SEPPO SUOMINEN

Critics review or preceding week's admissions explaining movie admissions

SUMMARY

A panel data method approach is used to explain weekly movie admissions in Finland in 2003. The results indicate that when word-of-mouth is taken into account, critical reviews do not seem to significantly explain weekly movie admissions. Since admission figures are typically highest during the first weeks, a variable "weeks since released" is used to control for this peak. The analysis shows that it is significant, as well as the price variable. Price elasticity of weekly movie admission is roughly –1. Panel data analysis also indicates that the fixed effects model is the most suitable for explaining weekly movie admissions in Finland in 2003.

The author thanks the editor, two anonymous referees, and seminar participants in 4th European Workshop on Applied Cultural Economics (EWACE, 2009), Aydin, Turkey and 36th Annual Conference of European Association for Research in Industrial Economics (EARIE, 2009), Ljubljana, Slovenia for helpful comments. All errors are mine.

1 INTRODUCTION

Critics and their opinions or critical reviews have been shown to have an impact on movie admissions. Critics or reviewers are typically invited to an early screening of the film and write critics before the film opens to the public. This information is important for many experience goods, like

SEPPO SUOMINEN
Haaga-Helia University of Applied Sciences • e-mail: seppo.suominen@haaga-helia.fi

restaurants, theaters, books, movies. Other information is also available after the first night. Word-of-mouth has been recognized as one of the prime resources of information transmission. It is natural that critical reviews have an impact on premiere weekend's movie admissions while word-of-mouth which is more important to explain overall (long run) admissions (Basuroy, Desai & Talukdar 2006).

The star power of actors, director power and awards or nominations for awards are movie-related characteristics that have been shown to have an impact on movie admissions (Hennig-Thurau, Houston and Walsh 2007). Production budget seems to correlate with opening weekend screens and post-filming actions like advertising have been found to bring about success to theatrical box office revenue (Hennig-Thurau, Houston and Walsh 2006). Conventional economics postulates that price affects demand, however, in the movie admission or movie box office literature the effect of price has been neglected. One possible explanation for this shortage is that theaters seem to use uniform pricing (Orbach and Einav 2007). There are several possible explanations for using uniform pricing. Demand uncertainty might result in uniform pricing. Consumers might assume that prices reflect quality, low prices for low quality movies, and high prices for high quality prices. To avoid this signaling, distributors choose uniform prices. Another explanation is that selling packages of several tickets would require monitoring mechanisms to prevent using low-price tickets and watching high-priced movies. Therefore uniform pricing is often used. But in Finland movie theater tickets are not totally uniform. Typically the ticket price for children and conscripts is lower and also during weekdays prices might be lower than weekends. A single ticket is cheaper within a package of several tickets; therefore the actual average price of a display is not uniform. However, a large portion of distributors' profits come from adjunct sales (e.g. popcorn, confectionery), and the price setting has minor importance (Chen 2009). It is also true during the last decade that the role of video (DVD, Blu-Ray) rental has increased the share in film producers' profits.

The objective is to study what the relevance of critical reviews and word-of-mouth is in explaining movie admissions. The contribution of this study is that Finnish weekly panel data is used to evaluate the role of critical reviews in weekly movie admissions with having other control variables, like the number of screens, the ticket price and so on. With panel data, conventional regression analysis cannot be used since the results might be biased. The benefits of using the panel data are that (1) individual heterogeneity can be controlled, (2) estimated parameters are more efficient and (3) with the panel data the dynamics of adjustment can be studied better (Baltagi 2008, 6–7). The panel data suggests that individuals or movies are heterogeneous. Time-series and cross-section studies that do not control heterogeneity might yield biased results.

The variables in the panel data of this study are partially conventional and partially new. Critical reviews published in newspapers and word-of-mouth measured as previous week's admission in Helsinki theaters are among the conventional variables. Weekly ticket price measured as the ratio of box office revenue and admissions is the new candidate to explain weekly admissions. The results of this study indicate that when word-of-mouth is taken into account, critical reviews do not seem to significantly explain weekly movie admissions. Since admission figures are typically highest during the first weeks, a variable "weeks since released" is used to control for this peak. The analysis shows that it is significant, as well as the price variable. The price elasticity of weekly movie admission is roughly –1. The panel data analysis also indicates that fixed effects model is the most suitable for explaining weekly movie admissions in Finland in 2003.

The article continues with a literature review, the presentation of empirical model and variables. This is followed by an analysis of why panel data models have been used. Section 4 presents estimation results, and section 5 concludes.

2 LITERATURE REVIEW

The correlation analysis of Eliashberg and Shugan (1997) has been very influential in explaining critical reviews on movie admissions. They show that critics could act as opinion leaders (influencers) who are considered more experienced and having more knowledge of the quality of movies. On the other hand, critics could act merely as predictors without any impact on early box office revenue. Influencers have an impact on early box office revenues, while predictors have an impact on overall box office revenues. The impact of critic reviews has been found positive in many studies. Basuroy, Desai and Talukdar (2006) also consider the impact of consensus in critics' opinion (from Variety magazine) on movie admissions.

Eliashberg and Shugan (1997) assess only the aggregate impact of critics, while Boatwright, Basuroy and Kamakura (2007) also consider individual critics reviews published in newspapers and magazines with large circulation, like Entertainment Weekly, LA Times, Chicago Tribune or New York Times. TV shows have even bigger audience, but Reinstein and Snyder (2005) do not find a significant impact of critics on movie admissions when such reviews are revealed in television talk shows (national, USA). A big majority of studies on movie admissions have been carried out with US data but there are interesting examples with other countries. Elberse and Eliashberg (2003) estimate demand (box office revenue) and supply (number of screens) equations for several countries: the USA, France, Germany, Spain and the UK. Critical reviews have a significant and positive impact on premiere week's demand in the USA and the UK but negative impact on first week's supply. The impact is not significant for France, Germany or Spain.

With Dutch data Gemser, Van Oostrum and Leenders (2007) show that the number and size of film reviews (in cm^2 on a newspaper page) have an impact on art house premier week's revenue and also overall box office revenue while the same impact for mainstream movies is valid only for overall or long run box office revenue. On the other hand, Hennig-Thurau, Houston and Walsh (2006) present results that indicate a positive impact of critical reviews on short-term theatrical box office but not on long-term box office nor video rental revenues of movies released during 1999–2001 in the USA. Recently Elliott and Simmons (2008) showed that higher average critic ratings are associated with greater box office revenues and increased advertising in the UK. They also remark that advertising is greater for films with higher US opening revenues and higher budgets.

Hence the influence of film reviews is supported in many studies, but d'Astous, Carú, Koll and Sigué (2005) argue that the influence depends strongly on cultural dimension. Using Hofstede's (1984) theoretical framework in predicting consumers' movie attendance they show that based on differences in power distance between Austria, Canada, Colombia and Italy, Austrian and Canadian moviegoers are more susceptible to value-expressive social influence than Colombian or Italian audience. The impact of consultation on film reviews is stronger among Austrian and Canadian moviegoers. Consistent with the level of uncertainty avoidance, Canadian audience appreciates more movie genres than Austrian, Colombian or Italian audience. Consumers with higher uncertainty avoidance are more brand loyal. In addition, d'Astous, Colbert and Nobert (2007) propose that moviegoers may be influenced by the movie's country of origin when they search for information about new movies. It is also true that critical reviews might be biased. Ravid, Wald and Basuroy (2006) propose that several critics are significantly affected by the film distributor's identity. High budget films seem to get more reviews, but these reviews are worse than average, also films with star decoration tended to get more reviews with positive assessment.

Experts (film critics) and non-experts (layman) do not necessarily value the quality of a film similarly. There is no solid consensus about the relationship among expert and non-expert evaluators of different creative products, like movies (Plucker, Kaufman, Temple and Qian 2009). However, d'Astous and Touil (1999) show that experts' and non-experts' evaluations are parallel when the judgment of the expert does not confront to the expert's style or when the judgment is inconsistent with expert's predisposition toward the film director and when other critics' judgment show favorable consensus.

