

Hollywood's Wage Structure and Discrimination

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Abstract

The labour market for actors remains mostly unexplored. In this paper, we start by analysing how Hollywood wages have changed over time. We then proceed to examine the determinants of wages. One of our key findings is that there are substantial wage differences among male and female actors in Hollywood. A Blinder-Oaxaca decomposition suggests that 55% of the differences in the gender-wage gap can be attributed to discrimination.

Keywords: Gender wage gap; discrimination; Superstars; Actors/Hollywood; Inequality

JEL Classification: J16, J31, J71, L82

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1. Introduction

During the last decades, a substantial literature has emerged on the so-called Economics of Superstars, i.e. the economics of people that earn enormous amounts of money in comparison to their colleagues, dominating the field in which they participate (Rosen, 1981). This literature has shed light on wage inequality and talent distribution in several labour markets, including sports, music and finance (Brandes et al., 2008; Franck and Nuesch, 2012; Giles, 2006; Ginsburgh and van Ours, 2003; Hamlen, 1991; Krueger, 2005; Lucifora and Simmons, 2003; MacDonald, 1988). Interestingly, a labour market that has not been explored in this context so far is that for Hollywood actors.

The lack of research in this area is unexpected for at least two reasons. First, the Hollywood movie industry employs more than 2 million workers per year, and is the largest of the creative industries - a sector that generates about 4 percent of the US GDP (National Endowment for the Arts and the US Bureau of Economic Analysis, 2012). Second, Hollywood constitutes an ideal example of the Superstar phenomenon: Hollywood stars comprise only a small fraction of the total number of Hollywood actors who appear in most of the movies released every year, and earn massively higher incomes than their peers even though, in some cases, differences in acting skills appear to be small (Terviö, 2011).

The first aim of this paper is to fill the existing gap in the literature by analysing a comprehensive dataset on wages and their determinants taken from IMDb and Box Office Mojo. We start our analysis by providing a pictorial representation of the long-run evolution of mean wages (adjusted for inflation). We show that, on average, Hollywood wages have been very high -consistent with the high incomes of the Superstar framework-, and display an upward trend throughout most of the twentieth century. We then proceed to explore the structure of wages. We find that the top 25 percent of actors earns between 50 and 80 percent of total wages, and that this fraction has decreased since the mid-1980s. Furthermore, by examining various measures of overall and upper tail wage inequality, we find that actors in the top 25 percent of the wage distribution earn about 5 times more than actors in the lower 25 percent of the distribution.

The second contribution of this paper is to investigate the existence of gender wage differences and discrimination among Hollywood actors and actresses. A notable example, which has appeared widely on different media sources, is the movie *American Hustle*.¹ For this movie, Christian Bale worked 45 days for \$2.5 million upfront and 9% of total profits, Bradley Cooper worked 46 days for \$2.5 million and 9% of total profits, while Amy Adams worked 45 days (same number of days as Christian Bale and just one day less than Bradley Cooper) and was paid \$1.25 million and 7% of total profits. In her speech at the 2015 Oscars, Patricia Arquette expressed the growing discontent among actresses regarding gender wage differentials, and further comments followed from Meryl Streep, Charlize Theron and Jennifer Lawrence over the topic of ‘equal pay for equal job’.

The research question of whether male actors are paid more than their female colleagues falls within the broader labour economics literature on gender wage differentials [see Blau and Kahn (2016) and Olivetti and Petrongolo (2016) for recent surveys]; and the non-negligible body of research that focuses on gender wage differentials among the highly paid (Bertrand and Hallock, 2001; Biddle and Hamermesh, 1998; Greg and Machin, 1993). Following previous studies, in this paper, we examine whether wages converge with actor’s years of experience by conducting a dynamic analysis of the gender gap in earnings (as in Bertrand *et al.*, 2010). We also conduct a Blinder-Oaxaca (1973) decomposition to determine the unexplained differences in the gender wage gap that can be attributed to discrimination. Finally, we discuss factors that can contaminate our discrimination measure.

2. Data

The data employed in this study is obtained from three main sources and, for most of the analysis, span the period from 1980 to 2015. The primary dataset, which is formed by salaries, gender, year of birth, ethnicity, nationality, Oscar’s awards and nominations, is downloaded from the biography section of the Internet Movie Database IMDb (www.imdb.com).³ Actors’ salaries are composed of a fixed and a variable compensation. The latter, which is a contingent compensation, depends on the film’s final box office

¹ See for example: <http://www.vanityfair.com/hollywood/2016/03/amy-adams-american-hustle-pay-gap>

² IMDb is one of the most visited entertainment webpages across the world:

<https://www.google.com/trends/explore?date=all&q=imdb>

revenues, and the corresponding cash breakeven point specified in the actor's contract (Caves, 2003; Epstein, 2012). Because we observe variable compensation with substantial measurement error, we focus (unless otherwise stated) on the fixed compensation part of salaries. If anything, this implies that the reported estimates are biased downwards, and thus our findings can be interpreted as conservative.⁴

The second data source is Box Office Mojo (www.boxofficemojo.com) which provides detailed information on release date, studio, lifetime box office revenues, total number of theatres, box office revenues the opening weekend, number of opening theatres, and labour market experience in its "People/Actors" section, as well as genre classification, MPAA rating, distributor, and production budget in its "Movie" section. Finally, data on TV and newspaper advertising expenditure for all Hollywood movies considered is obtained from Nielsen S.L.

Descriptive statistics and variable definitions for the variables in our sample are presented in Table 1. The sample consists of 1,344 movie-actor pairs, a total of 267 different actors, where 38% are female, 76% are US citizens, and 87% are white. Moreover, 16% have been nominated for an Oscar Academy award at least once, and 8% have won one or more Oscars for best leading character.

INSERT TABLE 1

In Table 1, we observe that most Hollywood movies, with the exception of those that gain positive word of mouth, earn their maximum box-office revenue in the first week of release. Gross box-office revenue in the opening weekend account for 26% of lifetime gross earnings, and the number of opening theatres constitutes 93% of the total lifetime number of theatres the movie will ever be shown at. The majority of movies in our sample, 70%, are distributed by the six big studios. These studios include Buena Vista, Twentieth Century Fox, Universal, Warner Brothers, Paramount and Sony-Columbia. The studio and distributor dummy coincide since studios tend to own distribution chains. Movies are high risk products due to the high cost of production and the uncertainty of success previous to the release. For this reason, as a way of minimizing risk we observe vertical integration between the initial agents of the supply chain, as it happens in other double sided and high risk markets such as that of Videogames (Gil and Warzynski, 2014; Grossman and Hart, 1986; Kranton and Minehart, 2000).

⁴ Results in the robustness checks section indicate that wage gaps using the fixed part of the actor's salary are smaller than those obtained when both fixed and variable compensation is considered.

Table 1 also shows the distribution of movies across genres. The three most common genres are Action, Comedy and Drama which account for 21.6%, 22% and 15.5% of the total number of movies, respectively. The corresponding figures for total box office revenues in our sample are 30%, 19% and 8% and 47%, 19% and 7% if we only consider movies released from 2010 onwards. The increasing importance in the box office of car crashes, special effects, superheroes and action in general is driven by the fact that 80% of movie goers these days are teenagers. Teenage audiences are the easiest to engage through not only TV advertising but also merchandising, tie-ins with fast food restaurants, toy companies, and other retailers. Teenagers are also avid consumers of soft drinks, snack foods and popcorn, which is the main source of profits for movie theatres. This trend of teenage movie goers is also reflected in the fact that 43% of the movies in our sample are recommended for people that are 13 and over and thus are classified with a PG-13 rating.

3. Empirical evidence

3.1. Long-run wages evolution

Although the above descriptive statistics and the econometric analysis of the paper are restricted to the period from 1980 to 2015 due to data availability,⁵ actors' salary data exists in the IMDb which dates back to 1927. These data allow us to have a look at wage trends in the very long run. Figure 1 displays the evolution of mean wages in real terms⁶ for the extended sample period. It is evident from the figure that, following an early period of stagnant wages up to the 1950s, wages have massively increased starting from below one million 1983 dollars in 1960, and reaching almost 5 million 1983 dollars in 2015. The observed time pattern and the extravagant salaries paid to actors in the most recent period are in line with changes in the Hollywood industry.

First, starting in the 1920s, a 'studio system' was in place in Hollywood, which forced actors to have exclusive contracts binding them to a specific movie studio for seven years. The fact that actors could not renegotiate their contract with the studio within this seven-year period implied that studios were enjoying most of the rents. The studio system broke down in the

⁵ Actor's wage availability before 1980 suffers from a couple of data quality related issues. From 1927 to early-1979, we observe wages for very good and well established actors at the beginning of their careers. We do not consider these observations in our econometric analysis not only due to the fact that they are thin but they correspond to wages of top stars and therefore will bias our average mean wages upwards.

⁶ Specifically, our salary measure is gross earnings per movie deflated by the annual consumer price index series obtained from Robert Shiller's website: <http://www.econ.yale.edu/~shiller/data.htm>

(early) 1950s, allowing actors to negotiate contracts on the spot, and thus increasing their bargaining power. This development together with the fact that studios widely recognize that a film's production and success crucially depends on the popularity of its casting, may well have resulted in Hollywood actors receiving a larger part of a movie's revenue (De Vany, 2004; Elberse, 2007; Epstein, 2012).⁷ Second, Hollywood's capacity to generate high incomes has also been increasing through time. Although revenues from cinema attendance have declined since the 1950s, revenues from other sources have increased.⁸ These days, studios make billions of dollars from distribution fees, and raise substantial funds from investors who are willing to get a tax credit relief both in the US and abroad, hedge funds, worldwide theatrical, pre-sales agreements to sell rights to foreign markets, product placement agreements with brands, licensing income, and government subsidies (Epstein, 2012).⁹ Both, the increase in bargaining power of Hollywood actors and the increase in movie revenues, can help to explain the stagnant first phase, and the upward trend of the second period.

