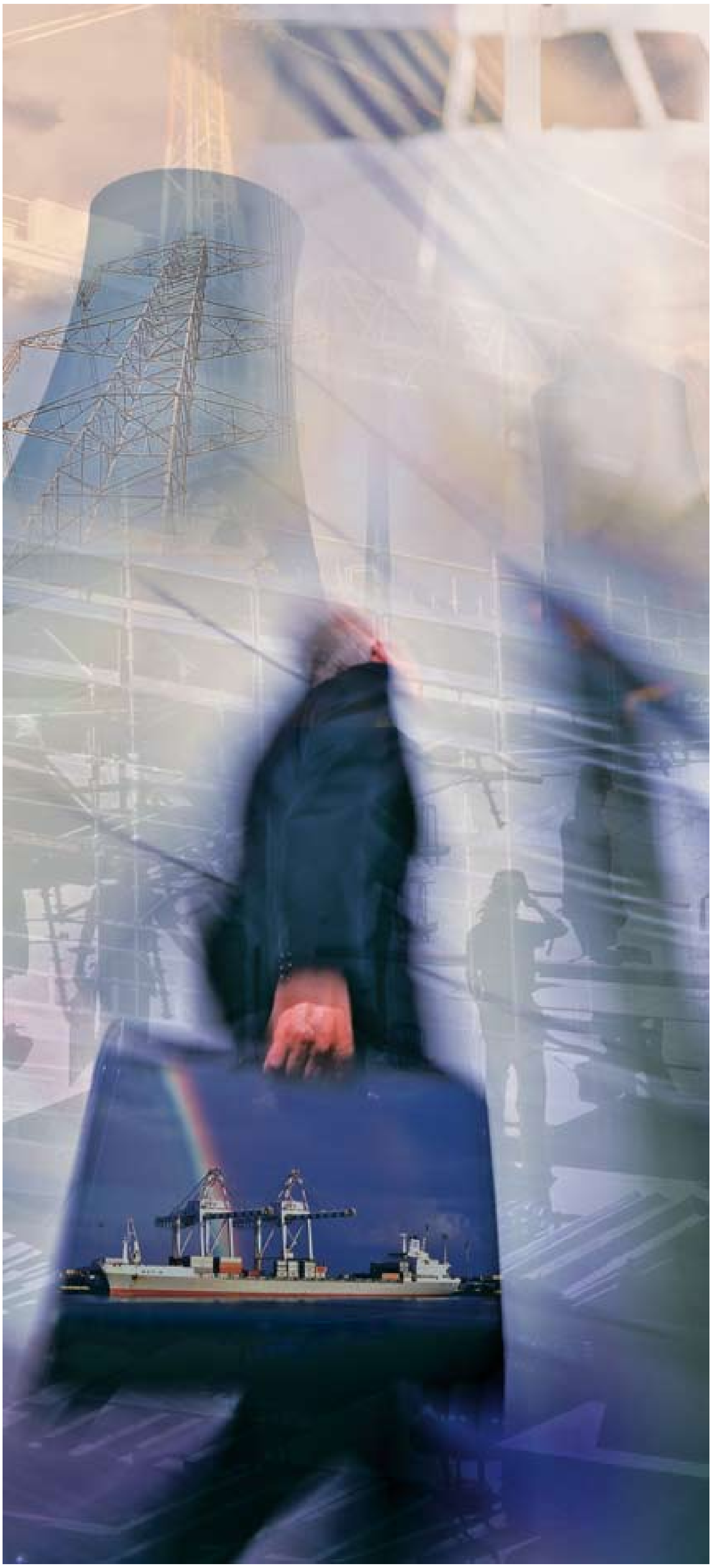

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Underlying Seasonality in the Presence of Increasing Returns to Information: Empirical Evidence from the Australian Motion Picture Industry

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March 27, 2008

Abstract

This paper investigates the apparent underlying seasonality in motion picture demand recently documented by Einav (2007). The research takes motivation from Einav's study but considers a statistical approach to the exploration of underlying seasonality. Specifically, this paper builds upon the 'increasing returns to information' class of model, or more generally Pareto law model, to explore underlying seasonality in box office returns. Using a nine year sample of Australian box office revenue data (1997-2005), the results suggest the seasonal amplification effect is considerably smaller (approximately 20%) under the Pareto model interpretation compared with Einav's discrete choice model specification (approximately 50%).

Keywords: Australian Box Office Revenue, Increasing Returns to Information, Underlying Seasonality

JEL Classification Numbers: Z11, C16

* I acknowledge the support of the Motion Picture Distributor Association of Australia (MPDAA) for supplying data used in this study. I am grateful to Arthur De Vany for guidance in earlier stages of this research.
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I INTRODUCTION

This paper investigates the apparent underlying seasonality in motion picture demand recently documented by Einav (2007) for the U.S. market. Underlying seasonality may differ from observed seasonality due to the endogenous release decisions of distributors who seek to release stronger titles during peak periods such as school holiday and Christmas/New Year holiday periods. The potential result is an amplification effect on the observed weekly revenues of films that may suggest an excessive pattern of seasonality to the industry. Using the discrete choice (nested logit) framework outlined by Berry (1994), Einav suggests the underlying seasonality to account for approximately two thirds of observed box office, or that the release of 'quality' films (defined as those having more box office 'potential and appeal') amplifies underlying seasonality by approximately 50%, in the U.S. market. Einav's model is based on a utility specification that considers film quality as a fixed effect and a linear decay pattern for films viewed later in their theatrical run. A potential shortcoming noted by Einav is that the model might not accurately account for information dissemination effects, and in an unreported sub-sample analysis, he assumes that most word-of-mouth effects take place before week two and conditions his analysis on films beyond week three of their run – the results, he states, are almost identical. The study also may be limited by the fact that his data set only reports films up to week 10 of their run. Given that some films develop legs and run well beyond this the results may suffer.

This study takes motivation from the insights of Einav but considers a different approach to exploring the notion of underlying seasonality. Specifically, this paper considers a statistical approach to the problem, in preference to the discrete choice framework adopted by Einav. A growing body of literature has documented the skewed nature of the box office returns and the role of information transmission in creating this result. This pattern was aptly defined ‘increasing returns to information’ by De Vany and Walls (1996) in their seminal study on the transmission of information in the film industry using a sample of over 300 films released in 1985-86 in the U.S. The statistical relationship they observed is based on the timeless Pareto distribution that has been shown highly suitable for describing size distributions throughout economics – such as incomes, firm size and city size. The deviation from the log linear Pareto distribution observed by De Vany and Walls implied an auto-correlated structure to revenue growth as initially defined by Ijiri and Simon (1971, 1974) for firm size data. The finding of non-linearity in the log size/rank Pareto relationship has since been verified on a number of other data sets for various countries and industries.[1] What hasn’t been documented as yet, however, is how such a relationship may interact with any potential underlying seasonality of demand. This study seeks to add to the literature by reconsidering the basic Pareto model to accommodate additional features of demand and, in particular, to explore the underlying seasonal influence on the robust ‘increasing returns to information’ model.

