Analysis of the Impact of Gender and Age of Protagonists in Top-Grossing Films from 2000-2019 on Film Success

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Abstract

The gender wage gap is prominent in many fields of work, but it is especially prevalent among actors in the film industry. According the U.S. Department of Labor, as of 2019 female annual workers were earning about 82.3% of their male counterparts. In a study of feature films released from 1980 to 2015, females were making only 56% of their male counterparts on average; this gap also has been shown to increase as female actors get older (Blau & Kahn, 2017; De Pater et al., 2014; Izquierdo Sanchez & Navarro Paniagua, 2017). In this paper I investigate the relationship between the gender and age of protagonists in the film industry and film success through a series of three regressions with film success defined as film total gross, critic reviews, and audience reviews. My data set is composed of 100 top-grossing films from each year 2000-2019. Through my statistical analysis I did not find any evidence that the gender or age of the protagonist influences film success. Thus my results do not show any evidence that the gender wage gap could be related to differences in film success.

JEL Codes: J16, J30, J70, J71
Keywords: Compensation, Wages, Labor Inequality, Women

1: Introduction

Prior to the 1980s working females[2] in the United States earned about 60 percent of what working males earned (U.S. Department of Labor). Wages rose sharply for women in the 1980s and then rose at a slower rate through 2019; by this time female full-time workers earned about 82% of what full-time male workers earned on an annual basis (U.S. Department of Labor). Labor market experience and education were shown to be large contributing factors to the wage gap in the past, but now women have more prior work experience on average, and actually more women than men attend college (Blau & Kahn, 2017). Blau and Kahn (2017) suggests that different attitudes in men and women could be contributing to the modern day wage gap; for example, men were found more likely to compete, take risks, and negotiate — three attributes that could result in a higher paying job (Blau & Kahn, 2017). Le et al. (2011) also examined various psychological attributes that could contribute to the gender wage gap, and they too identified that men are more likely to take economic risk than women.

While the gender wage gap has decreased, researchers have also identified a gender gap in representation in many fields in the workforce. Women still lag significantly behind men in leadership positions in all fields; Gharehgozli (2020) wrote that as of 2017 women held only 6.4% of CEO positions in S&P 500 companies according to Catalyst. In order to lower gender differences in representation it is important that more women are hired in senior roles in companies, because these positions are typically high paying and involve a higher degree of decision making (Gharehgozli, 2020).

One industry where gender differences have been explored is the film industry. There is a significant gender wage gap among actors; during 2020 the top ten male actors earned $545.5 million combined, while the top ten female actors earned $254 million combined (Berg, 2020). My original idea was to expand on existing studies of the gender wage gap in the film industry, but wage data was not available to me so I chose another route. Thus my paper focuses on how gender and age affect film success of top grossing films with film success defined as total gross, critic reviews, and audience reviews. My regression results suggest that gender has little impact on film gross and ratings, and this indirectly supports the view that the gender wage gap in the film industry cannot be explained by lower film success for films with female protagonists.

[2] In this paper the gender data is defined in binary categories rather than fluid ones

In the next section of this paper I synthesize literature on the roles of gender and age of actors in the film industry and explain how my research will build on these papers. In Section 3 I detail my data collection process, and in the following section I discuss summary statistics on the data. Lastly I explain my regression set up and analyze my regression results in Sections 5 and 6 respectively.

2: Literature Review

In this section I first review studies concerning women's status in the film industry by looking at occupational segregation and then at the wage gap. Next I turn to a review regarding possible explanations for gender and age differences in film.

Founder and Executive Director of the Center for the Study of Women in Television and Film at San Diego State University, Martha Lauzen, conducts an annual report, and in her report on films from 2019, she included 2,300 characters from the 100 top grossing films from 2019 (Lauzen, 2019). She found that 40% of protagonists were female (43% were male and 17% were ensemble), 37% of major characters were female (the rest were male), and 34% of speaking characters were female (the rest were male) (Lauzen, 2019). While the percentages of male and female protagonists were similar, the overall percentage of male characters highly exceeded the percentage of female characters (Lauzen, 2019). Looking at her previous studies, the percent of major characters and the percent of speaking characters that are female have not varied much from 2002 to 2019 (Lauzen, 2019). Lauzen also included actor race statistics in her study, and she found that for both females and males, actors were predominantly white (Lauzen, 2019). I think I can add to her study, because I will more formally analyze some of the gender differences she looked at through statistical testing.

In another yearly report, Lauzen found there were fewer female directors, writers, and females in general working behind the scenes of top grossing films (Lauzen, 2019). Lauzen studied the 250 top grossing U.S. films in 2020 and found that only 18% of directors and 17% of writers were female; she hypothesizes that more females off screen could contribute to more females on screen (Lauzen, 2019). However, she does not include her statistical analysis in her paper, so it is uncertain whether this is a causal effect or if her findings are statistically significant.

Similarly to Lauzen's yearly studies, Fleck and Hanssen (2016) analyzed 50,000 feature films released between 1920 and 2011 and found that males played 63% of leading roles and 73% of total roles. For the films in their study, the authors identified that there has not been much variation over time regarding the percent of leading roles given to men (Fleck & Hanssen, 2016). They also found that females played ⅔ of the roles that were for actors between ages 16 and 30; this shows that while older women are more infrequent, so are younger men (Fleck & Hanssen, 2016). Fleck and Hanssen also analyzed the effects of genre on the gender gap, and they identified that films categorized as romance typically have a gender balanced cast, but action films typically have a male dominated cast (Fleck & Hanssen, 2016). Like Lauzen, the authors examined the connection between female directors and female protagonists, finding that in the films they analyzed female directors were more likely to cast women; actually women played the majority of roles in the films that were directed by women (Fleck & Hanssen, 2016). This is why I decided to include female director as one of the variables in my data set.

Shifting to focus on the gender wage gap, Izquierdo Sanchez and Navarro Paniagua (2017) studied the wages of 246 male and female actors between 1980 and 2015 and found that on average female actors were paid 56% less than their male counterparts. This is equivalent to $2.2 million less per film (Izquierdo Sanchez & Navarro Paniagua, 2017). Additionally, their results show that the gender wage gap has remained virtually the same in the film industry from 1980 to 2015 (Izquierdo Sanchez & Navarro Paniagua, 2017). Their research identifies that for the actors studied the gender wage gap increased with increasing age; in fact the wage gap was on average $1 million per film for actors below 50 years old, but it quadrupled when actors were older than 50 (Izquierdo Sanchez & Navarro Paniagua, 2017). The source they used for wage data is unavailable to me, so I was unable to use it in my own regressions. The authors hypothesize that experience of actors could be contributing to the wage gap, because they found that for the actors studied female actors were on average six years younger and had four fewer years of experience than their male counterparts, with experience measured as the number of years since the actors made their first appearance in a film (Izquierdo Sanchez & Navarro Paniagua, 2017). However, their results showed that the starting salaries were higher for male actors than for female actors, possibly undermining the importance of experience (Izquierdo Sanchez & Navarro Paniagua, 2017). The researchers identified genre as an important control variable, and they found that for the films in their study from 2010 onward, action films account for 47% of box office revenues, and war films also brought in high revenues (Izquierdo Sanchez & Navarro Paniagua, 2017). Of the films studied only 21% of the cast of the action films and 23.5% of the cast of war films were female, showing that higher grossing genres often cast men, and this could be explaining part of the gender wage gap (Izquierdo Sanchez & Navarro Paniagua, 2017). Action films specifically are likely to have sequels, and this is the only paper I found that included a variable for sequel (Izquierdo Sanchez & Navarro Paniagua, 2017). I will use variables the researchers included in my own data set, but rather than using them to explain wage, I will use them to explain film success.

De Pater et al. (2014) also studied actor wage in relation to gender and age for 265 leading actors between 1968 and 2008. Their results showed that at the beginning of their careers male and female actors earned approximately the same amount (De Pater et al., 2014). However, on average, female actors earned increasing wages until age 34, but then their earnings rapidly decline; conversely for male actors average earnings were highest at age 51, and being older than 51 did not negatively impact male actors' wages (De Pater et al., 2014). This study has similar findings to the Izquierdo Sanchez and Navarro Paniagua study, because both studies identify a gender wage gap that increases with actor age.

