangeBMM	**0.6142 *** **	4.117
R-square	0.839	
Adjusted R- square	0.824	
# of observations	378	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

How many minutes the movie lasted (Time) and how many theaters the movie streamed (Theaters) have a significantly positive relationship with opening weekend revenue. Director's revenue per movie from the previous project in logarithm (log-DAV) is found to have a positive relationship with opening weekend revenue at the 0.1 significance level. Although it is weakly related to the movies with a director whose prior financial box office success is 10 percent more than the other directors, we expect the current movie of that director would be 2 percent more box office.

The logarithm of average revenue of actors/actresses per movie has a significantly positive relationship. I include the power of stars with financial terms as an average movie revenue of leading actors and actresses. “Buzz factor” is a common industry term describing a star's ability to generate consumer interest (Karniouchina, 2011). As mentioned before, I expect higher revenue when the revenues of the stars from their previous movies are high. Since the stars are known by previous successful movies, the audiences are familiar with them. Hence, I expect that a movie lover will be attracted by the new movie. I also include the average worth of the leading cast to the model. Although the findings of Wallace, Seigerman, and Holbrook (1993) show that the worth of stars might have changed over time, the average financial success of previous movies is a significant indicator for the next project. Karniouchina (2011) also mentions that “*stars have an impact on revenue, primarily due to their ability to generate buzz and drive audiences to the theaters during the opening week.*” In the empirical analysis, I do not have a person's worth but study the worth of the cast as a team. As seen in the table, the Season and anticipation of a movie (ANT) are not significant. However, most of the distribution companies are significant in estimating the opening revenue in 2019.

After estimating logOW, I also report the association between openshock and CAR for days (0, +5] in Table 7. Unfortunately, I could not find any significant relationship between them.

***Table 7*:** Dependent variable is CAR (0, +5]

	Estimate	t-value
Intercept	0.006	0.621
open shock	0.002	1.03
R-square	0.003	
Adjusted R- square	0.0002	
# of observations	416	

Significant codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

I also define CAR for days [-5, +5], and run regression between openshock and CAR. As seen in Table 8, the model is deficient explanatory power, although the intercept is significant at 0.1 level, open shock is not significant at any level. Nevertheless, it has a positive impact on Cumulative Abnormal Return.

***Table 8*:** Dependent variable is CAR [-5, +5]

	Estimate	t-value
Intercept	0.023 .	1.955
open shock	0.002	0.568
R-square	0.0008	
Adjusted R- square	-0.002	
# of observations	416	

Significant codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

As seen in Table 9, I add categorical genre variables into the model, but they have no significant contribution to understanding opening week revenue (logOW). Adjusted R-squared has increased slightly to 82.42 percent.

***Table 9*:** Dependent variable is logOW (with genre)

	Estimate	t value
Intercept	**6.024 *****	7.771
Series	0.316	1.236
US	0.137	0.777
Sale	-0.226	-1.427
BBC	-0.129	-0.597
logDAV	0.018	1.611
STAR	**-0.4616 ***	-2.359
Metascore	**-0.007082 ***	-2.561
MM1	0.5179	0.675
Time	**0.01669 *****	4.183
Theaters	**0.001304 *****	14.149
DIST		
AMC	-0.2927	-0.940
Amazon	**1.062 ***	2.588
Bona	1.3050	0.942
CIDM	**0.8699 ***	2.501
CJ ENM	0.0117	0.020
Comcast	**1.842 *****	5.172
COHN	-0.0935	-0.132
CSSE	-1.396	-1.647
Disney	**1.422 *****	4553
EROS	**1.613 *****	3.493
Entertainment One	1.166	1.620
Lai Sun Development	0.1762	0.127
Lionsgate	**1.768 *****	5.436
Maoyan Entertainment	-0.2158	-0.155
MGM	**1.466 ***	2.507
Netflix	**3.122 ****	3.125
PBS	-0.9003	-0.638
Paramount Pictures	**1.627 ****	3.055
Sony	**0.8968 ****	3.045
Warner Bros	**1.39 ****	3.271
Season	0.014	0.276
ANT	0.288	0.525
logAcAv	**0.1227 ****	2.996
ChangeBMM	**0.655 *****	4.307
Genre		
Fantastic	-0.117	-0.33
Horror	0.193	0.784
Crime	0.270	1.294
Adventure	0.234	0.972
Music	0.644	1.492
Animation	0.077	0.235
Biography	0.4453 .	1.737
R-square	0.8417	
Adjusted R- square	0.8242	
# of observations	371	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

From the regressions between CAR and open shock for days (0, +5] and [-5,+5], I find a positive and insignificant association between CAR and open shock (see Tables 10 and 11). CAR can be positively associated with a favorable opening when the movie has a higher opening weekend revenue than expected return. However, the regression result shows an insignificant relationship between CAR and open shock. When I run a regression at days [-5, +5], I cannot find a significant relationship between openshock and CAR.

***Table 10*:** Dependent variable is CAR (0, +5]

	Estimate	t-value
Intercept	0.006	0.621
open shock	0.002	1.012
R-square	0.003	
Adjusted R- square	0.00006	
# of observations	416	

Significant codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

***Table 11*:** Dependent variable is CAR [-5, +5]

	Estimate	t-value
Intercept	0.023 .	1.954
open shock	0.001	0.531
R-square	0.0007	
Adjusted R- square	-0.002	
# of observations	416	

Significant codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

Gross Revenue (GUSA) as Dependent Variable

In this section, I study the gross revenue of a movie using a slightly different model from an opening weekend model:

$$
\begin{aligned}
GUSA_i = {} & a0 + a1\ Series_i + a2\ US_i + a3\ Sale_i + a4\ Point_i + a5\ Rating_i + a6\ BBC_i \\
& + a7\ DAV_i + a8\ STAR_i + a9\ Metascore_i + a10\ Time_i + a11\ Theater_i \\
& + a12\ Week_i + a13\ DIST_i + a14\ Season_i + a15ANT_i + a16AcAVGross_i \\
& + error
\end{aligned}
$$

As seen in Table 12, the coefficient of Series is positive and significant, suggesting that when a movie is a sequel movie, one may expect an increase in the box office revenue. There is no significant relationship between U.S. production and IMDb point and the gross revenue of the movie released in the U.S.A. The rating that shows how many audience rates for a film for IMDb point has a significant and positive association with gross revenue. The finding of Rating has to be used cautiously because the number of ratings occurs after the audience watched the movie so that it might be the result of the revenue (Gazley, Clark and Sinha, 2010).