This study uses a nine year sample of weekly revenues and associated statistics of all 2,429 motion pictures released in Australian cinemas from January 1, 1997 to December 31, 2005 as recorded by the Motion Picture Distributors Association of Australia (MPDAA). Using a panel type data set of the weekly rankings of films’ revenues the study considers the auto-correlated pattern observed in the Pareto model with the inclusion of movie fixed effects, and calendar week fixed effects. Inference

[1] See, for example, Walls (1997), Hand (2001), and McKenzie (2007) on the movie industry; Maddison (2004) for Broadway theatre productions; and Giles (2005) for the popular music industry.

on the presence of underlying seasonality is made by comparing patterns in the estimated coefficients of the weekly fixed effect dummy variables in the model, with and without the inclusion of movie fixed effects. The approach is similar to Einav (2007) in this respect, but the theoretical foundation is not that of a discrete choice utility maximising individual, rather an established statistical relation that fits box office revenue data with high fidelity.

The results suggest the amplification effect is considerably smaller under this approach than that documented by Einav. Further, the results are robust to modification of the Pareto model to include an orthogonal decay pattern with respect to a film's age, and also with the inclusion of a trend variable to capture market expansion/contraction effects over the sample period. The movie fixed effects are also extracted and modelled separately with respect to films specific covariates such as budget, advertising, cast appeal, reviews, etc. Although significance is picked up in a number of such variables, the conclusion is of high uncertainty associated with predicting box office success.

II EMPIRICAL MODEL

The model specification is derived by considering the Pareto law which forms the basis of the 'increasing returns to information' class of model. This may be defined

$$SR^{\beta} = A \tag{1}$$

where S is size, R is (ordinal) rank, and A and β are constants. Taking a logarithmic transformation and introducing a quadratic term gives

$$\ln S = \ln A - \beta \ln R + \gamma (\ln R)^2 . \tag{2}$$

The quadratic term captures the 'size variance' as defined by Ijiri and Simon (1971) that might be observed in the log-log plot of size vs. rank and has been observed in box office returns. To motivate the empirical analysis (2) is rewritten as a regression of the form

$$\ln S_{i,t} = \alpha + \beta \ln R_{i,t} + \gamma (\ln R_{i,t})^2 + \varepsilon_{i,t} \tag{3}$$

where $S_{i,t}$ is defined as share of the population attending film i per screen in week t, and $R_{i,t}$ as the weekly ordered ranking of admissions share of population per screen of film i in week t.[2] To investigate seasonality, 52 (relative to week 53)[3] dummy variables are included and (3) is rewritten as a fixed effects model of the form

$$\ln S_{i,t} = \alpha_i + \beta \ln R_{i,t} + \gamma (\ln R_{i,t})^2 + \varphi_j \{D\}_{j=1}^{52} + \varepsilon_{i,t} . \tag{4}$$

In this setting the regression has some comparability with Einav's discrete choice formulation. To capture underlying seasonality motivation is taken from Einav's methodology and (4) is considered with and without the inclusion of movie fixed effects. Inference on underlying seasonality then comes from evaluating the standard deviation of the estimated weekly dummy coefficients, i.e. inf SD($\{\hat{\varphi}\}_{j=1}^{52}$).

Given that the aim of the fixed effect model is to disentangle a measure of movie quality (box office success) that deviates from the typical cross section pattern, there is a need to identify this effect separately in relation to the outside good. Einav proposes an orthogonal decay in utility to facilitate this identification. The rationale for this technique is captured in the following simple example adapted from Einav's

[2] Admission share of population per screen is chosen to maintain consistency with Einav's study and to capture the most accurate measure of screen attendance over a long time period with growing population, increasing cinema infrastructure, increasing ticket prices, and changing number of films. The results, however, are almost identical when 'weekly revenue' is used to describe size – as was done in earlier studies such as De Vany and Walls (1996).

[3] The week 53 dummy variable is used twice in the sample period due to the fact there are 365 days per year and that every fourth year is a leap year. This allows the week 52 dummy variable to always include boxing day (December 26) – the biggest earning day of the year at the Australian box office.

discussion. Assume there are two seasons with market size (M_S>1) in the strong season and (M_W =1) in the weak season. Assume also that there are two movies to be released, one of high quality (θ_H >1) and one of low quality (θ_L =1). Revenue in season t={S, W} for film of quality i={H,L} is given by $R_{i,t}=M_t\ \theta_i$. Assume firstly that films play only for one season. If the low quality film opens in the weak season then $R_{L,W}= M_W\ \theta_L$ =1, and if the high quality film opens in the strong season then $R_{H,S}= M_S\ \theta_H$. Effectively there is one equation with two unknowns it is impossible to identify θ_H .and M_S separately. Now if both play over two seasons and decay at a constant rate, λ, then a high quality film released in the strong season will have revenue $R_{H,S}=M_S\ \theta_H$ and $R_{H,W}= \lambda\ M_W\ \theta_H = \lambda\ \theta_H$ in the weak season. A low quality film released in the weak season will have revenue $R_{L,W}=M_W\ \theta_L$ =1 and $R_{L,S}= \lambda\ M_S$ in the strong season. This gives three equations and three unknowns allowing identification of movie quality. In the context of the current model, the relative ranking may go some way to achieving this end, but it may also be worthwhile to consider a decay parameter explicitly in terms of the current framework. The following regression is proposed

$$\ln S_{i,t} = \alpha_i + \beta \ln R_{i,t} + \gamma(\ln R_{i,t})^2 + \chi WK_{i,t} + \eta WK_{i,t}^2 + \varphi_j \{D\}_{j=1}^{52} + \varepsilon_{i,t} \qquad (5)$$

where $WK_{i,\mathrm{t}}$ refers to the week of the run. Note that the quadratic term is included to capture the possibility that quality decays in a non-linear way. The final extension to the basic framework addresses questions over the relative impact of the outside good, increasing infrastructure, increasing population and increasing ticket prices over the sample period. Specifically, a time trend T is included to assess such impacts

$$\ln S_{i,t} = \alpha_i + \beta \ln R_{i,t} + \gamma(\ln R_{i,t})^2 + \vartheta T + \varphi_j \{D\}_{j=1}^{52} + \varepsilon_{i,t} \,. \qquad (6)$$

Although, it may be difficult to pinpoint the cause of any growth (or decline) of share of population attending films over the sample period, the inclusion of the time trend is relevant for quantifying whether, after all obvious considerations are accounted for, there appears to be any significant changes in the share of population attending cinema screens over the weeks in the sample.

