

‘Cheap Tuesdays’ and Estimating Movie Demand: An Empirical Analysis of the Australian Cinema Industry

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[PRELIMINARY AND INCOMPLETE – Please do not quote]

Abstract

This paper estimates the demand for cinema attendance using a large sample of daily box office revenues from cinemas in the Sydney region of New South Wales, Australia, during the year 2007. Many movie markets are characterised by extensive uniform pricing practices, hampering the ability to estimate price elasticities of demand. In our sample, most cinemas offer cheap Tuesday ticket prices. We exploit this feature to identify price elasticities, using a random coefficients discrete choice model of demand. We control for explanatory variables relating to the film, theatre, day, and geographic/demographic characteristics of the local population.

Keywords: Motion pictures, cinema demand, discrete choice model.

JEL Classification Numbers: L82

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1. Introduction

Economists have for a long time been interested in explaining why certain markets periodically (and often predictably) mark-down or mark-up prices. Explanations put forward include price discrimination (Varian, 1980; Sobel, 1984), clearance sales (Lazear, 1986), demand uncertainty (Pashigian, 1988; Pashigian and Bowen, 1991), social influence (Becker, 1991), and exogenous demand (Warner and Barsky, 1995). Although there might be strong economic reasons for offering lower prices at certain times, in a number of countries (including the U.S.) the cinema exhibition industry has seemingly been ignorant of such profit opportunities. Indeed, as Orbach and Einav (2007) discuss in detail, the practice of (almost) uniform pricing in this industry is something of puzzlement to many observers. They examine two dimensions of the puzzle which they refer to as i) the movie puzzle (why different movies are priced the same); and ii) the show-time puzzle (why different times, days, and seasons are priced the same). They provide detail that during the pre-Paramount era (i.e. before 1948) variable pricing strategies were used with respect to films categorised by quality. This practice subsequently continued into the 1950s and 1960s where ‘event’ movies were often priced above other movies. There was also price variation with respect to weekday versus weekend ticket prices, and by the type of seat purchased within an auditorium. Orbach and Einav conclude that exhibitors could increase profits if they practiced variable pricing strategies.

A first step in determining the extent of the pricing puzzle, and in identifying profitable pricing strategies, is to calculate price elasticities of demand. Given the lack of variation in pricing in most movie markets, this is a challenging task. In Australia, however, uniform pricing behaviour is not the norm as almost all cinemas offer discounted tickets every Tuesday for the entire day.¹ Based on typical multiplex prices, this reduces the price of an adult ticket by about 40%, a student ticket by about 25%, and a child ticket by about 20%. In this study we exploit this (arguably) exogenous price shift to estimate demand. We employ a comprehensive data set of daily film revenues for cinemas in the greater Sydney region over the year 2007, and adopt a random coefficients discrete choice model. We control for a number of additional explanatory variables relating to the film itself (e.g. genre, budget,

¹ In the U.S. on certain days matinee performances may be priced lower, but not the evening sessions where there is likely to be more demand.

advertising, cast appeal), theatre characteristics (e.g. number of screens, number of seats), the day of observation (e.g. day of week, public/school holidays, weather), and the demographics of the local population (e.g. age, income, education).

Our estimation strategy relies on the assumption that the demand for movies is essentially the same for regular weekdays. That is, we assume the choice of Tuesday (as opposed to Monday, Wednesday or Thursday) as the cheap ticket day is not related to demand conditions. Under this assumption, an indicator variable for Tuesdays represents a valid instrument for prices. Moreover, it is an important instrument, accounting for much of the variation in prices. However, we are unable to explicitly test this assumption. Because the vast majority of weekly price variation is due to Tuesday discounts, we are unable to separately identify variation in demand on Tuesdays, but we have no reason to suspect demand differs systematically between Mondays, Tuesdays, Wednesdays, and Thursdays.² A consequence of this choice of instrument is that much of the identification of the price elasticity of demand stems from temporal variation in prices as opposed to cross-sectional variation. Common with much of the literature, we also consider rival product characteristics as instruments. The inclusion of these additional instruments permits some identification from cross-sectional variation in the data. In addition, we include population macro-moments (Imbens and Lancaster, 1994), allowing us to incorporate external information on consumption patterns by different demographic groups.

Over recent years an expanding body of empirical research has examined many aspects of the motion picture industry.³ Our research bears most similarity in its method to the studies of Davis (2006), Einav (2007) and Moul (2007) in that we adopt a discrete choice approach to modelling demand. Einav (2007) and Moul (2007) both employ a nested logit model and weekly revenue data, exploring seasonality of

² As detailed below, films are typically released on Thursdays in Australia leading to higher revenues in general on this day, but once the opening day effect is removed Thursday is similar to Mondays and Wednesdays.

³ The literature could be categorised as being microeconomic and macroeconomic in nature. The microeconomic literature focuses on issues such as the determinants of demand for individual films and various other aspects of the industry which may be relevant to distinct stages of production, distribution and exhibition. The macroeconomic literature on the other hand typically focuses on aggregate patterns of cinema demand (usually over a longer time horizon) and may consider the impact of various structural, economic and policy effects on the entire industry. A recent survey is provided by McKenzie (2009).

demand and word-of-mouth effects, respectively. Our data and method most closely resembles Davis (2006) in that we use daily film-at-theatre revenues and follow the approach of Berry (1994) and Berry, Levinson and Pakes (2005) by employing a random coefficients model. Like Davis, we exploit information about the spatial distribution of consumers and theatres in our empirical strategy. Relative to the dataset harnessed by Davis, our data has a more extensive time-series dimension (365 days compared to 7), but a more limited cross-section dimension (we only observe one distinct (geographical) market, in contrast to his 36).

The paper is organised as follows. In section 2 we provide a brief background of the Australian industry and the specific market we consider. In section 3 we outline the discrete choice demand framework. In section 4 we describe the estimation procedure. In section 5 we describe the data set. In section 6 we discuss the results, and in section 7 we provide a concluding discussion.

2. Industry Background and Market Characteristics

As in many other countries, distribution and exhibition are both highly concentrated in the Australian industry, with concentration of distribution especially pronounced. Theatrical distribution is dominated by the six major U.S. based studio distributors who accounted for 86% of turnover.⁴ This is also reflected in the number of U.S. productions released relative to the local content. Of the 314 films which opened in 2007, 172 of these were of U.S. production origin whilst only 26 were recorded as Australian by the Motion Picture Distributors Association of Australia (MPDAA). Although the cinema industry may be regarded as small by other industry standards, it is by far the largest of the ‘cultural’ sectors of the economy and in 2007 took over A\$895m in box office receipts (MPDAA).

The relationship between film distributors and cinema exhibitors operating in the Australian market is in many respects similar to the U.S. model. As in the U.S., distributors and exhibitors operate at ‘arms length’, and the typical exhibition contract resembles those observed in many other countries with a share division of box office

⁴ This figure also includes Roadshow who, whilst not a U.S. studio, operate a joint distribution arrangement with Warner Bros. Roadshow is also jointly owned by major exhibition companies Village and Greater Union.

revenues which shifts in favour of the exhibitor in the later weeks of a film's run.⁵ In Australia, the general rate of 'film rental' (the portion of box office remaining with the distributor) is commonly acknowledged to be in the region of 35-40%.

As is the case in most other countries, Australian distributors are legally precluded from specifying an admission price in the exhibition contract, but can choose not to supply a cinema should they deem the admission price too low to be profitable for them. Exhibitors naturally prefer a lower session price than a distributor given that they receive high profit margins from the sales of popcorn, drinks and other snacks. The question is, however, whether the market expansion effect from a lower ticket price would lead to higher revenues for each party, and this study will provide some evidence on this.

3. Model

The model developed resembles that of Davis (2006). Specifically, we use a discrete choice random coefficients approach as developed by Berry (1994), and Berry, Levinson and Pakes (1995) – hereafter BLP. The principal advantage of this approach (relative to the more computationally tractable multi-nomial logit model) is that, through the introduction of consumer heterogeneity, it permits more realistic substitution patterns. A useful discussion of this class of model is provided by Nevo (2000). We follow Davis' (2006) notation for ease of exposition.

The indirect utility enjoyed by consumer i by attending film f at theatre (house) h on day t is given by

$$u_{ifht} = x_{fht}\beta_i - \alpha_i p_{ht} - g(d(L_i, L_h); \lambda_i) + \xi_{fht} + \varepsilon_{ifht}, \quad (1)$$

where x_{fht} is a vector of product characteristics which can include information on the film (e.g. budget, advertising, cast, genre), the theatre (e.g. number of screens, shopping centre location), and information relating to the specific day (e.g. day of

⁵ Unlike many U.S. exhibition contracts, however, Australian exhibition contracts do not usually include the exhibitor's fixed costs known commonly as the 'house-nut'. The first week splits are therefore usually in the order of 60/40 revenue for the distributor/exhibitor rather than as much as 90/10 as is often the case in the U.S.

week, public or school holiday, weather). Price, p_{ht} , varies between location and time.⁶ In practice, most of the variation in price is across time rather than cinemas. The function $d(\cdot)$ measures the distance between the location of the consumer (L_i) and the theatre (L_h). The way distance enters the model is specified by $g(\cdot)$, which is parameterised by the $K_2 \times 1$ vector λ_i . The unobserved (by the econometrician) variable ξ_{fht} is common to (and observed by) all individuals and the variable ε_{ifht} is the idiosyncratic individual error component.

We define the vector of parameters which are specific to the individual as $\gamma_i = (\alpha_i, \beta_{i1}, \dots, \beta_{iK_1}, \lambda_i)$ and those which are equal across all individuals as $\gamma = (\alpha, \beta_1, \dots, \beta_{K_1}, \lambda)$, where K_1 is the number of observed product (film, location, time) characteristics. Following Nevo (2000) we further define

$$\gamma_i = \gamma + \Pi D_i + \sum v_i, \quad v_i \sim N(0, I_{K_1+K_2+1}) \quad (2)$$

where D_i is a $d \times 1$ vector of demographic variables, Π is a $(K_1+K_2+1) \times d$ matrix of coefficients which measures how the idiosyncratic individual demographics relate to the product characteristic parameters, and Σ is the covariance between an individual's unobserved taste components v_i . We follow BLP by scaling the variance of attribute k as $E(v_{ik})^2 = 1$, which implies that the estimated diagonal component of Σ , defined σ_k^2 , provides us with the variance of the random coefficient around the (common to all i) parameter mean value $-\beta_k$ for example.

The model is complete with the specification of an 'outside option'. The indirect utility of foregoing cinema attendance can be written

$$u_{i0} = \xi_0 + \pi_0 D_i + \sigma_0 v_{i0} + \varepsilon_{i0} . \quad (3)$$

Following the literature, we normalise the mean utility of the outside good, ξ_0 , to zero. The set of consumer types who choose film f at theatre h on day t is then

$$A_{fht}(x_t, p_t, L_t, \delta_t; \theta_2) = \{(L_i, D_i, v_i, \varepsilon_{ifht}) \mid u_{ifht} > u_{igl} \forall f, h, g, l \text{ s.t. } (f, h) \neq (g, l)\} , \quad (4)$$

where x_t are the $(J^t \times 1)$ observed product characteristics, p_t are the $(H^t \times 1)$ observed theatre prices, L_t are the $(H^t \times 1)$ theatre locations, and δ_t are the mean utilities (i.e.

⁶ As is discussed below, we are not able to observe ticket prices paid by individuals. This necessitated creating a (weighted) average ticket price based on the industry information of admission type percentages.

