The Impact of Oscar Nominations and Wins on Box Office Revenues

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Abstract:

The main objective of this paper was to assess the value in terms of their impact on the box office revenues of the most important Academy Award nominations and wins (best picture, best director, best actor/actress, best supporting actor/actress and best original and adapted screenplay). This impact has been seldom measured using panel data techniques that allow to control individual effects that are inherent to this market. We believe that controlling for the individual effect is crucial since award nominations are usually allocated to high quality movies and we need to disentangle whether awards or quality is responsible for high demand. Moreover, the impact of nominations can be very different depending on the current week on screens of the movie. For instance, we might expect a larger weekly effect if the nomination is known in an early stage of the commercial run of the movie. To consider this we estimate a semi-log functional form regarding nominations and wins on weekly box-office revenues. Using weekly data on box office revenues from the four main European movie markets and USA, we can use panel data techniques to control for the unobserved heterogeneity of movies and these national markets too. We also exploit the differences in the release dates of movies in these countries to evaluate the impact of Academy Awards nominations and wins. This framework enables us comparing revenues before and after the announcement of the nominations.

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KEYWORDS: Cinema, Box-office revenues, Academy Awards nominations and wins

1. Introduction

The paper tries to assess the value of the most important Oscar nominations and wins in terms of their impact on the box office revenues. Films that have a chance to be nominated are intentionally released at the end of the year in the United States in order to be eligible but also to still be on screen when nominations are announced and Oscars are awarded. However, if a film is no longer on screen and is nominated, it is very likely that it will be re-released in movie theatres to capitalize on the nomination. Obviously, the expected impact of a nomination or win will depend on the category of the nomination and wins (Best Picture, Best Director, Best Actor/Actress, Best Supporting Actor/Actress, and Best Screenplay); the Best Picture award is expected to have the largest effect. This impact has been seldom measured using panel data techniques that allow controlling for differences in movies' marketability and quality via the estimation of individual effects, which are inherent in this market. Controlling for individual effects is crucial since nominations and wins are not randomly allocated and usually go to higher quality movies.[1]

Starting with Litman (1983), this topic has been the subject of a large host of papers using regression models to determine what is important in explaining box office results. Most authors find that nominations and awards (that are separated by a couple of weeks) have a significant effect on revenues. They are, however, unable to separate the effect of the quality of a movie from the award effect since they use box office results in one country only,[2,3] which makes it difficult to control for the heterogeneity of movies. Our sample consists of the weekly box office results (starting with the week of release, and including the next 65 weeks, if the run long enough) of the 150 top box office films released in five countries (the United States, the United Kingdom, France, Germany and Spain) from 2002 to 2009. This allows us using panel data techniques to control for movie quality using individual movie dummies (or movie fixed effects), while

[1] See however Ginsburgh and Weyers (2014) who, using the test of time, show that many nominated are of better quality than those that received the Oscar for Best Movie.

[2] With exception of Craig et al. (2005) who consider several countries, but are not interested in the effect of awards. There are also examples of papers that do not take advantage of the panel structure of their data set. For instance, Elberse and Eliashberg (2003) "opt for a model that does not capture unobserved individual specific effects" and they run the regression separately for each country in their sample.

[3] United States: Chen et al. (2013), Deuchert et al. (2005), Ginsburgh (2003), Nelson et al. (2001), East Asia: Lee (2009).

the effect of awards will be picked up by dummies that take the value 1 after the nomination of a movie (0 if it was not nominated), as well as a dummies that takes the value 1 if the movie was awarded the Oscar (or 0, otherwise). This makes it possible to separate the effect of the quality of a movie from the effect of awards on demand. We also exploit the differences in the release dates of movies in these countries to evaluate the impact of nominations and wins. This framework enables comparing revenues before and after the announcement of nominations and awards and assessing the impact at particular points in time by matching running weeks in different countries, some before and others after the nominations.

