Cheap Tuesdays and the Demand for Cinema*

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Abstract

Many movie markets are characterised by extensive uniform pricing practices, hampering the ability to estimate price elasticities of demand. Australia presents a rare exception, with most cinemas offering cheap Tuesday ticket prices. We exploit this feature to estimate a random coefficients discrete choice model of demand for the Sydney region in 2007. We harness an extensive set of film, cinema, and time-dependent characteristics to build a rich demand system. Our results are consistent with a market expansion effect from the practice of discounted Tuesday tickets, and suggest that cinemas could profit from price dispersion by discounts based on observable characteristics.

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

JEL Classification: L13, L82

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"One of the more perplexing examples of the triumph of convention over rationality is movie theatres, where it costs you as much to see a total dog thats limping its way through its last week of release as it does to see a hugely popular film on opening night."

James Surowiecki (The Wisdom of Crowds, 2004, p.99).

1 Introduction

Product differentiation in movies is self-evident to even the most casual enthusiast. However, as Orbach and Einav (2007) discuss in detail, to the puzzlement of many observers, the practice of (almost) uniform pricing is a long-standing feature of the market for movies screened in cinemas. They examine two dimensions of this puzzle: i) the 'movie puzzle' (why different movies attract the same price); 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. Price variation between weekends and weekdays and by type of seat within an auditorium was also evident. This kind of price variation has more recently been largely absent in most markets. Orbach and Einav conclude that exhibitors could increase profits if they practiced variable pricing strategies.

Price uniformity itself hampers attempts to formulate an optimal pricing strategy. Without variation in price, demand elasticities cannot be inferred from the data, and the enterprise is destined for failure. We exploit rare (and arguably exogenous) price variation in the Sydney cinema market to estimate price elasticities, using a comprehensive data set of daily film revenues for cinemas in the greater Sydney region over the year 2007. In Sydney, 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%. Extracting elasticities represents a first step in designing an optimal pricing scheme, and examining the costs of maintaining uniform prices.

An additional contribution of our work is to document demand determinants based on an extensive data set. We assemble a rich data set, enabling us to estimate a detailed characteristics-based demand system. In particular, we control for film characteristics (e.g. genre, budget, advertising, reviews, cast appeal), theatre characteristics (e.g. location, 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).

We adopt a random coefficients discrete choice model of demand. We define a product as a combination of a film, a theatre and day of screening. There are a large number of such products in our sample, making a characteristic-based estimation strategy the only feasible means of extracting the full set of cross-price elasticities. To accommodate heterogeneous prefences for movie offerings, our strategy is based on the empirical model

[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.

of Berry et al. (1995) (hereafter, "BLP"). Following Nevo (2001), we permit heterogeneity in "observable" characteristics (local region-specific demographic characteristics) as well as "unobservable" characteristics; and we include movie-specific fixed effects. Following Davis (2006), we incorporate a spatial dimension to product characteristics that accounts for travel costs. In the spirit of Imbens and Lancaster (1994) and Petrin (2002), we include additional moment conditions based on external population demographic data.

Our estimation strategy relies on the assumption that the demand for movies is essentially the same as 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. We note that 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 attendance on Tuesdays from variation in price on Tuesdays. However, 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.

The profit maximisation problem of a cinema is a complicated one. In particular, we see the consideration of ancillary sales to be an important issue. We are not armed with data to rigorously tackle this problem.[3] Accordingly, we do not introduce supply side moment conditions, but rely only on our demand model to estimate demand parameters. Instead, given our estimated demand parameters, we consider the cinema's revenue maximisation problem in the absence of concerns about ancillary sales. Given the likely positive relationship between cinema attendance and concession sales, we argue that this places an upper bound on the cinema's profit-maximisation prices.

As in most applied settings, our data constrain the performance of our estimation strategy. In particular, we rely on repeated observations of a single (large) geographic market. This provides cross-sectional variation between connected local markets, but not between geographically separated markets. Our data exhibit intra-week temporal variation in price, but no other systematic time-series price variation; and cinemas charge the same price for all movies screened on a given day. Hence, it is intra-week temporal variation in price coupled with cross-sectional variation at the level of a cinema (rather than a film) that identifies our demand estimates. Further, films tend to be introduced simultaneously across multiple cinemas, constraining our ability to identify heterogeneity in preferences for films. We return to these issues in the discussion of our results.