I do not include MM1, since it shows first month popularity. However, Gross Revenue is finalized in more than a month. Median week the movie streamed is 8 weeks (see Table 3). As expected, the director's previous project and the number of theaters that stream the movie have a significantly positive impact on gross revenues. I find no significant relationship between gross revenue and the number of weeks the movie streamed. Disney (positive sign), Paramount Pictures, MGM, and Warner

Bros (negative) have significant coefficients. ANT is a dummy variable that indicates whether the movie is anticipated before the release, according to the article in MentalFloss. ANT is significantly positive for gross revenue. AcAvGross, which shows the previous financial success of cast as an average, is positive and significant, but has a small coefficient like expected because some movies have huge AcAvGross.

Table 12**:** Dependent variable is Gross Revenue in USA (GSUA)

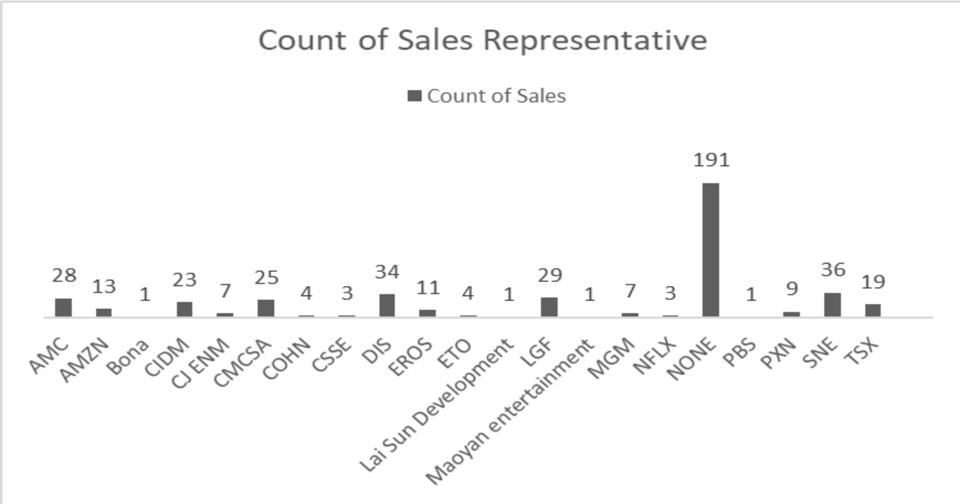
	Estimate	t value
Intercept	-1.035	-0.743
Series	**2.795 *****	4.906
US	0.169	0.426
Sale	-0.446	-1.208
Point	0.117	0.623
Rating	**0.000 *****	7.627
BBC	0.498	0.999
DAV	**0.000*****	7.720
STAR	**-1.149 ***	-2.481
Metascore	0.009	1.315
Time	-0.004	-0.472
Theaters	**0.001 ****	3.098
Week	0.015	0.527
DIST	0.000	
AMC	-0.237	-0.335
Amazon	0.336	0.339
Bona	1.148	0.340
CIDM	-0.200	-0.260
CJ ENM	0.571	0.428
Comcast	-0.1036	-0.122
COHN	-0.013	-0.008
CSSE	-0.132	-0.067
Disney	**2.576 *****	3.467
EROS	0.863	0.776
Entertainment One	-0.376	-0.217
Lai Sun Development	1.115	0.330
Lionsgate	-0.4146	-0.566
Maoyan Entertainment	1.223	0.361
MGM	**-2.786 ***	-1.997
Netflix	-0.216	-0.109
PBS	-4.417	-1.279
Paramount Pictures	**-4.085 ****	-3.109
Sony	-0.524	-0.785
Warner Bros	**-3.52 *****	-3.625
Season	-0.107	-0.888
ANT	**18.68 *****	15.257
AcAvGross	**0.000 *****	3.456
R-square	0.829	
Adjusted R- square	0.814	
# of observations	409	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1
All coefficients are divided by 10^7 for readibility

I run a similar model after taking the logarithm of gross revenue for the USA. I also take the logarithm of DAV, AcAvGross, and the number of ratings (Rating). As seen from Table 13, by smoothing the dependent variable, the model's explanatory power increases to 82.43 percent using the data from 409 movies.

First, I observe that a US company that produces the movie has significantly more gross revenue. When the movie has a sales representative, it seems that gross revenue declines significantly. As seen in Figure 1, the movies that have a distribution company do not prefer to have a sales representative. So, my finding that a movie with sales representative may not be measuring the success of the sales representative but capturing the small productions in 2019. It seems that small productions have significantly low gross revenues in 2019. Fee (2002) investigates the financing decision of the movie. My finding is matching with the study of Fee (2002). He suggests that some movies prefer independent financing to studio financing, so they can freely guarantee artistic quality. Independent financing movies majorly prefer sales representative compared to studio financing movies.

Figure 1: Sales Representative and Distribution Companies



The movie based on books or comics does not matter on the gross revenue in 2019. Similar to the previous model, how many audiences vote is a significantly positive effect on gross revenue.

Table 13**:** Dependent variable is Gross Revenue in logarithm (logGUSA)

	Estimate	t value
Intercept	**5.077 *****	6.406
Series	0.349	1.565
US	**0.299 .**	1.833
Sale	**-0.391 ****	-2.666
Point	0.134	1.757
log(Rating)	**0.588 *****	10.144
BBC	-0.012	-0.063
logDAV	0.013	1.178
STAR	-0.389 *	-2.143
Metascore	**-0.015 *****	-4.820
Time	0.002	0.505
Theaters	**0.001 *****	9.397
Week	**0.073 *****	6.334
DIST		
AMC	0.136	0.482
Amazon	**0.853 ***	2.158
Bona	1.067	0.795
CIDM	0.419	1.373
CJ ENM	0.483	0.907
Comcast	**1.492 *****	4.402
COHN	-0.163	-0.238
CSSE	**-3.311 *****	-4.209
Disney	**0.757***	2.497
EROS	**1.382 ****	3.129
Entertainment One	1.031	1.498
Lai Sun Development	-0.366	-0.272
Lionsgate	**1.299 *****	4.426
Maoyan Entertainment	0.414	0.307
MGM	**1.330 ***	2.403
Netflix	1.413 .	1.776
PBS	0.792	0.581
Paramount Pictures	**1.292 ***	2.535
Sony	0.516 .	1.930
Warner Bros	**0.816 ***	2.105
Season	0.02635	0.925
ANT	-0.350	-0.832
LogAcAv	0.069.	1.735
R-square	0.8382	
Adjusted R- square	0.8243	
# of observations	409	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

I find no impact of the director's previous project (logDAV) and STAR on the gross revenue of a movie released in the U.S.A. Interestingly, the movies with higher Metascore have significantly lower gross revenue at 0.001 level. The short or long run time movies do not make a significant effect on this model. There is no difference between shorter or longer movies because Time is found to be an insignificant coefficient. Even though run time matters significantly on explaining log value of opening week box-office, it has no impact on log values of gross revenue.