The impact of nominations on box office revenues may also change over time. For instance, if the nomination is revealed at an early stage of the commercial run of the movie, one can expect the (weekly) impact to be larger. To take this into account, we estimate an equation of weekly revenues on Oscar nominations and wins, as well as on weekly dummies during 20, and 40 weeks after the release of the movie in theatres in every year and country.

2. Sample and data base

This section summarizes the data we use to perform our empirical analysis. The sample consists of the weekly box office revenue of the 150 top box-office films each year released in the United States, United Kingdom, Germany, France and Spain during the period 2002-2009. It is built relying on several sources of information. A.C. Nielsen EDI is used for information on titles, distributors, number of theatres on each week of exhibition, weekly and cumulative box-office revenue, and certain film characteristics (official release date, identification of sequels, age rating). In the case of France, A.C. Nielsen EDI provides information about attendance instead of total box-office revenues. The Box Office Mojo website (boxofficemojo.com) is used for information about Oscar's nominations and winners.

This database has a panel data structure with three dimensions: movie, week and country. In order to arrive at this structure we first had to match the movies across countries because many movies were released with different titles in each country. This was done by using the information provided by the Internet Movie Database web site (imdb.com). We will try to use all these three dimensions of this data set to get “clean” assessments of Academy Awards’ impact on box office.

Since we are interested in the impact of nominations and wins and there is a 5-6 week gap between nomination announcements and wins, we withdraw from the final sample all movies with short runs (one month or shorter runs). Also, in order to have a better identification of temporal patterns, movie-week combinations observed only in one country were not considered. This implies, for instance, that movies released in only one country were removed from the sample. Our final database comprises 1182 movies: 700 released in France, 889 in Germany, 917 in Spain, 960 in UK and 939 in USA.

In the analysis we consider two different time frameworks for robustness checks. First, we estimate the models for the first 20 weeks (43,777 observations) and, then, we estimate models including movies up to their 40th week on screen (45,190 observations).

Table 1 displays the descriptive statistics of this particular sample. Dummy variables that distinguish Oscar nominated or winning films only take value one from the week in which this happened onwards. Obviously, USA has the largest average number of theatres where a movie is exhibited being the differences among the European countries less marked. Apart from these disparities in size, it is also noticeable that there is a lower prevalence of observations of weeks after a film has been nominated or awarded an Oscar in USA than in the European countries.

This could be due to the fact that movies racing for the Oscars are released before the end of the year in USA -in order to be eligible- and, usually, they are released later in Europe in order to take as much commercial advantage as possible of the “free” promotion of the nominations and wins. Therefore, our sample contains a lager number of weeks before nominations for the USA market observations, with all the dummies regarding the Oscars set equal to zero.

Table 2 shows the run length in weeks by country. It can be observed that the pattern is quite similar for all the countries in the sample, except France. In the French sample, almost three quarters of the movies do not reach 10 weeks on screen and only a 6 per cent of the movies manage to be more than 15 weeks. However, in the other four countries, around half the films remains more than 10 weeks and 20 per cent more than 15 weeks. It is important to mention that domestic films are more relevant in the French market than on the others and, therefore, Hollywood films less important. In fact, since the 150 box office top films have to be released at least in two countries in order to be included in our dataset, French observations cover 700 movies while for the other 4 countries they capture around 900 films. With our dataset we cannot check whether French domestic movies have larger runs than international films in France but it is clear that these have shorter runs than in other countries. In any case, by the twentieth week most of the films are no longer on screen.

Since we want to analyse the impact on the box office revenue of the major Oscars categories, we will check whether they capture different quality values or if this is not the case and including all of them in a regression model may lead to collinearity problems. Table 3 presents the correlation matrix between the Oscar nominations and wins considered in our analysis. In general terms, as expected, correlation coefficients are higher among nomination categories and lower within winners. Also, most of the correlation coefficients are quite low with many close to zero; however there are three categories with a very strong link: best picture, best director and best adapted screenplay, both as nominations and winners. We will see below that this has an effect on the estimated coefficients of the empirical model.