Aside from inference on the week to week seasonality of box office revenues, it may be enlightening to examine the estimated (film specific) fixed effects in relation to movies specific co-variates. An increasing literature has explored the relationship of revenues to various films specific covariates and while models specified with a range of variables – such as production budget, advertising/publicity expenditures, opening week screens, star power, critical acclaim and awards, etc – typically reveal significant relationships, and generally strong R^2 values, the relationships generally suffer in explaining the extremities of returns that can be achieved (or lost) in this industry.[4] The formulation of the second part of this research is similar to the approach used by Einav and considers a projection of estimated movie fixed effects onto various observable film specific variables. The point of this exercise in context of the current analysis is to determine whether those movies that do perform better (or worse) than others in a given week, relative to the typical pattern estimated, suggest any discernible features. The general structure of the models considered is

$$\hat{\alpha}_i = \beta' \mathrm{x}_i + u_i \tag{7}$$

where $\hat{\alpha}_i$ is the estimated fixed effect from equation (5) and x_i is a vector of films specific covariates, which may be defined.

$$\mathrm{x}_i = \{BUDGET_i\,, ADPUB_i,\ STAR_i, REVIEW_i, SEQUEL_i\, \Gamma(GENRE_i, RATING_i)\}.$$

The estimated fixed effect from equation (5) is chosen to give the best description of quality in relation to the identification issues discussed above. The continuous

[4] See De Vany and Walls (2004).

variables production budget ($BUDGET_i$), and advertising/publicity expenditure ($ADPUB_i$) are estimated in log form. Star power ($STAR_i$), critical review ($REVIEW_i$), sequel/prequel ($SEQUEL_i$) are dummy variables, and the variables contained in $\Gamma(.)$ are grouping of dummy variable. In order to validate this type of regression a similar regression is also estimated by instead defining the dependent variable as (log) cumulative revenue. This specification is not unlike numerous other studies and, concerns about thick tails of the revenue distribution not withstanding,[5] is the closest to an agreed specification of box office demand in the empirical literature.

III DATA

The primary data used in this study relate to the 2,429 films released at the Australian box office from January 1, 1997 to December 31, 2005 as recorded by the Motion Picture Distributors Association of Australia (MPDAA). The MPDAA data records weekly revenues, weekly screen counts and cumulative revenue for each title. Also recorded is information on advertising/publicity expenditures (for the MPDAA companies), official release dates, key creative elements (actors and directors), genres, and Office of Film and Literature (OFLC) classification ratings. Other data used in this study include estimates of production budgets (Internet Movie Data Base, IMDb, and the Australian Film Commission, AFC); critics' review information (*The Movie Show*, SBS, and *At the Movies*, ABC); population information (Australian Bureau of Statistics, ABS); inflation series (Reserve back of Australia, RBA, and the U.S. Federal Reserve). The data is now discussed in more detail.

[5] See De Vany and Walls (1999, 2004) and Walls (2005a, 2005b).

Table 1 reports summary statistics for a selection of variables used in this study. These include the continuous variables: cumulative revenue ($CUMEREV_i$), opening week revenue ($OPWKREV_i$), opening week screen counts ($OWKSCRN_i$), advertising/publicity expenditure ($ADPUB_i$), production budget data ($BDGT_i$); and the dummy variables representing star appeal ($STAR_i$), favourable critical reviews ($REVIEW_i$), and whether the film was a prequel sequel ($SEQUEL_i$). All variables containing dollar values are deflated to January 1997 prices – with inflation incremented biannually as recorded by the Reserve Bank of Australia (RBA) and Federal Reserve for the Australian and U.S. markets respectively. Australian budget data was converted to U.S. dollars at the average of the January 1997 bilateral exchange rate. The summary statistics suggest large levels of skew and (excess) kurtosis in the revenue distributions has had considerable attention in the literature.[6] The budget data also exhibit some level of skew and variance, however, the magnitude is nowhere near that of revenue.

[INSERT TABLE 1 ABOUT HERE]

To construct the size and rank variables for the Pareto regressions it was necessary to construct the per screen share of population attending film *i* in week *t*, and rank this series for each week of the sample. This was done by firstly converting weekly revenues to weekly screen averages, then approximating attendance by dividing this by the average annual ticket price as recorded by the MPDAA . This value was then divided by estimates of the population to give the variable $S_{i,t}$. This measure gives the most accurate account possible in relation weekly patterns of attendance with respect

[6] The revenue distribution has been shown to be suitably classed in the stable class of distribution noted for nesting extremities of skew and variance. See De Vany and Walls (1999, 2004), Walls (2005a) and McKenzie (2008).

to the relatively long sample period and the fact that population, ticket prices, and supply of cinema infrastructure all increased over this time.[7]

The categorical data used in this study are derived from a number of sources and require some definition and clarification. The variable $REVIEW_i$ is constructed in two stages. Firstly, the '5 star' review system is averaged across the five potential reviewers from the two network television show websites used in this study.[8] From the 1,517 films recorded, of which the average review is 3.24 stars (out of 5 stars), the dummy variable $REVIEW_i$ takes the value one if the averaged review equalled or exceeded 3.5 stars and is broadly defined to represent films that received generally favourable critical reviews. The variable $STAR_i$ is constructed from various publications of James Ulmer's Hollywood Hot List which is an annual to bi-annual publication ranking over 1800 actors and actresses based on surveys of "dozens of behind the scenes international power brokers"[9]. The dummy variable is assigned a value of one if any of the leading actors received an A or A+ ranking on the Ulmer Scale of 'bankability'.[10] In the sample, 209 films are defined to have an actor with 'star' power. The variable $SEQUEL_i$ defines the film as being a sequel (or prequel) to an existing film and in the sample there are 96 films that satisfy this definition. The set of dummy variables defined by $GENRE_i$ are categorised over sixteen definitions as recorded by the MPDAA. All estimations are done relative to the most prevalent

[7] Over the sample period ticket prices increased from an average of A$7.47 in 1997 to A$9.94 in 2005 (MPDAA). The population increased from 18.5 million in 1997 to 20.4 million in 2005 (ABS). The national number of cinema screens increased from 1422 in 1997 to 1943 in 2005.

8 Margaret Pomeranz and David Statton have been two leading Australian film critics for over 20 years. Up until 2004, they jointly hosted SBS's The Movie Show, and whilst the show continues on SBS with new reviewers (Fanella Kernebone, Megan Spencer and Jamie Leonarder), David and Margaret now host a similar show on ABC called At The Movies.

9 See http://ulmerscale.com/AboutHL.htm

10 This is consistent with the definition of 'star' used extensively by De Vany and Walls. See De Vany (2004) and in particular De Vany and Walls (1999, 2004).

genre of 'drama' which defines 819 films of the full sample.[11] Similarly, the set of dummy variables defined by $RATING_i$ are categorised over five definitions as recorded by the Office of Film and Literature Classification (OFLC), and all estimations are done relative to the most prevalent classification rating 'M' which defines 1,189 films of the full sample.[12]

IV RESULTS

The results of the regressions described in equations (3) – (6) are reported in Table 2 for films that at some point went into wide release in Australian cinemas – defined by the MPDAA as playing on 50 or more screens. The results suggest that for each specification linearity in the log-log relation can be rejected in favour of the quadratic specification. Figure 1 displays the downwardly concave relation and suggests the line of best fit can be suitably described with the quadratic shape for the specification without the inclusion of week effects (WKE) or movie fixed effects (FE). Introducing week effects and movie fixed effects into the model allows for structural shifts in the relation (i.e. the constant term) and therefore a range of predicted values at any given rank (denoted by FE, WKE in Figure 1), but the suggestion of downwardly concave relation is still evident and significant.