Amaral et al. (2020) examined gender differences in the film industry and potential causes of these differences. The authors were unable to find different levels of interest between female and male actors that could be contributing to the gender gap, while this is the case in other fields such as STEM (Amaral et al., 2020). In order to provide context of gender trends in the film industry in the 1900s, the paper hypothesizes that a step towards gender imbalance was the "emergence and consolidation of the Hollywood Studio System" which occurred between 1922 and 1950 (Amaral et al., 2020). Around this time there was also a reduction of about 25% in the fraction of female actors in films (Amaral et al., 2020). This consolidation included the formation of the Big 7 (now the Big 6), and this is the only paper I have found that explicitly relates the gender wage gap and the Big 6 (Amaral et al., 2020). The paper considers that one reason for this decrease in female actors was the increase in popularity of genres which typically have fewer females cast, and in regression analyses with statistically significant results the authors found that there was lower female representation in film genres action, adventure, crime, thriller, and western, typically high-grossing genres (Amaral et al., 2020). Similarly to the decline in the fraction of female actors, by the 1930s there was little to no female representation among directors and producers (Amaral et al., 2020) Their analysis found that when there were fewer female producers and directors there was also a lower number of other females in the industry including female actors, which is similar to what Lauzen and Fleck and Hanssen found (Amaral et al., 2020).

Several authors investigated if gender could influence financial success of films. Smith et al. (2020) researched how gender and race differences of protagonists could influence financial performance in 1,200 "popular" films in years 2007 to 2018. Looking only at summary statistics and not regression analysis, this study found that when the lead for a film was female, the film typically had a lower production budget, less money for marketing, and was released in fewer theaters, and thus earned less rent (rent is defined by this paper as "the dollar amount studios receive after exhibitors take their portion of the box office") (Smith et al., 2020). They found that these differences were even more stark for females of color (Smith et al., 2020). However, when the authors controlled for other factors, they found that access to resources and marketing were mainly what mattered for "rent"; however, it is important to realize gender, race, and ethnicity of leads could influence this access (Smith et al., 2020). Similarly, Treme et al. (2019) investigates how gender influences box office performance. They measured the "star power" of actors by looking at awards, and they found that for each star in a film, box office earnings increased by about 10% — these results were statistically significant (Treme et al., 2019). However, when a star was male, they found that this increased box office earnings by 12% (Treme et al., 2019). This research is similar my plan to analyze how gender and age differences in protagonists could contribute to differences in film financial performance in terms of film total gross.

The following three studies provide valuable summary statistics, qualitative explanations, and possible negative repercussions for the gender and age differences among actors. However, all three studies have fairly small sample sizes. Bazzini et al. (2019) identify ageist stereotypes in film, examining 100 top grossing films between 1940 and 1980. This study finds more representation of older males than older females in their data set; of the main characters analyzed 38% of male characters were older than 35, while only 8% of female characters were older than 35 (Bazzini et al., 2019). Additionally, in all cases except select films from the 1970s, female leading characters were at least six years younger than male leading characters (Bazzini et al., 2019). Bazzini et al. (2019) consider that this lack of representation of older women and negative depictions of older women when they are represented could be leading to something called "depletion syndrome." Therapists have identified this condition in older women, and it is "characterized by feelings of worthlessness, no interest in things, [and] a sense of hopelessness," (Bazzini et al., 2019). The Geena Davis Institute on Gender in Media, USC Viterbi, and TENA analyzed 32 top grossing films from 2019 in Germany, France, the UK, and the US. Of the characters studied, female characters only made up 25.3% of the characters older than 50, and there were no leads who were females and older than 30 (Davis). The study identifies "The

Ageless Test” which says that in order to pass the test a film must have at least one female character who is necessary for the plot and who is not presented with ageist stereotypes; only 25% of the films analyzed in this study pass the test (Davis). Similarly to Bazzini et al. this focuses more on qualitative effects using a fairly small data set. Lauzen and Professor at San Diego State University, David Dozier, studied the portrayal of aging male and female characters in the top 100 grossing films of 2002. The majority of male characters in the study were in their 30s and 40s, while the majority of female characters in the study were in their 20s and 30s (Lauzen & Dozier, 2005).

Another possible contributor to gender differences could be film reviews. In Lauzen’s report, “Thumbs Down 2019: Film Critics and Gender, and Why It Matters,” she found that out of “more than 4,750 reviews written by over 380 individuals working for print, broadcast, and online outlets during spring 2019 and whose work is included on the Rotten Tomatoes website,” 66% of film reviewers are male, and 68% of reviews are written by male reviewers (Lauzen, 2019). There are more male reviewers than female for every film genre and for every type of media outlet (Lauzen, 2019). Lauzen standardized the review ratings to be percentages, and she found that female writers on average award a 78% to films with female protagonists, while male writers on average award a 68% to films with female protagonists (Lauzen, 2019). Female writers award an average of 70% to films with male protagonists, while male writers award an average of 77% to films with male protagonists (Lauzen, 2019). Thus due to the fact that male reviewers write the majority of reviews and are on average rating films with female protagonists lower and films with male protagonists higher; people who read the reviews could be more incentivized to go see the films with male protagonists (Lauzen, 2019). This potentially causes the films with male protagonists to gross more and contributes to the gender gap (Lauzen, 2019). However, Lauzen does not conduct formal empirical analysis of this data which is something I will do in this paper. Basuroy et al. (2019) investigated the impact of film reviews on consumers and found that experts’ reviews mattered much more for film revenues than reviews from viewers. In my study I will investigate both critic and audience reviews by using them as dependent variables and measures of film success.

The ideas and findings of the above studies have been very helpful in informing my research, because many of these studies have identified age and gender differences in the film industry which is what my work will focus on. While some have analyzed actors with respect to the wages themselves, and some have done cursory analyses of film revenues, no one has evaluated film success in relation to age and gender of actors. For example, the Izquierdo Sanchez and Navarro Paniagua and De Pater et al. studies looked at actor success through wages, but they did not look at overall film success, and the Smith et al. and Treme et al. studies looked at film finances but not at reviews. Additionally, these studies did not include any interaction terms, but I plan to use an interaction term between age and gender in my own regression analysis to better understand the relationship between the two. The Fleck and Hanssen paper is the only other study that conducts a large-scale analysis that has a main focus of gender and age differences in the film industry, but their main data analysis only involved trends over time rather than regression analysis.

3: Data

The main focus of this paper is the effect of gender and age of protagonists on film total gross, critic reviews, and audience reviews. Thus I started my data collection process by focusing on finding data for these variables. There was no public data set on top-grossing films besides the one on Box Office Mojo which does not include any of my five main focus variables, so I created my own data set. All of the authors in my literature review created their own data sets as well, many with the help of Box Office Mojo.

Thus, I compiled a data set that consists of the top 100 grossing films for each year from 2000-2019, with 1,991 films total. The nine missing observations were due to lack of information on some of my control variables for these films. I chose to focus on the top-grossing films, because this is what Lauzen does in all of her studies (Lauzen, 2019). I also thought this would be a uniform way of choosing which films to analyze and thus would facilitate comparison of results. I used Box Office Mojo to obtain a list of the 100 top-grossing films for each year, stopping the data in 2019 due to the COVID-19 pandemic; I did not want any of my data to be skewed by the consequences of the pandemic on the film industry. I chose to focus solely on protagonists, because I think protagonists would have a higher effect on influencing film success than actors with minor roles would have, and many of the studies in my literature review focused on main characters in films in both their data and analysis (De Pater et al., 2014; Fleck & Hanssen, 2016; Lauzen, 2019).

3.1 Key Independent Variables

As mentioned above the two main independent variables of focus are gender and age. IMDb lists the top billed character for each film first in the actors section. Thus I used this to identify the protagonist and their gender and age information for each film in my data set.

3.2 Dependent Variables

The three dependent variables of focus are total gross, critic reviews, and audience reviews. I used Box Office Mojo to obtain total gross, because this is simply listed next to each film on Box Office Mojo. For total gross, I adjusted for inflation over the 20 year time period of my data set. I divided each total gross data point by Consumer Price Index (CPI) for each specific year, using the CPI numbers from the Federal Reserve Bank of Minneapolis; for these numbers the base year is chained from 1982-1984 (*Federal Reserve Bank of Minneapolis*). I used this same method for the two other monetary variables in my data set — opening weekend gross and budget.

I used Rotten Tomatoes to collect data on critic and audience reviews; Rotten Tomatoes ratings are on a scale of 0 to 100 and are created by gathering many different critics and audience reviews, standardizing them all into percentage form, and taking the average of them.