INSERT FIGURE 1

3.2. Wage inequality

The fact that average actor earnings have increased substantially over the last decades, does not necessarily imply proportional increases in all parts of the wage distribution. Dramatic differences exist between high and low earners in Hollywood, and it may well be the case that wage inequality has changed over time.

Figure 2 plots the entire earnings distribution for 2006. As can be clearly seen from the figure, the distribution is highly skewed with large differences in earnings between the Hollywood stars and the second ranked actors. The share of wages owned by the upper quartile of the earnings distribution in 2006 amounts to 68%, whereas the income share owned by the bottom quartile accounts for less than 1% of total earnings. Most notably, the best ever paid actor in our sample, Tom Cruise, received 75 million dollars in nominal terms

⁷ Stars only increase the odds of favourable events that are highly improbable (De Vany, 2015).

⁸ The economic mechanism of how the movie industry makes his money has changed dramatically throughout the twentieth century. In Hollywood's golden age (1920s-1940s) studios owned the major theatre chains and were making their profits out of theatre ticket sales. However, weekly cinema attendance has been declining since the early 1950s and studios do not make most of their money out of the box office anymore (Moretti, 2011; Pautz, 2002).

⁹ This licensing includes pay-TV, cable networks, television stations around the world, video stores, DVDs, Blu-rays, hotels and in-flight entertainment, video games, toy licencing, i-tunes, and other digital downloads.

in 2006 for Mission Impossible III, while the worst paid actor in the same year received 66 million less (Ryan Gosling in Half Nelson).

INSERT FIGURE 2

An interesting empirical regularity of the Hollywood industry is that these huge differences in earnings among actors can be coupled with small differences in acting skills, which are not discernible by the majority of movie goers (Rosen, 1981). In fact, a hierarchy in wages can exist even if there are no differences in talent (Adler, 1985). A potential explanation is that the large earnings inequality is not driven by talent scarcity but arise due to the way talent is discovered in the motion picture industry (Terviö, 2011). Talent, in this case, is industry-specific and differences in acting skills are only discovered on the job, and once revealed are publicly observed. How talent is discovered leads to a market failure in the form of an inefficiently low level of output and high wages being paid to ‘superstar’ actors.

Having looked at wage inequality in earnings of Hollywood actors in a specific year, we now proceed to examine how inequality has evolved in the last decades. A priori, one would have expected an increase in wage inequality to have taken place following the general trend in the US (Piketty and Saez, 2003), and also due to new technologies, which allow movies to be distributed to millions of people in the form of DVDs and streaming of online videos. A look at Figure 3, which shows the evolution of the income shares (in percentages) of the different quartiles of the wage distribution from 1980 to 2015, suggests that this hypothesis is not supported by the data. The income share of the top quartile started at around 70%, it declined substantially in the mid-2000s to around 50%, and then it remained stable at that level until the end of the sample. On the contrary, the share of wages owned by the lowest quartile (bottom 25%) remained stable throughout the whole period of study. Thus, it seems that the upward trend in actors’ wages that we observe in Figure 1 is driven by the third and second quartiles of the earnings distribution which have been gaining through time.

INSERT FIGURE 3

To shed further light on the wage structure, Figure 4 plots three different measures of aggregate wage dispersion. The first illustrates the evolution of the standard deviation of log earnings of actors. The second is a measure of changes in overall wage inequality summarized by the 75-25 log wage gap in earnings, and the third displays differential changes in inequality in the upper half of the wage distribution summarized by the 75-50 log wage gap. According to the figure, the earnings ratio between the 75th and 25th percentiles

from 1980 to 2015 is downward sloping until around the 2000s and then remains constant. In the 80s, actors at the 75th percentile of the earnings distribution earned about 7 times as much as actors in the 25th percentile. To have an idea of the magnitude, the 90-10 earnings ratio is 3.2 for economists and 2.4 for high school teachers. This log wage gap decreased by a factor of three by the early 2000s and from then onwards remained steady. Actors at the 75th percentile of the earnings distribution earn about 1.5 to 2 times as much as actors in the 50th percentile.

INSERT FIGURE 4

A potential concern in the decline in inequality is sample selection, i.e. that our sample is not representative of the population of movies. To investigate this possibility, we compare the evolution of inequality for box office revenues and for production budgets in our sample with a much larger sample (for which actor wages are not available) taken from Box Office Mojo. Figure A.1. in the Appendix shows that inequality between movies in terms of box office revenues and production budget has been increasing, following a similar pattern, in both samples. This suggests that movie-actor pairs do not suffer from biases associated with sample selection issues.

3.3. Determinants of wages

In this section, we move on to examine the determinants of wages in the film industry. In order to do this, we start by estimating the following standard earnings equation by OLS:

$$w_{ijt} = \alpha_0 + \beta_1 X_{it} + \beta_2 Y_j + \varepsilon_{ijt} \quad (1)$$

where w_{ijt} is our dependent variable that represents actor i wages for film j in period t , X_i is a vector which contains actor characteristics in time t such as gender, age, nationality, ethnicity and acting experience, Y_j is a vector which comprises both qualitative and quantitative film characteristics, and ε_{ijt} is the error term. The qualitative characteristics of films are genre, distributor and MPAA ratings. The quantitative characteristics of films include production budget, box office revenues and number of screens in which the film is projected.

We adopt an augmented specification procedure which consists of, initially, estimating regression (1) using year dummies and the dummy variable *female* (which captures the overall gender wage gap), and then extending the set of regressors sequentially. To draw statistical inference, we cluster standard errors at the actor level for all regressions. Table 2

shows the estimation results. Starting with the baseline model (Column 1), the coefficient estimate on the dummy variable *female* indicates that female actors earn on average around \$2.180 million less than male actors (this implies that, on average, females earn 56 percent less than males). Although this gap decreases when we include other regressors, it is still statistically significant and negative across columns. Specifically, by including actor characteristics (Column 2) the wage gap drops to \$1.465 million, and by adding the qualitative characteristics of movies (Column 4), the wage gap falls further to \$1.354 million. This is not surprising, given that there is some tendency for women to be concentrated in lower-paying movie genres. Finally, when we include actor's characteristics, and the qualitative and quantitative characteristics of movies (Column 7), the wage gap takes the value of \$1.319 million (which is around 28 percent).

INSERT TABLE 2

Turning to the other determinants of wages, an interesting result is that the coefficients on age and experience are statistically significant and positive for every specification, and that the coefficient for both terms squared is negative. This result indicates that wages increase with both age and experience, but there is a point beyond which as actors gain years of experience their wages decrease. With regards to movie-genre, we find that War, Comedy, and Action movies tend to pay higher salaries to their cast. Actor's wages are also found to be higher when i) the film has been produced and distributed by one of the big six studios, ii) the MPAA rating of the film is PG or PG-13, and iii) the film is successful, a blockbuster. The latter finding may be attributed to the higher preliminary expected demand: As the number of theatres increases, potential films with an expected high initial demand are more likely to end up being a blockbuster¹⁰ than the rest of films on screens, and so predicted successful films will be shown in a higher number of screens as exhibitors (Moretti, 2014). Similar results and conclusions can be derived from the production budget coefficient. A high budget production is considered a signal of potential success, producers spend higher amounts in advertising these movies and so they are more likely to become blockbusters. The expected higher revenues translate into higher actors' wages.

Following previous research papers, we have also examined the importance of Oscar nominations and awards in the Appendix (examples include Deuchart *et al.*, 2005; Gumbel *et*

¹⁰ However, several examples can be observed in the film industry across years. See for example *Tinker, Taylor, Soldier, Spy* in 2011 whose demand started to be moderated and it will not be until weeks later, due to word of mouth, that audience considerably increased becoming a blockbuster. These types of movies which exceed expectations are called in the jargon literature "sleepers or late-burners".

al., 1998, and Nelson *et al.*, 2011). Our results suggest that an Oscar nomination or an Oscar award does not have a clear and significant effect on wages.

3.3.1. Fixed Effects estimation

In order to examine whether, conditional on the same movie, wages differ between genders we extend regression (1) to allow for movie-specific fixed effects:

$$w_{ijt} = \alpha_j + \beta_1 X_{it} + \beta_2 Y_j + \varepsilon_{ijt} \quad (2)$$

The results reported in Column 1 of Table 3 show that a female actor earns on average around \$2.187 million less than a male actor when controlling for individual movie fixed effects, a coefficient which is nearly identical to that in the previous Table 2 (-2.180). Furthermore, adding extra controls does not reduce substantially the remaining gender compensation gap (Columns 2 to 7 in Table 3). For instance, when we include actor background characteristics (Column 2) the wage gap drops to \$1.5 million, and when we include both actor's characteristics and the qualitative characteristics of movies (Column 4) the wage gap becomes \$1.52 million. Columns 3 to 6 show that the female dummy variable stays unchanged when we add film invariant characteristics such as MPAA ratings and number of theatres, respectively. Finally, when we include all the regressors (Column 7), again we observe a slight decrease in the wage gap compared to the baseline, but the gap remains statistically significant and negative, around -1.548 million. Overall, the above results suggest that female and male actors receive differential treatment in terms of compensation within the same movie.

INSERT TABLE 3

3.3.2. Robustness Checks

We conduct a set of robustness checks by considering i) a dependent variable which includes both the fixed and variable parts of an actor's salary, ii) cohort specific dummies, and iii) log-level regressions. Table A.2 in the Appendix presents estimation results for these new specifications using the same set of covariates as in Section 3.3. The main conclusion that emerges is that, irrespective of the specification, the gender wage gap differential is negative and statistically significant. The most conservative estimate, which corresponds to the log-level regression with cohort fixed effects and all the covariates, indicates a difference in

compensation of around 39% between male and female actors that play in the same movie. These findings corroborate those of Olivetti and Petrongolo (2008, 2016) for the US. By using various imputation rules to take into account selection, the authors obtain a range for the median wage gap from 33.4 to 43.2 log points.¹¹

3.4. The gender wage gap

The above empirical findings highlight actor's gender as one of the main determinants of wages. In this section, we focus on the behaviour of the pay differences between male and female actors. We first look at summary statistics of gender wage gaps and their evolution over time, and then adopt a simple linear regression framework to explore how much of the wage gap can be attributed to factors such as experience, gender segregation by movie genre, and the under-representation of female actors in blockbusters.