[INSERT TABLE 2 ABOUT HERE]

[INSERT FIGURE 1 ABOUT HERE]

11 The other genre categories (and respective frequencies in sample) include action (234), adventure (58), animated (85), black comedy (42), comedy (524), crime (9), documentary (156), fantasy (23), horror (79), musical (27), romance (13), romantic comedy (133), science-fiction (61), suspense (129), and thriller (27).

12 The other rating categories (and respective frequencies in sample) include G (207), PG (383), MA15+ (519), and R18+ (106).

From Table 2 it is also evident that the inclusion of the *WK* and WK^2 variables aids in the model's fit and suggests an intuitive orthogonal decline in the per screen share of revenue as a film ages – *ceteris paribus*. This finding supports the model specification of Einav and aids in the identification of the movie fixed effect discussed in detail above. The results from regression (6), reported in columns (7) and (8) of Table 2, suggest that the screen share of cinema goers to be falling over the sample period consistent with reports of the MPDAA and is illustrated in Figure 2, where the trend line suggests that the share of population attending films per screen is falling over the sample period.[13]

[INSERT FIGURE 2 ABOUT HERE]

Recalling that the primary objective of this analysis is to investigate the potential underlying seasonality of cinema demand, inference is drawn evaluating the estimated coefficients of the 52 weekly dummy variables for the models with and without movie fixed effects. Figure 3 shows the average weekly admissions over the nine year sample period, where four distinct peaks are apparent, which (not surprisingly) coincide with Australian school holiday periods. Indeed, in each of the years observed this pattern fits with high fidelity in an almost perfectly auto-regressive fashion. Figure 4 shows the results of the base model (equations (3) and (4), reported in columns (1) and (2) in Table 2), where it can be seen that the estimated coefficients display an almost identical pattern to Figure 1 for both specifications with and without movie fixed effects. Figure 5 shows these relations for the models with the orthogonal week decay variables and the time trend variable, and again the four peak pattern is evident for each model. Inference on the magnitude of underlying seasonality is given by comparison of the standard deviation on the set of estimated

[13] MPDAA estimates suggest that admissions per screen peaked in 2001 at 4.75 cinema visits per head of population but declined to 4.03 by 2006.

coefficients of the weekly dummies from the Pareto regressions with and without movie fixed effects, as done by Einav using his discrete choice model.

[INSERT FIGURES 3, 4 & 5 ABOUT HERE]

Table 3 reports summary statistics of these estimated coefficients of the weekly dummy variables from the Pareto regressions. It can be noted that in comparison of the base model, decay model, and time trend model the specifications reveal an amplification effect of 21.7%, 19.9%, and 13.7% for the three models respectively when the standard deviations of the set of estimated coefficients are compared from the regressions with and without movie fixed effects. These are all significantly below Einav's finding of approximately 50% and the difference suggests a lower amplification effect under the Pareto model.[14] This finding suggests that once the thick tailed nature of the distribution vis-à-vis word of mouth effect is properly accounted for, amplified seasonality is not so pervasive and that cinema audiences are not as influenced by seasonal release considerations as may be implicated by Einav's analysis. This interpretation may also suggest that a good film, which builds strong word-of-mouth momentum, has the ability to transcend holiday periods once it gains 'legs' and implies that distributors should carefully consider the balance between an oversupply of films at peak periods, which may dissolve profits, against the alternative of staggering releases and giving their films a better opportunity to find an audience.

[INSERT TABLES 3 & 4 ABOUT HERE]

The favoured Pareto specification is the decay model as this provides the strongest theoretical foundation for the identification of movie fixed effects, and is also favoured empirically as it revealed the highest correlation of movie fixed effects with

[14] It was interesting to note that using Einav's specification a similar magnitude of amplification was found to his finding of approximately 50%. These results are not reported but are available from the author on request.

cumulative film revenues. The movie fixed effects of the decay model were extracted from regression (5) and the correlations with selected continuous variables are reported in Table 4. The estimated movie fixed effects were then projected onto the movie observables contained in the vector x_i of equation (7). The specifications are conditioned upon wide release, non IMAX films and films that were not a re-release. In the first specification (first column of Table 5) $BUDGET_i$, $STAR_i$ and $SEQUEL_i$ were used as explanatory variables (in addition to the control variable relating to $RATING_i$ and $GENRE_i$) and positive significance is found for each – but only at 10% for the $STAR_i$ variable. When $REVIEW_i$ was added in the second specification (second column of Table 5) the $STAR_i$ variable was no longer found to be significant, and in the third specification (third column of Table 5) when $ADPUB_i$ was added there was no longer significance evident on $BUDGET_i$, or $SEQUEL_i$ either.[15] For comparison to more conventional models of box office demand the same set of regressions were explored, but rather with (log) cumulative revenue as the dependent variable. The results are consistent with a-priori expectations and the findings of previous studies that have used similar regressors in their specifications.[16] The second specification does not suggest the inclusion of $REVIEW_i$ negates the effect of the $STAR_i$ variable, but the third specification suggests that $STAR_i$ ceases to have explanatory power when $ADPUB_i$ was included as well. It can also be noted that the magnitude of the estimated coefficients of $BUDGET_i$, $SEQUEL_i$, and $REVIEW_i$ are dramatically reduced with the inclusion of $ADPUB_i$, yet all remain significantly positive at the 1% level. Combined these results support the high level of uncertainty surrounding the ability of individual movie attributes to influence box office returns in a consistent

[15] The non-inclusion of advertising expenditure and its effect on estimating demand has recently been explored by Moul (2006).
[16] See, for exmple, Prag and Casevant (1994), De Vany and Walls (1999), Walls (2005a, 2005b), Reinstein and Snyder (2005), Jansen (2005), and Gemser, Van Oostrum and Leenders (2007).

manner. The apparent dominance of $ADPUB_i$ in both specifications, however, may be the result of an untreated endogeneity issue. Even though industry reports suggest the majority of advertising expenditure happens prior to (and to coincide with) release, if a film gains popularity distributors may re-launch or increase an existing advertising campaign. Unfortunately the data utilised in this study does not break down this expenditure, and there is no clear cut way to resolve this issue with the current data available.[17]

[INSERT TABLES 5 & 6 ABOUT HERE]

As a final point regarding seasonality, it may also be of relevance to ask the following questions regarding distribution strategy. If distributors are timing their stronger releases around peak periods of underlying demand, does this necessarily imply that they are releasing films with large production budgets and associated large advertising/publicity budgets? Anecdotal evidence would suggest so, and this is shown in Figure 6 where the average production budget and advertising/publicity expenditure is shown across the 52 weeks of the calendar year. Although the pattern is not as distinct as the revenue pattern for box office there is some evidence of peaks occurring throughout the year – and particularly around the Christmas/New Year period – that coincides with the four distinct peaks previously observed. This evidence is supportive of the results found of endogenous amplification of underlying seasonality, and then to the relation that movie observables were shown to have on the estimated movie fixed effects from the Pareto regressions. In short, when distributors seek to release titles with stronger appeal during periods of high demand, this often implies big budget films with higher levels of advertising support.