$\delta_{fht} = x_{fht}\beta - \alpha p_{fht} + \xi_{fht}$, where ξ_{fht} are the unobserved common characteristics). We partition the parameter vector into two components, $\theta=(\theta_1, \theta_2)$, where $\theta_1=(\alpha, \beta)$ contains parameters entering our moment conditions linearly, and $\theta_2=(\lambda, \Pi, \Sigma, \pi_0, \sigma_0)$ enter non-linearly.

The market share of film f at theatre h on day t is subsequently given by

$$s_{fht}(x_t, p_t, L_t, \delta_t; \theta_2) = \int_{A_{fht}} dP^*(L, D, v, \varepsilon) = \int_{A_{fht}} dP^*(\varepsilon)dP^*(v)dP^*(D|L)dP^*(L). \quad (5)$$

The second part of the equality in (5) follows from Bayes' rule and the assumption of independence of the error terms ε and v with location and demographics.⁷ The variables L and D are observed in our data set, but the variables v and ε are not.

It is well understood that the multi-nomial logit (MNL) model produces unreasonable substitution patterns (see BLP or Nevo (2000) for a discussion). For completeness, and to provide a benchmark, we also report results from the MNL model. Relative to our full model, the MNL model imposes $D_i = 0$, $d(L_i, L_h) = 0$ and $v_i = 0$. Individuals then differ only through the (unobserved) logit error ε . Under the MNL, market shares for film f at theatre h on day t are given by

$$s_{fht} = \frac{\exp(x_{fht}\beta - \alpha p_{fht} + \xi_{fht})}{1 + \sum_{g,l} \exp(x_{glt}\beta - \alpha p_{glt} + \xi_{glt})}. \quad (6)$$

4. GMM Estimation and Macro-Moments

Our estimation strategy must account for the joint determination of prices and market shares. Following Berry (1994) and BLP, we adopt a generalised method of moments (GMM) estimator. The following discussion of this procedure follows Nevo (2000). Defining $Z=[z_1, \dots, z_p]$ as a set of instruments, the population moment condition is $E[Z\xi(\theta^*)] = 0$, where θ^* represents the true values of the parameters. Following Hansen (1982), the GMM estimator is defined as

$$\hat{\theta} = \arg \min_{\theta} \xi(\theta)' Z \Phi^{-1} Z' \xi(\theta) \quad (7)$$

⁷ From the census data we describe in detail below, we have information on $P(D|L)$ and $P(L)$. We are only able to use some demographic information in the full model, however, because some joint distributions are not reported – for example, we can only use either education or income because their (unreported) joint densities are likely to be highly correlated. In the (base) multi-nomial logit model we can incorporate more demographics as they enter only as additional theatre characteristics.

where Φ is a consistent estimate of $E[Z'\zeta\zeta'Z]$. Intuitively, the weight matrix, Φ^{-1} gives less weight to moments (equations) with higher variance.

Implementing (7) requires solving for the structural error term ζ for a candidate parameter vector, θ . First, we exploit the market share inversion ‘trick’ of Berry (1994). Equating observed market shares with the market shares predicted by the model for a given parameter vector, θ , implicitly defines the mean utility vector, δ :

$$s(\delta_t, \theta_2) = S_t, \quad (8)$$

where S_t is observed market share. The left-hand side of (8) can be calculated analytically in the logit model, but must be computed by simulation in the full model.

Following Nevo (2000), the integral of (5) is approximated by the following

$$s_{fht}(p_t, x_t, \delta_t, P_{ns}; \theta_2) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{\exp[\delta_{fht} + \sum_{k=1}^K x_{fht}^k (\sigma_k v_{ik} + \pi_{k1} D_{i1} + \dots + \pi_{kd} D_{id}) - g(d(L_i, L_h); \lambda)]}{1 + \sum_{g,l} \exp[\delta_{glt} + \sum_{k=1}^K x_{glt}^k (\sigma_k v_{ik} + \pi_{k1} D_{i1} + \dots + \pi_{kd} D_{id}) - g(d(L_i, L_l); \lambda)]} \quad (9)$$

where (v_{i1}, \dots, v_{iK}) and (D_{i1}, \dots, D_{id}) , $i = 1, \dots, ns$, are draws from $P^*(v)$ and $P^*(D)$ respectively, and x_{fht}^k , $k = 1, \dots, K$ are the variables with random slope coefficients (for brevity of exposition, we have incorporated price in the product characteristic vector, x_{fht}). Note that $P^*(v)$ is drawn from a standard multivariate normal distribution and $P^*(D)$ is taken from the non-parametric census information on demographics (discussed further below). Also, note that in this specification travel costs enter as a function of the distance between the individual i and the theatre h .

We solve the system of equations in (9) numerically using the contraction mapping discussed by BLP

$$\delta_t^{r+1} = \delta_t^r + \ln S_t - \ln s(p_t, x_t, \delta_t^r, P_{ns}; \theta_2) \quad (10)$$

for $t=1, \dots, T$ and $r=1, \dots, R$, where $s(\cdot)$ is the predicted market shares from (9) and R is the smallest integer such that $\|\delta_t^R - \delta_t^{R-1}\| < \omega$ where ω is some pre-defined tolerance level. For a given set of parameters θ_2 , the mean utility is computed from (10) such that the observed shares equal the predicted market shares. Once δ_t is determined the error term is defined as the unobserved characteristic

$$\xi_{fht} = \delta_{fht}(S_{.t}; \theta_2) - (x_{fht}\beta - \alpha p_{ht}). \quad (11)$$

An important component of the empirical strategy is the choice of instrumental variables. We exploit the common practice of offering cheap Tuesday ticket prices by including a dummy variable for this day in our instrument set. Under the assumption that the choice to offer cheap tickets on Tuesday instead of Monday, Wednesday or Thursday is unrelated to demand conditions, this provides a valid instrument. BLP suggest that rival product characteristics may provide useful instruments. Davis (2006) considers the characteristics of rival theatres within five miles of the theatre, such as consumer service, DTS, SDDS, Dolby Digital, Screens, THX, weeks at theatre, first week of national release, and local population counts (of different definitions). Accordingly, we also include a range of other instruments which relate to i) the characteristics of the *nearest* rival cinema including number of seats, number of screens and distance from the reference cinema, ii) the characteristics of *all* rival cinemas within a certain distance of theatre h (e.g. total number of cinema screens, seats, or shopping centre theatres within [0,5], and [0,10] kms of h), and iii) the characteristics of other films showing at the same cinema on the same day (e.g. total advertising, total budgets, number of stars, etc).⁸

Finally, we also employ population macro-moment conditions to aid in identifying the model. We harness statistics reported by Roy Morgan Research on patterns of cinema attendance by demographic group. Specifying the sample analogue of the moment restriction described above as

$$g_1(\theta) = \frac{1}{FHT} \sum_{fht} Z'_{fht} \xi_{fht}(\theta) = 0, \quad (12)$$

we define the sample macro moment condition as

$$g_2(\theta) = \frac{1}{FHT} \sum_{fht} \sum_i [s_{ifht}(\theta) - \tilde{s}_{ifht}] | i \in d_j = 0, \quad (13)$$

where \tilde{s}_{ifht} is the observed probability with which an individual i attends a film f at a theatre h on a particular day t contingent upon belonging to some demographic cohort d_j , and $s_{ifht}(\theta)$ is the probability with which the same individual would patronise the

⁸ As discussed below, we only use these third class of instruments in the models in which we include film covariates rather than film fixed effects.

same film as predicted by the model. For example, this could be the probability a person aged between 15-19 years would patronise a cinema on a particular day. Intuitively the macro-moment conditions simply align the model's predictions of attendance by a particular demographic group to that which has been observed in other research.⁹ By defining the vector $g(\theta) = [g_1(\theta) \ g_2(\theta)]'$, we can write the new GMM estimate as

$$\tilde{\theta} = \arg \min_{\theta} g(\theta)' \hat{\Phi}^{-1} g(\theta) \quad (14)$$

where the weight matrix $\hat{\Phi}$ now also accounts for the extra macro conditions and once again the weighting system is imposed to give less weighting to moments for which the model's prediction differs from the observed macro condition.

5. Data

The data used in this study are primarily derived from Nielsen Entertainment Database Inc. (EDI). We observe every film at every cinema in the greater Sydney region playing from January 1, 2007 until December 31, 2007. Nielsen EDI track daily revenues of all films playing at all cinemas in this region, which for the purposes of this study includes 61 theatres. This sample is reduced to 50 cinemas by excluding Sydney's Darling Harbour IMAX theatre, a number of open-air (seasonal) cinemas, drive-ins, and occasional theatres on the grounds that they provide something of a different product to the typical cinema experience. One theatre – Merrylands, an eight screen Hoyts cinema complex – closed midway through the sample on June 21, meaning we only observed 49 cinemas in the second half of the year. The locations of the 50 cinemas across the greater Sydney area are shown in Figure 1.

[INSERT FIGURE 1 NEAR HERE]

Across these 50 theatres 377 distinct titles were recorded. Table 1 provides a summary of the national summary statistics (for which data were available) with regard to total box office, (national) opening week screens, advertising/publicity expenditure, and production budget. Data on revenue, opening week screens, and advertising were sourced from the MPDAA. The average film earned just over A\$3.5m, but the median is less than A\$1m. The 'hit' films skew the revenue distribution markedly as is apparent by the top film earning A\$35.5m (*Harry Potter*

⁹ In our model, as discussed below, we use the age profile of cinema goers as our macro-moment conditions.

and the *Order of the Phoenix*) – more than five standard deviations above the calculated mean.¹⁰ The average opening week number of screens was 106 and again the distribution is skewed as the biggest opening film was booked on 608 screens (*Pirates of the Caribbean: At World's End*).

Budget data was derived from IMDb, Box Office Mojo, and Nielsen EDI. The average budget was approximately US\$40m, and the most expensive of the sample was US\$300m (*Pirates of the Caribbean: At World's End*). Also included are a list of categorical dummy variables relating to whether or not the film was a re-release, sequel, contained a 'star' actor, or had been nominated or received an Academy Award. Re-release and sequel data were obtained from MPDAA and Nielsen EDI. The 'star' variable was constructed using James Ulmer's Hollywood Hot list, Volume 6, which rates stars according to their 'bankability' as derived from survey results of numerous industry professionals. We classify a star according to whether any of the leading actors were rated as an A+ or A actor on the Ulmer list. We also include two dummy variables for the effect of Academy Award nominations and awards in the categories Best Picture, Best Actor in a Leading Role, and Best Actress in a Leading role. For the 14 unique films which were nominated in these categories,¹¹ we assign a value of one to observations for dates equal to and beyond 23rd of January for nominations, and a value of one to the three winners (*The Departed*, *The Last King of Scotland*, and *The Queen*) for dates equal to and beyond the 25th of February.

[INSERT TABLE 1 NEAR HERE]

Tables 2 details daily film revenues per cinema as related to various film specific covariates. In total we observe 148,334 film-at-cinema data points over the 365 days of 2007. The statistics consistently reflect large levels of skew and (excess) kurtosis, a pattern consistent with the aggregated (national) revenue statistics reported in Table 1. The suggestion is that stars and sequels increase box office, but releases do not. There is also some evidence that 'Animation', 'Action' and 'Animated' are more successful genres, and 'PG' and 'G' films marginally outperform 'M' and 'MA15+' titles. First inspection of the Academy Award nomination/win effect might suggest that these films perform relatively worse, but it is important to note that unlike the

¹⁰ Explanations for the skewed nature of box office returns have been extensively investigated by De Vany and Walls (1996).