Table A.3 presents summary statistics for the variables in our sample by gender. The average wage (in millions of 1983 dollars) is 4.85 for actors and 2.72 for actresses, resulting in a raw wage gap of 2.13 million, and a female to male wage ratio of 0.56. A longitudinal perspective is presented in Figure 5, which plots raw male and female average real earnings from 1980 to 2015. In line with our previous analysis, we can observe that average salaries for both genders have been increasing over the last three decades. By comparing the two lines, we also see that there is a substantial wage gap, which persists throughout time. The persistence of the gender gap in Hollywood is particularly interesting given that the existing literature shows that US female to male wage ratios for full time workers have been converging over the last decades. Specifically, starting from 62.1% in 1980, wage ratios increased substantially in the 1980s, reaching 74.0% in 1989, and continued to converge afterwards but at a slower rate, reaching 77.2% in 1998 and 79.3% in 2010 (Altonji and Blank, 1999; Blau and Kahn, 2006, 2016; Blau, Ferber and Winkler, 2014).

INSERT FIGURE 5

Like in Section 3.3, the regression analysis of this section is based on equation (1), and utilizes a baseline model which includes year dummies and the gender variable. Results for this model are reported in Column 1 of Table 4. Columns 2 to 4 report results for three models that extend the baseline by including additional covariates. The first model includes age, experience and the square of these two variables; the second incorporates movie-genre

¹¹ Blau and Kahn (2016)'s estimated wage gap for the US amounts to 0.47.

dummy variables; and the last augments the baseline model with box-office revenues. Data for box-office revenues are not available for the entire sample of movies. To permit direct comparisons with the baseline, we estimate the baseline using the available subsample, and report the results in Column 5.

INSERT TABLE 4

With regards to age and experience, female actors are significantly different from their male counterparts in our sample. Actresses are, on average, 6 years younger and have 4 fewer years of experience (experience is measured as number of years since first movie appearance). We expect the relative youth and the lesser labour market experience of actresses to be an important determinant of the gender gap. Columns 1 and 2 of Table 4 show that this is indeed the case. Controlling for age and experience significantly reduces the gender gap coefficient from an original -2.180 to -1.538. That is, these two factors help to explain around 29% of the difference in compensation between genders.

Another potentially important determinant of the wage gap is gender segregation. Evidence on occupational sex segregation in other industries suggests that wage levels are substantially lower in predominantly female occupations (Killingsworth, 1990; Macpherson and Hirsh, 1995). Segregation patterns can partly be explained by a gender identity issue by which females tend not to participate in some types of occupations that are traditionally male dominated (Akerlof and Kranton, 2010). Like in other professions, we find that female actors also appear not to be allocated randomly across different types of movie genres. Specifically, in our sample, only 23.5%, 21%, and 26% of the cast in War, Action and Adventure related movies is female, which are the genres where wages are the highest (Table A.4 in the Appendix).¹² Looking at the regression results, a comparison of Column 1 and Column 3 reveals that incorporating genre specific dummies reduces the gender gap coefficient by 11%, from -2.180 to -1.934 million.

As discussed above, actors appear to receive higher wages for blockbuster movies. Column 4 of Table 4 shows results for the wage gap controlling for final box office revenues, and Column 5 presents results for the corresponding baseline model estimated on the available

¹² In Table A.4 in the Appendix, we observe that wages are higher for Oscar nominees, Oscar winners, actors if the movie was distributed by one of the Big six studios, and actors if performing in a movie rated as PG-13.

subsample of data. We observe that only 7% of the gender gap can be accounted for by the differential representation of female actresses in Blockbusters.

In summary, we find that age, experience, and genre segregation play an important role in explaining the gender wage gap. On the other hand, we find no evidence of a systematic allocation of actresses in low budget movies that leads to substantially lower wages.

3.4.1. Dynamics of the Gender Wage Gap for Actors

Figure 6 shows the actor and actress mean annual salaries (in million of 1983 dollars) by years since first movie appearance. The results show that from the beginning salaries are higher for actors than for actresses. This difference in wages notably increases from 2 to 3 years of experience, but after 4 years it starts to converge. Finally, actresses' salaries overtake actors', but from 17 years of experience wages are again higher for male than for female actors. The film industry market is highly competitive, there are thousands of actors and actresses trying to get a job but very few of them are demanded by the studios and audiences. Furthermore, both male and female actors are sometimes employed not just for their acting skills but also for their external appearance. Research from other markets suggests that this may make the careers longer for male than for female actors, and so the market dries up sooner for poor acting skilled actresses than for equivalent actors (Hamermesh and Biddle, 1987). However, poor skilled actors will soon also be removed from the market, and after a specific age and length of experience, both actors and actresses that remain will be the high skilled ones and the ones more demanded by the public and the industry. It is possible that at this stage the wage difference begins to converge.

INSERT FIGURE 6

In this section, we conduct a dynamic analysis of the gender wage gap as per Bertrand *et al.*, (2010) in order to find out whether the gender wage gap disappears and thus wages converge with actor's years of experience. We do this by examining the effect that years of experience have on the actor-actress wage gap. Using an OLS methodology we estimate the following regression:

$$w_{ijt} = \alpha_0 + \beta_1(F_i * E) + \beta_2X_i + \beta_3Y_j + \varepsilon_{ijt} \quad (3)$$

where $(F_i * E)$ represents the interaction between the dummy variable *Female* and several dummy variables that correspond to a set of *years of experience dummy variables* for actor i when acting in film j in period t .

Table 5 shows the results for equation 3. The first specification shows the results for our baseline specification, we observe that the wage gap decreases at a smooth rate with years of experience but we are not able to see a convergence. The same can be concluded for specifications 3 to 6, indeed the convergence we observed in Figure 6 cannot be seen in Table 5 until we include production budget in specification 7, and even then, after 10 years of experience the results show that the wage differential decreases but there is still a wage differential after 10 years of experience.

INSERT TABLE 5

3.4.2. Blinder-Oaxaca decomposition

In the subsequent analysis, we investigate the extent of discrimination against female actors by providing a quantitative assessment of the sources of actor-actress wage differences. Our measure of discrimination is based on the established Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973). This approach divides the raw wage gap between actors and actresses in two components:

$$\Delta\omega = \underbrace{(\alpha_{actor} - \alpha_{actress})}_A + \underbrace{(\beta_{actor} - \beta_{actress})\bar{X}_{actress} + \beta_{actor}(\bar{X}_{actor} - \bar{X}_{actress})}_B \quad (4)$$

The first component (A) corresponds to the part of the wage differential that is explained by group differences in observed characteristics such as years of labour market experience, Oscar awards, genre classification and MPAA ratings. The second component (B) corresponds to the remaining part that cannot be explained by group differences in wage determinants. This latter component is thus a measure of discrimination. As can be seen from equation (4), the Blinder-Oaxaca discrimination measure may be confounded by differences in unobserved variables which are relevant in explaining the actor-actress wage gap. We discuss potential factors that can lead to biases in the discrimination measure in the next section.

Table 6 shows the results for the Oxaca-Blinder decomposition when movie fixed effects are taken into account. Looking at the second specification, where just the actor characteristics

are included in the regression, differences in endowments account for about 37% (0.617/1.657) of the wage gap. The remaining 63% of the actor-actress differences in wages cannot be explained by differences in observed characteristics, and hence it is attributed to discrimination. When both actor background, and film quantitative and qualitative characteristics are included (specification 7), 55% of wage differences are attributed to discrimination.

INSERT TABLE 6

Although we view our unexplained wage gaps of 55% in the movie fixed effects estimations as remarkably large magnitudes, if we put these numbers into perspective, they lie between the unexplained wage gaps estimated by Blau and Kahn (2016) using the PSID for the US population. Specifically, their unexplained wage gaps are 71.4% in 1980 and 85.2% in 2010 for their human capital model, and 48.5% in 1980 and 38% in 2010 for their full specification model.

3.4.2.1. Unobserved Characteristics

While the unexplained gender compensation gap can be interpreted as evidence for taste discrimination against female actors, it could also be due (at least partially) to unobservable factors, such as differences in labour market flexibility, and attitudes towards risk and competition (see, e.g., Croson and Gneezy, 2009, for a survey). With regards to labour market flexibility, Bertrand *et al.*, (2010) find that females are more affected than males by workforce interruptions and shorter hours associated with motherhood. However, Hollywood actors do not have a traditional 9 to 5 working day, and are less credit constrained, thus motherhood penalties are expected to be lower for female actors in comparison to other professions.¹³

Regarding risk and competition preferences, Blau and Kahn (2016) conclude that psychological factors do account but only for a small to moderate portion of the economy-wide gender pay gap. Bertrand (2011) and Croson and Gneezy (2009) show that women are less likely than men to engage in competitive interactions such as negotiations (see also Rigdon, 2003; Card *et al.*, 2015); and Babcock *et al.*, (2006) show that avoiding negotiations can have consequences on pay.

¹³ Actors are subject to travel commitments.

The literature on personnel economics finds that women are less likely to have jobs with pay for performance than men (e.g., Niederle and Vesterlund, 2007; Manning and Saidi, 2010). This lower likelihood of opting for performance pay is typically attributed to women being more risk averse than men (Bertrand, 2011). Our dataset allows us to identify the actors who receive variable pay and in turn examine whether females are less likely to be paid on performance. We estimate variants of the model in equation (1) where the dependent variable is a dummy which takes value 1 if the actor gets any type of variable pay and 0 otherwise. If we view the variable part of the salary as performance related pay, the marginal effects from a probit model show that females are 4.2 percentage points less likely to be paid based on their performance; over a baseline of 0.069, this amounts to female actors being 61% less likely to get variable pay.