3. The Empirical Model

According to previous literature, the weekly box-office revenues of each film release in each country depend on the characteristics that determine the quality and the marketability of the film, the geographical availability of the movie and the time and seasonality in the underlying demand. Considering all these determinants, we define the following empirical model:

$$ln\_Rev_{ict} = \alpha_i + \alpha_c + \alpha_t + \alpha_0\, t + \alpha_i\, t + \alpha_c\, t + \sigma_c s_{ict} + \gamma\, ln\_thrs_{ict} + \sum_{j=1}^{8} \beta_j\, Dnom(j)_{ict} + \sum_{j=1}^{8} \delta_j\, Dwin(j)_{ict} + \epsilon_{ict}$$

where subscript *i* represents the movie, *c* stands for the country where it was exhibited and subscript *t* identifies the exhibition week in which the film revenues are collected and ε_{ict} is the error term.

The dependent variable ln_Rev_{ict} is the log of film i's weekly box-office revenues in each country.[4] The film-specific constant terms α_i captures observed and unobserved film characteristics that are fixed over time such as genre, budget, presence of stars or artistic quality. The country-specific effects, α_c, captures observed and unobserved characteristics of each national market in the sample such as market size, attractiveness of movies as a leisure activity, etc. The underlying demand, i.e., the within year seasonality is represented by s_{ict}. The average decay pattern of box office revenues over movies' life for the five markets and all films is captured by $\alpha_0\, t$ trend control. This pattern could change over the movie run, then a vector of weekly dummy variables, represented by α_t, is introduced to control for any possible deviations regarding this trend. Since the decay patter can also vary between movies (since films' characteristics can affect this temporal pattern) and between countries (since national markets might have a different structure and characteristics) we have also included trend controls by movie and country: $\alpha_i\, t$ and $\alpha_c\, t$. We also include as an explanatory variable the number of theatres in which the movie is shown each week in each country in log terms, ln_thrs, which measures the film's availability.

Finally, we include a set of dummy variables that identify the movies that have been nominated or have won an Oscar in the different categories, from the week in which this happened. It means that $Dnom(j)$ and $Dwin(j)$ take value 1 for movies that have been nominated or have won an Oscar, respectively, in the week in which the event took place and in the following weeks. The subscript j refers to the different categories of Oscars considered, namely: best picture, director, actor, actress, supporting actor, supporting actress, original screenplay and adapted screenplay.

As it has been many times pointed out in the literature, the motion picture industry is one of the most highly product-differentiated markets, as each movie is unique by nature. Consequently, there are relevant movie characteristics that are unobservable and even non measurable, but have an importance in order to explain (weekly) box office revenues. Thus, we will consider these characteristics by taking

[4]Due to data limitations, the dependent variable in France is weekly attendance instead of weekly box-office revenues. In the estimated model revenues are in log terms and differences in t for each film in each country are taken, then consider attendance in France implies the assumption that price for each movie in this country does not change from one week to the next.

advantage of the panel structure of our data set, which allows us to control for the individual effects of each film. In order to remove all the individual heterogeneity of movies, before estimating the model, we apply first differences in *t* by movie within each country:

$$ln\_Rev_{ict} - ln\_Rev_{ic(t-1)} = (\alpha_i - \alpha_i) + (\alpha_c - \alpha_c) + (\alpha_t - \alpha_{(t-1)}) + \alpha_0 (t - (t-1)) + \alpha_i(t-(t-1)) + \alpha_c (t-(t-1)) + \sigma_c(s_{ict} - s_{ic(t-1)}) + \gamma (ln\_thrs_{ict} - ln\_thrs_{ic(t-1)}) + \sum_{j=1}^{8} \beta_j \left[Dnom(j)_{ict} - Dnom(j)_{ic(t-1)}\right] + \sum_{j=1}^{8} \delta_j \left[Dwin(j)_{ict} - Dwin(j)_{ic(t-1)}\right] + \epsilon_{ict} =$$

$$\Delta_t ln\_Rev_{ict} = \Delta_t\alpha_t + \alpha_0 + \alpha_i + \alpha_c + \sigma_c\Delta_t s_{ict} + \gamma\Delta_t ln\_thrs_{ict} + \sum_{j=1}^{8} \beta_j \Delta_t Dnom(j)_{ict} + \sum_{j=1}^{8} \delta_j \Delta_t Dwin(j)_{ict} + \Delta_t\epsilon_{ict}$$