[INSERT FIGURE 6 ABOUT HERE]

[17] Several studies have directly examined the effect of advertising on box office success. See Prag and Casevant (1994), Vanderhart and Wiggins (2002), Elberse and Eliashberg (2003), Elberse and Anard (2006), and Elliot and Simmons (2007).

V CONCLUSION

This paper has investigated the potential amplification effect to underlying seasonality in the Australian motion picture industry. The cinema going audience is commonly acknowledged to follow a strong seasonal pattern of demand that coincides with school holiday and Christmas/New Year holiday periods. Distributors have been well aware of this feature of demand for many years and have frequently been observed timing the release of their major titles with the periods of strong underlying demand. The extent to which this type of behaviour has an amplification effect on sales has been the focus of this study. This research is motivated by the recent insightful study of Einav (2007), who showed that this amplification effect may be as large as 50% using a discrete choice (nested logit) framework. The approach used in this study differs, however, by instead exploiting the steadfast Pareto model to describe the revenue distribution. This relationship has been documented by an increasing body of literature exploring 'increasing returns to information' as a consequence of the pervasive word-of-mouth sharing that dominates the distribution of returns in many cultural industries such as that of motion pictures. The advantage in utilising this approach is that it doesn't require assumptions to be made about preferences, but more importantly recognises the information environment that films occupy, and the consistently observed skewed returns arising from information feedback effects. The results show strong support for the increasing returns argument both with and without movie fixed effects in the Pareto model. Comparison of the estimated weekly dummy coefficients then formed the basis for exploring the degree of amplification that arises once the movie fixed effects are removed. The degree of amplification was revealed to be in the approximate range 14-22% depending upon the specification, but the preferred decay model suggested 20% was the approximate magnitude. It is subsequently concluded that, although there may be a level of amplification to the industry by the endogenous release decisions of distributors, the magnitude is not as significant as that found by Einav. The logic for the difference between the two studies originates from the more fastidious attention to the importance of word-of-mouth, which (by his own admission) Einav may under represent.

The second part of the study extracted the movie fixed effects estimated from the Pareto (decay) model and regressed them on movie observables such as production budgets, advertising/publicity expenditures, star power, critical reviews and prequels/sequels – as well as the control variables rating and genre. All variables of interest were shown to provide some evidence of providing explanatory power that would be consistent with a-priori expectations, however, the inclusion of critical reviews dominated star power, and the inclusion of advertising dominated budget's explanatory power. A similar set of regression were also estimated with the dependant variable being (log) cumulative revenue. Similar results were observed in terms of signage and significance but the model was able to sustain more explanatory power with inclusion of additional regressors. The conclusion from this part of the analysis supports the notion of uncertainty in box office returns that has been extensively documented about the industry, and the inability of individual movie attributes to consistently influence box office success in a predictable manner.

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TABLE 1

Summary Statistics of Selected Variables [a]

Variable	Obs.	Mean	Median	Std. Dev	Min	Max	Skew	Kurtosis
$CUMEREV_i$	2,429	2,551,426	555,980	4,842,662	360	57,302,926	3.9	21.8
$OPWKREV_i$	2,302	835,690	178,188	1,559,209	25	16,931,976	4.0	23.0
$OPWKSCRNS_i$	2,302	86	42	98	1	552	1.3	1.4
$BUDGET_i$	1,453	32,267,966	22,620,170	30,888,562	19,126	198,216,056	1.5	2.6
$ADPUB_i$	1,191	693,926	504,118	638,327	378	3,469,397	1.0	0.4
$STAR_i$	2,429	0.1228	0	0.3282	0	1	2.3	6.3
$REVIEW_i$	1,497	0.4943	0	0.5001	0	1	0	1
$SEQUEL_i$	2,429	0.0398	0	0.1955	0	1	4.7	23.2

[a] $CUMEREV_i$, $OPWKREV_i$, and $ADPUB_i$ are expressed in Australian dollars deflated to January 1997 prices. $BUDGET_i$, is expressed in US dollars deflated to January 1997 prices. $STAR_i$, $REVIEW_i$, and $SEQUEL_i$ are dummy variables.

TABLE 2

Estimated Pareto Regressions with and without Movie Fixed Effects

Variable	Dependent Variable $\ln S_{i,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln R_{i,t}$	-0.0922***	-0.097***	-0.0987***	-0.1287***	-0.0768***	0.0024***	-0.1432***	-0.0812***
	(0.0208)	(0.0187)	(0.0176)	(0.0162)	(0.0176)	(0.015)	(0.0172)	(0.0153)
$(\ln R_{i,t})^2$	-0.2837***	-0.2833***	-0.2818***	-0.2702***	-0.2758***	-0.2153***	-0.2633***	-0.2328***
	(0.0058)	(0.0054)	(0.0049)	(0.0047)	(0.0049)	(0.0044)	(0.0049)	(0.0045)
$WK_{i,t}$					-0.0297***	-0.1314***		
					(0.0028)	(0.0035)		
$(WK_{i,t})^2$					0.0011***	0.0035***		
					(0.0001)	(0.0001)		
T							-0.0007***	-0.046***
							(0.00003)	(0.0015)
Week Dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Movie Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Constant	-9.4204***	-9.4119***	-8.9316***	-8.9113***	-8.8818***	-8.8959***	-8.7523***	2.8621***
	(0.0178)	(0.0156)	(0.0755)	(0.0676)	(0.075)	(0.061)	(0.0736)	(0.37904)
Adj R-squared	0.8161		0.8684		0.8704		0.8763	
- Within		0.8440		0.8849		0.9066		0.8981
- Between		0.7314		0.8146		0.6379		0.2270
- Overall		0.8162		0.8667		0.8159		0.1509
Observations	8,828	8,828	8,828	8,828	8,828	8,828	8,828	8,828
Groups		1,120		1,120		1,120		1,120

TABLE 3

Summary Statistics of Estimated Coefficients of Weekly Dummy Variables [a]

Explanation [b]	Obs	Mean	Std. Dev.	Min	Max
(a)	52	-0.491	0.230	-0.909	0.020
(b)	52	-0.491	0.189	-0.818	-0.085
(c)	52	-0.471	0.229	-0.891	0.034
(d)	52	-0.448	0.191	-0.757	-0.046
(e)	52	-0.481	0.233	-0.909	0.032
(f)	52	-0.497	0.205	-0.876	-0.063

[a] Summary statistics refer to estimated coefficients of weekly dummy variables ($\hat{\varphi}_{j=1}^{52}$) from Pareto model regressions of Table 2.