In summary, although there may be unobserved characteristics which explain part of the gender wage gap in Hollywood, their overall effect is most probably small, and should not substantially bias our estimated discrimination measure.

4. Conclusions

Following recent declarations from well-known actresses in the film industry this paper shows evidence of gender discrimination in the industry. The results are important for two main reasons, first the film industry is the largest of the creative industries, contributing the most in terms of GDP. Second it is an industry with a substantial influence on consumer behaviour. The impact of this paper not only highlights the current issues regarding superstars payments but also, given the exposure that the film industry the existence of this discrimination could lead to similar practises across other sectors.

To analyse wages and wage differentials in the film industry, we use an original dataset which comprises data for 267 actors and 1,344 movies from 1980 to 2015. First, we use a statistical analysis to shed light on the evolution of wages and the wage structure. We find that the labour market for Hollywood actors is characterized by a high level of wages, 4 million dollars on average, which is mainly driven by the upper-tail of the earnings distribution.

Second, we analyse the determinants of wages using an OLS and a movie fixed effects methodology, this analysis helps us to identify wage differences between actors and actresses. We find that female actors earn on average around 2.2 million dollars less than male actors.

From this wage differential, sex segregation by movie genre appears to explain around 11% of the gender gap. A difference in compensation of 1.319 and 1.548 million dollar still exists between male and female actors after we account for actor and movie characteristics, in the OLS and movie fixed effects specifications, respectively. This result is remarkably large, especially when compared with a study of high-level executives conducted by Bertrand and Hallock (2011) but not compared to wage gaps found in the literature for the US population (Blau and Kahn, 2016; Olivetti and Petrongolo, 2016).

Once the gender wage gap has been identified, we use a Blinder-Oaxaca decomposition methodology to investigate the extent of discrimination against female actors. We find that the unexplained gender compensation is between 65% (OLS) and 55% (FE) after one account for all observable differences between male and female actors. This unexplained gender compensation gap can be attributed to a taste for labour market discrimination against female actors. This discrimination measure is unlikely to suffer from substantial biases since gender differences in flexibility and attitudes towards risk and negotiation among the population of actors are expected to be smaller than those in the general population.

Finally, we study actors and actresses wage differentials by years since first movie appearance in order to analyse whether the gender wage gap disappears with years of experience. Our findings carry important implications for pay equity policies that aim to narrow the gender wage gap in the Hollywood industry. For instance, making contracts not blinded in the film industry and thus providing social information about what other co-stars earn can reduce the negotiation gap and therefore the residual wage gap.

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Figure 1. Actors' average real wages, 1930-2015 (1983=0)