The way we define the market for movies has potentially important implications for our demand estimates. We consider two definitions.[4] In the first, we consider the market

[2]Our correspondence with industry participants has not yielded a conclusive explanation for the emergence of "Cheap Tuesdays". However, the propensity for public holidays to fall on Mondays and new movies to be released on Thursdays suggests a narrowing down of the available days for an off-peak discount that is unrelated to demand (once we control for public holidays and opening days).

[3]By contrast, Davis (2006) and Moul (2008) attempt to overcome this problem by imposing assumptions about the relationship between these variables based on aggregate industry data.

[4]We thank Philip Leslie for suggesting this distinction.

for movies screened on a given day, whilst in the second, we consider the market to be over a seven-day week. As discussed in the body of our paper, this distinction allows us to comment on whether the increased demand observed on Tuesdays is a consequence of pure market expansion, or a substitution/cannibilisation effect from demand on other days.

To preview our results, consistently across the set of specifications we consider, we observe that: cinema demand is relatively elastic, with the median own-price elasticity of a film-at-theatre in excess of 2.5; cross-price elasticities are particularly low, leading us to believe that much substitution takes place with the outside good; there are intuitive relationships between cinema attendance and a range of film-, cinema-, and time-specific characteristics. Turning to our weekly market definition, even once we account for the possibility that consumers substitute across days of the week, our results are consistent with a market expansion effect arising from the common practice of Tuesday discounts. Finally, our revenue-maximisation problem is consistent with systematic overpricing for a substantial subset of cinema tickets. It is worth noting that we perform a demand estimation exercise rather than a forecasting exercise. Cinema managers are likely to have additional information at their disposal – such as film- and session-specific attendance information as it develops. If our demand study reveals opportunities to profitably vary price based on observable information, a forecasting exercise could be even more revealing.[5]

Our research bears most similarity in its method to the studies of Davis (2006), Einav (2007) and Moul (2007, 2008) in that we adopt a discrete choice approach to modelling demand. Einav (2007) and Moul (2007) both employ nested logit models on weekly revenue data, exploring seasonality of demand and word-of-mouth effects, respectively, whilst Moul (2008) uses similar data to explore distributor conduct in terms of rental pricing and advertising. Our data and method, however, most closely resembles Davis (2006) in that we use daily film-at-theatre revenues and follow the approach of Berry (1994) and Berry et al. (1995) by employing a random coefficients model. Like Davis (2006), 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 seven), but a more limited cross-section dimension (we only observe one distinct (geographic) 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 data set. In section 5 we describe the estimation procedure. In section 6 we discuss the results, and in section 7 we conclude.

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

[5] An important complicating factor is the role of word-of-mouth.

distribution is dominated by the six major U.S. based studio distributors who account for 86% of turnover in our sample.[6] 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 revenues which shifts in favour of the exhibitor in the later weeks of a film's run.[7] 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.

3 Model

3.1 Demand

We employ a random coefficients discrete choice model to estimate demand (see, for example, Berry (1994); Berry et al. (1995); and Nevo (2001) for a detailed discussion of this class of model). Our model most closely resembles that of Davis (2006), and we follow his exposition. Consumer choices depend on film and theatre characteristics. The indirect utility enjoyed by consumer i by attending film $f \in \{1, \dots, F_{ht}\}$ at theatre (house) $h \in \{1, \dots, H_t\}$ on day $t \in \{1, \dots, T\}$ is given by

$$u_{ifht} = \alpha_i p_{ht} + x_{fht}\beta_i - \lambda d_{ih} + \phi_f + \xi_{fht} + \epsilon_{ifht} \tag{1}$$

where p_{ht} is an average price that varies by cinema and time[8]; and x_{fht} is a $K_1 - 1 \times 1$ vector of other product characteristics relating to the film (e.g. budget, advertising, reviews, cast, genre), the theatre (e.g. number of screens, shopping centre location), or

[6] 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.

[7] 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.