¹¹ *The Queen* was nominated for both Best Picture and Best Actress in a leading role.

other variables in this table, these variables are time contingent and are only ‘switched-on’ after the nomination/win.¹²

[INSERT TABLE 2 NEAR HERE]

Table 3 reports summary statistics for daily film revenues per cinema by the day of the week for ‘opening days’, ‘non-opening days’, and ‘all days’. The summary statistics clearly show Saturday to be the highest revenue earning day of the week, followed by Sunday, then Friday. Of the other weekdays in the full sample, Tuesday outperforms Thursday, with Wednesday and Monday being the least profitable for theatres owners. Many, indeed nearly all, cinemas offer discounted tickets on Tuesdays which is driving the increased revenues observed on this day. In Australia, films typically open on a Thursday – although other days are not entirely uncommon. In fact, of the 4,658 openings recorded in this sample, 4,054 (87%) opened on Thursday. Once the opening day effect is removed from the week day summary statistics, however, Thursday revenues only marginally outperform Mondays and Wednesdays. This suggests to some extent that consumers implicitly treat all weekdays (excluding Fridays) as equal – an observation which we exploit in the empirical model described below.

[INSERT TABLE 3 NEAR HERE]

Table 4 reports summary statistics of daily film revenues by week of release (at cinema), whether the day was a public/school holiday, and weather. With regard to week of release, the negative weeks refer to films which were previewing of which there are 1,415 observations – most of these occurring one week before the official release. As expected daily revenues decline at higher weeks of release.¹³ Table 4 shows that films also typically earn more on public and school holidays.¹⁴ Einav (2007) documents the nature of underlying seasonality in the U.S. industry and observes peaks in admissions about school and public holiday periods. These peaks

¹² For example, by the time *The Departed* won Best Picture it was in its twelfth week of release at some cinemas.

¹³ The downward trend in box office revenues is well documented and has been often been integrated into models of demand (Davis 2006, Einav 2007, Moul 2007). The rationale can be attributed to the joint effect of saturation of potential audiences, and the desire for filmgoers to be ‘movie-mavens’ who prefer viewing a film early in its run.

¹⁴ These are NSW public holidays including New Years Day, Australia Day, Good Friday, Easter Saturday, Easter Monday, Anzac Day, Queen’s Birthday, Labour Day, Boxing Day and Christmas Day. NSW schools have four terms, and consequently four holiday periods, held in April, May/June, September/October, and December/January.

are also evident in the current data set – although, as Figure 2 illustrates, the peaks are most obvious in the weekdays rather than the weekend days.

[INSERT TABLE 4 NEAR HERE]

[INSERT FIGURE 2 NEAR HERE]

We also consider the weather's effect on daily admissions. No academic studies are known to have included the effect of weather as an explanatory variable in modelling film demand although a number of authors (e.g. Litman 1998; Moul 2005) have noted the potential for this variable's effect.¹⁵ Table 4 provides descriptive evidence that the weather does have an important bearing on daily film revenues per cinema. To gauge this, a metric relating the daily maximum temperature to the monthly average is created. The evidence suggests clearly that less people go to the cinema on (relatively) warmer days. Also, there appears to be increasing revenues the higher the daily rainfalls supporting the intuition that film provides an indoor leisure substitute for other outdoor leisure activities.

Table 5 summarises the 50 theatres of the sample by number of screens, number of seats, whether or not they are located in a shopping centre, and ticket prices. The average theatre in our sample has 6.8 screens and over 1,500 seats. The biggest cinema, George St. in the heart of Sydney CBD, has 17 screens and seating capacity in excess of 4,100. There were 21 theatres located in shopping centres. Of these the average number of screens was just below 10, and the minimum number of screens in a shopping centre was five. These types of cinemas are commonly referred to as multiplexes.

In this study we are not able to observe admissions by number or ticket type, only by revenue, which prevents us knowing the composition of audiences. We consequently derive an approximation for ticket prices as a weighted average of 'Adult', 'Student', 'Senior' and 'Child' ticket prices. The weights are derived from industry information supplied by Greater Union who report that, within their national chain over 2007, 44.7% of all ticket sales revenue came from adult ticket sales, 13.1% from student tickets, 10.9% from child tickets, and 3.1% from seniors/pensioners tickets – the

¹⁵ An industry study by WeatherBill (2007) in the UK has established significant relations between weekend box office vis-à-vis precipitation and temperature. The study established more cinema goes patronise theatres on rainy weekends and less on hotter weekends and that the effects were stronger in the summer months.

remainder being made up of group tickets, gift vouchers, promotional tickets, etc. In order to construct a single ticket price, we firstly create a weighted average for the (observed) ticket prices of our 50 cinemas by determining each cinema's proportion of total sales over the year and then weighting each cinema's adult, student, child and pensioner ticket price by this proportion. This gives us a (weighted) average ticket price for each of the four ticket types. We then divide the Greater Union sales revenue for each group by these ticket prices to give us an estimate of the number of admissions for each group and divide these by the total admissions of the four ticket types combined, which we use as weights for calculating a single ticket price over all groups. Using this method, the weights we apply are 0.56 to the price of an adult ticket, 0.21 to the price of a student ticket, 0.18 to the price of a child ticket, and 0.05 to the price of a pensioner ticket.

The weighting system was applied to all theatres in the sample after collecting ticket price information either directly from the cinema, or from the Australian Theatre Checking Service (ATCS). In instances where there had been a change in ticket price over the year, the highest price was used. The weighted average ticket price ranged from \$5.82 at Campbelltown Twin-Dumares (\$6 adult ticket), to \$14.90 at Academy Twin (\$16.50 adult ticket). Table 5 provides further information on the constructed ticket price variable by day of the week for the 50 theatres. The average day price of \$12.74 (when no theatres discount) is significantly lower on Tuesdays at \$9.73 when the vast majority of theatres offer discounted ticket prices. There are a couple of exceptions, however, as two theatres offer cheap Monday tickets (Academy Twin and Norton St. – both owned by Palace) and one theatre offers cheap Thursday tickets (Mt. Victoria Flicks). Of the remaining 47 theatres, only three independents don't offer cheap tickets. Table 6 summarises daily film revenues with respect to various characteristics of the theatre and suggests theatres located in shopping-centres outperform those which are not, and theatres with more screens (not surprisingly) earn higher daily film revenues.

[INSERT TABLE 6 NEAR HERE]

Because our demand model utilises admissions rather than revenues in construction of the dependent variable, it is necessary to estimate daily film admissions by cinema. Table 7 provides summary statistics of aggregated estimated daily admission across all cinemas by day of week. This variable was constructed by firstly estimating daily

cinema admissions per film as revenue/price, which were then aggregated across films by theatre by day, and then across all theatres by day. The estimates suggest, on average, 41,710 people attend the movies each day in the greater Sydney area, and that Saturday is the most popular day of the week followed by Sunday and then Tuesday. In fact, Tuesday records the highest attendance in a single day across the sample period on January 2, 2007 where almost 140,000 individuals were estimated to have patronised a cinema. The dramatic increase in Tuesday attendances above other days of the week is simply a reflection of cheap Tuesday tickets which are offered by almost all of the cinemas as previously discussed.

[INSERT TABLE 7 NEAR HERE]

Our discussion of the data is complete with details of the demographic variables we include in this study. Table 8 reports summary statistics of the demographic variables we observe in this study. We use the Australian Bureau of Statistics (ABS) Census data from 2006 to derive a number of indicators about consumers in the greater Sydney area. We restrict attention to ‘collection districts’ whose ‘centroid’ latitude and longitude coordinates place it no further than 30kms from a theatre location. We use Google Earth to ‘geo-code’ the latitude and longitude of each cinema and use this to create a distance variable from each collection district to each cinema. In doing this we are able to consider travel costs along with other demographics which may be important to explaining cinema patronage. Using our 30km definition, the total population of the greater Sydney region is a little over 4 million people. Given that the official ABS population count is a little over 4.3 million, this gives us approximately 93% coverage of the market. Over this area, there are a total of 6,587 collection districts with an average of 613 people in each.

[INSERT TABLE 8 NEAR HERE]

At least two organisations in Australia undertake extensive research profiling the cinema going audience on an ongoing basis across the country. The ABS¹⁶ and Roy Morgan and Co. Pty Ltd¹⁷ report statistics which are useful in our research in two important respects. Firstly, they help guide our hypotheses regarding variable signage, and secondly they allow us to create macro-moments as previously discussed and further detailed below. Regarding the hypotheses of our study, the ABS statistics suggest higher cinema attendance rates for younger people, higher income earners,

¹⁶ Attendance at Selected Cultural Ventures and Events, catalogue no. 4114.0

¹⁷ Cited by Screen Australia. See <http://www.afc.gov.au/gtp/cinema.html>

tertiary educated people, and those who are not from a non-English speaking background.

6. Estimation Issues and Results

In section 3, the general model was described but without specific discussion of the variables contained within the vector x_{jht} . We consider a number of explanatory variables relating to the ‘product’ which is a film playing at a particular theatre on a particular day. These may relate directly to the film (budget, advertising, national number of opening week screens, star appeal, re-release, sequel, genre, and rating), the theatre (number of screens and whether the theatre is in a shopping centre), and the particular day of observation (opening day at theatre, week of release at theatre, Academy Award nomination/win effects, day of week, public/school holiday, and weather). Unfortunately not all film information is available on all titles – in particular advertising and budget data. We (in part) address this problem by also considering film fixed effects in some of our models in place of detailed film specific covariates.

Before considering the full random coefficients model, we report multinomial logit model results. To provide an indication of the performance of our instruments, we present both stages of an instrumental variables regression for our MNL models. Table 9 provides first stage regression results where price is the dependent variable. The second stage IV MNL results are provided in Table 10. In this specification, all film covariates are included in the model. Column 1 reports results where no demographic variables are included, while columns 2-6 include respectively local population proportion (of total population), within area cinema-age (15-30 year olds) proportions, within area average median weekly incomes, within area proportion with tertiary education, and within area proportion of households which speak English as the first language. Column 7 includes all demographics jointly. Demographic variables are introduced into the multinomial logit model as additional ‘product characteristics’ and are considered as ‘distance rings’ around each theatre following Davis (2006). For example, the ‘Pop[0,5]’ variable is the proportion of the total population (approximately 4 million) living within 5 kilometres of theatre h , whereas ‘Pop(5,10]’ is the proportion of the population living between 5 and 10 kilometres away from theatre h .

[INSERT TABLE 9&10 NEAR HERE]

Considering the results displayed across columns 1-7 in Table 10, with the exception of ‘Re-release’, all variables are highly significant and conform to a-priori expectations. The main variable of interest ‘Price’ is (as expected) negative across all models and is estimated in the region 0.182 – 0.199 in absolute terms.¹⁸ Based on the estimate 0.199, this (somewhat crudely) implies an average own price elasticity of 2.52 (median 2.68, std. dev. 0.36) using $\eta = -\alpha p_{ht}(1-s_{ht})$.¹⁹ This magnitude is similar to other (mostly time series) studies which have found elastic own price demand.²⁰ The time invariant film variables relating to ‘Budget’, ‘Advertising/publicity expenditure’, ‘Star’ and ‘Sequel’ all have highly significant positive coefficients which suggest an increase in mean utility *ceteris paribus*. The negative coefficient of (national) ‘Opening Week Screens’ is a consequence of revenues being dissolved across an increased number of screens. That is, if a film is playing on alternate screens, mean utility from viewing on any given screen decreases. The time-variant, but theatre specific, film variables relating to ‘Opening Day’ and ‘Week of Release’ at theatre variables display positive and negative coefficients respectively which are highly significant. Again, these findings are consistent with a-priori expectations that consumers prefer to see a film earlier in its run and the opening day provides increased utility. These observations are consistent with the models and findings of Davis (2006), Einav (2007) and Moul (2007). Also, Academy Award nominations and wins are both shown to have a positive and highly significant effect on mean utility, but the effect of a nomination is greater than that of the win – an observation consistent with the findings of Deuchert, Adjamah and Pauly (2005).