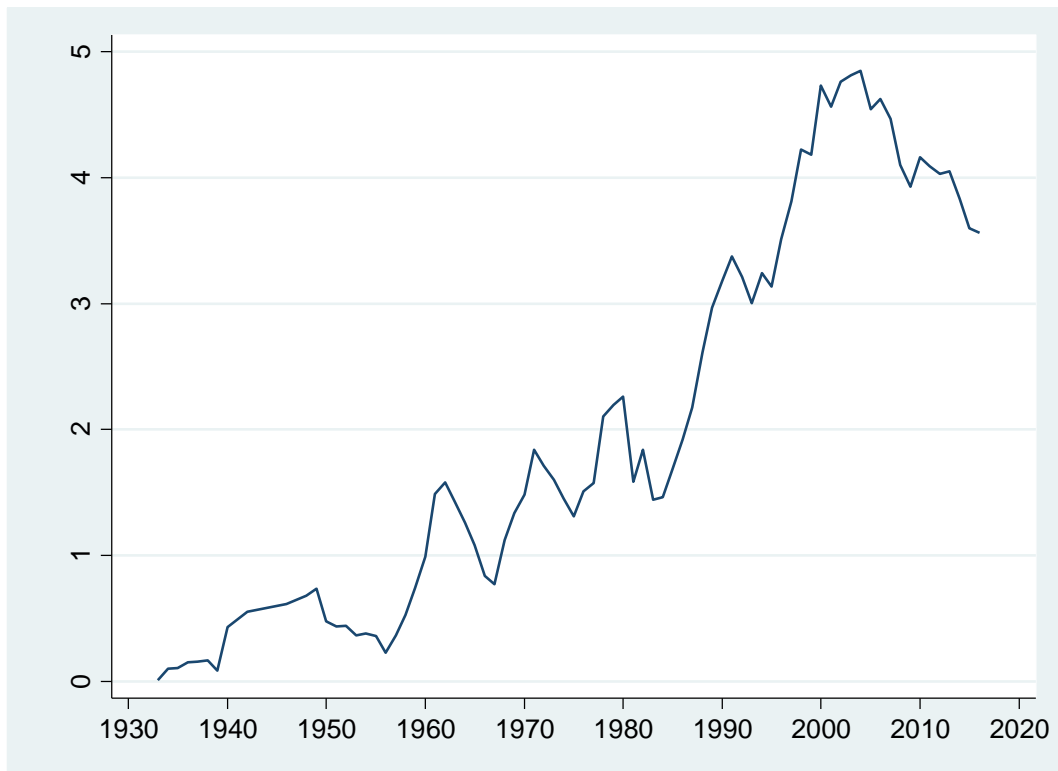


Figure 2. Histogram of Actor's Earnings for 2006

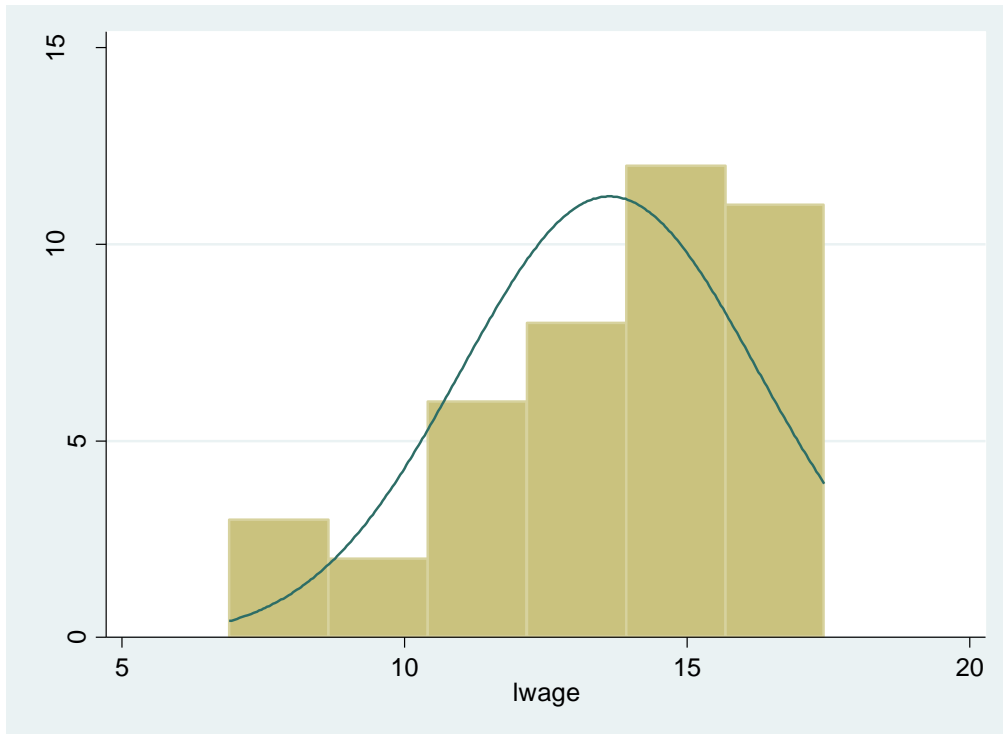


Figure 3. The Wage Income Shares in the Top and Bottom Quartiles, 1980-2015

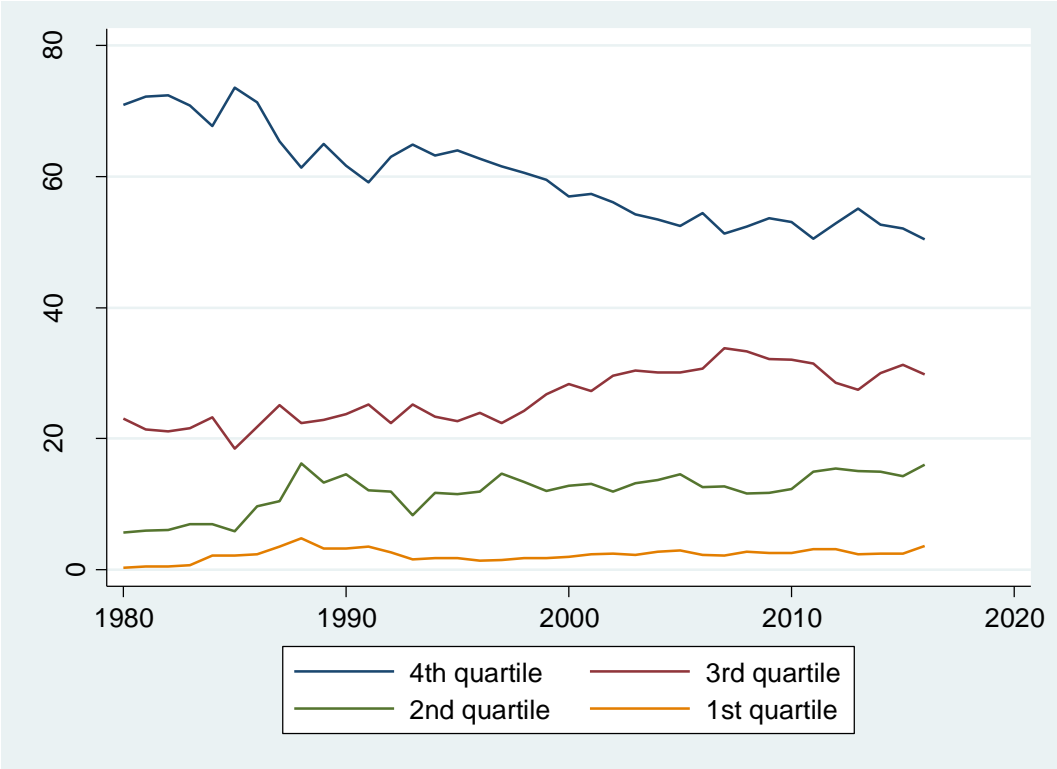


Figure 4. Overall and upper-half Wage Inequality

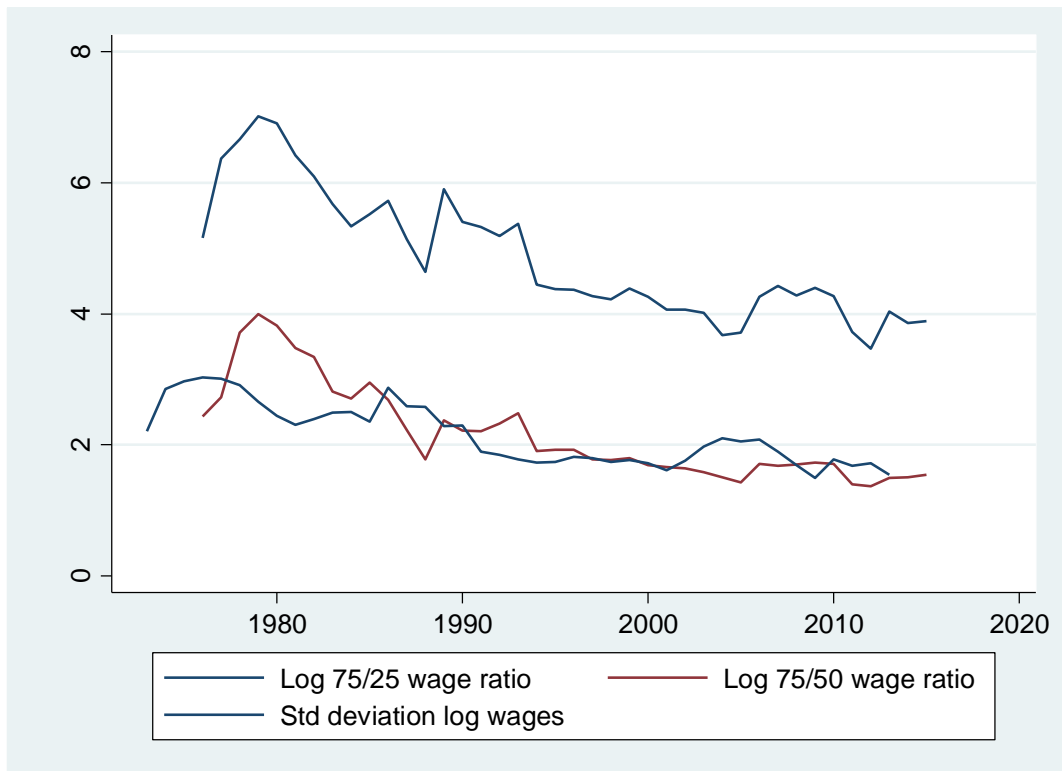


Figure 5. Actor and Actress Mean annual salaries, 1980-2015

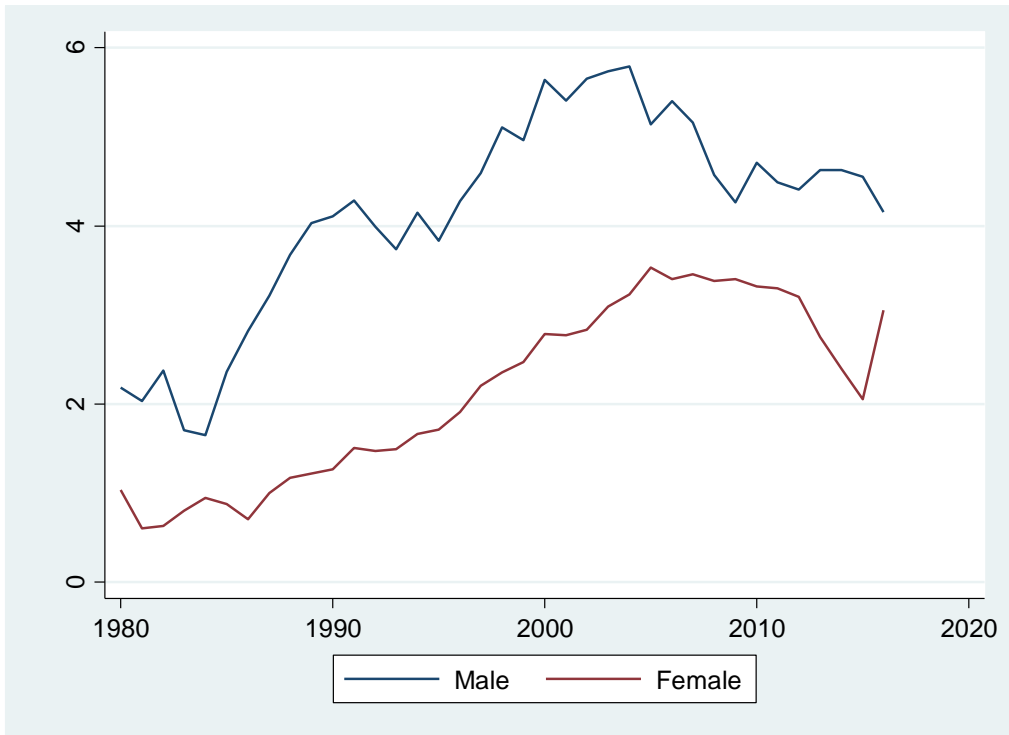


Figure 6.1. Male and Female wages by years since first movie appearance

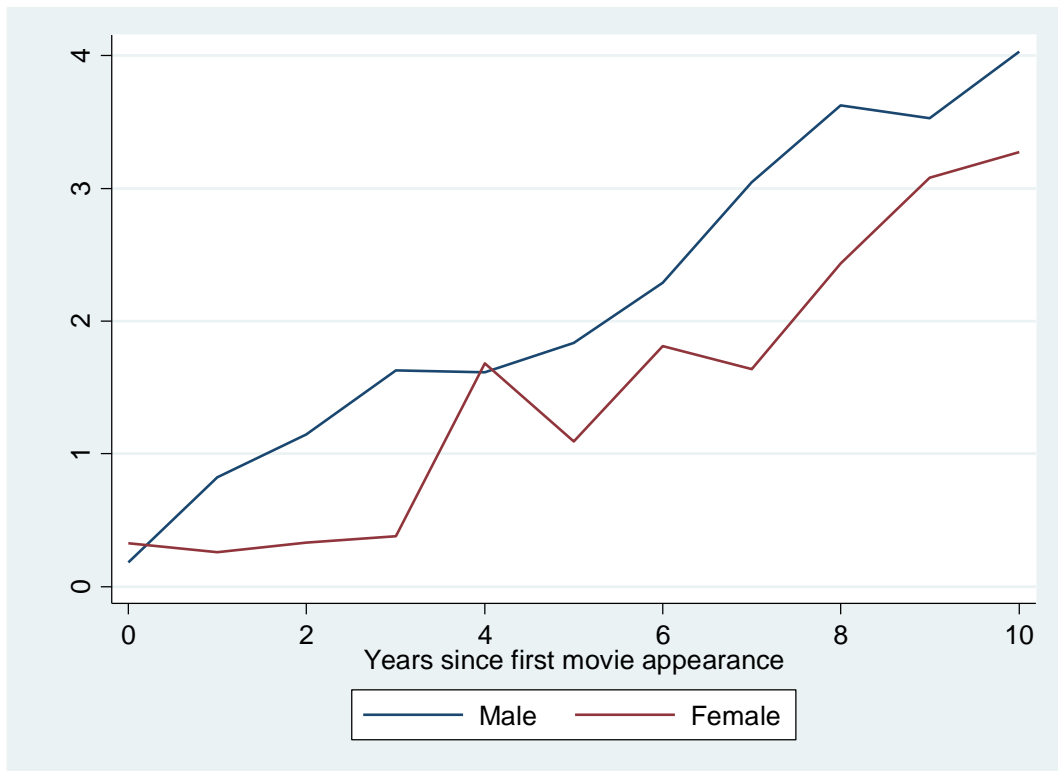


Figure 6.2. Male and Female wages by years since first movie appearance

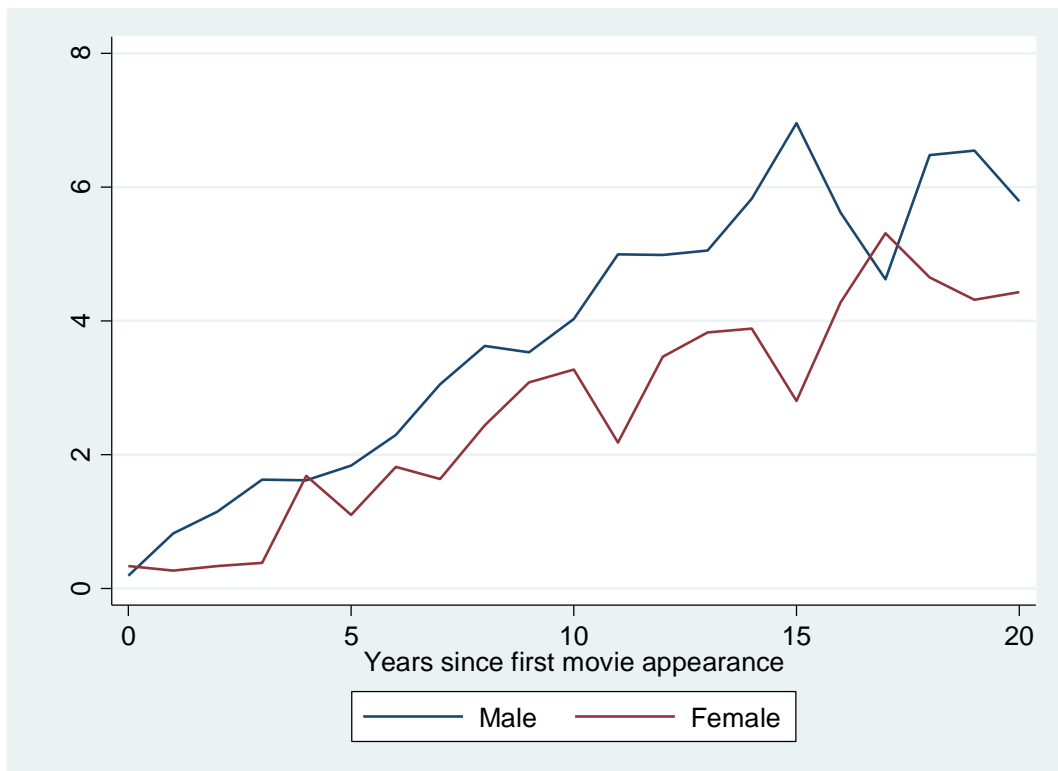


Table 1. Descriptive Statistics and variable definitions

Actor Characteristics	Mean	Std. Dev.	Variable definition
Salary (fixed)	4.09	4.53	Salary earned independently of the film performance.
log(wage) (fixed)	14.27	1.98	
Salary (fixed + variable)	4.38	5.12	Fixed salary plus % of final box office revenues previously agreed
Log(wage)(fixed + variable)	14.31	1.99	
Female	0.35	0.47	Dummy variable: 1=actress; 0=actor
Age	36.02	11.29	
Minor role	0.02	0.15	Dummy variable: 1=minor role played in film j ; 0=otherwise
Experience	14.20	10.19	Number of years acting before performing in film j
Race: Asian	0.01	0.11	Dummy variable: 1=Asian background; 0=otherwise
Race: Black	0.08	0.27	Dummy variable: 1=Black background; 0=otherwise
Race: Other	0.02	0.13	Dummy variable: 1=Other background; 0=otherwise
Race: White	0.88	0.32	Dummy variable: 1=White background; 0=otherwise
Nationality: USA	0.79	0.4	Dummy variable: 1=USA nationality; 0=otherwise
Oscar: Nomination supportive role	0.17	0.47	Number of times actor/actress i has been nominated to an Oscar prize for best supportive role.
Oscar: Nomination main role	0.33	0.71	Number of times actor/actress i has been nominated to an Oscar prize for best leading role.
Oscar: won main role	0.12	0.37	Number of times actor/actress i has won an Oscar prize for best supportive role.
Oscar: won supporting role	0.06	0.24	Number of times actor/actress i has won an Oscar prize for best leading role.
Won at least 1 Oscar: main role	0.06	0.24	Dummy variable: 1=Actor/actress i has won at least one Oscar for best leading role before acting in film j ; 0=otherwise
Won at least 1 Oscar: supporting role	0.22	0.41	Dummy variable: 1=Actor/actress i has won at least one Oscar for best supporting role before acting in film j ; 0=otherwise
At least 1 Oscar nomination: main role	0.14	0.35	Dummy variable: 1=Actor/actress i has been nominated at least to one Oscar for best leading role before acting in film j ; 0=otherwise

At least 1 Oscar nomination: supporting role	0.70	0.45	Dummy variable: 1=Actor/actress <i>i</i> has been nominated at least to one Oscar for best supporting role before acting in film <i>j</i> ; 0=otherwise
Film Characteristics	Mean	Std. Dev.	Description
Lifetime gross	91.88	94.83	Lifetime gross of movie <i>j</i>
Opening gross	23.63	30.58	First week gross of movie <i>j</i>
Theatres	2,402.4	1,044.6	Total number of theatres in which movie <i>j</i> was played.
Production Budget	71.47	50.83	Production budget of movie <i>j</i>
Distributor: big 6	0.7	0.45	Dummy variable: 1=if film <i>j</i> was produced-distributed by one of the big 6 Hollywood studios; 0=otherwise
Genre: Action	0.22	0.41	Dummy variable: 1=if the genre film <i>j</i> is Action; 0=otherwise
Genre: Adventure	0.05	0.22	Dummy variable: 1=if the genre film <i>j</i> is Adventure; 0=otherwise
Genre: Comedy	0.22	0.42	Dummy variable: 1=if the genre film <i>j</i> is Comedy; 0=otherwise
Genre: Crime	0.06	0.24	Dummy variable: 1=if the genre film <i>j</i> is Crime; 0=otherwise
Genre: Drama	0.15	0.36	Dummy variable: 1=if the genre film <i>j</i> is Drama; 0=otherwise
Genre: Other	0.16	0.37	Dummy variable: 1=if the genre film <i>j</i> is Other; 0=otherwise
Genre: Thriller	0.11	0.31	Dummy variable: 1=if the genre film <i>j</i> is Thriller; 0=otherwise