3.3 Control Variables

The rest of the variables in my data set are control variables, and I separated them into three categories: Actor Characteristics, Qualitative Film Characteristics, and Quantitative Characteristics. Actor Characteristics include experience, Golden Globes nominations, Golden Globes Wins, Oscar nominations, and Oscar wins. Qualitative Film Characteristics include Big 6, female director, a binary variable for each genre, a binary variable for each Motion Picture Association of America (MPAA) rating, rerelease, and sequel. Quantitative Film Characteristics include audience reviews, budget, opening number of theaters, opening weekend gross, and total number of theaters. All the control variables can be seen below in Table 1, and the sources for each variable are listed after in italics. The four sources I used are Box Office Mojo, IMDb, IMDbPro, and Box Office Mojo.

Table 1: List of Control Variables

Actor Characteristics	**Qualitative Film Characteristics**	**Quantitative Film Characteristics**
Experience — *IMDbPro*	Big 6 — *Box Office Mojo*	Budget — *IMDbPro*
Golden Globes nominations — *IMDbPro*	Female director — *IMDb*	Opening number of theaters — *Box Office Mojo*
Golden Globes wins — *IMDbPro*	Genre — *IMDb*	Opening weekend gross — *Box Office Mojo*
Oscar nominations — *IMDbPro*	MPAA rating — *Rotten Tomatoes*	Total number of theaters — *Box Office Mojo*
Oscar wins — *IMDbPro*	Rerelease — *Box Office Mojo*	
	Sequel — *IMDb*	

Note: Sources are in italics

3.3.1 Box Office Mojo

I used Box Office Mojo to obtain data on opening weekend gross, total number of theaters, number of opening weekend theaters, production company, and rerelease. The opening weekend gross is all the money a film grossed the first weekend it was released. Rereleases are films that were already released in the theaters once in a previous year but were released a second time. This variable is binary and equals one when a movie is a rerelease and zero when it is not. Rerelease was not used as a variable in any of the other studies in my literature review, but I decided to include it due to the implication that films were probably originally popular and higher grossing if they were chosen to be released again. I chose to include opening weekend gross, total number of theaters, and number of opening weekend theaters mainly because the Izquierdo Sanchez and Navarro Paniagua paper included them as control variables in their regression with wage as the dependent variable and included brief discussions on these variables.

Izquierdo Sanchez and Navarro Paniagua did include a binary variable for Big 6, but there was no discussion of this variable in their study; however, as discussed in my literature review the Amaral et al. study did hypothesize there was a connection between the creation of the Big 6 and the exclusion of women in the film industry (Amaral et al., 2020). The Big 6 includes the following production companies: Paramount Pictures, Sony Pictures Entertainment (previously known as Columbia Pictures Entertainment and listed this way in the earlier years on Box Office Mojo), Twentieth Century Fox, Universal Pictures, Walt Disney Studios Motion Pictures, and Warner Bros.

Box Office Mojo also included some data on the opening and closing date of films in theaters. I thought it would be interesting to include a measure of how long films were in the theater, but closing dates were unavailable for many of the films, especially in the earlier years of my study, so I decided not to pursue this further.

3.3.2 IMDb

I obtained the genre(s) of each film and if there was a female director from IMDb. I chose to include genre, because many studies in my literature review deemed that this was important in determining both the gender of actors and the amount a film grossed (Amaral et al., 2020, Fleck & Hanssen, 2016; Lauzen, 2019). I was originally uncertain where I should obtain my information on genre, because IMDb typically lists three genres for each film, and I was hoping to include one genre for each film to make it easier to analyze films. For example, on IMDb, the film *Oceans Eight* is listed as action, comedy, and crime. The American Film Institute (AFI) lists only one genre for each film, and this is what Izquierdo Sanchez and Navarro Paniagua used in their paper, but most of the other studies used IMDb as their data source for genre. On second thought I thought three genres would provide more accurate and comprehensive information. There are 24 different genres listed on IMDb, but two of them (film noir and superhero) are not a genre for any of the films in my data set. The 22 genres I am including are: action, adventure, animation, biography, comedy, crime, documentary, drama, family, fantasy, history, horror, music, musical, mystery, romance, sci-fi, short, sport, thriller, war, and western.

On IMDb there is also a section that lists all of the people behind the scenes of the film, and this is where I obtained the data on if there was a female director or not. I chose to include a variable for if there was a female director, because in my literature review three studies looking at the gender gap of on screen actors deemed this as important; one study included a variable for female director or writer, one study included a variable for female director or producer, and one study included a variable for solely female directors (Amaral et al., 2020; Fleck & Hanssen, 2016; Lauzen, 2019). Director was the one thing these three studies had in common, and from my own research it seems like the director(s) is the main person(s) influencing casting. Also it should be noted that some of the films in my data set have multiple directors, and for the films with both a male and a female director, I included them as having a female director. This is how Lauzen created her variable, and it is unclear how the other two studies created their variables. A possible avenue for extension of my research is to focus on the impact female directors and other females behind the scenes of films have on film success.

There are some films in my data set that are sequels so I included this as a variable. The Izquierdo Sanchez and Navarro Paniagua study is the only paper in my literature review that included a variable for sequel, so this study is the reason I am including this variable. I was able to look up each film in IMDb to see if it is a sequel. In my study sequel is a binary variable: it equals one if a film is a sequel and zero if it is not. I marked films that were third, fourth, etc. in a series as sequels as well.

3.3.3 IMDbPro

I used IMDbPro to find data on the following variables: Oscar nominations, Oscar wins, Golden Globes nominations, Golden Globes wins, experience, and budget. Izquierdo Sanchez and Navarro Paniagua included Oscar nominations, Oscar wins, experience, and budget in their regression, but they did not include Golden Globes nominations or wins. While the Oscars are more well known, the Golden Globes are still quite prominent and thus could influence film success.

To create the experience variable, I used IMDb's film history section for each protagonist and found the year that each protagonist starred in their first film. The Izquierdo Sanchez and Navarro Paniagua paper measures experience from the number of years acting before the film was released, but it is unclear what they define as acting.

3.3.4 Rotten Tomatoes

As mentioned above, I used Rotten Tomatoes to collect data on critic and audience reviews. I also obtained the MPAA rating (G, PG, PG-13, R, NR) through this search, because the Izquierdo Sanchez and Navarro Paniagua paper included these variables as some of their control variables.

3.4 Limitations

I wanted to include the two identity variables — race and sexuality — in my data set. However, most actors do not self-report these variables, and this data is not listed on IMDb or other websites that include qualitative characteristics about actors. I wanted to include race, because Lauzen's 2019 study and the Smith et al. study identified racial inequities in the film industry. I wanted to include sexuality, because it was barely discussed in any of the papers I read on gender differences in the film industry. Perhaps this lack of discussion was also due to the lack of data. Additionally, I am unable to collect data on marketing such as how much money was put into marketing, who the target audience was, and where the film was promoted. This data would be helpful to have, because it could affect how many people view a film which affects film total gross. It would have also given me more insight on the budget variable, because it is unclear how much of the budget was used on the actual film and how much was used on marketing.

One limitation to my data set is that in some films there is not a clear protagonist — instead there may be multiple main characters. However, in my data set I only list one protagonist for each film. Another limitation is that the percentage of critic and audience reviews on Rotten Tomatoes is based on different numbers of reviews. For some films this number was based on thousands of reviews while others there was a much smaller number. If films had barely any reviews Rotten Tomatoes didn’t assign a rating. The film ratings with smaller sample sizes of reviews are probably less accurate. A third limitation to the data set is that it does not account for seasonal factors. For example, during the summer and winter holiday seasons blockbusters are often released, and these films typically are higher grossing.

4: Summary Statistics & Industry Trends

Below I provided some summary statistics of my data set with a focus on gender and age. In the data there were 1,991 observations for protagonists: 523 were female, and 1,468 were male.