[b] Explanations: (a) and (b) refer to estimates relevant to Table 2 equations (3) and (4) respectively, i.e. without and with movie fixed effects; (c) and (d) refer to equations (5) and (6) without and with movie fixed effects; and finally, (e) and (f) refer to equations (7) and (8) without and with movie fixed effects.

TABLE 4

Correlation Matrix of Continuous Variables

	Movie FE ($\hat{\alpha}_i$)	$CUMEREV_i$	$ADPUB_i$	$BUDGET_i$
Movie FE ($\hat{\alpha}_i$)	1			
$CUMEREV_i$	0.5986	1		
$ADPUB_i$	0.5655	0.7689	1	
$BUDGET_i$	0.2963	0.5243	0.6084	1

TABLE 5

Projection of Estimated Movie Fixed Effects on Observables

Variable	Dependent Variable Estimated Movie Fixed Effects ($\hat{\alpha}_i$)		
ln(*BUDGET*$_i$)	0.0546***	0.0637***	-0.00734
	(0.0125)	(0.0143)	(0.0189)
ln(*ADPUB*$_i$)			0.299***
			0.0207
STAR$_i$	0.051*	0.0366	-0.0313
	(0.0267)	(0.0293)	(0.0270)
REVIEW$_i$		0.204***	0.122***
		(0.0268)	(0.0253)
SEQUEL$_i$	0.127***	0.169***	0.051
	(0.0404)	(0.0478)	(0.0431)
RATING$_i$			
G	0.0224	0.0552	-0.0208
	(0.0508)	(0.0642)	(0.0577)
PG	-0.066**	-0.0186	-0.035
	(0.0317)	(0.0371)	(0.0337)
MA15+	0.0296	0.0259	0.0453
	(0.0285)	(0.0327)	(0.0322)
R18+	0.0669	0.051	0.118
	(0.0892)	(0.0974)	(0.0886)
GENRE$_i$			
Action	-0.0988***	-0.0766*	-0.102***
	(0.0353)	(0.0396)	(0.0365)
Adventure	-0.0525	-0.0442	-0.102*
	(0.0630)	(0.0701)	(0.0593)
Animated	-0.0672	-0.0414	-0.0991
	(0.0625)	(0.0750)	(0.0638)
Black comedy	0.0537	0.0628	-0.0182
	(0.0965)	(0.0980)	(0.0897)
Comedy	-0.0749**	-0.0399	-0.0857**
	(0.0329)	(0.0386)	(0.0380)
Crime	-0.421**	-0.319*	-0.433**
	(0.1880)	(0.1810)	(0.1770)
Documentary	0.132	0.243	-
	(0.1910)	(0.3110)	-
Fantasy	0.0756	0.0956	-0.0444
	(0.0915)	(0.0959)	(0.0999)
Horror	-0.114**	-0.0163	-0.103
	(0.0537)	(0.0679)	(0.0759)
Musical	0.25	0.228	-0.00785
	(0.1640)	(0.1800)	(0.1460)
Romance	-0.324**	-0.345**	-0.321
	(0.1640)	(0.1570)	(0.1270)
Romantic comedy	0.118**	0.154***	0.109
	(0.0490)	(0.0546)	(0.0519)
Science Fiction	0.0139	0.0198	-0.0203
	(0.0595)	(0.0644)	(0.0570)
Suspense	-0.118	-0.0852	-0.0268
	(0.0466)	(0.0521)	(0.0499)
Thriller	-0.388***	-0.295***	-0.329***
	(0.0928)	(0.1020)	(0.0916)
Constant	-1.01***	-1.25***	-4.03***
	(0.2140)	(0.2470)	(0.3370)
Observations	938	657	488
R^2 *Adjusted*	0.08	0.165	0.442

*,**, and *** denote significance at 10%, 5%, and 1% respectively. Standard errors are in parentheses.

TABLE 6

Projection of Cumulative Revenue on Observables

Variable	Dependent Variable Log(Cumulative Revenue)		
log($BUDGET_i$)	0.626***	0.635***	0.0881**
	(0.0386)	(0.0396)	(0.0359)
log($ADPUB_i$)			1.26***
			(0.0314)
$STAR_i$	0.741***	0.547***	-0.0207
	(0.124)	(0.118)	(0.0662)
$REVIEW_i$		0.754***	0.387***
		(0.0967)	(0.0578)
$SEQUEL_i$	0.962***	0.869***	0.34***
	(0.2)	(0.209)	(0.112)
$RATING_i$			
G	0.744***	0.536**	0.0447
	(0.229)	(0.258)	(0.145)
PG	0.117	0.293**	0.0673
	(0.138)	(0.146)	(0.0821)
MA15+	-0.0698	-0.255**	-0.0058
	(0.114)	(0.114)	(0.0719)
R18+	0.0245	-0.234	0.164
	(0.256)	(0.239)	(0.17)
$GENRE_i$			
Action	0.378**	0.555***	-0.0988
	(0.156)	(0.156)	(0.0887)
Adventure	0.428	0.627**	-0.0122
	(0.28)	(0.282)	(0.148)
Animated	0.341	0.506*	-0.00173
	(0.277)	(0.302)	(0.158)
Black comedy	0.146	0.28	0.0794
	(0.32)	(0.283)	(0.178)
Comedy	0.115	0.389***	-0.0445
	(0.128)	(0.132)	(0.0834)
Crime	-0.368	0.309	0.301
	(0.588)	(0.563)	(0.378)
Documentary	0.0553	-0.259	0.957
	(0.454)	(0.497)	(0.677)
Fantasy	0.731*	1.04**	0.0601
	(0.441)	(0.415)	(0.259)
Horror	0.275	1.19***	0.00948
	(0.226)	(0.273)	(0.193)
Musical	0.156	0.917	0.21
	(0.482)	(0.614)	(0.33)
Romance	0.513	0.376	0.0368
	(0.627)	(0.523)	(0.296)
Romantic comedy	0.41**	0.87***	0.134
	(0.204)	(0.211)	(0.124)
Science Fiction	0.29	0.61**	0.0125
	(0.271)	(0.265)	(0.14)
Suspense	0.00289	0.115	0.0861
	(0.196)	(0.193)	(0.117)
Thriller	-0.889***	-0.0846	-0.247
	(0.368)	(0.363)	(0.238)
Constant	3.11***	2.8***	-3.78***
	(0.631)	(0.657)	(0.544)
Observations	1,381	936	600
R^2 *Adjusted*	0.325	0.436	0.843

*,**, and *** denote significance at 10%, 5%, and 1% respectively. Standard errors are in parentheses.