[8] As discussed in Section 4, we are not able to observe ticket prices paid by individuals. We have created a (weighted) average ticket price based on the industry information of admission type percentages.

the time of screening (e.g. day of week, public or school holiday, weather). In the spirit of Davis (2006), consumers incur travel costs, with $d_{ih} = \| L_i - L_h \|$ measuring the Euclidean distance between consumer i and theatre h. Film-specific fixed effects are captured by ϕ_f. The remaining error structure includes a common component, ξ_{fht}, capturing remaining unobserved product heterogeneity once film fixed effects, ϕ_f, have been accounted for; and an idiosyncratic term, ϵ_{ifht}, with a type-I extreme value distribution.

Consumer heterogeneity is embedded in our definition of a consumer type, $\tau_i = (L_i, D_i, \nu_i, \epsilon_i)$, where L_i is the consumer's location, D_i is a $K_D \times 1$ vector of (potentially observable) demographic variables, ν_i is a $K_1 \times 1$ vector of unobservable characteristics[9], and ϵ_i is a vector of the idiosyncratic disturbances. Heterogeneity in consumer types yields heterogeneity in preferences over price (α_i), other product characteristics (β_i), and theatre location (d_{ih}). We define $\theta_{1i} = [\alpha_i, \beta_i]$ as the vector of individual-specific parameters, and $\theta_1 = [\alpha, \beta]$ as the common component. Following Nevo (2001), we further define

$$\theta_{1i} = \theta_1 + \Pi D_i + \Sigma \nu_i, \qquad \nu_i \sim N(0, I_{K_1}) \tag{2}$$

where Π is a $K_1 \times K_D$ matrix of coefficients which measures how the idiosyncratic individual demographics relate to the product characteristics parameters, and Σ is a diagonal scaling matrix. Empirical distributions based on Census data are used for the demographic characteristics, D_i.

The model is completed with the specification of an outside good. The indirect utility of forgoing cinema attendance can be written

$$u_{it0} = \xi_0 + \pi_0 D_i + \sigma_0 \nu_{i0} + \epsilon_{it0}, \tag{3}$$

where we normalise the mean utility of the outside good, ξ_0, to zero.

We consider two separate definitions of a market. Our first definition equates a market with a day: consumers choose between all available films (plus the outside good) on a given day. This definition presumes that consumers see at most one movie each day. More restrictively, it prevents substitution between films on different days. Under this definition, the set of consumer types who choose film f at theatre h on day t is

$$A_{fht}(x_{.t}, p_{.t}, L_{.t}, \xi_{.t}; \theta) = \{\tau_i \mid u_{ifht} > u_{iglt} \ \forall \ f, h, g, l \ s.t. \ (f, h) \neq (g, l)\}, \tag{4}$$

where $x_{.t}$ and $\xi_{.t}$ are the $(J_t \times 1)$ observed and unobserved product characteristics, respectively; $p_{.t}$ are the $(H_t \times 1)$ observed theatre prices; $L_{.t}$ are the $(H_t \times 1)$ theatre locations; and $\theta = (\alpha, \beta, \lambda, \Pi, \Sigma)$ is a vector of parameters. Our second definition equates a market with a week. This permits substitution between films on different days of the week, while imposing a maximum of one film per week on our consumers. Equation (4) is analogously defined in this context.

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

$$s_{fht}(x_{.t}, p_{.t}, L_{.t}, \xi_{.t}; \theta) = \int_{A_{fht}} dP^*(L, D, \nu, \epsilon) = \int_{A_{fht}} dP^*(\epsilon) dP^*(\nu) dP^*(D|L) dP^*(L), \tag{5}$$

where the notation $P^*(\cdot)$ describes population distribution functions. The second part of the equality in equation (5) follows from Bayes' rule and the assumption of independence of the error terms (ϵ, ν) with location, L, and demographics, D.

[9] In principle, we could permit heterogeneity in preferences over all K_1 product characteristics. In practice, we restrict this to a much more limited set.

3.2 Simulation of revenue-maximising prices

Plausibly, the marginal cost of the attendance of an additional patron at a capacity unconstrained cinema is zero. A cinema manager could thus focus on maximising revenue if a session is not expected to sell out. However, the manager must also account for the important role played by concession sales.[10] We do not have data on concession sales or session-specific attendance rates. Accordingly, we do not attempt the joint estimation of parameters of the cinema's profit maximisation problem. Instead, we simulate revenue-maximising prices given our estimated demand parameters. Effectively, this delivers us the film- and theatre-specific profit-maximising price for capacity unconstrained sessions were cinema managers to be unconcerned with concession sales. In our sample, average attendance rates are low (we discuss this in more detail in Section 6). Thus, we view the omission of concession sales to be the more serious limitation. If sales of concession items are positively related to cinema attendance (as we would expect), then our simulation exercise places an upper bound on profit-maximising prices given our estimated demand parameters.