A hypothesis can be set as a summary: positive critic reviews have a positive effect on the spectator number.

Word-of-mouth (WOM) has also a powerful effect on movie admissions. Basuroy, Desai and Talukdar (2006) measure WOM as the cumulative number of screens since its release and they find a positive effect. WOM incorporates three effects: valence (positive, neutral, negative), volume of mouth-to-mouth discussion and persuasiveness of WOM generated. Neelamegham and Chingagunta (1999) on the contrary find no significant results between weekly revenue and WOM measured as cumulative viewership and they argue that cumulative viewership is not a good proxy for WOM. Elberse and Eliashberg (2003) used previous week's average revenue per screen as a proxy for WOM and they find significant positive results. Liu (2006) proposes that the volume of WOM (from Yahoo Movies Web site) offers significant explanatory power for both weekly and overall box office revenue, but the valence of WOM (measured as percentages of positive and negative messages) is not significant. WOM is more trustworthy than advertising or critical reviews since it comes from other moviegoers. Recently Duan, Gu and Whinston (2008) show that box office revenue of a movie and online WOM valence (measured on a daily basis from three web site sources: Variety.com, Yahoo!Movies and BoxOfficeMojo.com) have a significant impact on WOM volume which in turn leads to higher box office revenues. Moul (2007) proposes that WOM accounts for 10 % of the variation in the consumer expectations of movies, while distribution related effects, like the number of screens, release time and movie fixed effects, like star power, production budget comprise the great majority of observed variation in movie admissions. The nature of the WOM can be negative or positive. Since a bid proportion of movie goers are young, the role of social media (e.g. Yahoo Movies Web) must not be underestimated. However, since the data used here is so old (2003), the role of social media remains smaller.

The second hypothesis is therefore: Word-of-Mouth has a powerful effect on admissions. However, the direction of the effect is unclear since it depends on the nature of the WOM.

The information flow through WOM affects also supply. The number of screens must adapt as demand develops dynamically. The prior screen decisions made before the actual release must be adjusted as the attendance number is known during the first weeks after premiere. The demand – supply dynamics in the movie industry, however, is subject to high uncertainty (De Vany and Walls 1996) but DeVany and Lee (2001) show that WOM can be a credible means to share information about good and bad movies.

Movie related elements like the star power of actors (Bagella and Becchetti 1999, Neelamegham and Chintagunta 1999, Walls 2005, Elberse 2007 or Meiseberg, Erhmann and Dormann 2008), director power (Bagella and Becchetti 1999 or Jansen 2005) or awards/nominations (Deuchert, Adjamah & Pauly 2005) seem to correlate with higher box office revenue or movie admissions but the evidence is, however, mixed (see e.g. Elberse and Eliashberg (2003), Hennig-Thurau, Houston and Walsh (2006) or McKenzie 2009). Bagella and Becchetti (1999) show that star power of actors and directors have a positive impact on admission but, on the contrary, McKenzie (2009) reports the insignificance. Deuchert, Adjamah and Pauly (2005) prove that nominations generate extra income, while awards do not have this effect. On the other hand, Lee (2009) has recently proved that there is a negative relationship between drama awards and box office revenues as the cultural distance between the USA and country where the movie is shown grows. There is also strong evidence for a relationship between weekly revenues, opening week revenues or cumulative revenues and the number of screens (Elberse and Eliashberg 2003). Sequels also seem to collect a greater admission figure than contemporaneous non-sequels (Basuroy and Chatterjee 2008).

Movie distributors seem to release more hits (blockbusters) during high season, like the beginning of summer and during the Christmas holiday season. Collins, Hand and Snell (2002) show that action, adventure, horror or romantic comedy movies are more often blockbusters than other genre movies. Einav (2007) proposes that roughly two-thirds of the seasonal variation can be explained by underlying demand. The rest i.e. third is associated with the number and quality of movies. Einav also shows that wide release is often associated with heavy advertising[1] while word-of-mouth is more important in platform release. Wide release begins with a large number of screens with extensive national advertising. But only few widely released films are successful so that they are running many weeks (DeVany and Walls 1997). Platform release begins with a small number of initial screens and expands to additional screens and also to rural areas. Typically the movies with platform release cannot be classified as mainstream movies or actors are not well known stars. The production budget of a movie or prior advertising also seem to correlate with the number of premiere weeks screens (Elberse and Eliashberg 2003). Recently Moon, Bergey and Iacobucci (2010) have shown that high advertising spending on movies supported by high ratings maximizes the movie's revenues.

Only few studies have considered the role of the price of the ticket. Davis (2002) estimates that the theater price elasticities of demand are about –3. The six theaters in the sample displayed different number of movies ranging from 2 to 9 during a six-week period. Davis (2006) presents also similar consumer price sensitivity results. In Dewenter and Westermann (2005) the price elasticity is about –2½ with German long-term (1950–2002) annual data.

Several different methods have been used to study the relationship between box office revenue or movie admission and the explanatory variables, like correlation analysis (Eliashberg and Shugan (1997)), OLS, or partial least squares (Hennig-Thurau, Houston and Walsh (2006)).

Elberse and Eliashberg (2003) used OLS, 2SLS and 3SLS to explain the supply of movies (screens as dependent variable) or demand for movies (revenues as dependent variable) with various predictors (budget, stars, director, advertising expenditure, reviews, etc.). Both 2SLS and 3SLS take into account the endogeneity and simultaneity of screens and revenues. OLS is inconsistent since the endogeneous variable screens used as explaining variable in the revenues equation is correlated with the error term of the same equation. Such correlation may occur when the

1 Advertisers define heavy or heavy-up advertising as high concentration of advertising for a short period of time in a media schedule.

dependent variable causes at least one of the regressors ("reverse" causation), when there are relevant explanatory variables which are omitted from the model, or when the covariates are subject to measurement error. Since the error terms across equations may be correlated, a 3SLS method is more efficient than 2SLS. Elliott and Simmons (2008) also use 3SLS method to estimate simultaneously supply (opening screens), advertising and demand (total revenue).

Recently Einav (2007) estimated a nested logit demand model for weekly market shares for movies. Nested logit is a suitable method to assort two or more choice problems. With this model Einav distinguishes seasonality (first level: to go to a movie) and the quality of a movie (second level: to choose between different movies). Therefore the second level endogeneous variable is the market share of each movie. Also Ainslie, Drèze and Zufryden (2005) have estimated the market share of a movie using a random effects logit model with a gamma diffusion pattern. As consumers make the decision to see a movie, the time to decide and the time to act is derived from gamma distribution. They show that the impact of screens on movie sales may be lower than previously thought because screens act as a proxy for seasonality. Another interesting model is presented by Neelamegham and Chintagunta (1999). They use a Poisson count data model with the number of screens, distribution strategy, genre of a movie and stars explaining movie admissions. They find that the number of screens is the most important factor on admissions. An interesting model to predict box office success with neural networks is presented by Sharda and Delen (2006). Their neural network approach is suitable to classify movies into nine different categories ranging from flop (box office revenue less than 1 million USD) to blockbuster (revenue more than 200 million USD).

Davis (2002) uses the error components model (ECM) with unbalanced panel data. The data consists of sales, price and theater characteristics for six movie theaters and for a six-week period. A multinomial logit of demand for theaters is estimated and both own and cross price elasticities are reported. Theater demand is rather price sensitive, cross price elasticity between theaters not in the same group is practically zero but within group cross price elasticities are positive and rather large. Recently Davis (2006) using generalized method of moments (GMM) and a multinomial logit (MNL) demand model shows that low cross price elasticities between theaters is associated with (high) travel costs.