The day and date variables reveal that Saturday followed by Sunday, followed by Friday provide greater mean utility relative to weekdays – recalling that we treat all weekdays as essentially equal given that we explicitly include the ‘Opening Day’ variable and that we seek to identify price from cheap Tuesday ticket prices. Public and school holidays also increase mean utility of the representative individual, which is consistent with our expectations. The weather variables also show to be statistically

¹⁸ In unreported OLS estimation when price was not instrumented the price coefficient was found to be in the region -0.15 to -0.17, i.e. less elastic, in all specifications. This is consistent with expectations given that price endogeneity creates an upward bias on the OLS estimator.

¹⁹ See Nevo (2000, p. 552).

²⁰ For example, Deweneter and Westerman (2005) find the own price elasticity of demand to be in the range of 2.4-2.76 using annual German data between 1950 and 2002.

well defined with signage consistent with a-priori intuition. Specifically, mean utility is increasing with daily rainfall and decreasing the higher the daily maximum temperature above the monthly average. Intuitively, these findings suggest that, on average, more people go to the cinema on rainy days and less people on sunny days. Finally, the theatre characteristics also confirm a-priori expectations. Whether the cinema was located in a shopping centre and the number of cinema screens (at the theatre location) both increase mean utility – although it is worth noting that there is some variation in the magnitude of the shopping centre coefficient when demographics are included.

In column 2, the fact that the coefficient of ‘Pop[0,5]’ is positive and that ‘Pop(5,10]’ is negative suggests there are travel costs associated with cinema attendance. This observation is consistent with the finding of Davis (2006). Columns 3-6 similarly show that an increase in the proportion of 15-30 year olds, an increase in median weekly income, an increase in education levels, and a higher proportion of English speaking households all increase mean utility (or attendance), and that when these increase further away (i.e. 5 to 10 kilometres away), there is less effect on the theatre in question (and often go negative). This observation is consistent with the notion of travel costs and that changes in the demographic profile further away from a cinema have little direct bearing on its own performance.

The results of Table 10 are fairly robust to the inclusion of demographic variables as ‘product characteristics’, but unfortunately due to lack of complete film data (e.g. budgets and advertising) approximately a third of the available data is lost. In Table 11 and 12 we in part address this problem by considering film fixed effects as substitutes for the set of film covariates discussed above. There is also an advantage to including fixed effects beyond correcting for missing data in that we are able to capture more of the time invariant variation in attendance that our chosen covariates may not be able to explain in full. The use of fixed effects in this way is also consistent with the discussions of Davis (2006) and Nevo (2000). The results are robust to this modification and the price variable coefficient is again in the region -0.19 to -0.21 and highly significant across the 7 specifications. It is also noted that 39 observations are lost in the fixed effects model due to films appearing in our data set for just one day at one cinema. Again all other coefficients’ signs conform well to a-

priori expectations and are highly significant. The pattern across the demographic variables is consistent with Table 10 and again there is evidence that changing demographics further away from the theatre in question has little direct bearing on its patronage. For example, higher population density within [0,5] kms around a theatre increase demand, but the coefficient with (5,10] kms is indistinguishably different from zero suggesting positive travel costs. One slightly odd result was the finding of the cinema age proportion effect increasing from the [0,5] to (5,10] distance band for which we have no intuitive explanation.

[INSERT TABLE 11-12 NEAR HERE]

To validate the instruments chosen we consider tests for under-identification, weak identification, and over-identification. We use Anderson’s (1951) LM test for under-identification, Cragg and Donald’s (1993) test for weak identification, and the Sargan-Hansen test for over-identification as discussed by Hayashi (2000). As Tables 9 and 11 reveal the instruments used in both first stage regressions are valid and reject the null of the respective tests outlined. Also, Shea’s (1997) partial R^2 statistic reveals that there is good correlation between the instruments and price – primarily driven by the use of the Tuesday dummy variable which suggests that, on average, Tuesday prices are in the order of \$3.34 (fixed effects model) to \$3.41 (film covariates model) lower than on other days which is comparable to the observations of Table 5.

We now turn to the full random coefficients model with travel costs. Computational practicality dictates when estimating these models to consider only a small number of random coefficients and a relatively simple travel cost function. We therefore firstly estimate travel costs as a linear function (i.e. $g(d(L_i, L_h; \lambda)) = \lambda d(L_i, L_h)$) and interact only two demographic variables: age and income. These demographics are chosen because (using Bayes’ rule) we are able to establish conditional probabilities from the census information and consequently approximate the integral in (5). Defining a =age and y =income, we have $P(D|L) = P(a, y|L) = P(a|y, L)P(y|L)$. $P(L)$ is estimated from the non-parametric distribution of consumers, $P(v)$ is estimated from a standard multivariate normal distribution, and $P(\epsilon)$ is solved out analytically. Estimation proceeds by taking ‘draws’ from v , D , and L , for a set number of simulations and interacting these draws as described in (9). Due to computational burden we limit the number of draws to 200.

We introduce random coefficients to the constant, the price coefficient, the week of run coefficient, (log) budget coefficient, and the number of cinema screens at the theatre location. These particular variables are chosen given that for each variable a compelling case can be put forward as *why* each may be associated with a random coefficient. Notably, we propose consumers may differ with respect to their price sensitivities, the age of a film at a cinema, tastes for high budget films (blockbusters), and the theatre venue as described by the number of screens. We interact each of these with the random draw ν from the standard multivariate normal distribution as described in (9). We can then interpret σ as an estimated standard deviation of unobserved demographic effects. Although we have trialled other specifications, we only interact our observed demographics in D with the constant term, and thus only have estimates of π in relation to this term.

In addition to the rival product characteristic instruments described above, we also include the macro-moment conditions discussed in section 4. Specifically, these are the attendance rates reported by the Roy Morgan Research reported by Screen Australia. We observe the attendance rate of four age groups (15-24, 25-34, 35-49, and 50+), which gives us the percentage of each group who attended the cinema at least once over 2007, and we also observe the frequency of visits of those who did attend a cinema. Multiplying these we get the annual average admissions by each age group, which we divide by 365, then by the number of films available on that day to get the probability of a member of that age group going to one of the particular films at one of the particular theatres on a given day.

The results of the random coefficient model with film covariates are presented in Table 13. In all specifications price is instrumented using the variables described above. We present results without and with macro-moment conditions in columns (1) and (2) respectively. In each specification, coefficients' signage and significance is generally consistent with the MNL results. The most obvious difference, however, is that the price coefficient has notably increased in an absolute sense and particularly in the macro-moment model. Indeed this finding appears to be a by-product of modelling the price coefficient as random. Beyond the linear parameters, we find some interesting, if not peculiar, results with our non-linear parameters. In both specifications the linear travel cost parameter is estimated positive (recalling that it

enters utility with a negative sign), and is highly significant implying that consumers are affected by travel costs and prefer to attend cinemas closer to their location – a finding consistent with Davis’ (2006) study. There is, however, a question of magnitude as the estimated parameter is significantly larger in the model without macro-moments. The demographic interaction coefficients suggest that younger people and those with higher incomes are more likely to patronise cinemas, that is mean utility is increasing in income and decreasing in age. These are both consistent with a-priori expectations based upon the aggregated ABS and Roy Morgan survey analysis. Once again, however, there is an obvious divergence between magnitudes of the estimated parameters between the two models in this case with respect to (log) income. The only explanation for which we put forward relating to the robustness of this framework with 200 simulations. Finally, the interactions of constant, price, week, (log) budget, and cinema screens with the unobserved random variable v provide evidence that unobserved demographics are important in each case. The literal interpretation being that different consumers value these differently. Moreover, however, the magnitudes of the two specifications go some way to reconciling the MNL results when the estimates of σ are interpreted correctly as standard deviations of the mean parameter estimate and it is observed that the further away the random coefficient point estimate is from the MNL estimate, the larger the value of σ .

[INSERT TABLE 13 NEAR HERE]

We now turn our attention to estimating elasticities. Although the MNL model was able to provide product specific own price elasticities, it did not account for consumer heterogeneity and also failed to provide realistic substitution patterns. For each market t , the price elasticities of demand (market shares) in the random coefficients model are defined

$$\eta_{fh,gl} = \frac{\partial s_{fh} P_{gl}}{\partial P_{gl} s_{fh}} = \begin{cases} -\frac{P_{fh}}{s_{fh}} \int \alpha_i s_{ifh} (1 - s_{ifh}) dP^*(v) dP^*(D|L) dP^*(L) & \text{if } fh = gl \\ \frac{P_{gl}}{s_{fh}} \int \alpha_i s_{ifh} s_{igf} dP^*(v) dP^*(D|L) dP^*(L) & \text{otherwise} \end{cases} \quad (15)$$

where s_{ifh} is similar to the right hand side of (9) for a particular individual i . Practically the elasticities are not that dis-similar to the logit except consumer

heterogeneity is incorporated. The advantage of this specification over the logit model is that elasticity is no longer driven by a single parameter α , rather each individual will have a different price sensitivity which is averaged to a mean price sensitivity using the individual specific purchase probabilities as weights (Nevo, 2000). In Table 14 we provide an example of the own and cross price elasticities for the first day of our sample (January 1, 2007) for a selection of films and theatres. We choose three inner city cinemas that vary in their characteristics and are all within 3.5kms of each other. Two of these cinemas are multiplexes and the other is an independent. George st., with 17 screens, is located 1.5km from Broadway, a 14 screen multiplex within a shopping centre. Newtown is a 4 screen independent which, whilst mainly specialising in low to mid budget indies, is well aware that screening mainstream films is lucrative for its revenue stream. Newtown is located 3.5kms from George St. Observing the set of elasticities for each venue reveals a stronger pattern of substitution between the two major cinemas. That is, in all cases consumers prefer substituting to the other large cinema in preference to substituting towards the independent Newtown location. A stranger literal implication of the cross price elasticity with respect to Newtown theatre prices is that George St offers a better substitute than Broadway as implied by the larger cross price estimates – although this is very marginal. Another interesting finding of this model is the relatively lower cross price elasticities for films well into their run with smaller market shares. For example, in Table 14 in the ninth column the film *Open Season* at George St. has relatively lower elasticities relative to its contemporaries. The implication being that consumers are less likely to substitute to another film and more likely to substitute towards the outside good the older a film becomes.

[INSERT TABLE 14 NEAR HERE]

Not yet discussed are the apparently low cross price elasticities which seem to be symptomatic of this particular estimation procedure. In particular, the cross price is tangibly tied to the respective market shares of both the reference product and the product of interest. In the logit model, increasing the price of a particular film on a particular day would see cross price elasticities which are equal across alternatives – that is, no matter what the film or where it is showing would lead us to find the same cross price elasticity, implying all values in each column of Table 14 would be equal. We do not observe this in our model leading us to believe that this estimation procedure does enhance the MNL. But, in observing this, we are also aware that some

of the linear parameter point estimates do not stay intact when the random coefficients specifications are enacted.