See that, under this specification α_0, α_i and α_c are not the standard intercept and overtime movie and country fixed effects, but the average decay patter and the movie and country differences in the this decay patter. Hence, this specification allows us to control for the typical constant movie and country fixed effects but also for the possibility of different temporal patters in the evolution of the weekly box office revenue by films and country. Finally, if we assume that two consecutive weeks belong to the same year season we can drop the term $\sigma_c\Delta_t s_{ict}$ from this equation.

However, even in this model, some of the explanatory variables may be correlated with the film and country specific effects. Therefore, random-effects estimation of this equation generally leads to estimators of the parameters that are not consistent. The fixed-effects estimator would consistently estimate the coefficients of the time-varying variables since it remove all the time-invariant variables. It is noteworthy to mention that applying first difference and including dummy variables that identified the movies affected by the treatment (in our case award nominations and wins) is similar to use difference in difference (DID) estimator, but with panel data the differences over time are for the same movie release within each country (same cross section units).

4. Estimation and Results

For each time framework (20 and 40 weeks), we estimate five models that differ in the set of dummies regarding the major Oscar nominations and wins. We have estimated the potential impact on the box office of the nominations and eventual wins to the best picture award in all the models. Model 2 also includes best director category. Model 3 focus on the impact of best actor/actress. The screenplay awards are included in Model 4 and, finally, the impact of all these categories are together analysed in Model 5.

Considering a time framework of 20 weeks, starting by the control variables, we find a clear pattern of decaying revenues over time capture by α_0 coefficient which is negative and statistically significant in all models. On average for the five national markets and all movies, each film loses more than a quarter of its revenue week by week. Since this decay pattern may not be constant over time, we have also included weekly dummies (not reported here) to control for any possible deviations regarding the trend. This pattern of decay in revenues may also vary by film and country, due to the specific features of each movie, which are different products by definition, and the particular characteristics of the national markets. Regarding the markets, we observe that in the cases of USA, UK, Spain and Germany the decay is less pronounced than in France, which is our reference country. We also observe that the number of theatres in which the movie is shown each week, *ln_thrs*, has a significant positive impact on weekly box-office revenue, as expected. All these results are stable throughout the 5 models.

Now we focus our analysis on the variables that identify the nominations and wins. As the estimated models are defined, the coefficients for these dummies capture the percent impact on revenues linked to a nomination or win from the specific week when they were known onwards. In Model 1, considering only best picture category, the results imply that films that become nominated in the best film category will collect 25 percent more at the box office than similar films not running for the Oscars once nomination are announced. Moreover, movies that win the Oscar will increase their weekly revenues a 58 percent with regards to those films that do not get the award but were nominated. As it was pointed above, films nominated to best picture are usually nominated to other Oscar categories, especially to best director and best adapted screenplay. Therefore, when only the best picture nomination and win is considered, the estimated impact on revenues may also capture the effect of other nominations and wins. In any case, these estimations can be viewed as an upper limit.

In order to clean up the impact on revenues of best picture nominations and wins, in Models 2-5, we include and remove from the estimations some of the major Oscar categories. As expected, in all of them the estimated coefficient for best picture nominations and wins are lower than in Model 1 but these differences are not statistically significant.