As expected, the gross revenues of the movies that are streamed in many theaters and many more weeks are significantly higher. In 2019, the movies that are distributed by Disney, Paramount Pictures, MGM, Amazon, Comcast, and Warner Bros are significantly higher gross revenues. As explained before, the distribution company is an essential factor affecting the revenue of movies. The market is an oligopoly, and the dominant companies can allocate vast amounts of money to distribute the film and promote/advertise the movie. Interestingly, the gross revenues of movies distributed by Netflix and Sony are weakly significant in 2019. ANT is not significant in this model. LogAcAv, which shows the logarithm of AcAvGross, is significant at 0.1 level and significant.

I also examine whether the revenue of opening weekend is significant for gross revenue. First, I exclude variables that are used in explaining the opening weekend. Yet, I keep IMDb points, how many audiences vote for a movie, and how many weeks the movie streamed in the model. In this model, I introduce an interaction of the logarithm of opening weekend and number of weeks the movie streamed in the theaters. As seen in Table 14, opening weekend and the number of ratings are essential indicators for gross revenue. In line with Cabral and Natividad (2016), I find a positive and significant coefficient of opening weekend revenue on gross revenue. The number of weeks the movie streams in theaters is another significant predictor of gross revenue.

The exciting finding is that the interaction of logOW and Weeks has a negative and significant coefficient suggesting that the predicting value of opening weekend revenue decreases when the movie remains longer in the theaters.

Another interesting finding is that IMDb point (Point) is barely significant (at 0.10 significance level) in predicting the gross revenue. When the IMDb point is higher, it is expected that it can influence the audience's opinion. Doshi et al. (2010) highlight that rating sites produce snowball effects, primarily on IMDb. They argue that strong positive or negative reviews encourage or discourage potential viewers. They make sentiment analysis to predict the daily price change of movie stocks by focusing on individuals' perspectives towards movies. They find a significant result that IMDb point affects daily price change in movie stocks, where traded in Hollywood Stock Exchange. For our analysis with data from movies in 2019, we find no significant coefficient for IMDb.

Table 14**:** Dependent variable is Gross Revenue in logarithm (logGUSA)

	Estimate	t value
Intercept	0.144	0.432
Point	0.074.	1.876
log(Rating)	0.21***	7.765
lOW	0.877***	36.114
Week	0.18***	7.852
lOW: Week	-0.008 ***	-4.582
R-Square	0.952	
Adjusted R- Square	0.951	
# of Observations	411	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

Hollywood Stock Exchange (HSX) as Dependent Variable

In the movie industry, there is a virtual stock market in which there are several instruments traded. Movie stocks and their price reflect the potential domestic box office during its first four weeks. The value of TV Stocks depends on the number of episodes airs in the first season of the new TV series. There are also CelebStock, Starbonds, Moviefunds etc. HSX is founded in 1996. It has its own currency Hollywood Dollars, which are received when an investor opens an account. It is a virtual money not real money. However, the one could earn real money through Ebay sales of portfolios and rewards by HSX, which is given $1 per 1,000,000 Hollywood Dollars (Hayes, 2021). Its technology "*allows an unlimited number of consumers to trade thousands of virtual entertainment securities in a fair and orderly, supply-and-demand-based market.*" (HSX website). Investors can bet on different instruments in entertainment industry (Hayes, 2021). Elberse (2007) finds a significant relationship between casting announcements and change in star-bond traded in Hollywood Stock Exchange. She claims that HSX behaves like a real market.

Hayes (2021) says that HSX is a prediction market, tending to give accurate information. Also, he claims that HSX is related to "crowdsourcing" concept. Crowdsourcing is explained as "Crowdsourcing involves obtaining work, information, or opinions from a large group of people who submit their data via the Internet, social media, and smartphone apps". (Hargrave, 2021)

In the thesis, I only focus on the movie stocks traded in the Hollywood Stock Exchange. Following models about HSX are not applied in the literature. I run a regression to study the relationship between the Hollywood stock exchange and public awareness. Independent variables are Theaters, ANT, MM1 and Openshock. Dependent variable is opening price of stock. I also examine the effect of open shock on Hollywood stock exchange value. Thus, I have a relatively simple model:

$$HSXOW_i = b0 + b1\ Theaters_i + b2\ ANT_i + b3MM1_i + b4Openshock_i + error$$

where HSXOW is the price of the opening weekend warrant based on the weekend box office of a movie. Openshock is calculated based on prediction in Table 4. MM1 is calculated as 1/Moviemeter. As seen in the first column of Table 15, each variable is significant at the 0.001 significance level. A number of theaters (Theaters), whether the movie is anticipated before the release (ANT), and popularity index (MM1) are positively and significantly related to the stock price in HSX. Openshock has a small coefficient, but it is highly significant. In model 2 (second column of Table 15), Theaters, ANT and MM1 are only independent variables showing public awareness about the movie, which are significant at 0.001 level and R2 of the model is 70.5 percent. Model 3 (third column of Table 15) includes only openshock as an independent variable, and it has a positive and significant impact on HSXOW. The intercept is not significant at any level for the first two models, but it is significant in the third model. The intercept term is significant at 0.001 level and economically at high value to compensate the low coefficient of open shock. R2 of the model is 54.2 percent.

Dependent variable is not return between closing price and opening price because some stocks have opening price but not closing price or vice versa.

Table 15 : Hollywood Stock Exchange, Open Price (HSXOW)

	Model 1	Model 2	Model 3
Intercept	1.432	-1.131	8.594***
	(1.764)	(-1.342)	(9.322)
Theaters	0.003***	0.005***	
	(5.233)	(7.407)	
ANT	48.11***	64.151***	
	(9.443)	(11.573)	
MM1	47.94***	66.094***	
	(7.125)	(8.946)	
Open Shock	0.0000002***		0.0000005***
	(12.277)		(22.180)
R-Square	0.783	0.705	0.542
Adjusted R-square	0.78	0.73	0.541
# of Observations	413	445	416

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

I also run a regression to understand the effect of public awareness on closing stock price for a movie on the Hollywood Stock Exchange. In particular, I have the following regression model:

$$HSXClose_i = b0 + b1\ Theaters_i + b2\ Week_i + b3\ News_i + b4\ open\ shock_i + b5\ Theaters_i \times Week_i + error$$

where HSXClose indicates delist price of a movie. The stocks are delisted in a month. It is delisted before gross revenue is finalized. Delist means that investors cannot buy or sell the stock anymore. Therefore, I do not include gross revenue in the equation. In the HSXOW model, News was excluded. News is the number of articles and media releases about the movie, and it is almost finalized when the movie is not available in theaters. Therefore, number of news is not applicable for HSXOW and I only include News into the HSXClose model.