FIGURE 1

Pareto Distribution in Logs: with Movie Fixed Effects (FE) and Calendar Week Effects (WKE); and without FE and WKE

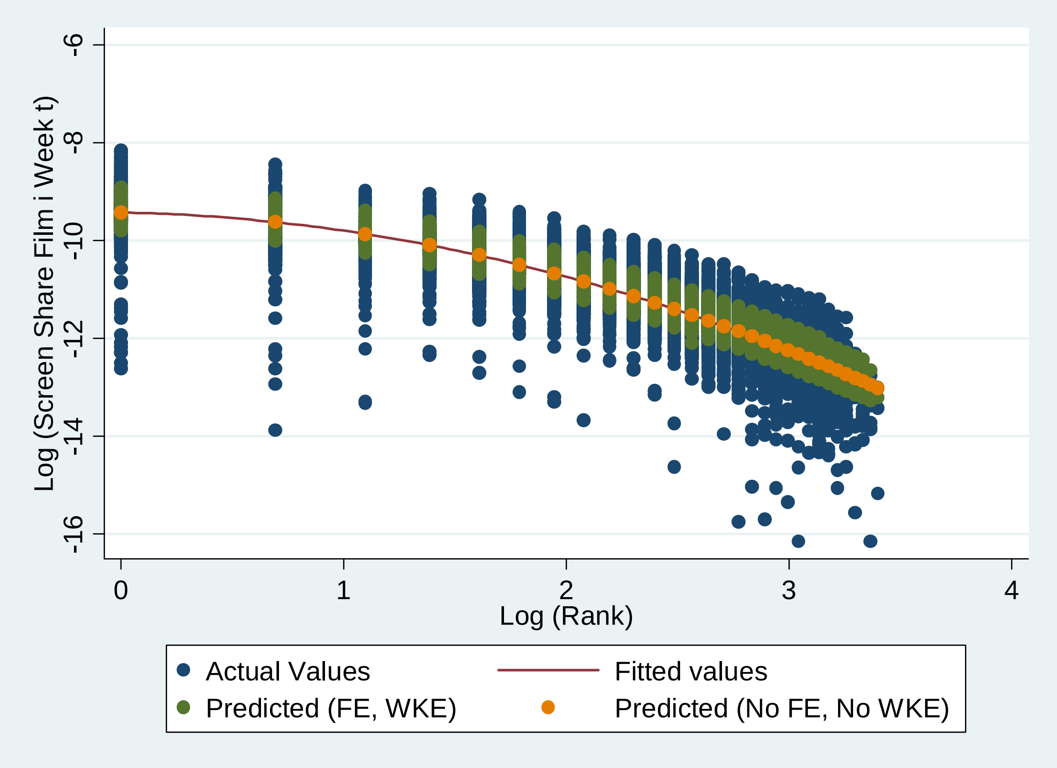

FIGURE 2

Screen Share of Population Attending film *i* in week *t* ($\ln S_{i,t}$) vs. Week (1997-2005)