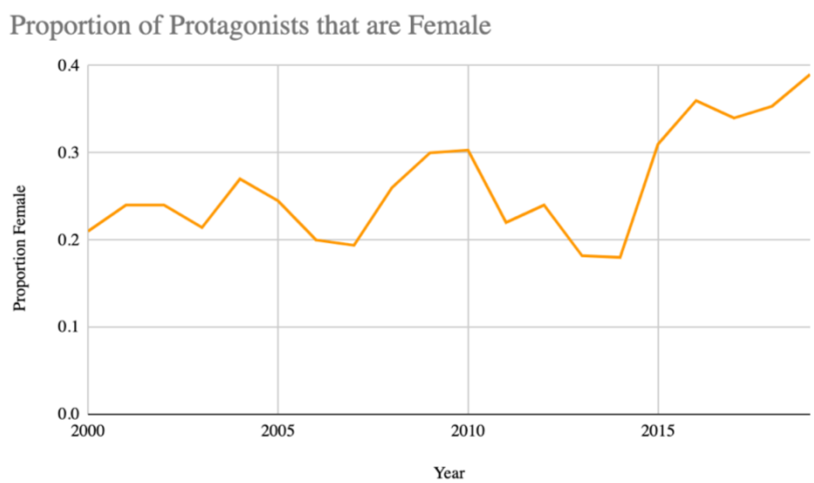
4.1 Proportion Female Protagonists over Time

I ran a regression on the proportion of protagonists in the top 100 grossing films that are female over time for 20 years. The results of the regression can be seen in Table 2 below. The numbers next to "Constant" and "Year" in the table are the coefficients, and the numbers in parenthesis underneath these numbers are the standard errors of these coefficients. The p-value for year is .005, and the coefficient on year is .0064561, showing that there was a small but statistically significant increase in the proportion of female protagonists over time. The data points used in this regression can be seen graphed in Graph 1.

Table 2: Regression Results

Constant	-12.71105 (4.038785)
Year	.0064561 (.0020098)
Adjusted R-squared	0.3291
# Observations	20

Graph 1: Proportion Female Protagonists



4.2 Protagonist Age Statistics

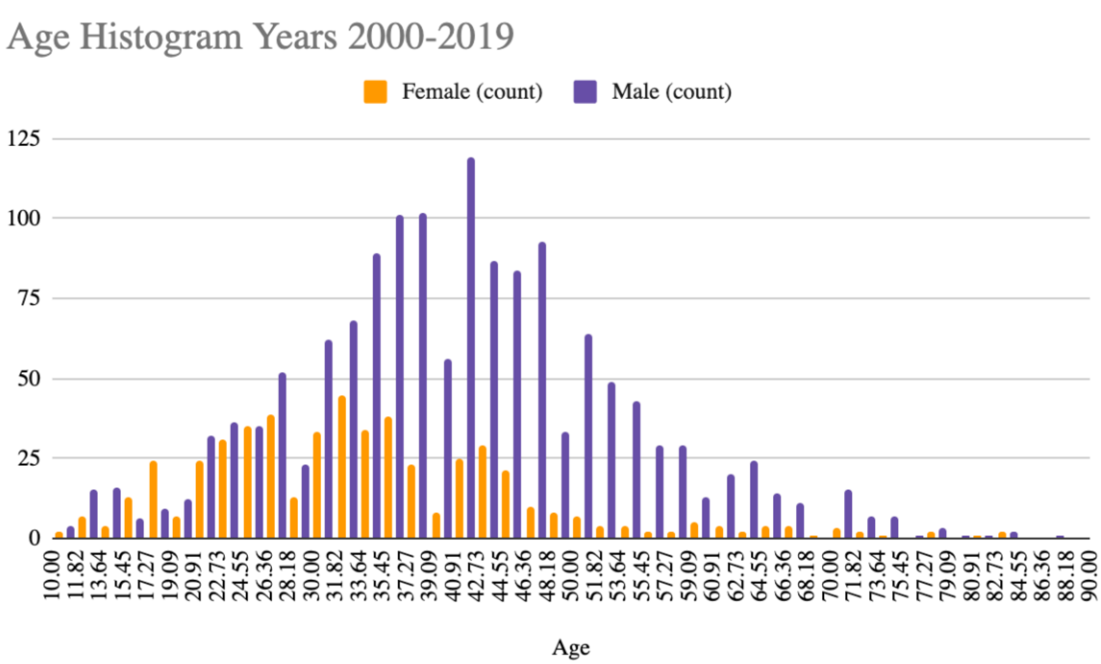
Age statistics can be seen below in Table 3. The mean age for female actors is about seven years lower than the mean age for male actors, and the median age for female actors is about eight years lower. It can also be seen that the range for female age is 72, while the range for male age is larger at 77.

Table 3: Age Summary Statistics

	Observations	**Mean**	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
Age	1,991	39.47865	39	12.9563	11	88
Female Age	523	34.46463	33	12.75484	11	83
Male Age	1,468	41.26499	41	12.55656	11	88

Graph 2 below shows an age histogram for the protagonists divided by gender — female is orange, and male is purple. There are more observations for male actors so naturally the purple bars are higher, but the male data is more centered while the female data appears more skewed toward younger ages.

Graph 2: Age Histogram for Female and Male Actors



4.3 Age over Time

Over all the years in my data set, the mean male age of protagonists was always greater than the mean female age of protagonists. I conducted a t-test using the data from all the years with the null hypothesis that mean female and mean male age were the same. The results were statistically significant showing that the null can be rejected and that there is a difference between the mean female and mean male age.

Looking specifically at female age over time, I ran a regression on the mean age of female protagonists in the top 100 grossing films over time for 20 years. The p-value for year was 0, and the coefficient for year was .3148508, showing that there was a small but statistically significant increase in the female mean age over time.

Similarly, I ran a regression on the mean age of male protagonists in the top 100 grossing films over time for 20 years. Again the p-value for year was 0, and the coefficient for year was .259442, showing that there was also a small but statistically significant increase in the male mean age over time.

4.4 Total Gross Statistics

One of the dependent variables I am using in this study is total gross. Table 4 below shows the total gross summary statistics for all films, for films with a female protagonist, and for films with a male protagonist. Here it can be seen that the mean and median total gross for films with male protagonists is higher than the mean and median total gross for films with female protagonists.

Here too, I conducted a t-test to compare the means of total gross for films with a female protagonist and for films with a male protagonist. The results were statistically significant showing that the null hypothesis that there is no difference between the two means can be rejected and that there is a difference between the means (the male mean is higher than the female mean).

Table 4: Total Gross Statistics

	Observations	Mean	Median	Standard Deviation	Minimum	Maximum
All Films	1,991	4.22e+07	2.80e+07	3.98e+07	8000450	3.95e+08
Female Protagonist	532	3.62e+07	2.30e+07	3.72e+07	8625465	3.95e+08
Male Protagonist	1,468	4.44e+07	3.01e+07	4.05e+07	8000450	3.50e+08

4.5 Critic and Audience Reviews Statistics

I am using critic reviews and audience reviews as the other two dependent variables in my regressions. Table 5 presents the summary statistics on critic reviews for the films in the data set. Critic reviews are highly variable with a large standard deviation and a range of 100.

Table 5: Critic Reviews Statistics

	Observations	Mean	Median	Standard Deviation	Minimum	Maximum
All Films	1,991	53.51984	53	26.73799	1	100
Female Protagonist	523	51.63098	49	27.09844	1	99
Male Protagonist	1,468	54.19278	55	26.40434	1	100

I conducted a t-test to compare mean female and mean male critic reviews. The results were not statistically significant, so the null hypothesis that there is no difference between the two means could not be rejected.

Essentially the same picture emerged for the summary statistics for audience reviews-films; films with female protagonists had lower mean and median audience reviews than films with male protagonists, and the t-test between the two means was not statistically significant.

5: Empirical Specification

Using the data set I created, I ran three regressions on film success. I had to omit age, because age and experience are highly correlated with a correlation coefficient of 0.84. I choose to include experience instead of age, because using experience instead of age increased the statistical significance of some of my coefficients without changing any of the signs on the coefficients. Thus I will be using experience as a proxy for age. I also included experience squared to allow for nonlinearity in the experience variable. To identify possible connections between age and being a female, I included an interaction term between female and experience and an interaction term between female and experience squared. I omitted opening weekend gross, because opening weekend gross and total gross were highly correlated with a correlation of 0.8910. For ratings, I chose PG-13 as the omitted category, because it was the most common rating, and for genre, I chose comedy as the omitted category, because it was the most common genre.