Genre: War	0.01	0.11	Dummy variable: 1=if the genre film <i>j</i> is War; 0=otherwise
MPAA: G	0.01	0.12	Dummy variable: 1=if film <i>j</i> was classified G; 0=otherwise
MPAA: NC 17	0.01	0.09	Dummy variable: 1=if film <i>j</i> was classified NC-17; 0=otherwise
MPAA: PG	0.12	0.33	Dummy variable: 1=if film <i>j</i> was classified PG; 0=otherwise
MPAA: PG 13	0.43	0.49	Dummy variable: 1=if film <i>j</i> was classified PG-13; 0=otherwise
MPAA: R	0.41	0.49	Dummy variable: 1=if film <i>j</i> was classified R; 0=otherwise
MPAA: U	0.1	0.3	Dummy variable: 1=if film <i>j</i> was classified U; 0=otherwise

Table 2. Determinants of Actors' Wages, OLS estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-2.180*** (0.434)	-1.465*** (0.425)	-1.319*** (0.391)	-1.354*** (0.386)	-1.256*** (0.359)	-1.188*** (0.330)	-1.319*** (0.424)
Age		0.274*** (0.063)	0.230*** (0.061)	0.218*** (0.062)	0.265*** (0.061)	0.269*** (0.058)	0.243*** (0.070)
Age ²		-0.361*** (0.077)	-0.304*** (0.073)	-0.284*** (0.072)	-0.332*** (0.069)	-0.336*** (0.067)	-0.300*** (0.080)
Race: Asian		-1.138* (0.678)	-1.556* (0.801)	-1.390* (0.712)	-1.831* (0.946)	-2.033** (0.925)	-1.764** (0.847)
Race: Black		0.154 (0.677)	0.073 (0.675)	0.124 (0.663)	-0.031 (0.640)	-0.138 (0.602)	-0.337 (0.737)
Race: Other		-0.961*** (0.367)	-0.647* (0.348)	-0.787** (0.340)	-0.706** (0.316)	-0.867*** (0.302)	-0.528 (0.443)
Nationality: USA		-0.132 (0.482)	-0.067 (0.469)	-0.026 (0.481)	0.220 (0.492)	0.086 (0.454)	0.400 (0.567)
Experience		0.309*** (0.061)	0.297*** (0.059)	0.297*** (0.060)	0.298*** (0.059)	0.283*** (0.055)	0.314*** (0.060)
Experience ²		-0.321*** (0.062)	-0.312*** (0.059)	-0.310*** (0.061)	-0.310*** (0.060)	-0.280*** (0.057)	-0.343*** (0.063)
Genre: Action			1.248*** (0.475)	1.255** (0.484)	1.236** (0.515)	0.667 (0.503)	0.900 (0.630)
Genre: Adventure			1.025 (0.702)	0.766 (0.728)	0.944 (0.637)	0.555 (0.699)	0.858 (0.788)
Genre: Comedy			0.548 (0.352)	0.427 (0.361)	0.868** (0.359)	0.672* (0.359)	1.230*** (0.437)
Genre: Crime			0.010 (0.482)	0.509 (0.473)	0.637 (0.495)	0.600 (0.496)	1.227* (0.733)
Genre: Drama			0.050 (0.447)	0.202 (0.434)	0.687 (0.469)	1.297*** (0.457)	2.317*** (0.686)

Genre: War		0.593 (0.406)	1.053** (0.419)	1.383*** (0.438)	1.056** (0.444)	1.451** (0.609)	
Genre: Other		2.090 (1.376)	2.602* (1.452)	2.378* (1.430)	1.948 (1.358)	1.971 (1.407)	
Distributor: Big 6		1.286*** (0.261)	0.987*** (0.235)	0.739*** (0.226)	0.301 (0.217)	0.029 (0.325)	
MPAA rating: NC17			-1.297 (1.147)	-1.091 (1.406)	0.220 (1.332)		
MPAA rating: PG			0.740 (0.856)	2.225* (1.284)	2.329* (1.207)	1.019 (1.756)	
MPAA rating: PG13			1.222 (0.867)	2.696** (1.321)	2.824** (1.234)	1.357 (1.775)	
MPAA rating: R			-0.059 (0.786)	1.874 (1.283)	2.499** (1.206)	1.054 (1.788)	
Oscar: won main role		0.516 (0.523)	0.517 (0.519)	0.479 (0.471)	0.548 (0.454)	0.599 (0.596)	
Oscar: won supportive role		-0.961* (0.577)	-1.060* (0.611)	-1.058* (0.616)	-1.105* (0.582)	-0.880 (0.730)	
Total box-office revenues				0.009*** (0.002)	0.002 (0.003)	-0.002 (0.003)	
Theatres					0.001*** (0.000)	0.001*** (0.000)	
Production budget						0.015*** (0.005)	
Constant		1.438** (0.563)	-6.110*** (1.333)	-6.495*** (1.307)	-5.168*** (1.921)	-9.049*** (2.434)	-10.431*** (2.121)
Year fixed effects		✓	✓	✓	✓	✓	✓
Observations		1,344	1,344	1,338	1,314	1,272	1,264
R-squared		0.096	0.246	0.279	0.292	0.314	0.346

Note: *, **, and *** indicate statistical significance at the 10%, the 5%, and the 1% levels, respectively. Standard errors are clustered at the actor level and appear in parentheses. (1) Column 1 includes the dummy variable female. (2) Column 2 adds to Specification (1) actor characteristics. (3) Column 3 adds the qualitative characteristics of films and Oscar information except for MPAA ratings. (4) Column 4 adds MPAA ratings to Specification (3). (5) Column 5 includes the quantitative characteristics of films except for production budget. (6) Column 6 adds production budget to Specification (6).