As a summary of the theoretical and previous empirical literature the following equation is reasonable:

admission = f(critics, WOM, Z)

in which Z includes the other explanatory variables. The main focus is the role of critical reviews (critics) and Word-of-Mouth (WOM). What is importance of critical reviews as the WOM is taken into account?

3 EMPIRICAL MODEL AND VARIABLES

The empirical study focuses on assessing the effects of various factors on weekly movie admissions in Finland in 2003. The Finnish Film Foundation (FFF) collects data from various distributors and importers. In 2003 the total number of films in distribution was 225 with only 177 premieres. Only 14 premieres were domestic, but the share of domestic movies in total admission was about 22%. Domestic film "Bad Boys – A True Story" got the biggest admission number: 614097 with roughly 4.4M€ total box office revenue. The ultimate week was the last week (53rd. i.e. Friday 26th December 2003 to Thursday 1st January 2004) when the top 20 movies collected 296495 admissions. The lowest figure was 48135 at the end of June. During the ultimate week "Lord of The Rings: Return of The King" have 165502 admissions in 68 screens and "Underworld" been last on the top 20 list with an audience of 606 in 2 screens. The median weekly admission was 138361 and the median screen number was 368 in 2003. Table 1 presents an overview of top 10 films in 2003 in Finland. The sample in this study has 1060 observations; there were 53 weeks with 20 biggest admission movies.

TABLE 1. Overview of top 10 films in 2003 in Finland, source: Finnish Film Foundation

Original title of the film	Release date	Screens	Total gross box office	Admissions	Country of Origin	Distributor
Bad Boys – A True Story (local)	17.1.2003	55	4413507	614097	Finland	BVI
Lord of The Rings: The Two Towers	18.12.2002	58	3610000	467644	USA	SF/FS
Lord of The Rings: Return of the King	17.12.2003	68	3060269	355739	USA	SF
The Matrix – Reloaded	21.5.2003	55	2364215	334206	USA	SMD
Bruce Almighty	25.7.2003	32	2103080	279485	USA	SF
Johnny English	11.4.2003	45	1912100	260643	UK	UIP
Sibelius	12.9.2003	50	1885625	257031	Finland	BVI
Pirates of The Caribbean	29.8.2003	44	1865774	245252	USA	BVI
Piglet's BIG Movie	29.8.2003	48	1398415	228421	USA	BVI
Helmiä ja sikoja (local)	29.8.2003	40	1586939	213385	Finland	Nordisk Film

Previous empirical evidence (good surveys: Hennig-Thurau, Walsh and Wruck 2001 and Eliashberg, Elberse and Leenders 2006) has shown that the demand for movies is determined by several factors. On the supply side, the number of screens is probably the most important factor. Once the movie production has been completed it is ready for distribution. The launch stage includes both the physical distribution of the prints to the theaters and the marketing activities. Einav (2007) points out that a wide release is associated with heavy advertising, while platform or narrower release is more often associated with information diffusion through word-of-mouth (WOM).

It is here merely assumed that the number of screens is positively associated with movie admissions. Weekly movie admissions and the number of screens ("prints this week") have been collected by FFF which is the source of data. Prints this week can include several showings during that week; typically there are some showings during the weekends, e.g. one at 3 p.m., second at 6 p.m. and the last at 9 p.m. Hence the number of screens underestimates the actual showings.

Expert reviews or ratings (critical reviews) and previous week's movie admission (WOM) can convey some information about the quality of a movie. Critical reviews can influence consumers in their selection process. This is the influence effect. On the other hand, reviews can forecast whether the film becomes a success or not. This is the prediction effect of critical reviews (Eliashberg and Shugan 1997). Different proxies have been used to measure WOM in the literature. In this study critics' review has been published weekly on Fridays in "Nyt" which is a supplement to Helsingin Sanomat that has the largest newspaper circulation in Finland. In 2003 the subscription number was about 420000, i.e. almost every twelfth Finnish citizen receives this newspaper home delivered. There are five reviewers that independently judge films in other newspapers than Nyt which simply collects and republishes these reviews. Three are Finnish and their critics are published in different newspapers and magazines: Helena Ylänen (Helsingin Sanomat), Antti Lindqvist (TV-maailma), and Tapani Maskula (Turun Sanomat). Helena Lindblad publishes her critics in Sweden (Dagens Nyheter) and Derek Malcolm in the UK (Guardian). Their judgement is published as stars ranging from 5 (superior) to 1 (loss of time). The average number of stars is published weekly and films are in descending order. The most liked film is on the top of the table and least liked film is on the bottom. In each week 10 movies are valued. For 43 movies the stars indicator is shown only once but there are movies for which the stars indicator is published in more than ten succeeding Nyt[2]. 133 movies were critically reviewed in Nyt. Ylänen reviewed 65, Lindqvist 118, Maskula 105, Lindblad 77 and Malcolm 75 respectively. But in the panel sample (20 top movies, 53 weeks, i.e. 1060 observations) there are e.g. 211 non-zero observations of Ylänen's critical reviews. The average value of critical reviews is used as explaining variable in the estimations.

Word-of-mouth is also based on tables printed in Nyt. The previous week's top 10 admission figures at theatres in Helsinki are listed on the same page as critical reviews. Typically the share of theatres in Helsinki in total admissions is about 35–40 %.[3] Both the actual number of admissions

2 Descriptive statistics for critical reviews is given in the appendix (table 2). It reveals that the critics of many "lower quality" is published only once or twice since the mean of critical review rank is decreasing in time (weeks).

3 In 2005 three important cities, Helsinki, Tampere and Turku had a 56% share in total admissions and a 57 % share in gross box revenue. Source: European Cinema Yearbook 2006 and ranking from 1 to 10 is printed. The film with the biggest admission in Helsinki theatres is ranked as number 1, and so on. Since that information is on the same page as critical reviews both of these variables are used to explain next week's movie admissions in whole Finland.

The proxy for word-of-mouth is this study (previous week's attendance in Helsinki) has a connection to what have been used elsewhere: cumulative number of screens since its release (Basuroy, Desai and Talukdar 2006), cumulative viewership (Neelamegham and Chingagunta 1999), and previous week's average revenue per screen (Elberse and Eliashberg 2003). Herr, Kardes & Kim (1991) or Grewal, Cline & Davies (2003) show that anecdotal information presented in a face-to-face manner (vivid WOM) has a greater impact on product judgments than the same information presented in printed-mode (e.g. advertising, critical reviews)[4]. In this study it is assumed that previous week's attendance in Helsinki theaters is a suitable measure for vivid WOM.

Seasonal variation is very important since many blockbusters are released during the high season. The highest movie admission month in Finland has been January during a five year period from 2003 to 2007 and June has been the lowest.

The weekly admission number is shown in appendix in figure 1. It reveals that the Christmas season and the end of May (the school year end) and late July/early August (the summer holiday end) are the peaks in movie admission. A proxy variable for seasonal variation is the number of all screens for all movies on that week. Admission is highest typically during the first weeks for blockbusters (e.g. Ainslie, Drèze and Zufryden 2006). The life cycle of sleeper movies is different since demand peaks later; weeks 4 and 5 from the release demand is highest. The mean duration of a movie run is typically 7 to 10 weeks in Western countries (Neelamegham and Chintagunta 1999, table 1). A control variable to the take the life cycle effect into account is needed: weeks since released. The median duration run of films with the biggest admission number in Finland is 17 weeks for the ultimate top 10 (1st to 10th) and roughly 10 weeks for the following 3 quantiles (from 11th to 40th)[5].