7. Conclusion

This paper has developed a random coefficients logit model of cinema demand using daily film-at-theatre box office revenues. The discrete choice class of model describes the product – defined as a film at a theatre on a particular day – particularly well. It must be stressed that in contrast to much of the empirical evidence using this sort of data, we do not explicitly seek to identify the determinants of a successful film. Rather we seek to examine the nature of cinema demand at a cross sectional level whilst controlling for such characteristics. We find that demand is price elastic and is influenced by a number of characteristics which relate to the film itself, the time of consumption, and the characteristics of the theatre. Critically we use the cheap Tuesday ticket price observed in the Australia market to aid in identifying demand in our model. Without such variation this exercise would be particularly strenuous given the observed uniformity of cinema ticket pricing throughout the rest of the week.

Although the fundamental approach of our model follows Davis (2006), we believe our data set is somewhat richer because of the longer time dimension and also somewhat more fortunate because of the cheap Tuesday price variation. What we don't model in our analysis is the supply side. This, however, is not a short-coming as prices are for the most part uniform in this market which suggests that firms are not pursuing profit maximisation objectives with regard to their pricing strategies. Towards pointing out the shortcomings of our model we note that we do not explicitly account for the dynamic nature of demand that is well known to exist in this industry. We are unable to gauge the magnitude of this effect but don't have any reason to believe it would dramatically alter our main findings given that we treat each day as a distinct market and are primarily interested in the cross sectional aspect of the model and identifying cinema demand price elasticities. Also, in some respects we control for saturation of demand by incorporating the week of the run into the demand function.

The initial results of the MNL highlight that demand is responsive to a range of variables. When we interact demographic variables as additional product

characteristics we confirm a number of a-priori expectations including the observation that younger consumers, higher income earners, tertiary educated people, and those from English speaking backgrounds all increase cinema patronage. Further, by introducing these demographics as ‘distance rings’ surrounding a location we are able to gauge that consumers are sensitive to travel costs and are more likely to patronise cinemas within 5kms of their location. The random coefficients model highlights that significant consumer heterogeneity does exist in this market, and that this heterogeneity manifests itself within key variables which are likely to drive a consumer’s consumption decisions. For example, variables which we consider sensitive observed and unobserved demographic effects include price, week of run, production budget, type of cinema (as proxied by screen count), and the outside good. We also find that travel costs are significant – although they appear sensitive to the particular specification we use. Finally, the random coefficients model also has the key advantage of providing more realistic substitution patterns of demand. That is cinemas which are closer together provide better substitutes and those which are further away, and cinemas which are more like each other in their characteristics (e.g. multiplexes) are closer substitutes for each other than cinemas which are not alike within a localised market. Further, the model also highlights that cross price elasticities tend to fall as a film gets further into its run suggesting that consumers are more likely to substitute towards the outside good the older a film becomes.

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Table 1
National Level Summary Statistics of Films used in Sample

	Obs.	Mean	Median	Std. Dev.	Min.	Max	Skew	Kurtosis
Total Box Office	358	3,598,320	959,366	6,193,204	1,040	35,500,000	2.83	11.80
Opening Week Screens	331	106	44	120	1	608	1.29	4.10
Advertising/Publicity	164	1,166,378	900,000	955,610	489	3,535,000	0.62	2.28
Budget (USD)	216	40,300,000	20,000,000	47,800,000	30,000	300,000,000	2.25	9.13
Re-release	377	0.12	0	0.32	0	1	2.35	6.51
Sequel	377	0.06	0	0.24	0	1	3.67	14.46
Star	377	0.13	0	0.34	0	1	2.20	5.84

Table 2
Summary Statistics of Daily Film Revenues per Cinema by Film Characteristic

	Obs.	Mean	Median	Std. Dev.	Min.	Max	Skew	Kurtosis
<i>Star</i>								
No	114,124	1,178	537	2,366	1	65,052	8.84	127.84
Yes	34,210	1,674	708	3,052	1	58,120	5.95	60.42
<i>Sequel</i>								
No	128,327	1,148	548	2,071	1	58,120	8.00	118.92
Yes	20,007	2,220	793	4,433	1	65,052	5.33	42.30
<i>Re-release</i>								
No	148,009	1,295	571	2,551	1	65,052	7.85	101.91
Yes	325	385	259	395	7	1,828	1.68	5.36
<i>Award Nomination</i>								
No	140,410	1,320	575	2,607	1	65,052	7.71	98.16
Yes	7,924	802	505	951	7	12,311	3.31	20.54
<i>Award</i>								
No	147,146	1,300	574	2,558	1	65,052	7.83	101.42
Yes	1,188	391	273	361	9	2,493	1.74	6.73
<i>Genre</i>								
Action	33,366	1,986	724	3,918	1	65,052	5.54	47.78
Adventure	9,502	1,257	751	1,647	1	22,717	3.76	26.54
Animated	7,129	1,911	812	4,102	1	55,085	6.16	52.45
Animation	1,798	3,681	1,438	6,871	7	57,201	3.84	20.67
Black Comedy	389	358	244	375	6	2,940	2.61	12.65
Comedy	35,535	1,170	571	1,680	1	22,198	3.51	20.97
Crime	2,273	804	394	1,184	1	10,877	3.59	19.92
Dance	374	288	193	294	7	2,493	2.69	14.52
Documentary	2,748	613	373	742	7	8,900	3.14	18.67
Drama	40,162	904	492	1,236	1	24,416	4.12	34.20
Family	92	120	87	104	7	494	1.43	5.00
Fantasy	846	533	368	529	9	4,109	2.29	10.67
Horror	4,348	721	453	786	2	8,385	2.78	15.75
Musical	507	560	380	554	9	4,076	2.30	10.28
Mystery	758	826	562	814	10	5,253	1.89	7.11
Romance	1,518	811	496	925	7	7,371	2.55	11.62
Sci-Fi	607	752	444	931	8	6,651	2.80	12.82
Sport	74	352	177	444	1	2,180	2.29	8.20
Suspense	771	849	422	1,132	1	11,147	3.25	19.24
Thriller	5,535	862	499	1,013	1	8,857	2.55	11.69
Western	2	165	165	-	165	165	.	.
<i>Rating</i>								
G	13,419	1,188	633	1,634	2	22,717	3.68	24.81
M	67,619	1,330	549	2,794	1	65,052	7.71	93.46
MA15+	31,865	1,074	558	1,612	1	50,773	6.09	90.31
PG	33,164	1,518	633	3,066	1	57,201	6.99	76.82
R18+	2,267	587	385	611	2	5,419	2.57	12.89
Total	148,334	1,293	570	2,549	1	65,052	7.85	102.09

Table 3
Summary Statistics of Daily Film Revenues per Cinema by Day of Week

	Obs.	Mean	Median	Std. Dev.	Min.	Max	Skew	Kurtosis
<i>Opening Days</i>								
Monday	30	771	546	1,074	113	5,839	3.70	17.82
Tuesday	49	1,568	1,044	1,869	25	11,564	3.50	18.21
Wednesday	199	8,843	3,567	12,171	54	65,052	2.28	8.22
Thursday	4,052	2,030	846	3,845	1	57,625	5.59	50.88
Friday	246	977	566	1,246	11	10,756	3.58	22.09
Saturday	40	648	387	789	84	3,783	2.35	8.55
Sunday	37	649	418	1,106	10	6,819	4.87	27.70
Total	4,653	2,230	850	4,622	1	65,052	5.88	51.38
<i>Non Opening Days</i>								
Monday	20,918	769	326	1,635	1	51,272	9.84	172.91
Tuesday	20,760	1,155	542	1,910	5	42,079	5.51	56.63
Wednesday	20,629	757	347	1,230	1	22,444	4.94	42.49
Thursday	16,671	842	366	1,731	1	50,744	11.20	216.92
Friday	21,170	1,437	696	2,609	1	54,841	6.98	80.81
Saturday	21,742	2,071	1,049	3,545	5	58,120	6.31	62.35
Sunday	21,791	1,661	817	3,014	1	57,201	6.74	70.37
Total	143,681	1,262	562	2,447	1	58,120	7.79	101.27
<i>All Days</i>								
Monday	20,948	769	327	1,635	1	51,272	9.84	172.96
Tuesday	20,809	1,156	543	1,910	5	42,079	5.51	56.53
Wednesday	20,828	835	352	1,878	1	65,052	13.05	291.79
Thursday	20,723	1,074	429	2,350	1	57,625	8.91	129.54
Friday	21,416	1,432	695	2,598	1	54,841	7.00	81.33
Saturday	21,782	2,068	1,048	3,543	5	58,120	6.31	62.44
Sunday	21,828	1,660	817	3,012	1	57,201	6.75	70.44
Total	148,334	1,293	570	2,549	1	65,052	7.85	102.09

Table 4
Summary Statistics of Daily Film Revenues per Cinema by Week, Holiday and Weather

	Obs.	Mean	Median	Std. Dev.	Min.	Max	Skew	Kurtosis
<i>Week of Release at Cinema</i>								
-3	25	1,089	1,132	631	60	2,301	0.13	2.17
-2	151	991	533	1,229	9	5,577	2.01	6.81
-1	1,239	870	479	1,156	1	10,044	3.34	18.25
1	30,226	2,280	1,034	4,193	1	65,052	5.67	48.48
2	29,474	1,679	809	2,867	1	53,227	5.97	59.15
3	25,414	1,157	589	1,686	1	32,881	4.39	36.44
4	20,565	879	454	1,191	1	14,621	3.36	19.99
5	14,802	722	383	965	1	13,182	3.42	21.12
6	10,111	572	319	727	1	8,932	3.15	18.73
7	6,571	472	272	597	1	6,428	3.24	18.52
8	3,978	416	234	544	1	6,188	3.60	23.05
9	2,114	404	226	509	1	4,763	3.20	18.52
10	1,263	463	289	521	1	4,313	2.45	11.11
<i>Public Holiday</i>								
No	144,450	1,256	555	2,497	1	65,052	8.10	108.31
Yes	3,884	2,640	1,438	3,794	10	51,272	4.46	34.81
<i>School Holiday</i>								
No	112,745	1,121	469	2,485	1	65,052	8.81	120.44
Yes	35,589	1,836	1,045	2,670	1	57,201	5.90	67.76
<i>Max-to-Average Temperature Difference (Celsius)</i>								
<= -5	684	1,899	1,345	1,805	21	15,690	2.27	11.70
>= +5	15,679	1,204	480	2,621	1	57,811	7.90	96.81
<i>Daily Rainfall (mm)</i>								
0	94,498	1,243	556	2,400	1	58,120	7.94	106.89
>=5	22,399	1,428	571	3,160	1	65,052	7.76	91.30
>=10	16,036	1,567	595	3,547	1	65,052	7.30	78.09
>=15	10,814	1,722	615	3,966	1	65,052	6.79	65.74
>=20	9,006	1,777	643	4,169	1	65,052	6.77	63.50
>=25	6,784	1,864	680	4,123	1	57,201	6.15	53.45
>=30	5,123	2,231	860	4,645	2	57,201	5.46	42.16
Total	148,334	1,293	570	2,549	1	65,052	7.85	102.09

Table 5
Theatre Summary Statistics (price is calculated as weighted average)

	Obs.	Mean	Median	Std. Dev.	Min.	Max
Screens	50	6.78	6.50	4.36	1.00	17.00
Seats	50	1,544	1,788	1,027	64	4,112
Shopping Centre	50	0.42	0.00	0.50	0.00	1.00
Ticket Price	50	12.55	13.34	1.82	5.82	14.90
<i>Ticket Price by Day of Week</i>						
Monday	50	12.55	13.34	1.76	5.82	14.79
Tuesday	50	9.73	10.00	1.45	5.85	14.90
Wednesday	50	12.74	13.49	1.67	5.82	14.90
Thursday	50	12.69	13.49	1.81	5.82	14.90
Friday	50	12.74	13.49	1.67	5.82	14.90
Saturday	50	12.74	13.49	1.67	5.82	14.90
Sunday	50	12.74	13.49	1.67	5.82	14.90