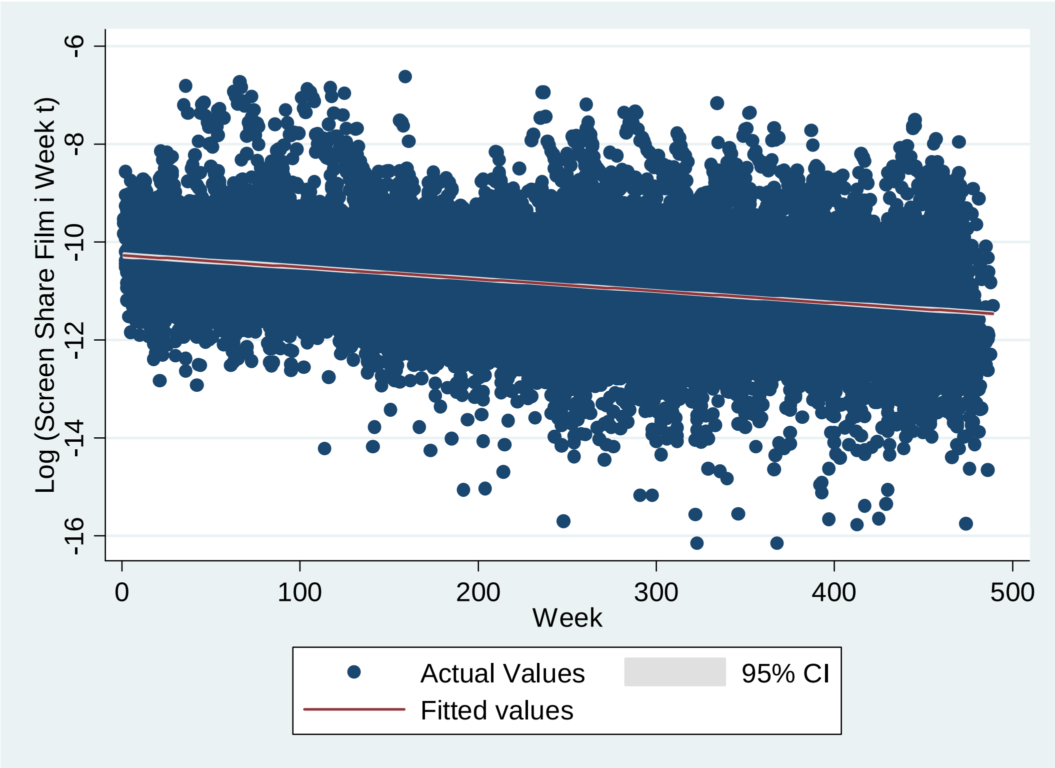

FIGURE 3

Average Weekly Admissions by Calendar Week of Year

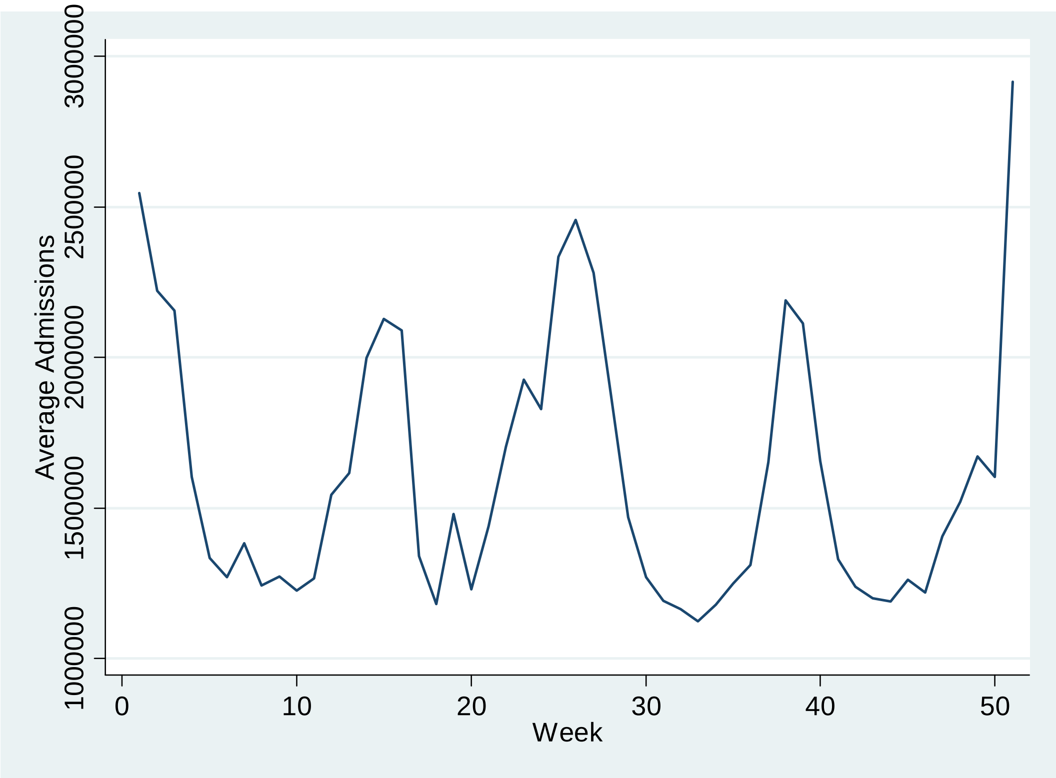

FIGURE 4

Estimated Coefficients of Weekly Dummy Variables from Base Model by Calendar Week of Year

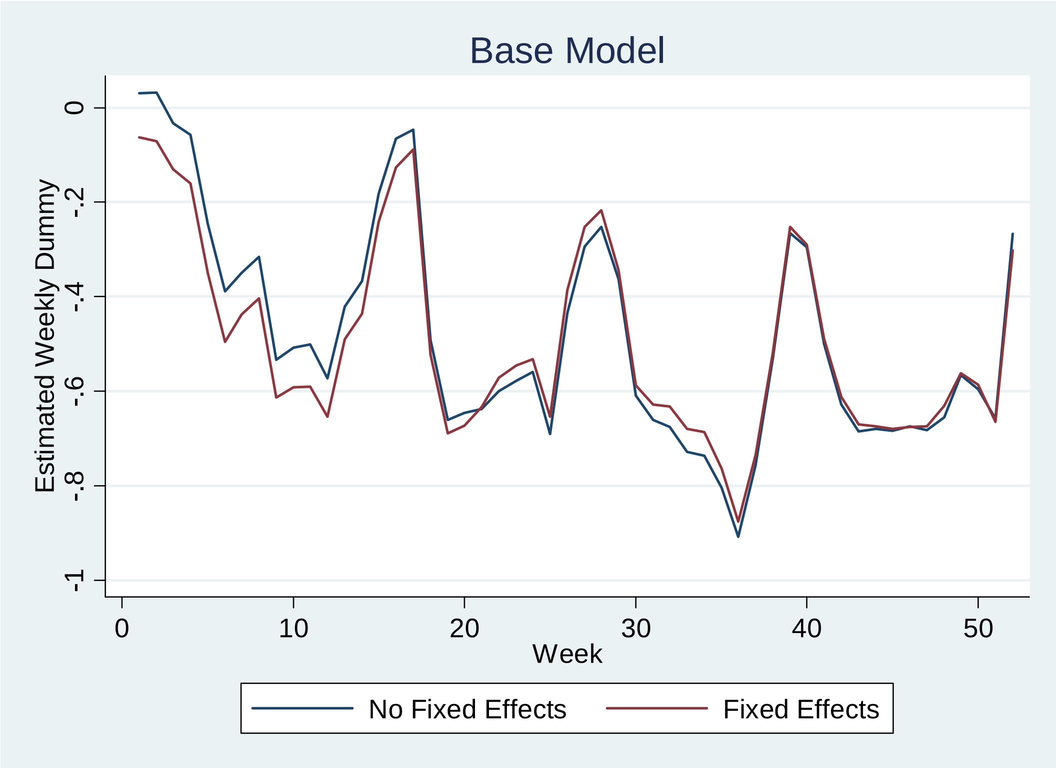

FIGURE 5

Estimated Coefficients of Weekly Dummy Variables from Decay Model and Time Trend Model by Calendar Week of Year

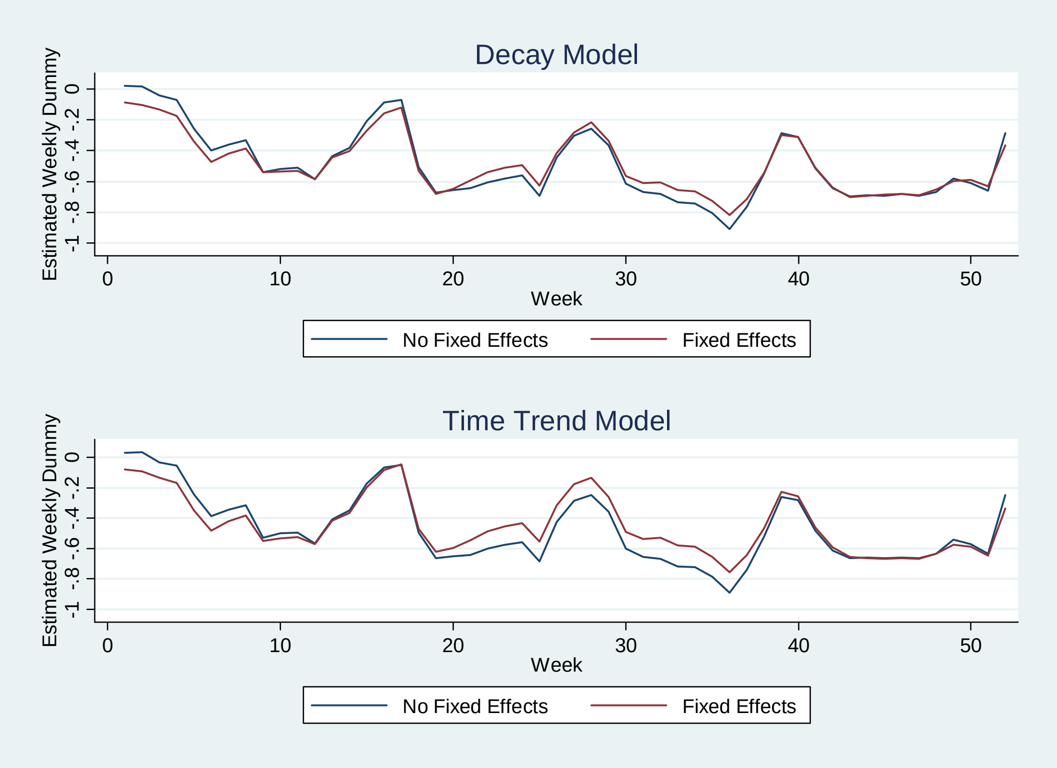

FIGURE 5

Average Advertising/Publicity Expenditures and Production Budgets by Calendar Week of Year