Descriptive statistics and the hypothesis (expected signs) are summarized in table 2. The sample consists 53 weeks with 20 top movies each week. The price variable is simply box office revenue/admission which takes into account both the difference between the price of using packages of several tickets and normal tickets as well as children/conscripts' lower prices com-pared with normal prices.[6] For some cases, especially among the lowest box office films, revenue data was not available and some approximation was needed. Either previous week's revenue was used or revenue was set lower than the lowest reported revenue. Only less than 10 films the

4 On the importance of WOM vs. public information, see Hidalgo, Castro & Rodriguez-Sickert (2006)
5 See appendix 3.
6 The percentiles (min, 10th, 20th, .., med, 60th, 70th, … max) in the price variable are: 1 – 5,95 – 6,52 – 6,83 – 7,07 – 7,27 (med) – 7,42 – 7,56 – 7,66 – 7,79 – 10,47 (max).

revenue data were missing and therefore price variables are approximated. Since all films in the sample have not been critically evaluated or not listed on Helsinki top 10, there are lots of zero observations. For the entire sample a dummy variable "not critically reviewed" (NOTCR) or "not top10" (NOTHK) are used. Otherwise the logarithmic values of variables are used and therefore the estimated parameters are elasticities.

TABLE 2. Descriptive statistics and sources of variables, * weekly, ** non-zero observations

Variable	Mean	Median	sd	min	max	valid observations	source	expected sign
Weekly Admission	6783,97	2240	14003,4	65	165502	1060	FFF	
Screens (SCR)	17,10	10	15,33	1	70	1060	FFF	+
All Screens (ALLSCR)	341,94	368	72,92	176	471	1060	FFF	+
Box office revenue (BOR)	50005	15825	109700	390	1165814	1060	FFF	
Price = BOR/Admission (PRICE)	7,04	7,27	0,88	1,00	10,47	1060		-
Critical reviews, average (CA)	2,83	3	0,90	1	5	133*	Nyt	+
Critical reviews, average (CA)	0,96	0	1,48	0	4,7	1060	Nyt	+
Critical reviews, average (CA)	2,98	3	0,87	1	4,7	340**	Nyt	+
WOM (previous week's admission in Helsinki) (HKIADM)	2391,12	1500	2606,40	239	21271	520**	Nyt	+
WOM (previous week's admission in Helsinki) (HKIADM)	1173	0	2181,63	0	21271	1060	Nyt	+
WOM (previous week's admission in Helsinki, rank) (TOP10)	5,44	5	2,86	1	10	520**	Nyt	–
WOM (previous week's admission in Helsinki, rank) (TOP10)	2,67	0	3,38	0	10	1060	Nyt	–
Weeks since released (WEEKSREL)	8,25	5	8,73	0	56	1060	FFF	–

4 ESTIMATION AND RESULTS

Since the data has both time-series (weekly) and cross-sectional (different movies) dimension, conventional regression analysis cannot be used. Panel data analysis enables regression analysis with both time-series and cross-sectional dimension. Panel data can have group effects (movies), time effects or both. Panel data models estimate fixed and/or random effects models using dummy variables. The core difference between fixed and random effect models lies in the role of dummies. If dummies are considered as a part of the intercept, it is a fixed effect model. In a random effect model, the dummies act as an error term[7]. The fixed effect model examines movie differences in intercepts, assuming the same slopes and constant variance across movies. Fixed effect models use least square dummy variable (LSDV), within effect, and between effect estima-

7 Hun Myoung Park: Linear Regression Models for Panel Data Using SAS, STATA, LIMDEP, and SPSS. http://www.indiana.edu/~statmath/stat/all/panel/panel.pdf accessed 5th February 2008

tion methods. Thus, ordinary least squares (OLS) regressions with dummies, in fact, are fixed effect models. The random effect model, by contrast, estimates variance components for groups and error, assuming the same intercept and slopes. The difference among groups (or time periods) lies in the variance of the error term. This model is estimated by generalized least squares (GLS) when the variance structure among genres, is known. The feasible generalized least squares (FGLS) method is used to estimate the variance structure the variance structure among genres is not known. Fixed effects are tested by the F test, while random effects are examined by the Lagrange multiplier (LM) test (Breusch and Pagan 1980). If the null hypothesis is not rejected, the pooled OLS regression is favoured. The Hausman specification test (Hausman 1978) compares fixed effect and random effect models. Table 3 (Park 2008) compares the fixed effect and random effect models. Group effect models create dummies using grouping variables (movie). If one grouping variable is considered, it is called a one-way fixed or random group effects model. Two-way group effect models have two sets of dummy variables, one for a grouping variable and the other for a time variable.

TABLE 3. Fixed Effect and Random Effect Models (Park 2008)

	Fixed Effect Model	Random Effect Model
Functional form assuming $\upsilon_{it} \sim IID(0,\upsilon\sigma^2)$	$y_{it} = (\alpha + \mu_i)+X_{it}'\beta + \upsilon_{it}$	$y_{it} = \alpha + X_{it}'\beta +(\mu_i+ \upsilon_{it})$
Intercepts	Varying across groups (movies) and/or times (weeks)	Constant
Error variances	Constant	Varying across groups and/or times
Slopes	Constant	Constant
Estimation	LSDV, within effect, between effect	GLS, FGLS
Hypothesis test	Incremental F test	Breusch-Pagan LM test

Least square dummy variable (LSDV) model, however, becomes problematic when there are many groups or subjects in the panel data. If the total number of periods is fixed and the total number of observations is vast, only coefficients of regressors are consistent. The coefficients of dummy variables are not consistent since the number of these parameters increases as N increases (Greene 2008, 197). This is so called the incidental parameter problem. Too many dummy variables may weaken the model for adequately powerful statistical tests. Under this circumstance, LSDV is useless, and another method might be used: the within effect model which does not use dummy variables, but uses deviations from group means.

Estimation results for the full sample with three different models are presented in table 4: conventional regression (OLS) analysis, fixed effects model and random effects model with all explanatory variables.

TABLE 4: Estimation results, full sample, n = 1060

Model	OLS without group dummy variables	LSDV, Fixed effects model (FEM)	Random effects model (REM)
Log SCR	0,780 (0,021)***	0,899 (0,030)***	0,862 (0,240)***
Log ALLSCR	0,314 (0,076)***	0,139 (0,089)	0,238 (0,079)**
Log PRICE	0,042 (0,125)	–0,088 (0,112)	0,001 (0,108)
Log WEEKSREL	–0,378 (0,022)***	–0,711 (0,027)***	–0,619 (0,023)***
Log HKIADM	0,177 (0,025)***	0,081 (0,022)***	0,091 (0,021)***
Log TOP10	–0,253 (0,049)***	–0,184 (0,041)***	–0,218 (0,040)***
Log CA	0,250 (0,099)**	–0,025 (0,100)	0,096 (0,093)
NotCR	–0,095 (0,139)	–0,345 (0,129)**	–0,249 (0,123)*
NotHK	0,551 (0,234)**	0,096 (0,205)	0,085 (0,197)
Constant	4,10 (0,523)***		5,42 (0,531)***
Depending variable is log of weekly admissions, n = 1060 Standard deviations in parenthesis			
Adjusted R-sq	0,811	0,897	0,784
F-test	507,55***	61,39***	
Diagnostic LL	1777,81***	2576,50***	

	Test statistics for the Classical Model			
	Constant term only (1)	Log Likelihood = –1720,44		LM test vs. Model (3) 395,01***
	Group effects only (2)	LL = –1461,90		Hausman test (FEM vs. REM): 122,39***
	X– variables only (3)	LL = –831,54		
	X-and group effects (4)	LL = –432,19		
	Hypothesis tests			
	(2) vs. (1)	LR test 517,09***	F test 3.99***	
	(3) vs. (1)	1777,80***	507,55***	
	(4) vs. (1)	2576.50***	61,38***	
	(4) vs. (2)	2059,41***	601,84***	
	(4) vs. (3)	798,69***	7,07***	

The test statistics indicate that fixed effects model is favoured. The number of screens, weeks since released, last week's admission in Helsinki theatres, movie shown in Helsinki top 10 listing and a dummy variable "not critically reviewed" are significant and correctly signed variables to explain weekly movie admissions. In Helsinki top 10 listing the movie with the biggest previous week's admissions is numbered as 1, the movie with the second biggest admission is numbered as 2, and so on up to 10. Hence TOP10 variable should get a negative coefficient. Since model is log-linear, other than dummy parameters are elasticises. Each movie has a different intercept (not shown). Since the other dummy variable "not top 10" (NOTHK) is not significant, another estimation is carried out beginning with the second week since released (i.e. NOTHK = 0). The sample size is now significantly lower, there are 515 observations.