Table 6
Summary of Daily Film Revenues by Theatre Type and Size

	Obs.	Mean	Median	Std. Dev.	Min.	Max	Skew	Kurtosis
<i>Shopping Centre</i>								
No	65,053	1,113	514	2,284	1	65,052	9.92	166.38
Yes	83,281	1,433	620	2,730	1	55,954	6.80	74.27
<i>Screens</i>								
Small (1-2)	14,199	611	335	829	5	10,486	3.84	26.31
Medium (3-5)	12,967	811	462	1,009	1	13,116	2.98	16.81
Large (5-10)	65,642	1,182	547	2,170	1	54,936	7.18	87.49
Multi (11+)	55,526	1,710	736	3,319	1	65,052	6.79	72.74
Total	148,334	1,293	570	2,549	1	65,052	7.85	102.09

Table 7
Summary of Daily Estimated Total Admission All Cinemas by Day of Week

	Obs.	Mean	Median	Std. Dev.	Min.	Max	Skew	Kurtosis
Monday	53	23,400	13,761	20,551	8,789	97,141	2.19	7.56
Tuesday	52	47,509	35,726	27,748	23,566	138,758	1.53	4.34
Wednesday	52	25,468	15,364	23,746	9,526	117,141	2.39	8.49
Thursday	52	32,443	24,008	19,348	13,222	93,850	1.43	4.51
Friday	52	44,758	38,397	19,062	24,905	100,619	1.37	4.17
Saturday	52	65,803	60,908	16,422	37,225	112,049	1.05	3.75
Sunday	52	52,938	47,246	18,441	31,451	126,697	1.60	6.47
Total	365	41,710	37,217	25,335	8,789	138,758	0.93	3.57

Table 8
Summary Statistics of (Collection District Weighted) Demographics

	Obs.	Mean	Median	Std. Dev.	Min.	Max	Skew	Kurtosis
Collection District Population	6,587	613.0	578.0	256.7	0	2,765	0.92	5.22
Minimum Distance to Cinema (kms)	6,587	4.47	2.90	5.25	0.02	29.99	2.76	10.96
% Aged 15 to 30	4,037,972	0.23	0.22	0.08	0	1	2.26	14.23
Median Weekly Income	4,037,972	568.2	536.0	213.3	0	2,000	0.99	4.57
% Tertiary Education	4,037,972	0.58	0.58	0.12	0	1	-0.02	2.77
% English Speaking	4,037,972	0.69	0.76	0.23	0	1	-0.77	2.58

Table 9
First Stage Results for Multinomial Logit with Film Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tuesday	-3.4088** (0.0091)	-3.4110** (0.0083)	-3.4104** (0.0079)	-3.4052** (0.0081)	-3.4077** (0.0080)	-3.4059** (0.0086)	-3.4118** (0.0068)
<i>Characteristics of Nearest Cinema</i>							
Screens	-0.3757** (0.0035)	-0.4462** (0.0033)	-0.5225** (0.0033)	-0.3455** (0.0033)	-0.4167** (0.0033)	-0.4182** (0.0033)	-0.4437** (0.0032)
Seats	0.0012** (0.0000)	0.0014** (0.0000)	0.0020** (0.0000)	0.0009** (0.0000)	0.0013** (0.0000)	0.0012** (0.0000)	0.0012** (0.0000)
Distance	0.1363** (0.0015)	0.1823** (0.0014)	0.1743** (0.0013)	0.1385** (0.0013)	0.1634** (0.0013)	0.1628** (0.0014)	0.1827** (0.0015)
<i>Combined Characteristics of Cinemas within [0,X] kms</i>							
ΣScreens [0,5]	0.0272** (0.0029)	-0.0434** (0.0027)	0.0674** (0.0031)	-0.0635** (0.0028)	-0.0177** (0.0028)	-0.0151** (0.0028)	0.0796** (0.0034)
ΣScreens [0,10]	-0.0778** (0.0013)	-0.1086** (0.0012)	0.0089** (0.0013)	-0.1232** (0.0013)	-0.1077** (0.0012)	-0.1041** (0.0013)	-0.1502** (0.0017)
ΣSeats [0,5]	-0.0004** (0.0000)	-0.0002** (0.0000)	-0.0007** (0.0000)	0.0002** (0.0000)	-0.0001** (0.0000)	-0.0002** (0.0000)	-0.0001** (0.0000)
ΣScreens [0,10]	0.0004** (0.0000)	0.0003** (0.0000)	0.0000** (0.0000)	0.0005** (0.0000)	0.0003** (0.0000)	0.0004** (0.0000)	0.0004** (0.0000)
ΣShopping [0,5]	0.9498** (0.0088)	0.9950** (0.0087)	1.0750** (0.0077)	1.0578** (0.0079)	1.0545** (0.0078)	1.0423** (0.0086)	0.7464** (0.0083)
ΣShopping [0,10]	0.2524** (0.0058)	-0.2254** (0.0066)	0.3763** (0.0055)	0.3560** (0.0064)	0.5407** (0.0057)	0.1010** (0.0073)	0.5338** (0.0085)
ΣTheatres [0,5]	0.1994** (0.0071)	0.4320** (0.0069)	0.3720** (0.0063)	-0.0727** (0.0068)	-0.0716** (0.0066)	0.1825** (0.0067)	-0.4014** (0.0083)
ΣTheatres [0,10]	-0.0342** (0.0042)	0.1934** (0.0043)	0.0412** (0.0037)	0.1177** (0.0044)	0.1536** (0.0040)	0.1371** (0.0046)	0.3672** (0.0044)
<i>Combined Characteristics of Other Films at Cinema on Same Day</i>							
Σlog(Budget)	0.0012** (0.0002)	0.0006** (0.0002)	0.0020** (0.0002)	0.0002 (0.0002)	0.0001 (0.0002)	0.0010** (0.0002)	0.0016** (0.0002)
Σlog(Adpub)	-0.0021** (0.0002)	-0.0019** (0.0002)	-0.0023** (0.0002)	-0.0005* (0.0002)	-0.0010** (0.0002)	-0.0015** (0.0002)	-0.0022** (0.0002)
Σlog(OpWkScrns)	-0.0365** (0.0012)	-0.0288** (0.0011)	-0.0410** (0.0010)	-0.0217** (0.0011)	-0.0168** (0.0011)	-0.0402** (0.0011)	-0.0117** (0.0009)
ΣStar	0.0421** (0.0023)	0.0302** (0.0021)	0.0351** (0.0020)	0.0432** (0.0021)	0.0286** (0.0020)	0.0430** (0.0022)	0.0216** (0.0017)
ΣRe-release	-0.1962** (0.0210)	-0.1463** (0.0193)	-0.0772** (0.0183)	-0.1145** (0.0188)	-0.0469 (0.0184)	-0.1231** (0.0199)	0.0376 (0.0159)
ΣSequel	-0.0274** (0.0029)	-0.0298** (0.0026)	-0.0419** (0.0025)	-0.0423** (0.0026)	-0.0399** (0.0025)	-0.0397** (0.0027)	-0.0335** (0.0022)
ΣFilms	0.1335** (0.0045)	0.1082** (0.0042)	0.1297** (0.0040)	0.0346** (0.0041)	0.0287** (0.0040)	0.1294** (0.0043)	0.0037 (0.0036)
Under Identified (P-Value)	64,078 (0.000)	68,336 (0.000)	70,854 (0.000)	69,400 (0.000)	70,509 (0.000)	67,140 (0.000)	74,817 (0.000)
Weakly Identified (P-Value)	10,171 (0.000)	12,526 (0.000)	14,297 (0.000)	13,233 (0.000)	14,033 (0.000)	11,794 (0.000)	17,942 (0.000)
Over Identified (P-Value)	7,154 (0.000)	6,703 (0.000)	7,214 (0.000)	4,397 (0.000)	4,816 (0.000)	6,154 (0.000)	5,152 (0.000)
N	95,836	95,836	95,836	95,836	95,836	95,836	95,836
Partial R ²	0.6686	0.7131	0.7393	0.7242	0.7357	0.7006	0.7807
R ²	0.7581	0.7957	0.8163	0.8058	0.8135	0.7823	0.8636

Notes: Dependent variable is price. All regressions contain all other explanatory variables as reported in Table 10. *Characteristics of Nearest Cinema* includes the number of screens, seats, and the distance to the nearest rival cinema. *Combined Characteristics of Cinemas within [0,X]kms* includes total number of screens, seats, shopping centre theatres, and the actual number of theatres located within 5 or 10kms of reference theatre. *Combined Characteristics of Other Films at Cinema on Same Day* includes total budget, advertising, (national) opening screens, star film, re-releases, sequels, and the number of films playing at the reference theatre on the same day – to be consistent with stage 2, budget, advertising, and national opening week screens are summed in log form. Partial R² refers to the excluded instruments reported in table. R² is centred. * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses unless otherwise stated.