The basic regression equation is:

$$(1).\quad \boldsymbol{FilmSuccess}_{ijt} = \beta_0 + \beta_1 Female_{ijt} + \beta_2 Experience_{ijt} + \beta_3 Experience_{ijt}^2 + \beta_4 Female * Experience_{ijt} + \beta_5 Female * Experience^2{}_{ijt} + \beta_6 ActorCharacteristics_{it} + \beta_7 QualitativeFilmCharacteristics_{it} + \beta_8 QuantitativeFilmCharacteristics_{it} + e_{ijt}$$

In the regression i denotes the film, j denotes the protagonist of the film, and t denotes the year of the film. As outlined in Table 1, *ActorCharacteristics* is a vector of experience, Golden Globes nominations, Golden Globes wins, Oscar nominations, and Oscar wins. *QualitativeFilmCharacteristics* is a vector of the following binary variables in my data set: Big 6, female director, rerelease, sequel, 21 genre variables, and four MPAA rating variables. *QuantitativeFilmCharacteristics* is a vector of budget, opening number of theaters, opening gross, and total number of theaters.

In my study film success is measured in three ways: total gross, critic reviews, and audience reviews. These are my three dependent variables in my three regressions. Based on the research in my literature review there appears to be biases against women both across the workforce in the United States and specific to the film industry. Thus I expected to see that in a negative coefficient on the female binary variable in these regressions. I was unsure what the sign of the coefficient on experience would be; in the Izquierdo Sanchez and Navarro Paniagua study the researchers got a positive and significant coefficient for the age variable in their regression where actor wage was the dependent variable and a negative and statistically significant coefficient for age squared. Though I was not directly looking at actor wage as those authors were, actor wage could be related to film success, so I thought it was possible that my regressions will show similar results. I expected the coefficient on the interaction term between female and experience squared to be lower in value than the coefficient on the interaction term between female and experience. This was because studies in my literature review identified that gender biases in the film industry increase as females get older (Fleck & Hanssen, 2016; Izquierdo Sanchez & Navarro Paniagua, 2017; Lauzen, 2019).

Among the control variables, I expected the sign of the genre variable action to be positive and to be larger than most of the other genre variables, given that the sources in my literature review found that action was one of the top-grossing genres. I expected the coefficients for experience, Golden Globes nominations, Golden Globes wins, Oscar nominations, and Oscar wins to be positive, because these five variables explain actor experience, prominence, and popularity. I also expected Golden Globes wins and Oscar wins to have larger coefficients than Golden Globes nominations and Oscar nominations. I expected the coefficients on sequel and rerelease to be positive. In my literature review I noted that Izquierdo Sanchez and Navarro Paniagua found that actors who play in sequels tend to receive higher wages; rereleases were in the theaters twice, thus probably generating more money, and they were most likely rereleased because they were originally popular.

6: Regression Results & Discussion

6.1 Total Gross Regression

I ran a baseline ordinary least squares (OLS) regression with all of the variables in my data set (except for the intentionally omitted ones discussed in the previous section). None of the five focus variables — female, experience, experience squared, the interaction term between female and experience, and the interaction term between female and experience squared — were statistically significant.

Many of the control variables were also insignificant, so I removed some of them from the regression to obtain more focused results. For example, none of the rating variables (G, PG, R, and NR) were statistically significant individually, and when I conducted an F-test they also were not significant as a group. Thus they did not impact my focus variables in a statistically significant way, so I decided to omit them from the regression. This makes sense that the rating did not have an impact on total gross, because with the exception of children and R-rated films ratings probably do not impact if a person wants to see a film.

Golden Globes nominations was the only awards variable that was statistically significant; I did a F-test to test the statistical significance of the award variables as a group, and the results were statistically significant at the 10% level. When I omitted Golden Globes nominations from the F-test, the other three variables as a group were not statistically significant, so I only kept Golden Globes nominations in my final regression, because it was the only variable that had a statistically significant impact. I am uncertain why this was the only awards variable that was statistically significant — perhaps this indicated that the awards variables did not need to be included in this study as control variables. The study in my literature review that included these control variables looked at the wages of the specific actors that were winning these awards, while this regression focuses on the overall film (Izquierdo Sanchez & Navarro Paniagua, 2017). Thus the awards of the protagonist may be less relevant for my specific research.

Next I focused on the 21 genre variables as a group, and an F-test of the variables as a group was statistically significant at the 1% level. Then I did an F-test for all the genres that were not statistically significant individually, and the results were no longer statistically significant — thus I dropped all the genre variables except for action, documentary, family, horror, and short. I created a new variable other genre for the if a film had one of the omitted genres, and this variable was not statistically significant.

Lastly I dropped the variables for female director and rerelease from the regression, because they were not statistically significant. This makes sense for rerelease, because the total gross for the rereleases only counts the individual rerelease and not the original release as well. This also makes sense about the female director variable, because the content of the film should matter to moviegoers rather than the gender of the director.

6.1.1 Results

Then I ran a pared down the version of the original regression omitting all the variables discussed above. In this final regression there were 1,989 observations, which is almost 100 observations for each of the 20 years in my data set. The adjusted R-squared for the regression was .47532707, and this means that 47.53% of the total variation in total gross is explained by the regression. I conducted a Variance Inflation Factor (VIF) test for this regression to check for correlations between variables. All the control variables had a VIF number lower than 5, showing that they were not highly correlated with one another and thus that multicollinearity would not be an issue. However, the five focus variables did have higher VIF values, because these five variables are correlated with each other due to the nature of the squared terms and interaction terms.

The results of the regression can be seen below in Table 6; for the sake of comparison both columns labelled (1) are results from my baseline regression (all variables included), and both columns labelled (2) are from my final pared down regression. The standard errors lie beneath the coefficient estimates in parenthesis, and they are corrected for heteroskedasticity.

Table 6: Total Gross Regression Results

VARIABLES	All Variables (1)	Significant Control Variables (2)	VARIABLES	All Variables (1)	Significant Control Variables (2)
Female	4.13E+06	4.66E+06	Biography	2.66E+06	—
	(3.66E+06)	(3.59E+06)		(2.14E+06)	
Exp	-242,488.50	-239,425.00	Crime	-1.22E+06	—
	(2.14E+05)	(2.02E+05)		(1.65E+06)	
Exp^2	5,440.00	5,435.52	Drama	1.27E+06	—
	(4,835.29)	(4,449.72)		(1.52E+06)	
Female*Exp	-360,048.00	-323,585.70	Fantasy	-115,898.10	—
	(3.86E+05)	(3.73E+05)		(2.65E+06)	
Female*Exp^2	8,288.28	7,485.21	History	-2.46E+06	—
	(7,864.62)	(7,485.21)		(3.20E+06)	
GG Nom	-1.067e+06*	-885,160.70**	Music	921,594.80	—
	(5.49E+05)	(3.47E+05)		(2.58E+06)	
Action	-6.879e+06***	-7.659e+06***	Musical	5.97E+06	—
	(1.56E+06)	(1.53E+06)		(1.02E+07)	
Documentary	1.650e+07***	1.960e+07***	Mystery	1.19E+06	—
	(5.27E+06)	(6.15E+06)		(1.91E+06)	
Family	-3.37E+06	-5.811e+06**	Romance	1.51E+06	—
	(2.97E+06)	(2.34E+06)		(1.61E+06)	
Horror	-4.874e+06***	-4.999e+06***	Scifi	3.02E+06	—
	(1.83E+06)	(1.56E+06)		(3.34E+06)	
Short	2.422e+07*	3.513e+07***	Sport	951,377.80	—
	(1.36E+07)	(7.86E+06)		(2.91E+06)	
Other Genre	—	2.03E+06	Thriller	-1.10E+06	—
		(1.62E+06)		(1.47E+06)	
Big 6	-3.709e+06***	-3.399e+06**	War	-5.62E+06	—
	(1.35E+06)	(1.33E+06)		(5.50E+06)	
Sequel	1.197e+07***	1.203e+07***	Western	-1.19E+07	—
	(2.76E+06)	(2.70E+06)		(1.57E+07)	
Opening T	8625.75***	-8,760.68***	F Director	2.97E+06	—
	(1,247.83)	(1,208.31)		(2.99E+06)	
Total T	26,693.75***	26,139.88***	Rerelease	-1.07E+07	—
	(2,009.00)	(2,014.78)		(9.29E+06)	
Budget	0.79***	0.80***	G	2.94E+06	—
	(0.06)	(0.06)		(4.83E+06)	
Oscar Nom	-125,640.80	—	PG	-2.89E+06	—
	(7.04E+05)			(2.53E+06)	
Oscar Win	-853,325.70	—	R	57,544.31	—
	(1.39E+06)			(1.28E+06)	
GG Win	1.37E+06	—	NR	3.46E+07	—
	(1.13E+06)			(2.14E+07)	
Adventure	270,468.90	—	Constant	-3.054e+07***	-3.010e+07***
	(1.98E+06)			(4.19E+06)	(4.14E+06)
Animation	-1.01E+06	—			
	(3.39E+06)		Observations	1,989	1,990
Robust standard errors in parentheses			R-squared	0.484	0.48
*** p<0.01, ** p<0.05, * p<0.1			Adj. R^2	0.473	0.473

6.1.2 Analysis

With this second version of the regression still none of the five focus variables are statistically significant. This is an interesting result, because I expected all these variables to be statistically significant and to help explain the wage gap. I will spend the next paragraphs discussing the numerical values of the coefficients and their possible economic significance.