Fixed effects model is favoured, and screens, weeks since released and movie shown in Helsinki top 10 lists are significant, but the only dummy variable "not critically reviewed" is not significant. Therefore a new estimation is carried out without dummy variables.

The estimation results in table 6 and 7 indicate that word-of-mount measured as last week's admission in Helsinki theatres seem to explain movie admissions, but critical reviews published in newspaper "Nyt" is not significant in fixed effects model that is favoured (Hausman test). Movie admission is price sensitive with approximately –1 price elasticity. Test statistics for the classical model indicate that conventional regression analysis (OLS) without group dummy variables is not suitable for explaining weekly movie admissions. The t-statistics for critical reviews variable that illustrates significance is misleading due to misspecified model.

With Finnish data, movie admission is inelastic with respect to number of screens. The screen variable does not take into account the number of actual seats in the hall. Blockbusters with a vast admission are shown in larger auditoriums and with more daily showings than arts movies. Increasing the number of screens is not as flexible as increasing daily showings if the movie turns out be a blockbuster. If the number of screens is still increased, these are probably with lower number of actual seats and therefore the relative admission increase is lower, and that might explain the inelasticity.

Two important hypotheses were imposed. Positive critical reviews should have a positive impact on movie attendance but the results indicate that this is not true. On the contrary when the Word-of-Mouth (second hypothesis) is taken into account critics do not explain attendance.

TABLE 5. Estimation results, all movies with previous admission in Helsinki, n = 515

Model	OLS without group dummy variables	LSDV, Fixed effects model (FEM)		Random effects model (REM)
Log SCR	0,613 (0,031)***	0,665 (0,043)***		0,710 (0,032)***
Log ALLSCR	0,177 (0,112)	–0,034 (0,111)		0,167 (0,098)*
Log PRICE	–0,773 (0,295)**	–0,408 (0,245)		–0,511 (0,232)*
Log WEEKSREL	–0,169 (0,043)***	–1,006 (0,050)***		–0,713 (0,041)***
Log HKIADM	0,487 (0,057)***	0,077 (0,042)		0,148 (0,041)***
Log TOP10	–0,160 (0,082)	–0,235 (0,061)***		–0,268 (0,058)***
Log CA	0,444 (0,104)***	0,056 (0,088)		0,242 (0,082)**
NotCR	0,422 (0,143)**	0,030 (0,108)		0,162 (0,103)
Constant	3,73 (0,712)***			6,757 (0,652)***
Depending variable is log of weekly admissions, n = 515 Standard deviations in parenthesis				
Adjusted R-sq	0,837	0,946		0,777
F-test	332,20***	81,03***		
Diagnostic LL	943,96***	1638,67***		
	Test statistics for the Classical Model			
	Constant term only (1)	Log Likelihood = –781,75		LM test vs. Model (3) 167,74***
	Group effects only (2)	LL = –554,44		Hausman test (FEM vs. REM): 151,36***
	X– variables only (3)	LL = –309,78		
	X-and group effects (4)	LL = 37,57		
	Hypothesis tests			
	(2) vs. (1)	LR test 454,62***	F test 5,45***	
	(3) vs. (1)	943,95***	332,19***	
	(4) vs. (1)	1638,67***	81,02***	
	(4) vs. (2)	1184,05***	448,27***	
	(4) vs. (3)	694,71***	10,76***	

TABLE 6. Estimation results, all movies critically reviewed and with previous week's Helsinki admission, n = 205

Model	OLS without group dummy variables	LSDV, Fixed effects model (FEM)		Random effects model (REM)
Log SCR	0,647 (0,053)***	0,531 (0,095)***		0,775 (0,051)***
Log ALLSCR	0,028 (0,172)	0,072 (0,174)		0,171 (0,146)
Log PRICE	–0,361 (0,522)	–1,123 (0,373)**		–1,133 (0,339)**
Log WEEKSREL	–0,275 (0,075)***	–1,134 (0,068)***		–0,851 (0,060)***
Log HKIADM	0,621 (0,085)***	0,163 (0,054)**		0,248 (0,051)***
Log TOP10	0,091 (0,133)	–0,004 (0,856)		–0,000 (0,080)
Log CA	0,380 (0,113)**	0,133 (0,114)		0,196 (0,097)*
Constant	2,519 (1,214)*			6,994 (0,950)***
Depending variable is log of weekly admissions, n = 205 Standard deviations in parenthesis				
Adjusted R-sq	0,852	0,966		
F-test	169,39	89,70***		
Diagnostic LL	399,47	779,77***		
	Test statistics for the Classical Model			
	Constant term only (1)	Log Likelihood = –325,59		<u>LM test vs. Model (3)</u> 60,44***
	Group effects only (2)	LL = –151,72		<u>Hausman test (FEM vs. REM):</u> 78,36***
	X– variables only (3)	LL = –125,86		
	X-and group effects (4)	LL = 64,28		
	Hypothesis tests			
	(2) vs. (1)	<u>LR test</u> 347,74***	<u>F test</u> 10,68***	
	(3) vs. (1)	399,47***	169,39***	
	(4) vs. (1)	779,76***	89,70***	
	(4) vs. (2)	432,02***	141,44***	
	(4) vs. (3)	380,29***	12,31**	

Table 7: Estimation results, all movies critically reviewed and with previous week's Helsinki admission, n = 205

Model	OLS without group dummy variables	LSDV, Fixed effects model (FEM)		Random effects model (REM)
Log SCR	0,631 (0,050)***	0,528 (0,092)***		0,775 (0,049)***
Log PRICE	–0,284 (0,505)	–1,058 (0,329)***		–0,988 (0,313)**
Log WEEKSREL	–0,268 (0,073)***	–1,139 (0,066)**		-0,860 (0,058)***
Log HKIADM	0,586 (0,058)***	0,166 (0,038)***		0,252 (0,036)***
Log CA	0,381 (0,111)***	0,136 (0,112)		0,205 (0,096)*
Constant	2,977 (1,064)**			7,677 (0,715)***
Depending variable is log of weekly admissions, n = 205 Standard deviations in parenthesis				
Adjusted R-sq	0,853	0,967		0,802
F-test	238,43***	93,69***		
Diagnostic LL	398,64***	779,51**		
	Test statistics for the Classical Model			
	Constant term only (1)	Log Likelihood = –325,59		LM test vs. Model (3) 60,84***
	Group effects only (2)	LL = –151,72		Hausman test (FEM vs. REM): 79,72***
	X– variables only (3)	LL = –126,27		
	X-and group effects (4)	LL = 64,15		
	Hypothesis tests			
	(2) vs. (1)	LR test 347,74***	F test 10,68***	
	(3) vs. (1)	398,63***	238,43***	
	(4) vs. (1)	779,50***	93,69***	
	(4) vs. (2)	431,76***	200,62***	
	(4) vs. (3)	380,86***	12,53***	

5 CONCLUSIONS AND SUGGESTIONS

In the movie admission or movie box office literature the importance of word-of-mouth has been well documented. Word-of-mouth has a positive effect on movie admissions (Elberse and Eliashberg 2003, Basuroy, Desai and Talukdar 2006, Liu 2006, Moul 2007, Duan, Gu and Whinston 2008). The evidence on the impact of critical reviews on movie admissions is mixed. Eliashberg and Shugan (1997) argue that critics could act as influencers or predictors. Influencers can predict opening box office revenue while predictors can classify films either to successful or not-successful films in terms of revenue in the longer term. Hence the impact of critical reviews is not uniform. Some predict well short-term revenue and some better long-term revenue. Not only the existence of reviews but also the variation or consensus of critics can have an impact on admission (Basuroy, Desai and Talukdar 2006). The impact is also different depending on genre (Gemser, van Oostrum and Leenders 2007), country of origin (d'Astous, Colbert and Nobert 2007, King 2007) and cultural dimension (d'Astous, Carú, Koll and Sigué 2005). Critical reviews may be biased towards distributor's identity (Ravid, Wald and Basuroy 2006). This study shows with weekly Finnish data and using panel data estimation methods that word-of-mouth has a significant impact on movie admissions while critical reviews have not. The critical review variable is the average value of five independent critics published in newspaper Nyt. The impact of individual critic's reviews has not been tested in this study and it needs to be done in the future. Are there differences among different genres? Are action movie lowers (younger and) less relying on critical reviews and more relying on word-of-mouth than drama and/or romance audience? Collins and Hand (2005) show with the UK data that richer and younger people are most likely to go to the movies, also the residential neighborhood matters.