In Model 2, we include dummies for the best director category. Regarding this category, only winning an Oscar has an impact on the revenues when the best picture category is considered too. However, it is only significant at the ten percent. Furthermore, the estimated coefficients of the dummies for the best film category are smaller than in Model 1. All these results can be due to the very high correlation between both categories (see Table 3). Then, in Model 3, apart from best film category, we include best actor/actress and supporting actor/actress categories. The results show that having a nomination or winning an Oscar in best actor/actress category is important in terms of revenues. No significant effects were estimated regarding supporting actors or actress. It is important to highlight that, in any case, actors and actress awards and, especially, nominations seem to be more relevant for the commercial success of a film than those linked to directors.

In Model 4 we include original and adapted screenplay categories. Original screenplay nominations and wins have an average impact on weekly revenues of about 9 percent and 26 percent, respectively. However, adapted screenplay category is less important and it only has a significant impact when a particular film is awarded the Oscar (17 percent higher weekly revenues but significant at the ten percent). Notice that this pattern is very similar to what we get for best director in Model 2. It is remarkable that the highest correlations among Oscar nominations and wins take place for best director and adapted screenplay. Therefore, although many pictures that were nominated or won the best picture Oscar in our sample were also nominated or won the best director or adapted screenplays; commercial glory goes with the most important award of this cluster.

Finally, Model 5 includes all the categories above mentioned simultaneously. In this case, categories that were significant when they were included separately remain significant but in some cases with a lower estimated coefficient, although, these drops are not statistically significant. The only exception is the best director win that now is not significant. Also, best adapted screenplay suffers an important drop that is not significant.

In order to make a robustness check, we expand the temporal framework of our analysis to include up to the first 40 weeks. It is important to bear in mind that most of the picture do not survive for so long: only 82 out of 1182 movies in the sample have a career longer than 25 weeks; 41 longer than 30 weeks and 10 longer than 40 weeks. Therefore, results regarding the temporal trend can be very affected by these influential observations. Regarding the commercial impact of the considered Oscar categories, it can be observed that the results remain very similar to the estimations for the 20 weeks horizon. It is only noteworthy two changes for Model 5. First, best supporting actress wins are now significant with a 13 percent increase in the weekly revenues but significant at the 10 percent level. Second, adapted screenplay wins are not significant now.

5. Conclusions

The main objective of this paper was to measure the impact on the box office revenues of the major Academy Award nominations and wins (best picture, best director, best actor/actress, best supporting actor/actress and best original and adapted screenplay) taking into account the temporal pattern of release-nomination-win that candidate films follow. We have used panel data techniques that allow controlling the films individual effects that are inherent to this market. This is critical since award nominations are usually allocated to high quality movies and we need to disentangle whether awards or quality is responsible for higher revenues. Using weekly data on box office revenues from USA and four main European movie markets (France, Germany, Spain and UK), we could use panel data techniques to control for the unobserved heterogeneity these national markets too. We have also taken advantage of the differences in the release dates of movies in these countries to evaluate the impact of Academy Awards nominations and wins. This framework enables us comparing revenues before and after the announcement of the nominations and to quantify the impact on the box office revenue of the announcements of the nominations and wins.

To check the robustness of our findings, we have estimated 5 alternative models considering two alternative time frameworks: 20 weeks and 40 weeks. We find a marked decay pattern over time for the weekly box office revenues. On average, for the five national markets and all movies, each film loses more than a quarter of its revenue week by week. Using a first difference panel estimation, this general trend was obtained after controlling for specific film and country decay patterns. Concerning these country effects, we noted that for USA, UK, Spain and Germany the decay is less pronounced than in France.

Regarding the variables identifying Academy Awards nominations and wins, a best picture nomination will imply a rise in its weekly box office of about 25 per cent more than similar films not running for the Oscars from the weekend the nomination was announced. Moreover, a movie that wins the Oscar will increase their weekly revenues a 50 per cent after the Oscar ceremony with regards to those films that do not get the award but were nominated. Results vary when other awards and nominations are considered but these changes are not statistically significant.