Table 10
Second Stage IV Multinomial Logit with Film Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price	-0.1924** (0.0026)	-0.1991** (0.0025)	-0.1824** (0.0025)	-0.1910** (0.0024)	-0.1955** (0.0024)	-0.1834** (0.0025)	-0.1982** (0.0025)
<i>Time Invariant Film Variables</i>							
log(Budget)	0.1467** (0.0065)	0.1492** (0.0064)	0.1476** (0.0065)	0.1560** (0.0063)	0.1547** (0.0064)	0.1515** (0.0064)	0.1561** (0.0063)
log(Adpub)	0.5043** (0.0071)	0.4989** (0.0071)	0.5021** (0.0071)	0.4817** (0.0070)	0.4854** (0.0070)	0.4914** (0.0071)	0.4762** (0.0070)
log(OpWkScrns)	-0.0752** (0.0105)	-0.0541** (0.0105)	-0.0654** (0.0105)	-0.0301** (0.0103)	-0.0355** (0.0104)	-0.0675** (0.0104)	-0.0227** (0.0103)
Star	0.0787** (0.0083)	0.0767** (0.0083)	0.0781** (0.0083)	0.0652** (0.0081)	0.0667** (0.0082)	0.0701** (0.0082)	0.0661** (0.0081)
Re-release	0.0239 (0.1317)	0.0698 (0.1313)	0.0399 (0.1315)	0.0017 (0.1291)	0.1012 (0.1297)	-0.1473 (0.1302)	-0.0107 (0.1287)
Sequel	0.2953** (0.0102)	0.2871** (0.0102)	0.2923** (0.0102)	0.2729** (0.0100)	0.2757** (0.0101)	0.2895** (0.0101)	0.2693** (0.0100)
<i>Time Variant Film at Theatre Variables</i>							
Week	-0.3356** (0.0016)	-0.3370** (0.0016)	-0.3360** (0.0016)	-0.3389** (0.0016)	-0.3378** (0.0016)	-0.3368** (0.0016)	-0.3392** (0.0016)
Opening Day	0.4720** (0.0201)	0.4787** (0.0200)	0.4650** (0.0200)	0.4669** (0.0197)	0.4693** (0.0198)	0.4607** (0.0198)	0.4726** (0.0196)
Oscar Nomination	0.7097** (0.0175)	0.7103** (0.0174)	0.7098** (0.0175)	0.7003** (0.0171)	0.7008** (0.0172)	0.7052** (0.0173)	0.6985** (0.0171)
Oscar Award	0.2595** (0.0457)	0.2574** (0.0456)	0.2614** (0.0457)	0.2339** (0.0448)	0.2462** (0.0450)	0.2451** (0.0452)	0.2548** (0.0446)
<i>Day and Date Variables</i>							
Friday	0.6432** (0.0100)	0.6494** (0.0100)	0.6347** (0.0100)	0.6418** (0.0098)	0.6456** (0.0098)	0.6348** (0.0099)	0.6481** (0.0098)
Saturday	1.0900** (0.0099)	1.0960** (0.0099)	1.0810** (0.0099)	1.0890** (0.0097)	1.0930** (0.0098)	1.0820** (0.0098)	1.0950** (0.0097)
Sunday	0.8426** (0.0099)	0.8488** (0.0099)	0.8337** (0.0099)	0.8419** (0.0097)	0.8457** (0.0098)	0.8343** (0.0098)	0.8483** (0.0097)
Public Holiday	0.4387** (0.0212)	0.4408** (0.0211)	0.4340** (0.0212)	0.4397** (0.0208)	0.4407** (0.0209)	0.4367** (0.0210)	0.4435** (0.0207)
School Holiday	0.5401** (0.0081)	0.5382** (0.0080)	0.5387** (0.0081)	0.5351** (0.0079)	0.5347** (0.0079)	0.5424** (0.0080)	0.5375** (0.0079)
<i>Weather</i>							
Rainfall	0.0043** (0.0003)	0.0042** (0.0003)	0.0043** (0.0003)	0.0043** (0.0003)	0.0042** (0.0003)	0.0043** (0.0003)	0.0042** (0.0003)
Max to av. Diff	-0.0285** (0.0011)	-0.0283** (0.0011)	-0.0284** (0.0011)	-0.0279** (0.0011)	-0.0280** (0.0011)	-0.0283** (0.0011)	-0.0279** (0.0011)
<i>Theatre Variables</i>							
Shopping Centre	0.0492** (0.0073)	0.0782** (0.0074)	0.0456** (0.0074)	0.2660** (0.0080)	0.2564** (0.0082)	0.1419** (0.0076)	0.2617** (0.0085)
Cinema Screens	0.1215** (0.0010)	0.1175** (0.0010)	0.1186** (0.0010)	0.1161** (0.0010)	0.1146** (0.0010)	0.1257** (0.0010)	0.1182** (0.0010)
<i>Demographics</i>							
Pop[0,5]		6.0930** (0.2231)					10.5500** (0.4131)
Pop(5,10)		-1.2500** (0.1013)					1.4270** (0.1849)
Age[0,5]			0.7644** (0.0945)				-3.4030** (0.1717)
Age(5,10)			0.8420** (0.1720)				0.5214* (0.2379)
log(Income)[0,5]				0.9584** (0.0289)			0.1508 (0.0885)
log(Income)(5,10)				-0.1499** (0.0356)			0.2216* (0.1078)
Education[0,5]					2.5070** (0.0893)		0.1517 (0.2518)
Education(5,10)					-0.6358** (0.1092)		-1.2300** (0.3016)
English[0,5]						1.0900** (0.0375)	1.3510** (0.0830)
English(5,10)						-0.2657** (0.0523)	-0.0225 (0.0867)
Constant	-18.9 (0.1175)	-19.02 (0.1171)	-19.41 (0.1258)	-24.2 (0.1611)	-20.1 (0.1192)	-19.6 (0.1183)	-21.45 (0.4140)
N	95,836	95,836	95,836	95,836	95,836	95,836	95,836
R ²	0.4956	0.4993	0.4969	0.5155	0.511	0.5073	0.5197

Notes: Dependent variable is $\ln(s_{it}) - \ln(s_{0t})$. All regressions include Genre and Rating dummy variables. Price is instrumented as reported in stage 1 results of Table 9. Pop(a,b), Age(a,b), log(Income)(a,b), Education(a,b), English(a,b) denote population proportion (of total), weighted average age proportion of 15-30 year olds, (log) weighted average median weekly income, weighted average proportion with tertiary education, and weighted proportion of households which speak English as first language respectively of people living with 'a' to 'b' kilometres of theatre h . * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses.

Table 11
First Stage Results for Multinomial Logit with Film Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tuesday	-3.3442** (0.0076)	-3.3455** (0.0071)	-3.3464** (0.0068)	-3.3450** (0.0070)	-3.3452** (0.0068)	-3.3444** (0.0073)	-3.3474** (0.0061)
<i>Characteristics of Nearest Cinema</i>							
Screens	-0.3928** (0.0028)	-0.4494** (0.0027)	-0.4997** (0.0027)	-0.3565** (0.0028)	-0.4186** (0.0027)	-0.4188** (0.0028)	-0.3553** (0.0028)
Seats	0.0013** (0.0000)	0.0015** (0.0000)	0.0019** (0.0000)	0.0011** (0.0000)	0.0014** (0.0000)	0.0013** (0.0000)	0.0009** (0.0000)
Distance	0.1217** (0.0012)	0.1672** (0.0012)	0.1575** (0.0012)	0.1147** (0.0012)	0.1409** (0.0011)	0.1462** (0.0013)	0.1922** (0.0013)
<i>Combined Characteristics of Cinemas within [0,X] kms</i>							
ΣScreens [0,5]	0.0837** (0.0023)	0.0341** (0.0022)	0.1302** (0.0025)	0.0140** (0.0023)	0.0567** (0.0023)	0.0422** (0.0022)	0.0241** (0.0027)
ΣScreens [0,10]	-0.0923** (0.0011)	-0.1209** (0.0010)	-0.0214** (0.0011)	-0.1347** (0.0011)	-0.1231** (0.0010)	-0.1169** (0.0011)	-0.1228** (0.0015)
ΣSeats [0,5]	-0.0005** (0.0000)	-0.0004** (0.0000)	-0.0008** (0.0000)	0.0000 (0.0000)	-0.0003** (0.0000)	-0.0003** (0.0000)	0.0001** (0.0000)
ΣScreens [0,10]	0.0004** (0.0000)	0.0003** (0.0000)	0.0001** (0.0000)	0.0005** (0.0000)	0.0004** (0.0000)	0.0004** (0.0000)	0.0003** (0.0000)
ΣShopping [0,5]	0.8245** (0.0074)	0.8272** (0.0074)	1.0010** (0.0068)	0.8974** (0.0069)	0.9274** (0.0068)	0.8803** (0.0074)	0.5850** (0.0071)
ΣShopping [0,10]	0.2931** (0.0049)	-0.2192** (0.0059)	0.3874** (0.0047)	0.3802** (0.0055)	0.5422** (0.0049)	0.1194** (0.0064)	0.2847** (0.0073)
ΣTheatres [0,5]	0.0270** (0.0058)	0.1961** (0.0056)	0.1788** (0.0052)	-0.2443** (0.0057)	-0.2539** (0.0056)	0.0200** (0.0056)	-0.4775** (0.0068)
ΣTheatres [0,10]	0.0240** (0.0033)	0.2025** (0.0034)	0.0701** (0.0030)	0.1529** (0.0036)	0.1810** (0.0033)	0.1699** (0.0037)	0.3286** (0.0036)
Under Identified (P-Value)	94,200 (0.000)	99,884 (0.000)	1.0e+05 (0.000)	1.0e+05 (0.000)	1.0e+05 (0.000)	97,550 (0.000)	1.1e+05 (0.000)
Weakly Identified (P-Value)	21,602 (0.000)	25,614 (0.000)	28,214 (0.000)	26,330 (0.000)	27,927 (0.000)	23,857 (0.000)	32,941 (0.000)
Over Identified (P-Value)	6,897 (0.000)	6,044 (0.000)	6,432 (0.000)	3,278 (0.000)	3,902 (0.000)	6,207 (0.000)	3,820 (0.000)
N	148,295	148,295	148,295	148,295	148,295	148,295	148,295
Partial R ²	0.6367	0.6751	0.6959	0.6811	0.6938	0.6593	0.7277
R ²	0.7251	0.7590	0.7766	0.7657	0.7756	0.7430	0.8228

Notes: Dependent variable is price. All regressions contain all other explanatory variables as reported in Table 12. *Characteristics of Nearest Cinema* includes the number of screens, seats, and the distance to the nearest rival cinema. *Combined Characteristics of Cinemas within [0,X]kms* includes total number of screens, seats, shopping centre theatres, and the actual number of theatres located within 5 or 10kms of reference theatre. Partial R² refers to the excluded instruments reported in table. R² is centred. * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses unless otherwise stated.

Table 12
Second Stage IV Multinomial Logit with Film Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price	-0.1957** (0.0021)	-0.2079** (0.0021)	-0.1887** (0.0021)	-0.1985** (0.0021)	-0.2026** (0.0021)	-0.1903** (0.0021)	-0.2028** (0.0021)
<i>Time Variant Film at Theatre Variables</i>							
Week	-0.2123** (0.0011)	-0.2144** (0.0011)	-0.2141** (0.0011)	-0.2160** (0.0011)	-0.2145** (0.0011)	-0.2125** (0.0011)	-0.2182** (0.0011)
Opening Day	0.5738** (0.0158)	0.5854** (0.0157)	0.5701** (0.0157)	0.5716** (0.0155)	0.5731** (0.0156)	0.5677** (0.0157)	0.5788** (0.0154)
<i>Day and Date Variables</i>							
Friday	0.6010** (0.0081)	0.6121** (0.0081)	0.5953** (0.0081)	0.6040** (0.0080)	0.6073** (0.0080)	0.5962** (0.0081)	0.6084** (0.0080)
Saturday	1.0570** (0.0081)	1.0690** (0.0080)	1.0520** (0.0080)	1.0610** (0.0079)	1.0640** (0.0080)	1.0530** (0.0080)	1.0650** (0.0079)
Sunday	0.8146** (0.0081)	0.8264** (0.0081)	0.8089** (0.0081)	0.8183** (0.0080)	0.8217** (0.0080)	0.8099** (0.0080)	0.8230** (0.0079)
Public Holiday	0.4705** (0.0177)	0.4741** (0.0176)	0.4672** (0.0176)	0.4726** (0.0174)	0.4738** (0.0175)	0.4703** (0.0176)	0.4741** (0.0173)
School Holiday	0.6037** (0.0077)	0.5991** (0.0077)	0.5995** (0.0077)	0.5942** (0.0076)	0.5955** (0.0076)	0.6037** (0.0077)	0.5907** (0.0075)
<i>Weather</i>							
Rainfall	0.0047** (0.0002)	0.0047** (0.0002)	0.0047** (0.0002)	0.0047** (0.0002)	0.0047** (0.0002)	0.0047** (0.0002)	0.0047** (0.0002)
Max to av. Diff	-0.0203** (0.0009)	-0.0202** (0.0009)	-0.0203** (0.0009)	-0.0201** (0.0009)	-0.0201** (0.0009)	-0.0203** (0.0009)	-0.0201** (0.0009)
<i>Theatre Variables</i>							
Shopping Centre	0.1103** (0.0063)	0.1493** (0.0063)	0.1037** (0.0063)	0.3091** (0.0069)	0.3036** (0.0071)	0.1679** (0.0065)	0.2913** (0.0073)
Cinema Screens	0.1041** (0.0008)	0.0990** (0.0008)	0.1017** (0.0008)	0.0982** (0.0008)	0.0978** (0.0008)	0.1056** (0.0008)	0.0958** (0.0008)
<i>Demographics</i>							
Pop[0,5]		4.7070** (0.1790)					9.3270** (0.3485)
Pop(5,10]		0.1108 (0.0833)					2.6860** (0.1499)
Age[0,5]			0.8013** (0.0750)				-3.2340** (0.1445)
Age(5,10]			2.1260** (0.1353)				0.1106 (0.1882)
log(Income)[0,5]				0.9522** (0.0243)			0.4893** (0.0734)
log(Income)(5,10]				-0.2045** (0.0298)			0.5296** (0.0868)
Education[0,5]					2.4520** (0.0753)		-1.0560** (0.2051)
Education(5,10]					-0.7093** (0.0919)		-1.5210** (0.2423)
English[0,5]						1.0020** (0.0317)	1.2840** (0.0662)
English(5,10]						-0.5490** (0.0435)	-0.3588** (0.0690)
N	148,295	148,295	148,295	148,295	148,295	148,295	148,295
R ²	0.359	0.363	0.362	0.379	0.374	0.367	0.385

Notes: Dependent variable is $\ln(s_{fnt}) - \ln(s_{0v})$. All regressions include Film Fixed Effects. Price is instrumented as reported in stage 1 results of Table 11. Pop(a,b), Age(a,b), log(Income)(a,b), Education(a,b), English(a,b) denote population proportion (of total), weighted average age proportion of 15-30 year olds, (log) weighted average median weekly income, weighted average proportion with tertiary education, and weighted proportion of households which speak English as first language respectively of people living with 'a' to 'b' kilometres of theatre h . * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses.