For exposition, let us start by assuming the manager of cinema h seeks to maximise the static profit of cinema h. She then solves the following problem at time t:

$$\max_{\{p_{fht}\}_{f=1}^{F_{ht}}} M \sum_{f=1}^{F_{ht}} s_{fht}(x_{.t}, p_{.t}, L_{.t}, \xi_{.t}; \theta) p_{fht}, \tag{6}$$

where M is the size of the market. This leads to a set of first order conditions for all films at all theatres:

$$s_{fht} + \sum_{g=1}^{F_{ht}} \frac{\partial s_{ght}}{\partial p_{fht}} p_{ght} = 0, \qquad t = 1, \dots, T, \qquad h = 1, \dots, H_t, \qquad f = 1, \dots, F_{ht}, \tag{7}$$

where we omit the arguments of s_{fht} and its partial derivative for convenience. Rewriting equation (7) in matrix notation, we have

$$s_t + \Omega_t \; .* \; D_p s_t \; p_t = 0 \tag{8}$$

where Ω_t is an ownership matrix, discussed below; $[X \; .* \; Y]$ indicates element-by-element multiplication; and $D_p s_t$ represents a matrix of partial derivatives of market shares with respect to prices with typical element $D_p s_t(a, b) = \frac{\partial s_{bt}}{\partial p_{at}}$. We can rewrite equation (8) to form the basis of a simple recursive algorithm to simulate profit-maximising prices:

$$p_t^{k+1} = -\left(\Omega_t \; .* \; D_p s_t(p_t^k)\right)^{-1} s_t(p_t^k). \tag{9}$$

Initialising p_t^0 to be a $J_t \times 1$ zero vector, we iterate equation (9) until convergence. See, for example, Davis (2010) for details.

We consider three alternative definitions of the ownership matrix Ω_t, corresponding to three forms of theatre competition. First, we consider the possibility outlined above

[10] See McKenzie (2008) for an entertaining discussion of the relationship between cinema ticket pricing and concession sales.

that theatre managers seek to simply maximise profits of their own theatre: $\Omega_t(f, g) = 1$ if films f and g are exhibited at the same theatre at time t, and 0 otherwise. Next, we account for the ownership structure of theatres by assuming that each theatre manager seeks to maximise the profits of the "circuit" (owner) to which her theatre belongs. That is, $\Omega_t(f, g) = 1$ if films f and g are exhibited at theatres belonging to the same circuit at time t, and 0 otherwise. Finally, we also examine the joint-revenue maximisation problem of the industry by defining Ω_t as a matrix of ones.

4 Data

4.1 Film characteristics and other explanatory variables

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 61 cinemas in this region. 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. Of these 50 cinema, 13 are owned by Hoyts, 12 by Greater Union, 4 by Palace, 3 each by Dendy and United, with the remainder being independents. 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. Across these 50 theatres 373 distinct titles were recorded. From these, a further 59 films were dropped because they were either re-releases (45 films), or had 6 or less screenings in 2007 (14 films). In total we observe 145,430 daily film-at-theatre revenue data points over the 365 days of 2007. The daily film-at-theatre revenue data consistently reflect large levels of skew and (excess) kurtosis. In our sample, the average (median) daily film-at-theatre revenue was A$1,290 (A$570), with the top earning film, *Harry Potter and the Order of the Phoenix*, making A$65,052 on its opening day at Macquarie Megaplex.

Table 1 provides summary statistics of the 314 films used in estimation. Data is incomplete in relation to some of these variables (in particular advertising, budgets, and reviews).[11] Data on total box office revenue, opening week screens, and advertising were sourced from the Motion Picture Distributors Association of Australia (MPDAA). At the national box office level, the average film earned just over A$3.65m, but the median is less than A$1m. As observed in the daily film-at-theatre revenues, the 'hit' films skew the revenue distribution markedly as is apparent by the top film earning A$35.5m (*Harry Potter and the Order of the Phoenix*)—more than five standard deviations above the calculated mean.[12] The average opening week number of screens is also highly skewed, with the largest opening film (*Pirates of the Caribbean: At World's End*) taking up 608

[11] We, in part, address this problem by the use of film fixed effects in estimation.