Regarding the best director category only wins have an impact on the weekly revenues when the best picture category is considered too; but it is important to bear in mind that there is a very high correlation between both categories and it seems that the relevant signal on quality is the best movie category. Regarding the performance categories, results show that having a nomination or winning an Oscar in best actor/actress category have a significant impact on revenues; however no relevant effects were estimated for supporting actors or actress. In any case, actors and actress awards and nominations seem to be more relevant for the commercial success of a film than those linked to directors.

Finally, original screenplay nominations and wins have an average impact on weekly revenues of about 9 percent and 26 percent, respectively. However, adapted screenplay category is less important and it only has a significant impact when a particular film is awarded the Oscar. This pattern is very similar to what we get for best director but again we observed a very high correlation between best picture and best adapted screenplay categories. Therefore, although many pictures that were nominated or won the best picture Oscar were also nominated or won for best director or adapted screenplays; commercial glory goes with the best movie Academy Award.

When we considered the 40 weeks framework, the results remain very similar to the estimations for the 20 weeks horizon. It is only noteworthy two changes when all the Oscar categories were considered simultaneously. First, best supporting actress wins were significant with a 13 per cent increase in the weekly revenues but significant at the 10 per cent level and, second, adapted screenplay wins lost its significance.

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TABLES

Table 1. Descriptive Statistics up to the exhibition week #40

	France (n=6481)		Germany (n=10691)		Spain (n=10598)		United Kingdom (n=10800)		USA (n=11167)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
ln_theatre	5.1305	1.0308	4.7644	1.2437	3.9498	1.6233	4.0400	1.7717	6.2262	1.5402
nom_picture	0.0477	0.2131	0.0534	0.2249	0.0531	0.2243	0.0432	0.2034	0.0317	0.1752
win_picture	0.0091	0.0950	0.0111	0.1049	0.0117	0.1075	0.0062	0.0785	0.0053	0.0725
nom_director	0.0475	0.2128	0.0504	0.2188	0.0484	0.2146	0.0435	0.2040	0.0278	0.1646
win_director	0.0080	0.0892	0.0117	0.1075	0.0104	0.1014	0.0069	0.0825	0.0054	0.0731
nom_actor	0.0341	0.1815	0.0436	0.2042	0.0438	0.2046	0.0397	0.1953	0.0241	0.1533
win_actor	0.0086	0.0926	0.0074	0.0856	0.0072	0.0844	0.0081	0.0899	0.0033	0.0575
nom_actress	0.0276	0.1639	0.0303	0.1714	0.0292	0.1683	0.0256	0.1578	0.0185	0.1349
win_actress	0.0110	0.1041	0.0130	0.1133	0.0084	0.0913	0.0081	0.0899	0.0059	0.0767
nom_sup.actor	0.0329	0.1783	0.0353	0.1845	0.0368	0.1883	0.0302	0.1711	0.0209	0.1429
win_sup.actor	0.0042	0.0644	0.0092	0.0953	0.0092	0.0957	0.0053	0.0725	0.0033	0.0575
nom_sup.actress	0.0310	0.1975	0.0445	0.2299	0.0425	0.2313	0.0369	0.2144	0.0227	0.1704
win_sup.actress	0.0059	0.0764	0.0091	0.0948	0.0060	0.0775	0.0065	0.0803	0.0028	0.0526
nom_orig.screenplay	0.0204	0.1413	0.0348	0.1833	0.0300	0.1706	0.0220	0.1468	0.0136	0.1159
win_orig.screenplay	0.0049	0.0701	0.0076	0.0867	0.0062	0.0787	0.0047	0.0686	0.0010	0.0314
nom_adap.screenplay	0.0341	0.1815	0.0360	0.1863	0.0383	0.1920	0.0326	0.1776	0.0241	0.1533
win_adap.screenplay	0.0071	0.0840	0.0105	0.1018	0.0100	0.0995	0.0072	0.0847	0.0042	0.0647