Table 13
Full Random Coefficients Logit with Film Covariates

	(1)	(2)
Price	-0.2817** (0.0070)	-0.3553** (0.0279)
<i>Time Invariant Film Variables</i>		
log(Budget)	0.1140** (0.0085)	0.1228** (0.0085)
log(Adpub)	0.5025** (0.0098)	0.5008** (0.0083)
log(OpWkScrns)	-0.0267** (0.0152)	-0.0239** (0.0129)
Star	0.0914** (0.0107)	0.0840** (0.0084)
Re-release	-0.2518* (0.1097)	-0.0574 (0.1232)
Sequel	0.2246** (0.0130)	0.2615** (0.0103)
<i>Time Variant Film at Theatre Variables</i>		
Week	-0.9273** (0.0463)	-0.3560** (0.0041)
Opening Day	-0.0369 (0.0444)	0.4440** (0.0227)
Oscar Nomination	0.6063** (0.0222)	0.7534** (0.0186)
Oscar Award	0.3723** (0.0591)	0.1399** (0.0516)
<i>Day and Date Variables</i>		
Friday	0.6541** (0.0135)	0.6633** (0.0111)
Saturday	1.1362** (0.0132)	1.1332** (0.0134)
Sunday	0.8494** (0.0133)	0.8632** (0.0116)
Public Holiday	0.4153** (0.0295)	0.4446** (0.0245)
School Holiday	0.6447** (0.0121)	0.5761** (0.0096)
<i>Weather</i>		
Rainfall	0.0044** (0.0004)	0.0048** (0.0003)
Max to av. Diff	-0.0283** (0.0014)	-0.0311** (0.0012)
<i>Theatre Variables</i>		
Shopping Centre	-0.1041** (0.0130)	0.2376** (0.0110)
Cinema Screens	0.1095** (0.0029)	0.0352** (0.0121)
<i>Travel Cost</i>		
Travel Cost	0.1186** (0.0024)	0.0107** (0.0006)
<i>Demographics</i>		
Age*[Constant]	-0.0674** (0.0067)	-0.0514** (0.0023)
log(Income) *[Constant]	2.0426** (0.1132)	0.1420** (0.0502)
<i>Random Variable (Std Dev)</i>		
Constant	0.0640 (0.0786)	0.2025** (0.0046)
Price	0.1426** (0.0054)	0.1624** (0.0107)
Week	0.4894** (0.0242)	0.0504** (0.0112)
log(Budget)	0.0576** (0.0040)	0.0277* (0.0134)
Cinema Screens	0.0535** (0.0060)	0.1677** (0.0068)
Constant	-26.32** (0.9947)	-16.27** (0.2051)
N	95,836	95,836
Number of Simulated Consumers	200	200

Notes: Columns (1) is random coefficients model without macro-moment conditions, Column (2) includes macro-moments. Both models include Genre and Rating dummy variables. *Demographics* refer to interaction with variable in square brackets. *Random Variables* refer to estimated coefficients σ of the random standard normal variable v interacting with noted variable coefficient. See text for more details. * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses.

Table 14
Own and Cross Price Elasticities of Selected Films and Cinemas for January 1, 2007

Cinema		Broadway	Broadway	Broadway	Broadway	Broadway	George St.	George St.	George St.	George St.	George St.	George St.	Newtown	Newtown
	Film	Babel	Borat	Casino Royale	Flushed Away	Happy Feet	Babel	Borat	Casino Royale	Flushed Away	Happy Feet	Open Season	Babel	Borat
Broadway	Babel	-2.018900	0.000564	0.001481	0.000579	0.002759	0.001333	0.001030	0.003127	0.000545	0.003263	0.000042	0.000434	0.000093
Broadway	Borat	0.000806	-2.010800	0.001561	0.000606	0.002887	0.001392	0.001094	0.003281	0.000567	0.003398	0.000044	0.000432	0.000094
Broadway	Casino Royale	0.000785	0.000580	-2.038000	0.000593	0.002823	0.001384	0.001075	0.003257	0.000566	0.003388	0.000044	0.000431	0.000093
Broadway	Flushed Away	0.000767	0.000562	0.001481	-2.043300	0.002762	0.001353	0.001042	0.003175	0.000554	0.003315	0.000043	0.000433	0.000092
Broadway	Happy Feet	0.000768	0.000563	0.001481	0.000580	-2.033900	0.001347	0.001039	0.003161	0.000551	0.003300	0.000043	0.000433	0.000093
George St.	Babel	0.001215	0.000888	0.002377	0.000930	0.004411	-2.661100	0.002100	0.006564	0.001153	0.006872	0.000088	0.000458	0.000101
George St.	Borat	0.001272	0.000946	0.002501	0.000971	0.004607	0.002844	-2.686800	0.006756	0.001178	0.007028	0.000091	0.000472	0.000106
George St.	Casino Royale	0.001267	0.000931	0.002487	0.000971	0.004602	0.002919	0.002218	-2.730200	0.001213	0.007227	0.000092	0.000464	0.000103
George St.	Flushed Away	0.001236	0.000901	0.002420	0.000949	0.004495	0.002871	0.002166	0.006792	-2.719000	0.007114	0.000091	0.000457	0.000101
George St.	Happy Feet	0.001230	0.000897	0.002407	0.000943	0.004470	0.002843	0.002147	0.006724	0.001182	-2.696300	0.000090	0.000458	0.000101
George St.	Open Season	0.001274	0.000942	0.002505	0.000975	0.004625	0.002907	0.002219	0.006901	0.001207	0.007194	-2.727500	0.000467	0.000105
Newtown	Babel	0.000338	0.000235	0.000632	0.000254	0.001211	0.000391	0.000297	0.000890	0.000157	0.000944	0.000012	-1.759800	0.000098
Newtown	Borat	0.000337	0.000239	0.000633	0.000252	0.001204	0.000402	0.000312	0.000922	0.000161	0.000969	0.000013	0.000457	-1.719200

Notes: Cross price elasticities are measured for row *i* column *j*, where a 1% change in the price of the product in column *j* gives the percentage change in the share of the product in row *i*. *Babel*, *Flushed Away*, and *Happy Feet* were all in week 2 of their run, *Casino Royale* week 4, *Open Season* week 5, and *Borat* week 6. Broadway is a 12 screen Hoyts multiplex cinema located in a shopping centre, George St. a 17 screen GU/Hoyts multiplex located in the CBD, and Newtown a 4 screen cinema owned by independent cinema company Dendy. Broadway is 1.5kms from George St. and 2km from Newtown. Newtown is 3.5kms from George St.

Figure 1
Locations of Cinemas in Greater Sydney Region

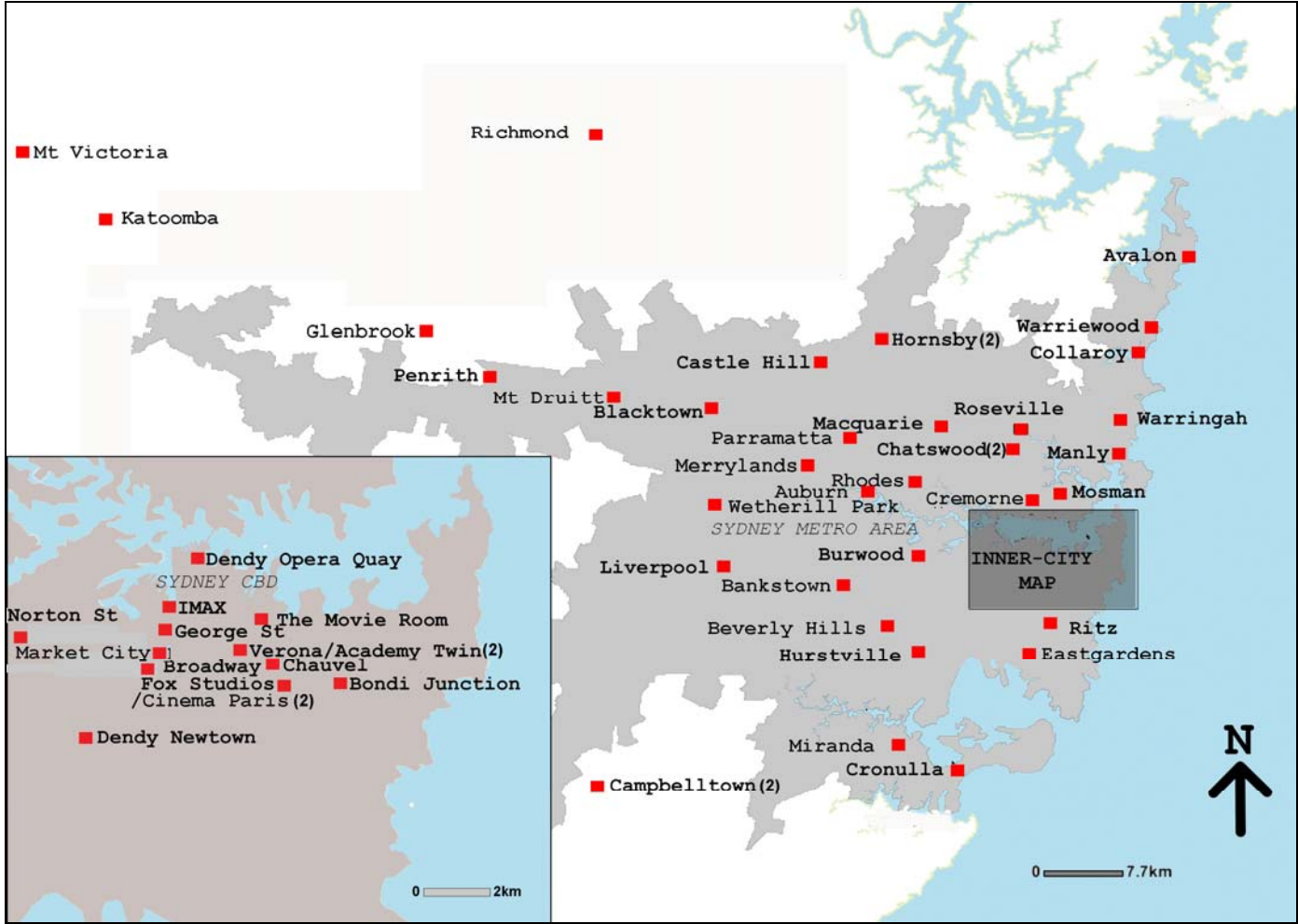


Figure 2
Day Admissions over Year by Day of Week