Table 16: Hollywood Stock Exchange, Close Price (HSXClose***)***

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	1.458	-10.936***	6.539*	-5.237 .	23.18 ***
	(0.501)	(-3.586)	(2.098)	(-1.659)	(9.93)
Theaters	-0.016***	0.013***	-0.013***	0.009 ***	
	(-5.522)	(8.240)	(-4.862)	(6.593)	
Week	-0.878**	0.412	-0.708*	0.815*	
	(-3.045)	(1.374)	(-2.065)	(2.434)	
News	0.050***	0.067***	0.036***	0.045***	
	(13.256)	(17.612)	(10.419)	(12.024)	
Open Shock			0.0000006***	0.0000007***	0.000001***
			(11.410)	(12.756)	(21.29)
Theaters:Week	0.003***		0.002***		
	(11.280)		(9.524)		
R-Square	0.72	0.639	0.787	0.74	0.522
Adjusted R-square	0.717	0.637	0.785	0.738	0.52
# of Observations	445	446	412	413	416

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

The movies that are streamed in many theaters are significantly higher closing price in HSX, which is shown in Table 16. However, when I include the interaction of Theaters and Week, which is significant at 0.001, it causes each variable to be negative. Multiplication of theaters and week dominates the separate effect of weeks and theaters. Open shock is positive and significant at 0.001 level for all models.

Subsample Analysis (Listed Distribution Companies)

In this design, I form a database of movies produced and distributed by publicly traded companies. Overall, I have 259 movies in 2019. In order to save space, I only study the models with log transformation of dependent variables and the CAR calculations for opening weekend revenue (see Table 17 and Table 18).

From an R-squared of 84.5 percent, the model in this design has higher explanation power. Series, U.S. production, Sale, and BBC (based on books or comics) variables are insignificant like the model in design 1. Director's financial worth (logDAV) is not significant, which was significant in design 1. A star in the cast (STAR) shows a significantly negative influence on both designs.

Metascore and MM1 are insignificant, whereas run time (Time), number of theaters (Theaters), and the change in popularity (changeBMM) variables are found to be significant. Distribution companies, which are significant for this design, are also significant for design 1. Season and ANT variables are insignificant for both.
LogAcAv variable is insignificant in this design which was significant in the empirical analysis using the sample of all movies released in 2019 (Design 1).

As documented in Table 17, I could not find any significant relationship between the director's previous revenues and opening weekend revenue in this design. Similarly, the previous financial success of casting does not have a significant effect on opening weekend revenue. Also, popularity measure does not have a significant influence on opening weekend revenue. However, a change in popularity makes a significant impact on the financial success of a movie.

Table 17: Dependent variable is log (OW) (publicly traded distribution company)

	Estimate	t value
Intercept	**6.905*** **	5.134
Series	0.390	1.557
US	0.036	0.149
Sale	-0.231	-1.193
BBC	0.148	-0.632
logDAV	0.020	1.535
STAR	**-0.81*** **	-3.66
Metascore	-0.004	-0.884
MM1	0.858	1.194
Time	0.011.	1.907
Theaters	**0.001*** **	12.943
DIST		
Amazon	**1.325** **	2.866
Bona	1.191	0.900
CIDM	**1.000***	2.412
CJ ENM	0.082	0.126
Comcast	**2.339*** **	5.572
COHN	-0.15	-0.213
CSSE	-1.614 .	-1.910
Disney	**1.905 *** **	4.715
EROS	**2.143 *** **	4.147
Entertainment One	**1.541 ***	2.167
Lai Sun Development	0.09	0.067
Lionsgate	**2.278 *** **	5.802
Maoyan Entertainment	-0.06	-0.048
MGM	**2.040 *** **	3.366
Netflix	**3.256 *** **	3.404
PBS	-0.82	-0.624
Paramount Pictures	**2.292 *** **	4.062
Sony	**1.319 *** **	3.604
Warner Bros	**2.092 *** **	4.533
Season	0.091	1.407
ANT	0.372	0.754
logAcAv	0.098	1.374
ChangeBMM	**0.519 ** **	3.269
R-square	0.866	
Adjusted R- square	0.845	
# of observations	209	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

From opening week estimations, I calculate openshock and then run a regression between openshock and CAR for days (0, +5] (see Table 18):

***Table 18*:** Dependent variable is CAR (0, +5]

	Estimate	t-value
Intercept	0.001	0.592
open shock	-0.0008	-0.196
R-square	0.0002	
Adjusted R- square	-0.004	
# of observations	242	

Significant codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

Among movies that are released by publicly traded companies, when the opening weekend revenue is higher than the expected return, an insignificant decrease is observed in the cumulative abnormal returns.

Subsample Analysis (Movies listed in HSX)

In this design, I focus on the movies that have data in Hollywood Stock Exchange. In this design, we have relatively few variables such as MM1, Theaters, Series, and ANT that are significant (see Table 19). As one of the main variables of interest in this thesis, popularity is found to have a significantly positive effect on opening weekend revenue. Except for Amazon, big distribution companies like Disney, Lionsgate, Sony, and Warner Bros are significantly positive. As compared to other designs, Design 3 has small number of observations and less explanatory power (R-squared of 66.1).

***Table 19* :** Dependent variable is logOW (HSXOW constraint)

	Estimate	t value
Intercept	**1.114*** **	6.339
Series	**0.709*** **	3.665
US	0.345	1.174
Sale	-0.106	-0.611
BBC	0.109	0.559
logDAV	0.014	1.14
STAR	-0.284	-1.43
Metascore	0.003	0.612
MM1	**1.091***	2.342
Time	-0.004	-0.804
Theaters	**0.0003** **	2.858
DIST		
Amazon	**-2.085***	-2.362
Comcast	**1.386*** **	3.784
Disney	**1.269** **	3.354
EROS	**1.095***	2.550
Entertainment One	0.339	0.532
Lionsgate	**1.101** **	2.965
MGM	0.451	1.088
Paramount Pictures	**1.396*** **	3.424
Sony	**1.120** **	2.975
Warner Bros	**0.990***	2.607
Season	-0.109.	-1.901
ANT	**0.932** **	3.038
logAcAv	0.167.	1.764
ChangeBMM	0.277	0.548
R-square	0.729	
Adjusted R- square	0.661	
# of observations	95	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

As seen in Tables 20 and 21, I could not find any significant relationship between openshock and CAR (for days (0, +5] and days [-5, +5]) when there is a Hollywood Stock Exchange constraint.

Table 20**:** Dependent variable is CAR (0, +5] (HSXOW constraint)

	Estimate	t-value
Intercept	0.011.	1.696
open shock	-0.002	-0.236
R-square	0.0005	
Adjusted R- square	-0.008	
# of observations	118	

Significant codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

Table 21**:** Dependent variable is *CAR* [-5, +5] (HSXOW constraint)

	Estimate	t-value
Intercept	0.025*	2480
open shock	0.01	0.635
R-square	0.003	
Adjusted R- square	-0.005	
# of observations	118	

Significant codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

The openshock for HSXOW is based on the estimation in Table 22. In this table, data only covers the movie Stocks that are traded in the Hollywood Stock Exchange. As it can be seen in the table, there are very few significant traditional factors: Star is significant at 0.1 level, and it is negative, similar to our previous findings. Director’s average revenue (DAV) is significant at 0.001 level. The coefficient is quite small because the range of variable is extremely wide (between 0 and 363 million dollars).