The coefficient on female is 4,660,333, and the p-value is 0.194, meaning that female is not statistically significant. Looking at the potential economic significance of the variable, the average gross of the films in my data set is about $91 million, and the coefficient on female is a little over 5% of average total gross. Thus the female coefficient has a moderate positive economic significance which is the opposite of what I expected to see given the gender wage gap in film, but no conclusions can be drawn because the coefficient is not statistically significant.

The experience coefficient is -239,425.4, and it's p-value of 0.235; the coefficient on experience squared is 5,435.517 with a p-value of 0.222. The signs of the experience and experience squared coefficients can be interpreted as younger ages having an expected negative impact on total gross and older ages having an expected positive impact on total gross. The absolute values of the coefficients on experience and on experience squared are both less than 1% of average total gross, so the coefficients are neither statistically significant nor economically significant.

The coefficient for the interaction term between female and experience is -323,585.7 (p-value is 0.385), and the coefficient for the interaction term between female and experience squared is 7,941.006 (p-value is 0.289). The signs show that younger female protagonists have an expected negative impact on total gross, and older female protagonists have an expected positive impact on total gross. Papers in the literature review showed that the gender wage gap increased with age, so instead I had expected to see younger female protagonists having a positive effect on total gross and older female protagonists having a negative effect on total gross. However, no conclusion can be made regarding the two interaction terms because of the lack of statistical significance. The coefficients are also not economically significant; similar the coefficients on the experience terms, they are both less than 1% of average total gross.

Due to the fact that none of the five main variables were significant, it is important to investigate if any of the control variables in the study could be driving total gross. The only variable in the Actor Characteristics category that I ended up including in the regression was Golden Globes nominations, and this was significant at the 5% level. The coefficient is -885,160.7, and the absolute value of this coefficient is less than 1% of average total gross; thus the coefficient is not economically significant. The coefficient is negative which does not make a lot of sense — one would think that more nominations would make an actor more popular and make an actor be considered better at acting. Both of these factors could make a film more popular resulting in it grossing more rather than less. However, due to the fact that the coefficient is not economically significant, one cannot conclude much from this result anyways.

For the Qualitative Film Characteristics category I included action, documentary, family, horror, short, and sequel — these are all significant at least at the 5% level. Specifically, short has a very high economic impact, because the coefficient is 38.58% of average total gross. I was surprised by this, because I expected some of the other genres — like action, drama, romance, and scifi — to have higher positive and statistically significant coefficients based on some of the results from studies I included in my literature review. Contrary to this expectation, the coefficient on action was negative. Action had a fairly large economic impact — 8.41% of average total gross. Big 6 also had a negative coefficient; I had expected the coefficient on Big 6 to be positive, because production companies in the Big 6 are typically more prominent, and I thus thought that films they produce would gross more money. This coefficient had some economic significance, because it was almost 4% of average total gross. I expected the coefficient on sequel to be positive and fairly large in magnitude, and this expectation held true — it was positive and made up a little over 13% of average total gross. Again, this is logical, because if viewers really liked the previous film(s) in a series they would probably be more likely to see a subsequent film.

For the Quantitative Film Characteristics category I included budget, opening theaters, and total theaters, and these were all significant at the 1% level. Budget has no zero economic significance, because the coefficient on budget is merely .797. Total theaters and opening theaters also have very minimal economic significance, because their coefficients each make up much less than 1% of average total gross. I was surprised by these results, because I expected these coefficients to be statistically and economically significant and positive. It is possible that this is due to the fact that there was not a large amount of variation in the films in my data set — all of my films were in the top 100 grossing films for each year. Thus they all probably had budgets that were high enough for the film to be produced well. Additionally it is possible that all these films were anticipated to do well so they all may have had high numbers of opening theaters and continued to do well (because they ended up being high grossing films) having high numbers of total theaters.

To sum up, gender and experience of the protagonist do not have a statistically significant impact on total gross. Instead film qualitative characteristics were found to be statistically and economically significant and appear to be the main factors driving film total gross in my regression.

6.2 Critic Reviews Regression

For this regression critic reviews lie between 0 and 100. I originally thought of conducting a logit regression, but I was unable to do this, because my dependent variables were continuous rather than discrete. Thus in order to still apply OLS I transformed the critic reviews data. In the following equation Y is critic reviews, and Z is the transformed dependent variable: $Z = \frac{Y}{100-Y}$. The transformed variable, Z, is increasing in critic reviews, so higher critic reviews cause higher values of Z. Z ranges from 0 when critic reviews equal 0 to infinity when critic reviews equal 100. I used this same transformation process for audience reviews.

Thus I ran a OLS regression using my transformed critic reviews variable, Z, as my dependent variable. I included all my independent variables in this initial regression, and none of my gender or experience variables were significant. Similarly to the previous regression, a lot of my control variables were insignificant, so I again went through a process of eliminating some of them to formulate a pared down regression.

R was the only significant film rating variable; I conducted a F-test of the four rating variables and this was significant at the 5% level, and then I conducted an F-test of the three insignificant genres, and the results were not significant. Thus G, PG, and NR also were not significant as a group, so I eliminated them. I generated a new binary variable for other rating that equals one if a film is one of the omitted ratings.

Next I studied the awards variables, and Oscar wins and Golden Globes nominations were the only significant ones. However, Oscar nominations, and Golden Globes wins were significant at the 5% level together when I did an F-test with only the two of them, so I kept all four award variables. Perhaps it makes sense that critics would care more about the accolades of the protagonists than people who are going to see a film, because critics typically do more research into films. This could explain why the awards variables were statistically significant in this regression but not in the previous regression.

The significant genres were animation, drama, fantasy, horror, and sport. I did an F-test with all the genres, and they were significant at the 1% level as a group. When I did a second F-test of the insignificant genres, the results were not significant, so I removed those and only kept the significant ones. Like I did in my total gross regression, I generated a variable for other genre for if a film had one of the insignificant genres I deleted.

Female director, Big 6, and sequel were all also statistically insignificant so I deleted them. Logically, it makes sense that Big 6 and female director would not be significant, because these should not be apparent in the film content which is theoretically the aspect that is getting reviewed. I had anticipated that sequel would be significant and positive, but perhaps the reason it is not is because critics do not judge films based on past films in the series. However, on second thought, some sequels tend to be worse than the originals, so any excitement a film could have gained from critics from being a sequel could have been cancelled out by it being a worse film than the original.

6.2.1 Results

Then I ran a regression with the variables I had left; I had 1,988 observations, and the adjusted R-squared was .12041185, which means that 12.04% of the total variation in the adjusted critic reviews variable is explained by the regression. I conducted a VIF test for this regression, and like the total gross regression, the only variables with high VIF values were the five focus variables due to their correlation with each other. In Table 7 below the results from my initial regression (columns labelled (1)) and final regression (columns labelled (2)) can be seen with standard errors corrected for heteroskedasticity and in parenthesis below the coefficient estimates.