An important implication for movie distributors in Finland is that they should use a wide release strategy when the expected WOM is negative. In many cases, the release weekend is later than it is in larger and English spoken countries. Hence there is some knowledge about the WOM in other countries. With wide release strategy, this negative WOM has less influence since the strategy puts more weight on the first week and the WOM has less circulation time. On the contrary if the expected WOM is positive, movie distributors should use platform release with a small number of initial screens and expanding later.

The results are compatible with d'Astous, Carú, Koll and Sigué (2005) who present evidence that the influence of reviews depends strongly on cultural dimension (Hofstede 1984). The results with this Finnish data indicate that reviews do not have any influence on attendance. However, since the influence of Word-of-Mouth and critical reviews are both dimensions of susceptibility to value-expressive influence that are important in Hofstede's dimensions, the differences of the effects are difficult to separate.

In the estimated equation the variable Z represents other variables than Critics and WOM. The ticket price, the number of screens, and the time factor (weeks since released) are all significant variables to explain movie attendance. All of these are plausible, price elasticity is –1, the admission is inelastic with respect to screens and the time factor shows that the admission is highest during the first weeks.

The star power of actors, director power or awards or nominations for awards have not been tested with Finnish data since the share of domestic films in 2003 was only 14 % in premieres or 22 % in total admissions. The biggest admission film in 2003 was domestic and several main actors had received Jussi Awards some years before. Jussi Award is the most important Finnish award. It remains an open question whether these awards or well-known actors have had any impact on admissions or box office revenue.

The role of theater ticket price has been missing in international movie admission literature. Although the variation in prices is rather small, this study shows that movie admission is price sensitive. Davis (2002) showed that the theater demand is elastic with respect to price (about –2,3 to –4,1). With Finnish data, movie demand is roughly unit elastic. Conventional regression (OLS) analysis does not bring about significant and reasonable price elasticity estimates. Only panel data methods, specially fixed effects models are suitable for producing proper estimates. ■

REFERENCES

AINSLIE, ANDREW, DRÈZE, XAVIER and ZUFRYDEN, FRED (2005): Modeling Movie Life Cycles and Market Share. *Marketing Science 24*, 3: 508–517

d'ASTOUS, ALAIN, CARÚ, ANTONELLA, KOLL, OLIVER and SIGUÉ, SIMON PIERRE (2005): Moviegoers' Consultation of Film Reviews in the Search for Information: A Multi-country Study. I*nternational Journal of Arts Management 7*, 3: 32–45

d'ASTOUS, ALAIN, COLBERT, FRANÇOIS and NOBERT, VÉRONIQUE (2007): Effects of Country-Genre Congruence on the Evaluation of Movies : The Moderating Role of Critical Reviews and Moviegoers' Prior Knowledge. *International Journal of Arts Management 10*, 1: 45–51

d'ASTOUS, ALAIN and NAID TOUIL (1999): Consumer Evaluations of Movies on the Basis of Critics' Judgments. *Psychology & Marketing 16*: 677–694

BAGELLA, M and BECCHETTI, L. (1999): The Determinants of Motion Picture Box Office Performance: Evidence from Movies Produced in Italy. *Journal of Cultural Economics 23*, 4: 237–256

BALTAGI, BADI H. (2008): Econometric Analysis of Panel Data. 4th Edition, John Wiley & Sons Ltd

BASUROY, SUMAN and CHATTERJEE, SUBIMAL (2008): Fast and frequent: Investigating box office revenues of motion picture sequels. *Journal of Business Research 61*: 798–803

BASUROY, SUMAN, DESAI, KALPESH KAUSHIK and TALUKDAR, DEBABRATA (2006): An Empirical Investigation of Signaling in the Motion Picture Industry. *Journal of Marketing Research 63*: 287–295

BOATWRIGHT, PETER, BASUROY, SUMAN and KAMAKURA, WAGNER (2007): Reviewing the reviewers: The impact of individual film critics on box office performance. Quantitative Marketing and Economics 5, 4: 401–425

BREUSCH, T. and PAGAN, A. (1980): The LM Test and Its Applications to Model Specification in Econometrics. *Review of Economic Studies 47*: 239–254

CHEN, CHIEN-PING (2009): A Puzzle or a Choice: Uniform Pricing for Motion Pictures at the Box. *Atlantic Economic Journal 37*, 73–85

COLLINS ALAN and CHRIS HAND (2005): Analyzing Moviegoing Demand: An Individual-level Cross-sectional Approach. *Managerial and Decision Economics 26*: 319–330

COLLINS ALAN, CHRIS HAND and MARTIN C. SNELL (2002): What Makes a Blockbuster? Economic Analysis of Film Success in the United Kingdom. *Managerial and Decision Economics 23*: 343–354

DAVIS, PETER (2002): Estimating multi-way error components models with unbalanced data structures. *Journal of Econometrics 106*: 67–95

DAVIS, PETER (2006): Spatial competition in retail markets: movie theaters. *Rand Journal of Economics 37*, 4: 964–982

DEUCHERT, EVA, ADJAMAH, KOSSI and PAULY, FLORIAN (2005): For Oscar Glory or Oscar Money? *Journal of Cultural Economics 29:* 159–176

DeVANY, ARTHUR and CASSEY LEE (2001): Quality signals in information cascades and the dynamics of the distribution of motion picture box office revenue. *Journal of Economic Dynamics and Control 25*: 593–614

DeVANY, ARTHUR and W. DAVID WALLS (1996): Bose-Einstein dynamics and adaptive contracting in the motion picture industry. *The Economic Journal 106*: 1493–1514

DeVANY, ARTHUR S. AND W. DAVID WALLS (1997): The market for motion pictures: Rank, revenue, and survival. *Economic Inquiry 35*: 783–797

DEWENTER, RALF and MICHAEL WESTERMANN (2005): Cinema Demand in Germany. *Journal of Cultural Economics 29:* 213–231

DUAN, WENJING, GU, BIN and WHINSTON, ANDREW B. (2008): The dynamics of online word-of-mouth and product sales – An empirical investigation of the movie industry. *Journal of Retailing 84*, 2: 233–242

EINAV, LIRAN (2007): Seasonality in the U.S. Motion Picture Industry. *Rand Journal of Economics 38*, 1: 127–145

ELBERSE, ANITA (2007): The Power of Stars: Do Star Actors Drive the Success of Movies? *Journal of Marketing 71*, 4: 102–120

ELBERSE, ANITA and ELIASHBERG, JEHOSHUA (2003): Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures. *Marketing Science 22*, 3: 329–354

ELIASHBERG, JEHOSHUA, ELBERSE, ANITA and LEENDERS, MARK A. A.M. (2006): The Motion Picture Industry: Critical Issues in Practice, Current Research, and New Research Directions. *Marketing Science 25*, 6: 638–661

ELIASHBERG, JEHOSHUA AND SHUGAN, STEVEN M. (1997): Film Critics: Influencers or Predictors. *Journal of Marketing 61*, 2: 68–78