Cast’s previous revenue (AcAvGross) is significant, and it has a small coefficient as well. The reason is the same as with the DAV variable. When the movie is anticipated from the release (ANT), it has a positive effect on gross revenue. Only Disney is significant for this data set, and it has a huge impact on revenue. Season is significant and negative, suggesting that revenue decreases through the year. Series variable is significant, and it has a relatively big coefficient. When the movie is a sequel movie, the movie has a higher gross revenue.

Table 22: Dependent Variable is Gross Revenue (HSXOW Constraint)

	Estimate	t value
Intercept	-0.033	-0.001
Series	20**	3.213
US	3.364	0.391
Sale	-5.939	-1.1
BBC	5.748	0.926
DAV	0.000***	4.021
STAR	-11.43 .	-1.924
Metascore	0.1707	1.005
MM1	21.72	1.441
Time	0.210	1.263
Theaters	-0.001	-0.328
DIST		
Amazon	2.644	0..097
Comcast	5.9	0.508
Disney	28.89 *	2.378
EROS	16.21	1.240
Entertainment One	15.14	0.747
Lionsgate	8.064	0.685
MGM	8.215	0.597
Paramount Pictures	-3.059	-0.236
Sony	-1.226	-0.101
Warner Bros	-1.763	-0.146
Season	-3.648 *	-2.005
ANT	53.48 ***	5.338
AcAvGross	0.000 *	2.143
ChangeBMM	-32.37 *	-2.018
R-square	0.778	
Adjusted R- square	0.722	
# of observations	95	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

All coefficients are divided by 10^6 for readibility

The following table (Table 23) includes movies that have HSXClose prices. The number of observations is 213. LogDav, Time, Theaters, and popularity change (ChangeBMM) are significant and positive. When the popularity of movies increases, revenue is expected to increase. Star and Metascore are significant and negative, suggesting that involving a star as a cast causes a decrease in opening weekend revenue. Higher Metascore has a negative effect, which is similar to the study of Addis and Halbrook (2018). Cast's average revenue from previous movies (logAcAv) is positive but significant at only 0.1 level.

Table 23: Dependent variable is logOW (HSXClose constraint)

	Estimate	t value
Intercept	7.333***	5.393
Series	0.426	1.61
US	0.317	1.452
Sale	0.095	-0.531
BBC	0.159	0.673
logDAV	0.029*	2.257
STAR	-0.554**	-2.734
Metascore	-0.015**	-3.185
MM1	0.687	2.342
Time	0.012*	2.125
Theaters	0.001***	13.483
DIST		
AMC	-1.272***	-3.738
Amazon	0.222	0.464
CIDM	-0.053	-0.108
Comcast	1.223***	3.513
COHN	-1.242	-1.37
CSSE	-1.208	-0.811
Disney	0.561	1.513
EROS	1.260*	2.475
Entertainment One	0.284	0.309
Lionsgate	1.079***	3.367
MGM	0.978.	1.808
PBS	-2.191.	-1.709
Paramount Pictures	1.070*	2.149
Sony	0.129	0.430
Warner Bros	0.786.	1.935
Season	0.085	1.385
ANT	0.492	1.023
logAcAv	0.137.	1.86
ChangeBMM	0.485**	2.878
R-square	0.873	
Adjusted R- square	0.855	
# of observations	213	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

I could not find a significant relationship between CAR and openshock based on the data of HSXOpen constraint.

Table 24**:** Dependent variable is CAR (0, +5]

	Estimate	t-value
Intercept	-0.006	-0.404
open shock	0.002	0.31
R-square	0.0004	
Adjusted R- square	-0.004	
# of observations	242	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

Table 25 **:** Dependent variable is CAR [-5, +5]

	Estimate	t-value
Intercept	0.011	0.701
open shock	0.001	0.165
R-square	0.0001	
Adjusted R- square	-0.004	
# of observations	242	

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

Hollywood Stock Exchange and Financial Success

Here, I study factors affecting the stock price of a movie on the Hollywood Stock Exchange by looking HSXOW and HSXClose. Where HSXOW is the stock price derived from opening weekend revenue (Table 22), and HSXClose is the price based on the demand-supply relationship of the stock. Similar to previous models, I run the following equation:

$$HSXOW_i = c0 + c1\ Theaters_i + c2\ MM1_i + c3\ ANT_i + c4\ openshock_i + error$$

As summarized in Table 26, all variables are significant at 0.001 level. The coefficient of openshock is exceptionally low, but because some of the movies have billions of dollars of opening weekend revenue, the coefficient seems to be expected. Theaters and intercept are negative. The model is based on 115 movies, and R2 is 83.6 percent. In Table 26, I have two more models. In model 2, I look at the relationship between openshock and HSXOW and in model 3, I am endeavoring to find the relationship between HSXOW and public awareness, which includes theaters, MM1, and ANT variables. Openshock is significant at 0.001 level, the R2 is 21 percent in model 2. When I exclude public awareness from the model, the explanation power of the model decreases notably, and the coefficient of intercept turns extremely high indicating that it captures the missing value of the public awareness effect. All variables are significant and positive. When the movie is streamed in more theaters (Theaters) when the movie is popular (MM1) and when the movie is anticipated before the release, the HSXOW increases.

***Table 26*: Dependent variable is HSXOW (HSXOW Constraint)**

	Model 1	Model 2	Model 3
Intercept	-12.71*	29.21***	-12.71
	(-1.984)	(7.828)	(-1.320)
Theaters	-0.007***		0.007*
	(3.624)		(2.410)
MM1	64.55***		64.55***
	(6.736)		(4.480)
ANT	60.94***		60.94***
	(8.368)		(5.565)
Open Shock	0.0000001***	0.0000001***	
	(12.135)	(5.602)	
R-square	0.836	0.21	0.626
Adjusted R-square	0.83	0.2	0.616
# of Observations	115	118	116

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

I also study how public awareness affects HSXClose in Table 27. The following equation is used to test the model:

$$\text{HSXClose}_i = c0 + c1\ \text{Theaters}_i + c2\ \text{Week}_i + c3\ \text{News}_i + c4\ \text{open shock}_i + c5\ \text{Theaters}_i \times \text{Week}_i + \text{error}$$

I do not include gross revenue into the equation because when the movie's stock had been delisted, revenue was not finalized. All variables are significant in both models. The amount of news about the movie (News) is significant and positive in both models, suggesting that news might increase public awareness of the movie. Interaction between News and Theaters is significant when it is applied. Their multiplication is positive, which shows the general availability of a movie. However, when I add the interaction to the equation, Theaters and Week variables are negative, suggesting that availability in weeks to audience dominates each variable. The number of theaters the movie streamed in the first week (Theaters) is significant for the two models at least 0.01 level. The amount of news, theaters, and weeks are significant and have a positive effect on the close price of the Hollywood Stock Exchange. Openshock is significant and positive for all models, suggesting that when actual opening weekend revenue is higher than estimated revenue, the closing price of stock increases.