Table 7: Critic Reviews Regression Results

VARIABLES	All Variables (1)	Significant Control Variables (2)	VARIABLES	All Variables (1)	Significant Control Variables (2)
Female	-0.0742	-0.0911	Adventure	0.5254	—
	(0.8619)	(0.8440)		(0.3937)	
Exp	0.0135	0.0108	Biography	0.9207	—
	(0.0595)	(0.0583)		(0.7810)	
Exp^2	6.70E-04	7.64E-04	Crime	-0.3496	—
	(0.0012)	(0.0012)		(0.3860)	
Female*Exp	0.0263	0.0351	Documentary	0.2697	—
	(0.0787)	(0.0780)		(1.0310)	
Female*Exp^2	-0.0012	-0.0014	Family	-1.2147*	—
	(0.0017)	(0.0017)		(0.6655)	
Oscar Nom	0.3035	0.3438	History	-0.0553	—
	(0.2391)	(0.2445)		(0.8419)	
Oscar Win	-0.6627**	-0.6631**	Music	-0.5991	—
	(0.3371)	(0.3327)		(0.5928)	
GG Nom	-0.4381***	-0.4576***	Musical	-1.3471	—
	(0.1357)	(0.1381)		(1.0583)	
GG Win	0.3846	0.3653	Mystery	-0.1674	—
	(0.3209)	(0.3234)		(0.4068)	
Animation	3.4969***	4.6904***	Romance	-0.7825	—
	(1.0743)	(1.1667)		(0.5267)	
Drama	0.7718**	0.9158***	Scifi	0.4913	—
	(0.3505)	(0.3142)		(0.4909)	
Fantasy	-0.7345*	-0.8399**	Sport	-0.4724	—
	(0.3835)	(0.3402)		(0.5563)	
Horror	-1.0544**	-0.7071*	Thriller	0.1330	—
	(0.4318)	(0.3874)		(0.3773)	
Short	6.9836***	8.3823**	War	-1.5318	—
	(2.3851)	(3.5776)		(1.5611)	
Other Genre	—	-0.5924	Western	0.9738	—
		(0.5400)		(3.5965)	
R	1.0700***	0.9967***	Big 6	-0.6066	—
	(0.3544)	(0.3356)		(0.4190)	
Other Rating	—	0.2933	F Director	1.0694	
		(0.3103)		(1.3739)	
Rerelease	16.3580**	17.0280**	Sequel	-0.2512	—
	(8.3259)	(8.4334)		(0.6051)	
Opening T	-2.88E-03	-3.03E-03***	G	2.9665	—
	(5.38E-04)	(5.07E-04)		(2.2320)	
Total T	0.0030***	0.0030***	PG	0.3231	—
	(6.09E-04)	(5.99E-04)		(0.4847)	
Budget	1.84E-08	1.92e-08**	NR	-1.9480	—
	(-1.13E-08)	(-9.41E-09)		(3.4071)	
Action	-0.8653**	—	Constant	1.4399	1.5601
	(0.4153)			(1.1026)	(1.1303)
Robust standard errors in parentheses			Observations	1,988	1,988
*** p<0.01, ** p<0.05, * p<0.1			R-squared	0.139	0.13
			Adj. R^2	0.12	0.12

6.2.2 Analysis

Since my regression used the transformed critic reviews variable, Z, ranging from zero to infinity, the coefficients need to be adjusted in order to be interpreted in terms of the raw critic reviews data that ranges from zero to 100. This adjustment procedure is discussed in the appendix. Like was the case with the regression on total gross, none of the five focus variables are statistically significant in this regression. The converted value of the female coefficient is -1.96813 with a p-value of 0.914. This can be interpreted as meaning films with a female protagonists are expected to get reviews from critics that are about two points lower than films with male protagonists. Mean critic reviews is 53.51984, so this coefficient is almost 4% of mean critic reviews; thus female does have some economic significance, but this is basically irrelevant due to its lack of statistical significance. This negative coefficient on female was what I expected to find due to Lauzen (2019) in my literature review, but the coefficient is not statistically significant.

The coefficient values for experience and experience squared have converted values of 0.23332 (p-value 0.853) and 0.01651 (p-value 0.507) respectively. These individually each comprise less than 1% of mean critic reviews and thus have no economic significance. The interaction term between female and experience has a converted value of 0.75830 with p-value 0.653 and makes up about 1.42% of average critic reviews, so this coefficient has basically no economic significance and again no statistical significance. Similarly, the interaction term between female and experience squared has no statistical significance, but it also has no economic significance — the coefficient is -0.02938 with p-value 0.653. The coefficients on experience and experience squared are both positive, but on the interaction terms the coefficient on female and experience is positive, and the coefficient on female and experience squared is negative. These signs indicate that for older female actors critic reviews are lower than for younger female actors, but the lack of significance does not allow me to make this conclusion.

Due to the fact that none of the five variables of focus are significant, the control variables are mostly the ones driving critic reviews in this regression. In the Actor Characteristics category the statistically significant coefficients are Oscar wins and Golden Globes nominations. The signs on these coefficients are negative which was not what I expected, because I thought that actors who receive awards would also receive higher audience reviews. For Qualitative Film Characteristics I included animation, drama, fantasy, horror, short, other genre, release, R and other rating, and these are all statistically significant except for other genre and other rating (which makes sense, because these variables represent the non-significant ratings and genres). Specifically animation, short, and rerelease are very large in magnitude, and they are all positive. It is logical that rerelease would be positive, because if a film received positive reviews the first time it makes sense that it would be released again and continue to earn positive reviews. For Quantitative Film Characteristics, budget, opening theaters, and total theaters are all statistically significant, but they have no economic significance.

Thus for this regression gender and experience were not seen to be statistically significant in determining critic reviews; like for the total gross regression other factors — particularly actor characteristics and qualitative film characteristics — were driving results.

6.3 Audience Reviews Regression

Initially I ran an OLS regression with the adjusted audience reviews variable as the dependent variable and all the control variables included. Experience squared was the only one of my five focus variables that was statistically significant, and it was significant at the 10% level. It was positive (while the coefficient on experience was not) indicating that films with older protagonists earned higher audience reviews. Then as I did with the two previous regressions I pared down this initial version of the regression by deleting some of the insignificant control variables.

None of the ratings variables were significant individually and after conducting an F-test on the rating variables together, I found they were also not significant as a group, so I omitted them from the regression. This makes sense that audience members would not take rating into consideration when writing a review of the movie; instead they would probably focus on plot, acting, cinematography, etc.

For the awards variables, Golden Globes nominations and Golden Globes wins were significant at the 1% and 5% level respectively. I did an F-test on the four awards variables as a group, and the results were significant at the 1% level as a group. When I did an F-test of solely Oscar wins and Oscar nominations the results were not significant, so I deleted these two variables.

Next I focused on the genres, and as shown by an F-test the 21 genre variables were significant at the 1% level as a group. Individually, the only genres that were significant were animation, biography, drama, and horror. I did an F-test of the nonsignificant genres, and the results were not significant, so I dropped all of the genres except for the four significant ones. Like the previous two regressions, I created a variable for other genre for if a film has one of the non-significant genres.

Then like in the critic reviews regression I dropped female director and sequel, because they were not significant in the regression. Again dropping female director here makes sense, because it is unlikely that this would be taken into consideration by audience members while they are viewing a film.

6.3.1 Results

In the final version of my regression there are 1,990 observations, and the adjusted R-squared for the regression is 0.136 meaning that 13.6% of the total variation of the adjusted critic reviews variable is explained by the regression. I conducted a VIF test for this regression, and like the other two previous regression only the five focus variables had VIF values above 5, because they are correlated with each other. Thus multicollinearity is not an issue. The results of the baseline regression can be seen below in Table 8 in columns labelled (1), and the results of the final regression are in columns labelled (2). Again the coefficients of each variable are listed with their standard errors beneath them, and the standard errors are corrected for heteroskedasticity.