[12] De Vany and Walls (1996) examine the kurtotic nature of box office distributions which they attribute to the leveraging effects from word-of-mouth information transmission.

screens. Budget data, derived from IMDb, Box Office Mojo, and Nielsen EDI, are also skewed, with the most expensive film of the sample costing US$300m (*Pirates of the Caribbean: At World's End*).

Reviews were compiled from weekly Thursday, Friday and Saturday editions of *The Sydney Morning Herald*—the second largest circulation newspaper in Sydney and with the most comprehensive set of film reviews available—based on a five star system. Although there are many other review sources available to consumers, we argue this particular source is likely to be amongst the most visible to Sydney filmgoers and provide the best proxy for the potential effect of critical reviews. Also, because of the fact reviews from this source generally appear before, on, or the day after release, this source is likely to capture any potential 'influence' (beyond simply a 'prediction' effect) as discussed by Eliashberg and Shugan (1997) and Reinstein and Snyder (2005). Reviews ratings were obtained for 257 out of the total 314 films of the sample.

We also include a number of film specific dummy variables to account for the effects of sequels, stars, awards, genre, and rating. Sequel data were obtained from MPDAA and Nielsen EDI and represent approximately 6 per cent of the sample. 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. Star films represent approximately 13% of all films in our sample.

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, 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. We include three dummy variables for the main genre categories: action, comedy, and drama. The numeraire category is the composite of all other genres.[13] Finally, rating is classified under G, PG, M, MA15+, and R18+ as defined by the Office of Film and Literature Classification.

In addition to the award-nomination/-win variables, which are obviously time-variant, we consider other time-variant variables relating to what point of the run the film was at the specific cinema of observation. We consider films at preview stage (mostly one week prior to actual release), opening day at theatre, and week-of-run at theatre. As expected, (unreported) average daily revenues decline at higher weeks of release. We account for week-of-run in two ways in our model. Firstly, we consider a flexible pattern with individual dummy variables for weeks 1-10, and secondly, we consider a linear specification for week-of-run.

We also consider school/public holidays and daily weather as important time-variant explanatory variables in the local Sydney market. Consistent with Einav (2007), we observe that films typically earn more on public and school holidays. Relative to Einav (2007), our daily data suggests the additional insight that the peaks are most obvious

[13]The full data set actually defines genre over 20 categories. We focus on the largest three for computational practicality (in estimation). These collectively account for 73% of all observations.

in the weekdays rather than the weekend days. We control for weather by including measures of temperature and rainfall. Our temperature measure is the difference between the daily maximum temperature and the monthly average, while rainfall is measured by the daily rainfall. Both temperatures and rainfall are measured at Sydney's Observatory Hill weather station as recorded by the Bureau of Meteorology. We are only aware of two recent studies (Dahl and DellaVigna (2009) and Moretti (2011)) that have considered weather in broader models of movie demand.

4.2 Theatre characteristics, ticket prices, and admissions

Table 2 summarises the characteristics of the 50 theatres in our sample. There is considerable heterogeneity across cinemas. The largest cinema, George St. in the heart of Sydney CBD, has 17 screens and seating capacity in excess of 4,100, while the smallest has just 64 seats. Cinemas located in shopping centres (known as multiplexes) account for 21 of the theatres, with an average size of just under 10 screens.