***Table 27*:** Dependent variable is *HSXClose* (*HSXClose* Constraint)

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	14.60*	-24.82***	11.13.	-28.43***	38.82***
	(2.000)	(-3.658)	(1.734)	(-4.654)	(8.607)
Theaters	-0.019***	0.014**	-0.014***	0.017***	
	(-4.506)	(5.561)	(-4.028)	(7.755)	
Week	-3.788***	1.349.	-2.716***	2.360***	
	(-4.316)	(1.739)	(-3.561)	(3.415)	
News	0.051***	0.066***	0.025***	0.037***	
	(10.569)	(12.469)	(5.227)	(9.303)	
Open shock			0.0000008***	0.0000009***	0.000001***
			(10.512)	(9.303)	(11.223)
Theaters:Week	0.003***		0.003***		
	(9.098)		(10.193)		
R-Square	0.716	0.62	0.805	0.72	0.342
Adjusted R-square	0.711	0.62	0.801	0.716	0.339
# of Observations	245	246	238	239	242

Significant codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1

CHAPTER 4

CONCLUSION

In this thesis, I examine the factors affecting the movie's financial success; whether unexpected revenue affects the cumulative abnormal return of the distribution company and the factors influencing stock prices of movies that are traded in the Hollywood Stock Exchange.

I can reject all hypotheses except hypothesis 3, which is 'unexpected revenue in opening weekend has no impact on the stock price of distributors' company following week of the release date.'

My finding shows that the popularity of a movie and the previous success of actors, actresses, and directors are significant factors in predicting a movies' revenues in 2019. I examine the popularity of the movie in the opening week and the change in popularity afterward. I find that both variables have a positive and significant influence on box office. The director of movie can be considered as a CEO of the movie. In the thesis, I define the quality of the CEO by using his/her previous financial success and relate to the movie performance. My results show that it is significant to predict the box office.

I also examine the previous financial success of the cast (especially stars). I find that cast financial success significantly and positively influences the revenue, albeit having a star in the cast has a significantly negative impact on the revenue. This result may be consistent with De Vany and Walls (1994) findings, which state that it is a 'curse of superstar'. Obviously, star worth may change over time and including a star may not induce an increase in the revenue consistently (Wallace, Seigerman, and Holbrook, 1993). In another words, the worth of a Star when he/she is included in the movie is not the same as when he/she acts in a previous movie. Thus, when I consider the average gross earnings of the previous projects of the leading actors/actresses, I introduce a better measure to study the star effect because it measures the worth of the cast rather than a single star. In the empirical analysis, I show that casting value is a significant factor for predicting a movie's financial success. Human capital is important value to determine financial success of a movie, which is similar to findings of Han and Ravid (2020).

My findings for 2019's box office figures indicate that effects of classical attributes like a season, number of theaters, number of weeks, genre, whether the movie is a sequel or not, whether a U.S. company produces the movie, etc., are consistent with the literature.

When I calculate the relationship between open shock and cumulative abnormal return of distributor's company, I find no significant relationship. In subsample analysis, I eliminate the movies that do not have distributor company's stocks, but my results are still insignificant for each model. This might happen because the market is an oligopoly. Few companies dominate the market, successful movies are distributed by giant companies. Also, the risks of the giant companies are smaller compared to other companies, which causes stable cumulative abnormal returns (CAR), while small companies have fluctuating CAR.

The results exhibit that public awareness, which I measure by the number of articles in the media about the movie, listed among the most anticipated movie of the year, number of theaters that is releasing the movie, popularity index during the first week and number of weeks that the movie is streamed, lead to a significant increase in the Hollywood Stock Exchange price. Also, openshock, unexpected gain, increases the stock price of a movie.

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APPENDIX

MOVIES USED IN THE STUDY [2]