Table 8: Audience Reviews Regression Results

VARIABLES	All Variables (1)	Significant Control Variables (2)	VARIABLES	All Variables (1)	Significant Control Variables (2)
Female	0.1579	0.1571	Documentary	0.6007	—
	(0.5151)	(0.5244)		(0.4687)	
Exp	-0.0381	-0.0356	Family	-0.1587	—
	(0.0283)	(0.0267)		(0.4100)	
Exp^2	9.76E-04*	9.54E-04*	Fantasy	-0.2722	—
	(5.31E-04)	(4.93E-04)		(0.2000)	
Female*Exp	-0.0703	-0.0711	History	-0.0512	—
	(0.0493)	(0.0486)		(0.6151)	
Female*Exp^2	1.31E-03	1.27E-03	Music	-0.0028	—
	(1.06E-03)	(1.05E-03)		(0.5043)	
GG Nom	-0.2569***	-0.2283***	Musical	0.9477	—
	(0.0602)	(0.0517)		(0.7014)	
GG Win	0.2345**	0.2012**	Mystery	0.0721	—
	(0.1115)	(0.0961)		(0.2440)	
Animation	0.5068	0.5281**	Romance	0.0953	—
	(0.3421)	(0.2580)		(0.2150)	
Biography	3.2070***	3.2624***	Scifi	0.2598	—
	(0.9925)	(0.9413)		(0.2691)	
Drama	1.0366***	0.9651***	Short	1.3815*	—
	(0.1790)	(0.1667)		(0.8114)	
Horror	-0.7522***	-0.8591***	Sport	1.1111	—
	(0.2370)	(0.1573)		(1.0931)	
Other Genre	—	0.2667	Thriller	0.1139	—
		(0.2135)		(0.1775)	
Big 6	-0.3564	-0.4127**	War	0.6534	—
	(0.2188)	(0.2037)		(1.0630)	
Rerelease	3.9570***	3.9645***	Western	1.2001	—
	(1.3255)	(1.3265)		(1.6193)	
Opening T	-1.27E-03***	-1.28E-03***	F Director	0.4593	—
	(3.58E-04)	(3.36E-04)		(0.4041)	
Total T	0.0012***	0.0012***	Sequel	0.2627	—
	(4.49E-04)	(4.26E-04)		(0.2024)	
Budget	1.35e-08***	1.30e-08***	G	0.1657	—
	(4.79E-09)	(4.27E-09)		(0.4853)	
Oscar Nom	0.0791	—	PG	0.2355	—
	(0.0815)			(0.3019)	
Oscar Win	-0.2145	—	R	0.1335	—
	(0.1357)			(0.2813)	
Action	0.0540	—	NR	-1.0736	—
	(0.2538)			(0.8246)	
Adventure	0.2053	—	Constant	2.3723***	2.4342***
	(0.2322)			(0.6931)	(0.7288)
Crime	0.4693	—			
	(0.4755)				
			Observations	1,989	1,990
Robust standard errors in parentheses			R-squared	0.149	0.144
*** p<0.01, ** p<0.05, * p<0.1			Adj. R^2	0.132	0.136

6.3.2 Analysis

For this regression I went through the same process of converting my coefficient results to become meaningful as I did for the critic reviews regression [See Appendix]. As was the case in my baseline regression on audience reviews, experience squared is also significant at the 10% level in this final version. However, none of my other four focus variables are statistically significant. I will still spend the following paragraph discussing the coefficients on all five focus variables.

For female the converted coefficient is 2.19144 (p-value is 0.765), and this is about 3.5% of average audience reviews; thus it has some economic significance. This coefficient can be interpreted as films earning higher audience reviews if a protagonist is female, but this conclusion cannot be drawn because of the lack of statistical significance of the coefficient. The converted coefficient for experience is -0.49691 with a p-value of 0.183, and the converted coefficient for experience squared is 0.01332 with a p-value of 0.053. Even though experience squared is statistically significant, neither one of these coefficients is economically significant. The signs of the two coefficients indicate that older actors receive higher audience reviews. This would make sense, because typically older actors are more experienced, but this does not take into account the gender of the protagonists yet. The converted coefficients for the interaction terms between female and experience and female and experience squared are -0.99243 with p-value 0.143 and 0.01773 with p-value 0.226 respectively. The coefficient between female and experience has some economic significance (being about 1.58% of average audience reviews), and the signs of the two interaction terms indicate that for films with female protagonists the films with younger females receive lower audience reviews which is the same thing we saw for male and female protagonists when they were grouped together. Again, no conclusions can be drawn due to the lack of statistical significance.

Looking at my control variables, in the Actor Characteristics category I included Golden Globes nominations and Golden Globes wins. I was surprised that the coefficient on Golden Globes nominations was negative, because similarly to what I noted in the critic reviews regression discussion, I assumed films whose starring actors had more awards would have higher reviews. For the Qualitative Film Characteristics category I included animation, biography, drama, horror, other genre, Big 6, and rerelease. Specifically, the coefficients for biography and rerelease were large in magnitude and positive; again this makes sense for rerelease, because a film that was chosen to be released again probably was popular and received high reviews. Consistent with what I found to be the case for the two prior regressions, opening theaters, total theaters, and budget were all statistically but not economically significant.

Thus with the exception of the experience squared the five focus variables were not statistically significant, and none of the five focus variables were economically significant. Like with the critic reviews regression actor characteristics and qualitative film characteristics seem to be most important for the regression outcome.

7. Conclusion

All of my empirical results point to there being no significant difference between the success of films with female protagonists versus those with male protagonists. This is true for each of my regressions regardless of whether success is measured by a film's total gross or by reviews either from film critics or audience members. In all three of the regressions the coefficient for female was not statistically significant, meaning that having a female protagonist (versus a male protagonist) does not impact film success in any way in my data set and regressions. This is not what I was expecting to find — I thought the female coefficient would be negative for at least one of the regressions, because this could have helped explain the gender wage gap in film discussed by several authors in my literature review (Izquierdo Sanchez & Navarro Paniagua, 2017; De Pater et al., 2014). In my literature review Treme et al. (2019) found that for the films in their data set if a film star was male the film was expected to gross slightly more, and this is not consistent with what I found in my study. None of the interaction terms were of statistical significance for any of the regressions either. I had expected the coefficient on the interaction term between female and experience squared to be smaller than the coefficient on the interaction term between female and experience for at least one of the regressions, because this could have explained the gender wage gap in film widening with age (Izquierdo Sanchez & Navarro Paniagua, 2017; De Pater et al., 2014). Additionally, Lauzen hypothesized in two of her studies in my literature review that films with male protagonists receive higher reviews than films with female protagonists, but, again, I did not find this in my study.

Many of my control variables were statistically and economically significant in my regression equations, showing that there are other factors such as awards, genre, production company, budget, and theaters that instead are some of the factors influencing film success. In some of my regressions I got unexpected results about the sign and magnitude of some of these control variables, so in future research I suggest potentially including different control variables. For example, some of the papers in my literature review focused on the connection between gender and genre in their papers, but I was unable to draw any conclusion on this in my paper (Amaral et al., 2020; Fleck & Hanssen, 2016). I also suggest using a more varied data set beyond top grossing films, because this could shed light on overall trends and identify if my findings still hold true.

Based on my results I see no evidence that when a film has a female protagonist it is less successful. Despite these findings, female protagonists, as discussed earlier, earn significantly less than their male counterparts. My results suggest that this gender wage gap in the film industry is not a result of differences in film success related to differences in the gender of the protagonist. Economist, Gary Becker, studies the economics of discrimination, and in his theory he "suggests that discrimination reflects the taste of employers, coworkers, or customers," (Berson, 2016). My regressions suggest that differences regarding gender pay in film is not coming from customer tastes, because adjusted for other control variables, moviegoers are attending films the same (because there is no statistically significant difference in film total gross), and critics and audience members are rating films similarly whether there the protagonist is male or female.

Some steps towards gender equity in the film industry are emerging. For example, the #MeToo movement has strived to elevate the voices and rights of women in Hollywood and around the world; this movement gained national attention in Hollywood in 2017 when there were sexual assault allegations against producer, Harvey Weinstein (Langone, 2018). While this started as a movement to encourage women to speak up, it has evolved into a movement that also advocates for more equal and positive representation of women on and off the screen in the film industry (Langone, 2018). Another possible avenue for extending this paper would be looking at the #MeToo movement to see if this has had any influence on the relationship between gender and age and film success.

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Appendix

Manipulated Critic and Audience Reviews Variables Explanation

I needed to go through a series of equations in order to interpret my critic reviews and audience reviews regression results due to the fact I manipulated my critic reviews and audience reviews variables. In the equation below Y is critic or audience reviews depending on the regression, and Z is the transformed dependent variable. $Z = \frac{Y}{100-Y}$ However, rather than looking for the relationship between critic or audience reviews, Y, and dependent variable, Z, I am looking for the relationship between critic or audience reviews, Y, and independent variable, X. Thus I solved the initial equation for Y. $Y = \frac{100Z}{1+Z}$ Next I took the derivative with respect to the dependent variable, Z. $\frac{dY}{dZ} = \frac{100}{(1+Z)^2}$ I used the chain rule with the previous equation and the coefficient estimates beta to find the desired relationship between critic or audience reviews, Y, and independent variable, X: $\frac{dY}{dX} = \frac{100}{(1+Z)^2}\beta$ To solve this relationship for a numerical value, beta is the coefficient estimate, and the value of dependent variable, Z, can be found using the first equation. To solve the first equation for Z, I estimated Y by setting it equal to the mean of critic or audience reviews.