Table 3. Determinants of Actors' Wages, movie fixed effects estimation

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-2.187*** (0.486)	-1.516*** (0.509)	-1.527*** (0.513)	-1.527*** (0.513)	-1.445*** (0.513)	-1.445*** (0.513)	-1.548*** (0.592)
Age		0.310** (0.140)	0.321** (0.144)	0.321** (0.144)	0.377** (0.145)	0.377** (0.145)	0.335** (0.157)
Age ²		-0.381** (0.162)	-0.396** (0.169)	-0.396** (0.169)	-0.480*** (0.172)	-0.480*** (0.172)	-0.456** (0.186)
Race: Asian		-3.908** (1.960)	-3.898** (1.968)	-3.898** (1.968)	-3.851** (1.953)	-3.851** (1.953)	-3.724* (2.032)
Race: Black		-1.786** (0.886)	-1.787** (0.890)	-1.787** (0.890)	-1.750** (0.883)	-1.750** (0.883)	-1.896* (0.984)
Race: Other		0.299 (1.770)	0.291 (1.778)	0.291 (1.778)	0.245 (1.764)	0.245 (1.764)	1.190 (2.122)
Nationality: USA		1.071* (0.645)	1.074* (0.649)	1.074* (0.649)	0.988 (0.645)	0.988 (0.645)	0.908 (0.718)
Experience		0.272*** (0.083)	0.269*** (0.084)	0.269*** (0.084)	0.292*** (0.084)	0.292*** (0.084)	0.339*** (0.095)
Experience ²		-0.295** (0.125)	-0.294** (0.125)	-0.294** (0.125)	-0.319** (0.125)	-0.319** (0.125)	-0.373*** (0.136)
Oscar: won main role			0.206 (0.785)	0.206 (0.785)	0.339 (0.781)	0.339 (0.781)	0.319 (0.937)
Oscar: won supportive role			0.198 (1.252)	0.198 (1.252)	0.263 (1.243)	0.263 (1.243)	0.398 (1.403)
Constant	4.873*** (0.205)	-4.746* (2.732)	-4.885* (2.780)	-4.851* (2.780)	-5.868** (2.810)	-5.852** (2.810)	-4.720 (3.068)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓
Observations	1,344	1,344	1,338	1,314	1,272	1,264	866
R-squared	0.075	0.235	0.235	0.235	0.245	0.245	0.242
Number of movies	1,092	1,092	1,086	1,062	1,022	1,014	653

Table 4. Explanations of the gender wage gap

	(1)	(2)	(3)	(4)	(5)
Female	-2.180*** (0.434)	-1.538*** (0.392)	-1.934*** (0.406)	-2.048*** (0.415)	-2.215*** (0.429)
Age		0.271*** (0.063)			
Age ²		-0.355*** (0.077)			
Experience		0.305*** (0.062)			
Experience ²		-0.318*** (0.063)			
Genre: Action			2.146*** (0.502)		
Genre: Adventure			1.426* (0.791)		
Genre: Comedy			0.987*** (0.318)		
Genre: Crime			0.683 (0.546)		
Genre: Drama			0.280 (0.460)		
Genre: War			1.423*** (0.446)		
Genre: Other			3.332** (1.574)		
Total box-office revenues				0.008*** (0.002)	
Observations	1,344	1,344	1,338	1,272	1,272
R-squared	0.096	0.244	0.125	0.122	0.098

Table 5. Gender Wage Gap by Years since First Movie Appearance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female*0-years experience	-4.525*** (0.425)	-1.152* (0.675)	-0.640 (0.653)	-0.317 (0.758)	-1.550** (0.688)	-1.695** (0.789)	-0.714 (1.257)
Female*1-year experience	-4.594*** (0.348)	-2.483*** (0.458)	-2.208*** (0.493)	-1.878*** (0.476)	-1.689*** (0.507)	-1.278* (0.695)	-1.142* (0.630)
Female*2-years experience	-4.524*** (0.363)	-1.322* (0.706)	-1.374* (0.725)	-1.376** (0.657)	-1.013 (0.768)	-0.671 (0.778)	0.333 (1.196)
Female*3-years experience	-4.474*** (0.354)	-2.509*** (0.599)	-2.022*** (0.501)	-1.985*** (0.501)	-2.421*** (0.578)	-2.147*** (0.515)	-1.577** (0.656)
Female*4-years experience	-3.173*** (0.588)	-1.416** (0.665)	-1.138* (0.653)	-1.228* (0.674)	-1.023 (0.660)	-1.032 (0.646)	-1.700* (0.938)
Female*5-years experience	-3.760*** (0.438)	-2.838*** (0.555)	-2.846*** (0.532)	-2.829*** (0.523)	-2.752*** (0.511)	-2.679*** (0.503)	-3.169*** (0.762)
Female*6-years experience	-3.040*** (0.574)	-1.352** (0.675)	-1.269** (0.580)	-1.476** (0.592)	-1.205* (0.631)	-0.867 (0.595)	-0.190 (0.996)
Female*7-years experience	-3.217*** (0.453)	-2.231*** (0.526)	-2.000*** (0.492)	-1.961*** (0.503)	-1.824*** (0.465)	-1.630*** (0.454)	-1.508*** (0.523)
Female*8-years experience	-2.617*** (0.653)	-1.780*** (0.686)	-1.614** (0.675)	-1.789** (0.718)	-1.713** (0.731)	-1.708** (0.663)	-1.951** (0.975)
Female*9-years experience	-1.773** (0.718)	-0.626 (0.671)	-0.744 (0.670)	-0.700 (0.655)	-0.523 (0.611)	-0.397 (0.584)	-0.450 (1.124)
Female* ≥ 10-years experience	-1.097** (0.460)	-1.193** (0.533)	-1.097** (0.488)	-1.154** (0.484)	-1.024** (0.455)	-1.044** (0.422)	-1.089** (0.514)
Observations	1,344	1,344	1,338	1,314	1,272	1,264	866
R-squared	0.079	0.202	0.242	0.255	0.279	0.313	0.302

Note: *, **, and *** indicate statistical significance at the 10%, the 5%, and the 1% levels, respectively. Standard errors are clustered at the actor level and appear in parentheses. All controls as per Table 2.

Table 6. Oaxaca decomposition with movie specific fixed effects

	Total gap	Gap due to skill differences	Unexplained gap
Specification 2	1.657*** (0.2)	0.617*** (0.12)	1.039*** (0.193)
Specification 3	1.674*** (0.201)	0.782*** (0.132)	0.891*** (0.183)
Specification 4	1.664*** (0.203)	0.715*** (0.141)	0.949*** (0.186)
Specification 6	1.679*** (0.207)	0.797*** (0.148)	0.882*** (0.182)
Specification 7	1.705*** (0.208)	0.771*** (0.154)	0.933*** (0.179)

Note: The specifications correspond to the column number in Table 3.