100 Acres of Hell

10E

21 Bridges*

3 Faces

3 from Hell*

47 Meters Down- Uncaged*

A Beautiful Day in the Neighborhood

A Dog's Journey

A Dog's Way Home*

A Faithful Man

A Hidden Life*

A Madea Family Funeral*

Abominable *

Ad Astra*

After*

After The Wedding*

Aga

Aladdin*

Alita: Battle Angel*

All is true*

Always Miss You

American Woman*

An Acceptable Loss*

An Elephant Sitting Still

Angel Has Fallen*

Aniara*

Anna*

Annabelle 3 *

Arctic*

Arctic Dogs*

Ashfall

Asterix: The Secret of the Magic Potion

At war

Avengers: Endgame*

Badla

Ballet Blanc

Batla House

Before You Know it*

Being Frank

Bennett's War

[2] * shows the movies traded in HSX

Better Days

Bharat

Birds of Passage*

Black and Blue*

Black Christmas*

Blinded by the Light*

Body at Brighton Rock*

Bombshell*

Booksmart*

Breakthrough*

Brian Banks*

Bricked

Brightburn*

Britt- Marie Was Here

Brittany Runs a Marathon*

Bunuel in the Labyrinth of the Turtles

By the Grace of God

Canal Street*

Captain Marvel*

Captive State*

Cats*

Chained for Life

Charlie Says*

Charlie's Angels*

Chasing the Dragon 2

Chhichhore

Child's Play*

Chokehold

Clemency*

Cliffs of Freedom

Clinton Road

Cold Blood

Cold Pursuit*

Countdown*

Crawl*

Crown Vic *

Cyrano, My Love*

Dabangg 3*

Dark Waters*

Daughter of Mine

De De Pyaar De

Diamantino

Diane

Division 19

Doctor Sleep*

Dogman*

Donnybrook*

Don't Let Go*

Dora and the Lost City of Gold*

Downton Abbey*

Dragon Ball Super: Broly

Dumbo*

ECCO

Edie

Ek Ladki Ko Dekha Toh Aisa Laga

El Chicano*

El Coyote

End of the Century

Escape Room*

Everybody Knows*

Exit

Extreme Job

Fagara

Faith, Hope& Love

Family*

Fast Color*

Fast&Furious Presents: Hobbs&Shaw*

Fate/stay night (Heaven's Feel) 2. Lost Butterfly

Faustina: Love and Mercy

Fighting With My Family*

First Love*

Five Feet Apart*

Ford v Ferrari*

Frankie *

Freaks*

Frozen 2*

Funan*

Furie

Game Day

Gemini Man*

Genesis

Giant Little Ones*

Girls of the Sun*

Give me Liberty

Glass*

Gloria Bell*

Godzilla 2*

Good Boys*

Greener Grass*

Greta*

Gully Boy

Hagazussa

Hampstead*

Happy Death Day 2U*

Harriet*

He matado a mi marido

Hellboy*

Her Smell*

High Life*

High on the Hog

Hollywould

Honey Boy*

Hotel by the River

Hotel Mumbai*

Housefull 4

How to Train your Dragon 3*

Hustlers*

I Do Not Care if we go down in history as Barbarians

I got the Hook up 2

Iceman

I'll Take Your Dead

Immortal Hero

In Like Flynn

India' Most Wanted

Intuitions

Invisible Life*

Ip Man 4: The Finale*

Is it wrong to try pick up girls in a dungeon

Isn't it Romantic*

It Chapter Two*

Jay and the Silent Bob Reboot*

Jexi*

John Wick 3*

Jojo Rabbit*

Joker*

Judy*

Jumanji: The Next Level *

Junglee

K-12

Kalank

Killer Unicorn

Killerman*

Killing Sarai

King of Thieves*

Kinky Boots the Musical

Knife + Heart

Knives Out*

Konosuba! Legend of crimson

Last Christmas*

Late Night*

Leo Da Vinci: Mission Mona Lisa

Light from Light

Light of My Life*

Line of Duty

Line Walker 2: Invisible Spy

Little*

Little Joe*

Little Q

Little Women*

Little Woods*

Long Shot*

Looking Up

Lords of Chaos*

Loro*

Los Domirriquenos 2

Lost& Found

Luce*

Lucy in the Sky*

Luka Chuppi

Ma*

Made in Abyss: Journey's Dawn

Made in Bangladesh

Maleficent: Mistress of Evil*

Marjaavaan

Mary Magdalene*

Master Z: The Ip Man Legacy*

Men in Black: International*

Menteur

Mia and the White Lion*

Mickey and the Bear*

Midnight Diner

Midsommar*

Midway*

Mine 9

Miss & Mrs. Cops

Miss Bala*

Missing Link*

Mission Mangal

Mister America*

Mobile Suit Gundam Narrative

Mojin The Worm Valley

Money

Monos*

More Than Blue

Mother of a Day

Motherless Brooklyn*

Ms. Purple*

My Dear Liar

My People, My Country

Nancy Drew and the Hidden Staircase*

Ne Zha

No Manches Frida 2*

Non-Fiction*

Nothing to Lose 2

Ode to Joy*

Off Season

Official Secrets*

On the Basis of Sex*

Once Upon a Time in Hollywood*

One Cut of the Dead

One Piece: Stampede

Ophelia*

Our Time

Out of Blue*

Out of Liberty

Overcomer*

P Storm

Pagalpanti

Pain and Glory*

Palau the Movie

Panipat

Papi Chulo*

Parasite *

Pati Patni Aur Woh

Patrick the Pug

Penguin Highway

Peppa Celebrates Chinese New Year

Perfect Strangers*

Pet Sematary*

Peterloo *

Photograph*

Piercing*

Pilgrim's Progress

Piranhas

Play the Flute

Playing with Fire*

Playmobil: The Movie*

Ploey

Pokemon Detective Pikachu*

Poms*

Prassthanam

Promare

Queen& Slim*

Rafiki

Rambo- Last Blood*

Ramen Shop

Ready or Not*

Red Joan*

Redoubt

Replicas*

Richard Jewell*

Rocketman*

Rojo

Romeo Akbar Walter

Rosie

Round of Your Life

Ruben Brandt, Collector*

Run the Race*

Saaho*

Saga of Tanya the Evil

Saint Judy*

Sauvage/ Wild

Savage

Scary Stories to Tell in the Dark *

Seberg*

Serenity*

SGT. Will Gardner

Shaft*

Shazam!*

Shed of the Dead

Slaugherhouse Rulez*

Slut in a Good Way

Sonchiriya

Sorry Angel

Sound! Euphonium the movie

Spider- Man: Far From Home*

Spies in Disguise*

Spiral Farm

Star Wars IX - The Rise Of Skywalker*

State Like Sleep*

Stockholm*

Storm Boy*

Stuber*

Student of the Year 2

Styx

Suburban Birds

Sunset *

Super 30

Sword of Trust*

Sympathy for the Devil

Synonyms

Tall Tales from the magical Garden

Tazza: One-Eyed Jack

Teen Spirit*

Tel Aviv on Fire

Terminator: Dark Fate*

The Addams Family*

The Aftermath*

The Angry Birds Movie 2*

The Art of Racing in the Rain*

The Art of Self-Defense*

The Aspern Papers*

The Bad Guys: the Movie

The Body

The Bravest

The Captain*

The Chambermaid

The Chaperone*

The Church

The Climbers*

The Crossing

The Current War *

The Final Wish

The Gangster, the Cop, the Devil

The Golden Glove

The Goldfinch*

The Good Liar*

The Great Alaskan Race

The Ground Beneath My Feet

The Heiresses

The Hole in the Ground*

The Hummingbird Project*

The Hustle*

The Image Book

The Intruder*

The Iron Orchard

The Kid*

The Battle of Jangsari*

The Beach Bum*

The Best of Enemies*

The Curse of La Llorona*

The Day Shall Come*

The Dead Don't Die

The Death of Dick Long*

The Death& Life of John F. Donovan

The Divine Fury

The Divine Move 2

The Farewell*

The Fighting Preacher

The Kid Who Would Be King*

The Kitchen*

The Last Black Man in SF*

The Last Tree