ELLIOTT, CAROLINE and SIMMONS, ROB (2008): Determinants of UK Box Office Success: The Impact of Quality Signals. Review of Industrial Organization 33, 2: 93–111

GEMSER, GERDA, VAN OOSTRUM, MARTINE and LEENDERS, MARK A.A.M. (2007): The impcat of film reviews on the box office performance of art house versus mainstream motion pictures. *Journal of Cultural Economics 31*: 43–63

GREENE, WILLIAM H. (2008): Econometric Analysis. 6th Edition, Pearson Prentice-Hall

GREWAL, RAJDEEP, THOMAS W. CLINE & ANTHONY DAVIES (2003): Early-Entrant Advantage, Word-of-Mouth Communication, Brand Similarity, and the Consumer Decision-Making Process. *Journal of Consumer Psychology 13*, 187–197

HAUSMAN, J. (1978): Specification Test in Econometrics. *Econometrica 46:* 1251–1271

HENNIG-THURAU, THORSTEN, HOUSTON, MARK B. & WALSH, GIANFRANCO (2006). The Differing Roles of Success Drivers Across Sequential Channels: An Appication to the Motion Picture Industry. *Journal of the Academy of Marketing Science*, 34 (4): 559–574

HENNIG-THURAU, THORSTEN, HOUSTON, MARK B. AND WALSH, GIANFRANCO (2007): Determinants of Motion Picture Box Office and Profitability: An Interrelationship Approach. *Review of Managerial Science 1*, 1: 65–92

HENNIG-THURAU, THORSTEN, WALSH, GIANFRANCO AND WRUCK, OLIVER (2001): An Investigation into the Factors Determining the Success of Service Innovations: The Case of Motion Pictures. *Academy of Marketing Science Review 6:* 1–23

HERR, PAUL, FRANK KARDES & JOHN KIM (1991): Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research 17*, 454–462

HIDALGO R, CÉSAR A., ALEJANDRA CASTRO & CARLOS RODRIGUEZ-SICKERT (2006): The effect of social interactions in the primary consumption life cycle of motion pictures. New Journal of Physics 8, 52

HOFSTEDE, G. (1984): Dimensions of National Cultures in Fifty Countries and Three Regions. In *Explications in Cross-cultural Psychology,* Deregowski, J.B., Dziurawiec, S. and Annis, R.C. (eds). Swets & Zetilinger, p. 144–155

HOLBROOK, MORRIS B. (1999): Popular Appeal Versus Expert Judgments of Motion Pictures. *Journal of Consumer Research 26*: 144–155

JANSEN, CHRISTIAN (2005): The Performance of German Motion Pictures, Profits and Subsidies: Some Empirical Evidence. *Journal of Cultural Economics 29*: 191–212

KING, TIMOTHY (2007): Does film criticism affect box office earnings? Evidence from movies released in the U.S. in 2003. *Journal of Cultural Economics 31*: 171–186

LEE, FRANCIS L.F. (2009): Cultural discount of cinematic achievement: the academy awards and U.S. movies' East Asian box office. *Journal of Cultural Economics 33*, 4, 239–263

LIU, YONG (2006): Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing 70*, 3: 74–89

MCKENZIE, JORDI (2009): Revealed Word-of-Mouth Demand and Adaptive Supply: Survival of Motion Pictures at the Australian Box Office. Mimeo, *Journal of Cultural Economics 33: 279–299*

MEISEBERG, BRINJA, ERHMANN, THOMAS and DORMANN, JULIAN (2008): We Don´t Need Another Hero – Implications from Network Structure and Resource Commitment for Movie Performance. *Schmalenbach Business Review 60*: 74–98

MOUL, CHARLES C. (2007): Measuring Word of Mouth's Impact on Theatrical Movie Admissions. *Journal of Economics & Management Strategy 16*: 859–892

MOON, SANGKIL, PAUL K. BERGEY and DAWN IACOBUCCI (2010): Dynamic Effects Among Movie Ratings, Movie Revenues, and Viewer Satisfaction. *Journal of Marketing 74*: 108–121

NEELAMEGHAM, RAMYA and CHINGAGUNTA, PRADEEP (1999): A Bayesian Model to Forecast New Product Performance in Domestic and International Markets. *Marketing Science 18*: 115–136

NELSON, PHILIP (1970): Information and Consumer Behavior. *Journal of Political Economy 81*: 311–329

ORBACH, BARAK Y. and EINAV, LIRAN (2007): Uniform prices for differentiated goods: The case of the movie-theater industry. *International Review of Law and Economics 27*: 129–153

PARK , HUN MYOUNG: Linear Regression Models for Panel Data Using SAS, STATA, LIMDEP, and SPSS. http://www.indiana.edu/~statmath/stat/all/panel/panel.pdf accessed 5th February 2008

PLUCKER, JONATHAN A., JAMES C. KAUFMAN, JASON S. Temple and Meihua Qian (2009): Do Experts and Novices Evaluate Movies the Same Way? *Psychology & Marketing 26*: 470–478

RAVID, S. ABRAHAM, WALD, JOHN K. and BASUROY, SUMAN (2006): Distributors and Film Critics: Does it take two to Tango? *Journal of Cultural Economics 30*: 201–218

REINSTEIN, DAVID and SNYDER, CHRISTOPHER M. (2005): The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics. *The Journal of Industrial Economics 53*: 27–52

SHARDA, RAMESH and DELEN, DURSUN (2006): Predicting box-office success of motion pictures with neural networks. *Expert System with Applications 30*: 243–254

WALLS, W. DAVID (2005): Modeling Movie Success when 'Nobody Knows Anything': Conditional Stable-Distribution Analysis of Film Returns. *Journal of Cultural Economics 29*: 177–190

Data sources: Finnish Film Foundation (www.ses.fi); Helsingin Sanomat, Nyt – available at Päivälehden museo, Ludviginkatu 2–4, Helsinki, Finland (www.paivalehdenmuseo.fi)

Estimation method: LIMDEP – NLOGIT 4.0 (www.limdep.com)