Appendix

Figure A.1. Overall inequality in box office revenues and production budgets

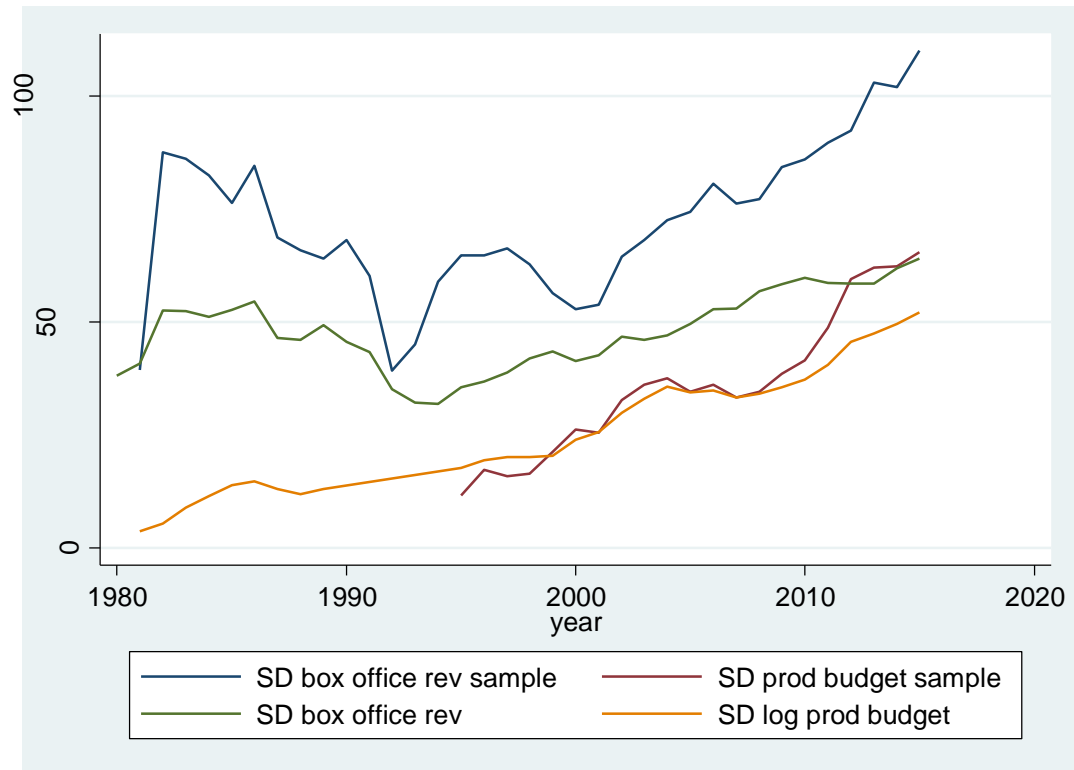


Table A.1: Oscar prizes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-2.180*** (0.434)	-1.465*** (0.425)	-1.319*** (0.391)	-1.354*** (0.386)	-1.256*** (0.359)	-1.188*** (0.330)	-1.319*** (0.424)
<i>OLS</i>							
Oscar: won main role			0.516 (0.523)	0.517 (0.519)	0.479 (0.471)	0.548 (0.454)	0.599 (0.596)
Oscar: won supportive role			-0.961* (0.577)	-1.060* (0.611)	-1.058* (0.616)	-1.105* (0.582)	-0.880 (0.730)
Observations	1,344	1,344	1,338	1,314	1,272	1,264	866
R-squared	0.096	0.246	0.279	0.292	0.314	0.346	0.333
<i>Fixed effects</i>							
Oscar: won main role			0.206 (0.785)	0.206 (0.785)	0.339 (0.781)	0.339 (0.781)	0.319 (0.937)
Oscar: won supportive role			0.198 (1.252)	0.198 (1.252)	0.263 (1.243)	0.263 (1.243)	0.398 (1.403)
<i>log(wage): OLS</i>							
Oscar: won main role			0.313** (0.131)	0.334** (0.130)	0.299** (0.122)	0.319** (0.123)	0.353*** (0.105)
Oscar: won supportive role			-0.002 (0.187)	-0.042 (0.200)	-0.029 (0.201)	-0.040 (0.173)	0.006 (0.171)
<i>log(wage): Fixed effects</i>							
Oscar: won main role			0.150 (0.236)	0.150 (0.236)	0.188 (0.235)	0.188 (0.235)	0.124 (0.252)
Oscar: won supportive role			0.049 (0.376)	0.049 (0.376)	0.068 (0.374)	0.068 (0.374)	0.193 (0.377)

Note: (1) *, **, and *** indicate statistical significance at the 10%, the 5%, and the 1% levels, respectively. Robust standard errors are in parentheses. (2) Column 1 just includes the dummy variable female. Column 2 includes actor/actress characteristics except for Oscar information. Column 3 includes the qualitative characteristics of films an Oscar information except for MPAA ratings. Column 4 includes MPAA ratings. Column 5 includes the quantitative characteristics of films except for production budget. Column 6 includes production budget.

Table A.2. Estimates of the gender wage gap, movie fixed effects

Panel A		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wage (fixed)	Female	-2.187***	-1.516***	-1.527***	-1.527***	-1.445***	-1.445***	-1.548***
		(0.486)	(0.509)	(0.513)	(0.513)	(0.513)	(0.513)	(0.592)
	Obs	1,344	1,344	1,338	1,314	1,272	1,264	866
	R-sq	0.075	0.235	0.235	0.235	0.245	0.245	0.242
	#movies	1,092	1,092	1,086	1,062	1,022	1,014	653
Wage (fixed & variable)	Female	-2.839***	-2.177***	-2.175***	-2.175***	-2.077***	-2.077***	-2.358***
		(0.586)	(0.619)	(0.624)	(0.624)	(0.625)	(0.625)	(0.730)
	Obs	1,344	1,344	1,338	1,314	1,272	1,264	866
	R-sq	0.086	0.228	0.229	0.229	0.239	0.239	0.237
	#movies	1,092	1,092	1,086	1,062	1,022	1,014	653
Wage (fixed) Cohort fixed effects	Female	-1.389**	-1.617***	-1.600***	-1.600***	-1.237**	-1.237**	-1.332*
		(0.558)	(0.581)	(0.586)	(0.586)	(0.586)	(0.586)	(0.716)
	Obs	1,344	1,344	1,338	1,314	1,272	1,264	866
	R-sq	0.466	0.532	0.535	0.535	0.553	0.553	0.567
	#movies	1,092	1,092	1,086	1,062	1,022	1,014	653
Panel B								
Log Wage (fixed)	Female	-0.745***	-0.439***	-0.444***	-0.444***	-0.421***	-0.421***	-0.523***
		(0.147)	(0.153)	(0.154)	(0.154)	(0.155)	(0.155)	(0.159)
	R-sq	0.093	0.257	0.258	0.258	0.267	0.267	0.268
Log Wage (fixed & variable)	Female	-0.793***	-0.489***	-0.493***	-0.493***	-0.469***	-0.469***	-0.583***
		(0.149)	(0.155)	(0.157)	(0.157)	(0.157)	(0.157)	(0.162)
	R-sq	0.101	0.263	0.264	0.264	0.273	0.273	0.275
Log Wage (fixed) Cohort fixed effects	Female	-0.442***	-0.429**	-0.420**	-0.420**	-0.315*	-0.315*	-0.392**
		(0.164)	(0.174)	(0.176)	(0.176)	(0.177)	(0.177)	(0.188)
	R-sq	0.505	0.549	0.549	0.549	0.564	0.564	0.603

Note: *, **, and *** indicate statistical significance at the 10%, the 5%, and the 1% levels, respectively. Standard errors are clustered at the actor level and appear in parentheses. (1) Column 1 includes the dummy variable female. (2) Column 2 adds to Specification (1) actor characteristics. (3) Column 3 adds the qualitative characteristics of films and Oscar information except for MPAA ratings. (4) Column 4 adds MPAA ratings to Specification (3). (5) Column 5 includes the quantitative characteristics of films except for production budget. (6) Column 6 adds production budget to Specification (6).

Table A.3. Descriptive statistics by gender

	Males		Females	
	Mean	Sd	Mean	Sd
Salary	4.853	5.121	2.719	2.721
Age	38.329	11.784	31.867	8.978
Experience	15.696	11.165	11.51	7.437
Race: Asian	0.012	0.107	0.0145	0.12
Race: Black	0.107	0.31	0.039	0.195
Race: Other	0.006	0.076	0.044	0.205
Race: White	0.875	0.331	0.902	0.297
Nationality: USA	0.744	0.437	0.887	0.316
Oscar: nomination supporting role	0.15	0.452	0.221	0.518
Oscar: nomination main role	0.384	0.768	0.245	0.597
Oscar: won main role	0.116	0.376	0.129	0.376
Oscar: won supporting role	0.063	0.242	0.062	0.242
Genre: Action	0.267	0.442	0.127	0.334
Genre: Adventure	0.059	0.236	0.037	0.19
Genre: Comedy	0.211	0.408	0.251	0.434
Genre: Crime	0.061	0.238	0.061	0.238
Genre: Drama	0.139	0.347	0.183	0.387
Genre: Other	0.144	0.352	0.198	0.399
Genre: Thriller	0.104	0.304	0.134	0.341
Genre: War	0.015	0.122	0.008	0.091
MPAA: G	0.012	0.107	0.023	0.152
MPAA: NC 17	0.013	0.113	0.004	0.065
MPAA: PG	0.126	0.332	0.124	0.329
MPAA: PG 13	0.422	0.494	0.456	0.498
MPAA: R	0.428	0.495	0.392	0.488
Life time gross	98.871	98.096	79.086	87.218
Opening gross	25.541	31.821	20.138	27.866
Theatres	2,460.53	1,036.716	2,295.96	1,052.004
Production budget	77.018	52.096	60.843	46.579
Distributor: big 6	0.716	0.451	0.683	0.465

Table A.4. Average wages by categories

Actor Characteristics	mean (salary)	sd (salary)
Male	4.85	5.12
Female	2.72	2.72
Race: Asian	3.17	3.19
Race: Black	4.37	4.17
Race: White	4.1	4.61
Race: Other	2.91	2.81
Nationality: USA	4.11	4.66
Nationality: Other	4.03	3.97
Oscar won: main role 0	3.9	4.52
Oscar won: main role 1	5.42	3.74
Oscar won: main role 2	7.3	6.23
Oscar won: supportive role	5.32	3.66
Oscar nomination: main role 0	3.32	3.53
Oscar nomination: main role 1	6.83	6.31
Oscar nomination: main role 2	7.7	6.87
Oscar nomination: main role 3	4.99	4.61
Oscar nomination: supportive role 0	3.94	4.51
Oscar nomination: supportive role 1	5.2	4.85
Oscar nomination: supportive role 2	2.76	1.92
Oscar nomination: supportive role 3	5.31	3.02
Won at least 1 Oscar: main role	5.76	4.31
Won at least 1 Oscar	5.32	3.66
Nomination at least 1 Oscar: main role	6.8	6.29
Nomination at least 1 Oscar: supportive role	4.95	4.59
Film Characteristics	mean (salary)	sd (salary)
Distributor: Big Six	4.61	4.82
Distributor: Other	2.84	3.45
Rating: G	1.96	2.84
Rating: NC17	0.21	0.36
Rating: PG	3.32	3.86
Rating: PG13	4.99	5.15
Rating: R	3.66	3.95
Genre: Action	5.43	5.62
Genre: Adventure	4.69	4.59
Genre: Comedy	3.98	3.74
Genre: Crime	3.73	4.07
Genre: Drama	3.18	4.73
Genre: Thriller	4.48	4.3
Genre: War	7.11	6.95
Genre: Other	2.79	2.95