The Least of These: The Graham Staines Story

The Lego Movie 2: The Second Part *

The Lighthouse*

The Lion King*

The Load

The Lumber Baron

The Meanest Man in Texas

The Mountain*

The Mustang*

The Nightingale*

The Other Side of Heaven 2: Fire of Faith*

The Other Story

The Peanut Butter Falcon*

The Perfect Race

The Prodigy*

The Reliant

The Reports on Sarah and Saleem

The School Idol Movie: Over the Rainbow

The Secret Life of Pets 2*

The Sky is Pink*

The Song of Names*

The Sound of Silence*

The Souvenir*

The Sower

The Sun is Also a Star*

The Third Wife

The Tomorrow Man*

The Untold Story

The Upside*

The Wandering Earth

The Wandering Soap Opera

The Warrior Queen of Jhansi*

The Wedding Guest*

The Whistleblower

The Whistlers

The White Storm 2: Drug Lords

The Wild Pear Tree

The Wind

The Wonderland

The Zoya Factor

Them that Follow*

Three Peaks*

Todas Caen*

Tolkien*

Too Late to Die Young

Total Dhamaal

Touch Me Not

Toy Story 4*

Transit

Tremors

Trial by Fire*

Trinity Seven the Movie 2

Triple Threat*

Ugly Dolls*

Uncut Gems*

Under the Eiffel Tower*

Under the Silver Lake*

Union

Unplanned*

Uri: The Surgical Strike

Us*

Vault

Vita& Virginia *

Wallflower

War

Waves*

What Men Want*

Where'd You Go, Bernadette*

White Snake

Wicked Witches

Wild Rose*

Wonder Park*

Working Woman

X-Men Dark Phoenix*

Yesterday*

Yomeddine

Zombieland: Double Tap*

Table A128

	Based on book/Comic	Series	IMDb point	Rating	Metascore	User Review	Critics	US Production	Sales	Season	OW	logOW	Gross USA	logAG	Run time (min)	News Article	Week	Theaters	Foreign Language	HSX (OW)	HSX (Close)	High	Low	DAV	logDAV	AcAverage	logACAv	STAR
Based on book/Comic	1																											
Series	0.063614186	1																										
IMDb point	0.131733881	-0.00785	1																									
Rating	0.196614976	0.256795	0.30238763	1																								
Metascore	0.03872437	-0.07679	0.450444276	0.258904994	1																							
User Review	0.18305787	0.266559	0.214177734	0.927530176	0.191011498	1																						
Critics	0.171480639	0.242305	0.345392626	0.821220344	0.493938259	0.769075538	1																					
US Production	0.085422404	0.068619	-0.072646539	0.244649998	0.149603527	0.238973868	0.3477	1																				
Sales	-0.025202386	-0.17934	0.080897019	-0.064088164	0.30114228	-0.087595183	0.044828	0.022420553	1																			
Season	0.034978874	0.089271	0.027421751	0.079560607	-0.05114243	0.070782781	0.08443	0.044313904	-0.03907	1																		
OW	0.176894715	0.391765	0.182121251	0.7237683	0.172487241	0.771406866	0.611826	0.245195844	-0.13232	0.021523	1																	
logOW	0.068803614	0.20591	0.134374024	0.421788793	0.237874839	0.422811292	0.570886	0.314570034	-0.08438	0.073481	0.426721	1																
Gross USA	0.174625285	0.395189	0.214363098	0.751565293	0.199741398	0.764048967	0.648163	0.259624123	-0.12983	0.05228	0.975251	0.450185	1															
logAG	0.143103008	0.314114	0.249602682	0.524844093	0.244097703	0.507086243	0.69052	0.38648014	-0.15066	0.095632	0.496478	0.77314	0.537206	1														
Run time (min)	0.072053434	0.070756	0.231329538	0.279094026	0.034979261	0.286191081	0.235737	-0.088178001	-0.1828	0.129573	0.208354	0.221251	0.202141	0.225564	1													
News Article	0.191613002	0.275396	0.219929704	0.734963073	0.266437909	0.788635704	0.715102	0.240538552	-0.05129	0.066582	0.738959	0.402518	0.76371	0.497996	0.206764262	1												
Week	0.027045103	0.108836	0.395836809	0.361888764	0.345574688	0.292600655	0.416861	0.147860816	0.021027	0.010302	0.294557	0.250083	0.333908	0.391456	0.0529656	0.31720336	1											
Theaters	0.170677993	0.332864	0.152306724	0.552201594	0.253365437	0.54012439	0.723146	0.472554174	-0.12256	0.065009	0.573621	0.708257	0.608345	0.839411	0.105132455	0.525480137	0.327844	1										
Foreign Language	-0.064739201	-0.02327	0.106085505	-0.203139191	-0.207613496	-0.203825356	-0.34231	-0.752879626	-0.12466	-0.02825	-0.21081	-0.28021	-0.22596	-0.34321	0.177097773	-0.213397327	-0.12094	-0.44853	1									
HSX (OW)	0.173048161	0.386468	0.185784205	0.730230785	0.178059168	0.773170447	0.619774	0.249301699	-0.12755	0.02328	0.997874	0.425178	0.977415	0.497965	0.208347326	0.745188212	0.299372	0.579183	-0.216451094	1								
HSX (Close)	0.182467443	0.400704	0.203891049	0.74224212	0.196757016	0.767213869	0.643799	0.263319463	-0.13041	0.051912	0.981959	0.448715	0.996593	0.533073	0.202384017	0.759463954	0.324003	0.609312	-0.231319198	0.982179	1							
High	0.179021073	0.439158	0.182024446	0.719921517	0.204430642	0.75543358	0.677718	0.303729246	-0.13699	0.058972	0.959213	0.493992	0.968259	0.579335	0.199760759	0.760753154	0.327122	0.677505	-0.271155229	0.961198	0.974126252	1						
Low	0.129373392	0.41257	0.166615438	0.638349251	0.16721379	0.682519032	0.59705	0.253158207	-0.13029	0.068487	0.89419	0.424092	0.931284	0.500211	0.172300607	0.740079174	0.302681	0.588586	-0.218792213	0.897542	0.934463148	0.953244	1					
DAV	0.092701626	0.339193	0.120962051	0.492448526	0.165939464	0.516211674	0.510346	0.258300703	-0.14324	0.063709	0.619333	0.4015	0.618006	0.49574	0.139818177	0.433164277	0.216003	0.571665	-0.261707609	0.62102	0.625314782	0.678755	0.641293	1				
logDAV	0.13884608	0.186699	0.083545482	0.341735974	0.2132349	0.321081329	0.460011	0.230681141	-0.07758	0.085015	0.297512	0.435435	0.316955	0.491711	0.294394574	0.290545369	0.22987	0.464042	-0.267459656	0.298945	0.316888366	0.355017	0.3067	0.506431	1			
AcAverage Gross USA	0.104423497	0.188975	0.11500108	0.411324482	0.228005213	0.419932352	0.499675	0.389539302	0.000929	0.044982	0.468254	0.449354	0.498684	0.510359	0.042791702	0.431777376	0.210076	0.574899	-0.440498618	0.479036	0.501569981	0.550337	0.519033	0.418249	0.280432	1		
logACAv	0.09120403	0.070889	0.005595256	0.267459115	0.22143136	0.259819581	0.38619	0.432973924	0.05208	-0.01574	0.241965	0.375796	0.259809	0.452307	-0.016671108	0.266074846	0.066584	0.460863	-0.548662174	0.246188	0.2624111	0.301838	0.252612	0.281674	0.257038	0.67674548	1	
STAR	0.185138995	0.120202	0.085298094	0.328610645	0.280189556	0.310126921	0.479425	0.365003652	0.09176	0.057853	0.296799	0.419918	0.31615	0.454363	0.07143312	0.335601534	0.169345	0.501787	-0.430884769	0.300869	0.31919978	0.379367	0.326672	0.384418	0.376187	0.591294437	0.532552	1