APPENDICES

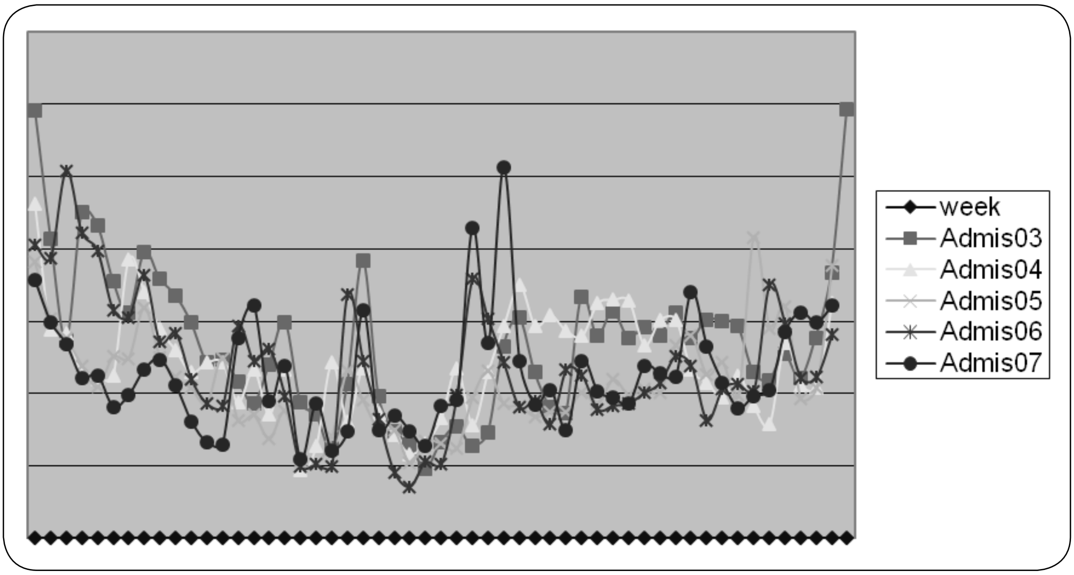

FIGURE 1. Weekly Total Admission, Years 2003 to 2007

APPENDIX 1.Distributors' premieres in 2001 – 2003

Distributor	2001	2002	2003	examples in 2003 (or late 2002)
Columbia Tristar Egmo	27	27	28	Terminator 3, Charlie's Angels, Bad Boys 2
FS Film	28	28	26	Lord of The Rings: The Two Towers, Lord of The Rings: Return of The King
Buena Vista	12	20	24	Bad Boys – A True Story, Sibelius, Pirates of The Caribbean
Scanbox	6	16	19	The Hours, The Human Stain, A la Folie
Sandrew Metronome	26	25	19	The Matrix Reloaded, The Matrix Revolutions, Harry Potter and The Chamber…
Cinema Mondo	19	17	16	The Pianist, Spirited Away, Stupeur & Treblements
Kamras Film Group	10	15	12	Good Bye Lenin, Nirgendwo in Africa, Cidade de Deus
UIP	20	17	12	Johnny English, Ring, Catch Me If You Can
Future Film	9	9	11	Swimming Pool, Evil Dead, Les vacances M Hulot
Senso Films	9	11	4	L'Ultimo bacio, Movern Callar, Last Orders
Rest; Kinoscreen, Rapid Eye Movie, Finnkino	5	7	6	Bella Martha aka Mostly Martha, Lejontämjaren, Pure
All premieres	171	192	177	

APPENDIX 2. Descriptive statistics for critical review rank (scale 1 – "top" to 10 – "lowest")

Variable	Mean	Median	sd	min	max	valid observationms	source	notes
Critical review, rank, 1st occurrence, display	6,92	8	2,57	1	10	133	Nyt	43 films are reviewed only once
Critical review, rank, 2nd display	6,11	6,5	2,50	1	10	90	Nyt	Critical reviews (index: 1 to 5) is shown twice for 27 films
Critical review, rank, 3rd display	5,75	6	2,66	1	10	63	Nyt	
Critical review, rank, 4th display	5,33	5	2,96	1	10	51	Nyt	
Critical review, rank, 5th display	5,14	4	2,93	1	10	37	Nyt	
Critical review, rank, 6th display	4,67	4	2,90	1	10	27	Nyt	
Critical review, rank, 7th display	3,90	3	2,85	1	10	19	Nyt	
Critical review, rank, 7th display	3,88	3	2,87	1	10	16	Nyt	
Critical review, rank, 8th display	2,75	2	1,93	1	7	12	Nyt	
Critical review, rank, 9th display	3,4	2	2,46	1	8	10	Nyt	
Critical review, rank, 10th display	3	3	1,58	1	5	9	Nyt	11 weeks: 1 film, 12 weeks: 2 films 14 weeks: 3 films, 15 weeks: 1 film 18 weeks: 1 film, 20 weeks: 1 film

APPENDIX 3. Duration of movie run, quantiles

Variable	Mean	Median	Screens, five first weeks, mean	Screens, first week, mean	Screens, second week, mean	Screens, third week, mean
Top 10, duration of movie run, weeks	17,3	17	44,5	29,8	46,1	49,3
Films 11–20, duration of movie run, weeks	13,8	10,5	39,0	31,6	43,2	45,5
Films 21–30, duration of movie run, weeks	13,9	10,5	30,1	28,7	34,1	33,2
Films 31–40, duration of movie run, weeks	10,9	9	28,3	25,6	31,2	30,2
Films 41–50, duration of movie run, weeks	7,8	7,5	21,8	17,4	24,2	27,7
Films 51–60, duration of movie run, weeks	10	10,5	12,3	9,9	13,6	13,4
Films 61–70, duration of movie run, weeks	6,6	6,5	8,2	8,9	9,3	7,9
Films 71–80, duration of movie run, weeks	5,6	5	8,2	10,0	11,7	8,9
Films 81–90, duration of movie run, weeks	5,3	5	3,6	4,7	4,8	3,4
Films 91–100, duration of movie run, weeks	3,4	3,5	4,0	6,1	5,1	4,7
Films 101–110, duration of movie run, weeks	4	4,5	4,5	5,8	5,4	5,0
Films 111–120, duration of movie run, weeks	3	3,5	2,0	3,4	2,9	1,8
Films 121–130, duration of movie run, weeks	1,5	2	2,3	6,3	4,9	0,5

APPENDIX 4. Estimation results, n = 345

Model	OLS without group dummy variables	LSDV, Fixed effects model (FEM)		Random effects model (REM)
Log SCR	0,955 (0,034)***	0,691 (0,068)***		0,929 (0,038)***
Log ALLSCR	0,131 (0,141)	0,119 (0,169)		0,093 (0,139)
Log PRICE	1,174 (0,454)*	–0,942 (0,381)*		-0,249 (0,340)
Log WEEKSREL	–0,471 (0,043)***	–1,079 (0,048)***		-0,893 (0,041)***
Log HKIADM	0,263 (0,079)**	0,123 (0,057)*		0,116 (0,052)*
Log TOP10	0,018 (0,119)	0,050 (0,092)		-0,009 (0,083)
Log CA	0,374 (0,111)****	0,123 (0,127)		0,195 (0,104)
NotHK	2,009 (0,762)**	0,985 (0,579)		0,859 (0,522)
Constant	1,210 (1,161)			6,214 (1,020)***
Depending variable is log of weekly admissions, n = 345 Standard deviations in parenthesis				
Adjusted R-sq	0,838			
F-test	217,86***			
Diagnostic LL	628,75***			
	Test statistics for the Classical Model			
	Constant term only (1)	Log Likelihood = –589,43		<u>LM test vs Model (3)</u> 118,15***
	Group effects only (2)	LL = –312,10		<u>Hausman test (FEM vs REM):</u> 103,30***
	X– variables only (3)	LL = –275,05		
	X-and group effects (4)	LL = 0,667		
	Hypothesis tests			
	(2) vs (1)	<u>LR test</u> 554,65***	<u>F test</u> 10,61***	
	(3) vs (1)	628,74***	217,85***	
	(4) vs (1)	1180,21***	70,22***	
	(4) vs (2)	625,56***	155,19***	
	(4) vs (3)	551,46***	10,15***	

APPENDIX 5. Estimation results, all movies critically reviewed and with previous week's Helsinki admission, n = 205

Model	OLS without group dummy variables	LSDV, Fixed effects model (FEM)		Random effects model (REM)
Log SCR	0,642 (0,050)***	0,740 (0,103)***		0,866 (0,052)***
Log PRICE	0,052 (0,529)	–0,976 (0,313)**		–0,880 (0,301)**
Log WEEKSREL	–0,284 (0,076)***	–1,150 (0,059)***		–0,959 (0,054)***
Log HKIADM	0,545 (0,060)***	0,125 (0,034)***		0,184 (0,033)***
Constant	3,129 (1,117)*			8,167 (0,665)***
Depending variable is log of weekly admissions, n = 205 Standard deviations in parenthesis				
Adjusted R-sq	0,841	0,971		0,777
F-test	268,51***	74,02***		
Diagnostic LL	376,61***	792,65***		
	Test statistics for the Classical Model			
	Constant term only (1)	Log Likelihood = –322,30		LM test vs Model (3) 72,04***
	Group effects only (2)	LL = –141,72		Hausman test (FEM vs REM): 70,56***
	X– variables only (3)	LL = –133,99		
	X-and group effects (4)	LL = 74,02		
	Hypothesis tests			
	(2) vs (1)	LR test 361,16***	F test 11,69***	
	(3) vs (1)	376,60***	268,51***	
	(4) vs (1)	792,65***	106,18***	
	(4) vs (2)	431,48***	255,71***	
	(4) vs (3)	416,04***	15,62***	