Table 2. Maximum number of weeks on screen

Max. number of weeks on screen	FR	GR	SP	UK	USA
5	83	35	34	62	38
6	98	56	52	104	75
7	81	80	99	107	87
8	92	100	109	97	83
9	83	78	90	72	83
10	72	103	92	74	106
11	41	56	68	61	68
12	50	68	74	54	65
13	20	48	48	46	46
14	17	44	51	53	61
15	20	28	39	44	37
16	7	27	27	38	30
17	8	34	26	29	26
18	4	20	20	22	22
19	6	14	15	21	19
20	4	19	15	18	17
21	3	16	10	9	13
22	2	12	10	12	11
23	1	7	7	8	10
24	0	10	5	6	11
25	1	9	7	4	5
26-30	5	9	12	7	13
31-35	2	10	5	7	6
36-40	0	2	1	1	2
+40	0	4	1	4	5
Total	700	889	917	960	939

Table 3. Correlation matrix between major Oscar nominations and wins (evaluated once per movie)

CATEGORIES	Best picture	Director	Leading actor	Leading actress	Supporting actor	Supporting actress	Original screenplay
WINS							
Best picture	1						
Director	0.7898	1					
Leading actor	-0.0379	0.2151	1				
Leading actress	0.1347	0.1413	-0.0357	1			
Supporting actor	0.3287	0.3401	0.1776	0.1957	1		
Supporting actress	0.2890	-0.0368	-0.0265	-0.0357	-0.0294	1	
Original screenplay	-0.0334	-0.0324	0.2346	-0.0314	0.2081	-0.0233	1
Adapted screenplay	0.6786	0.9034	0.2431	-0.0448	0.1303	-0.0333	-0.0292
NOMINATIONS							
Best picture	1						
Director	0.9159	1					
Leading actor	0.4641	0.4676	1				
Leading actress	0.2989	0.3383	0.0415	1			
Supporting actor	0.5510	0.5516	0.3532	0.2775	1		
Supporting actress	0.4264	0.4092	0.1857	0.2283	0.5500	1	
Original screenplay	0.3646	0.3556	0.2526	0.0331	0.1349	0.1959	1
Adapted screenplay	0.6273	0.6225	0.2853	0.2871	0.6100	0.3886	-0.1259

Table 4. Estimations for 20 weeks

Δln_Rev										
	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.
α_Spain	0.0237***	[0.005]	0.0237***	[0.005]	0.0234***	[0.005]	0.0236***	[0.005]	0.0234***	[0.005]
α_Germany	0.0221***	[0.005]	0.0221***	[0.005]	0.0220***	[0.005]	0.0221***	[0.005]	0.0221***	[0.005]
α_UK	0.0433***	[0.005]	0.0432***	[0.005]	0.0430***	[0.005]	0.0433***	[0.005]	0.0431***	[0.005]
α_USA	0.0757***	[0.005]	0.0756***	[0.005]	0.0754***	[0.005]	0.0758***	[0.005]	0.0755***	[0.005]
Δln_theatre	0.5916***	[0.010]	0.5915***	[0.010]	0.5913***	[0.010]	0.5915***	[0.010]	0.5912***	[0.010]
Δnom_picture	0.2508***	[0.037]	0.2208**	[0.091]	0.1704***	[0.029]	0.2410***	[0.050]	0.1972**	[0.079]
Δwin_picture	0.5769***	[0.115]	0.4012***	[0.138]	0.5450***	[0.137]	0.4503***	[0.109]	0.4040***	[0.138]
Δnom_director			0.0361	[0.091]					-0.0081	[0.086]
Δwin_director			0.2219*	[0.130]					0.0751	[0.106]
Δnom_actor					0.1151***	[0.042]			0.1098***	[0.042]
Δwin_actor					0.3029***	[0.080]			0.2481***	[0.069]
Δnom_actress					0.1144**	[0.051]			0.1121**	[0.050]
Δwin_actress					0.1551***	[0.040]			0.1678***	[0.037]
Δnom_sup.actor					0.0231	[0.044]			0.0316	[0.040]
Δwin_sup.actor					0.0360	[0.069]			0.0211	[0.078]
Δnom_sup.actress					0.0180	[0.029]			0.0187	[0.030]
Δwin_sup.actress					0.0200	[0.064]			0.0413	[0.050]
Δnom_orig.screenplay							0.0937*	[0.055]	0.0573	[0.050]
Δwin_orig.screenplay							0.2556***	[0.099]	0.2012**	[0.080]
Δnom_adap.screenplay							-0.0370	[0.055]	-0.0722	[0.058]
Δwin_adap.screenplay							0.1686*	[0.100]	0.0997*	[0.058]
α_0	-0.2612***	[0.035]	-0.2612***	[0.035]	-0.2617***	[0.035]	-0.2619***	[0.035]	-0.2620***	[0.035]
α_t	yes		yes		yes		yes		yes	
Number of obs.	43777		43777		43777		43777		43777	
Number of groups	1182		1182		1182		1182		1182	
BIC	45676.327		45694.249		45739.113		45706.434		45794.69	
AIC	45459.156		45459.704		45452.447		45454.515		45455.903	

*Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level*

Table 5. Estimations for 40 weeks

Δln_Rev										
	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.	Coefficient	RobustStd. Err.
α_Spain	0.0224***	[0.005]	0.0225***	[0.005]	0.0223***	[0.005]	0.0224***	[0.005]	0.0223***	[0.005]
α_Germany	0.0241***	[0.005]	0.0242***	[0.005]	0.0241***	[0.005]	0.0242***	[0.005]	0.0242***	[0.005]
α_UK	0.0416***	[0.005]	0.0416***	[0.005]	0.0414***	[0.005]	0.0417***	[0.005]	0.0415***	[0.005]
α_USA	0.0728***	[0.005]	0.0728***	[0.005]	0.0726***	[0.005]	0.0729***	[0.005]	0.0727***	[0.005]
Δln_theatre	0.5874***	[0.010]	0.5873***	[0.010]	0.5870***	[0.010]	0.5872***	[0.010]	0.5870***	[0.010]
Δnom_picture	0.2641***	[0.038]	0.2347**	[0.094]	0.1814***	[0.029]	0.2474***	[0.052]	0.2005**	[0.080]
Δwin_picture	0.5820***	[0.108]	0.3852***	[0.131]	0.5106***	[0.132]	0.4402***	[0.109]	0.3630**	[0.145]
Δnom_director			0.0359	[0.094]					-0.0059	[0.086]
Δwin_director			0.2467**	[0.120]					0.0745	[0.112]
Δnom_actor					0.1182***	[0.042]			0.1122***	[0.042]
Δwin_actor					0.3163***	[0.072]			0.2594***	[0.066]
Δnom_actress					0.1041**	[0.052]			0.1010**	[0.051]
Δwin_actress					0.1425***	[0.041]			0.1528***	[0.038]
Δnom_sup.actor					0.0269	[0.044]			0.0341	[0.040]
Δwin_sup.actor					0.1016	[0.069]			0.0998	[0.079]
Δnom_sup.actress					0.0227	[0.029]			0.0221	[0.030]
Δwin_sup.actress					0.1082	[0.082]			0.1292*	[0.072]
Δnom_orig.screenplay							0.1046*	[0.056]	0.0688	[0.051]
Δwin_orig.screenplay							0.2456**	[0.099]	0.1847**	[0.081]
Δnom_adap.screenplay							-0.0337	[0.056]	-0.0692	[0.059]
Δwin_adap.screenplay							0.1894*	[0.101]	0.1054	[0.064]
α_0	-0.0236	[0.123]	-0.0239	[0.123]	-0.0241	[0.123]	-0.0235	[0.123]	-0.0241	[0.123]
α_t	yes		yes		yes		yes		yes	
Number of obs.	45190		45190		45190		45190		45190	
Number of groups	1182		1182		1182		1182		1182	
BIC	48906.66		48923.303		48962.323		48935.73		49017.853	
AIC	48514.321		48513.527		48500.236		48508.517		48503.454	

*Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level*