Table 2 also includes pricing information by theatre. Our price and quantity data are constructed from 3 sources. Dataset 1, our primary dataset, described above, contains daily revenues by theatre and film. Dataset 2 contains pricing information disaggregated by ticket type for each theatre. Most theatres in our dataset had a fixed menu of prices throughout our sample, with prices varying by ticket type. In most instances, a separate menu of prices operated on Tuesdays. Ticket price information was collected 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.[14] Dataset 3 comprises annual revenue for the Greater Union national chain, disaggregated by ticket type. In 2007, within their national chain, the revenue share of 'Adults', 'Students', 'Seniors', and 'Children' was 44.7%, 13.1%, 10.9%, and 3.1%, respectively.[15]

Because our primary data source contains daily revenues aggregated across ticket types, we construct daily weighted average prices and admissions by theatre and film. Using superscripts to specify datasets and subscripts to indicate the dimension of variation, and abusing our earlier notation, we use the following procedure: i) calculate a set of theatre weights by dividing theatre-specific annual revenue by aggregated annual revenue from our primary dataset, $w_h = R^1_h/R^1$; ii) use these theatre weights and our disaggregated ticket prices to construct weighted average ticket prices by ticket type, $p_{kt} = \sum_h w_h p^2_{hkt}$, where the time subscript indicates intra-weekly variation (e.g. cheap Tuesdays) and k indexes ticket type; iii) use our Greater Union revenue data to construct quantity-based weights by ticket type, with quantities calculated as the ratio of revenue to our ticket-type price index, $q_k = R^3_k/p_k$ and weights given by $w_k = q_k/(\sum_k q_k)$;[16] iv) use these weights to construct theatre-specific prices, aggregated across ticket types, $p_{ht} = \sum_k w_k p^1_{hkt}$; and v) use our constructed weighted average prices and the revenue data to construct admissions (quantity) data, $q_{fht} = R^1_{fht}/p_{ht}$. Using this method, the

[14] Unfortunately cinema managers were unable to report when these price changes occured exactly leading us to use the higher price.

[15] The remainder are made up of group tickets, gift vouchers, promotional tickets and the like.

[16] We use non-Tuesday prices in this construction. That is, $p_k \equiv p_{kt}$, $t \neq Tuesday$.

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 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). The nature of temporal variation in prices is highlighted by Table 2. With the vast majority of theatres offering Tuesday discounts, the theatre-average price is substantially lower on Tuesdays than for most other days. 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 do not offer cheap tickets.

Using our (weighted) average cinema ticket prices, the top panel of Table 3 provides summary statistics of aggregated estimated daily admission across all cinemas by day of week. The estimates suggest, on average, approximately 42,000 people (about 1% of the population) attend a cinema each day in the greater Sydney area, and that Saturday is the most popular day of the week followed by Sunday then Friday and Tuesday, which have approximately equal average (and median) attendance rates. 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.

One of our critical assumptions in identification relies on the fact that weekdays (Monday-Thursday) are implicitly treated the same by consumers. The top panel of Table 3 suggests that Monday and Wednesday generate similar levels of attendance but Thursday tends to attract more attendance. In Australia, however, films typically open on a Thursday. In fact, of the 4,542 openings recorded in this sample, 3,988 (88%) opened on Thursday. Once the opening day effect is removed from the week day summary statistics, Thursday attendance is very similar to Mondays and Wednesdays as shown in the bottom panel of Table 3. This is consistent with consumers treating all weekdays (excluding Fridays) as equal. As discussed in more detail in section 5, we exploit this observation in our estimation strategy.

4.3 Market definition, demographics, and survey data

Our discussion of the data is complete with details of our market size, demographic information, and the additional industry survey data we employ as extra moment conditions in estimation. Table 4 reports summary statistics of the demographic variables we use, based on Australian Bureau of Statistics (ABS) Census data from 2006. We include "collection districts" (see Figure 2) 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. Using our 30km definition, the total population of our market (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. In our final model, we restrict attention to demographic information on income and age. For these variables we are able to construct an empirical distribution conditional on location.[17]

Finally, we exploit additional information on the profile of the cinema going audience. In particular, we obtain cinema attendance rates by age in 2007 from Roy Morgan and Co. Pty Ltd., and cinema attendance rates by income in 2006 from the ABS based on the *Attendance at Selected Cultural Venues and Events* (cat no 4114.0). As discussed in Section 5, we use this information to introduce an additional set of moment conditions. The Morgan and ABS statistics suggest higher cinema attendance rates for younger people and higher income earners.

5 Estimation

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.[18] Our first set of moment conditions requires the existence of a set of instrumental variables, $Z = [z_1, \ldots, z_{L_z}]$, that are correlated with market price, but uncorrelated with the unobserved product characteristics, ξ:

$$g_1(\theta) \equiv E\left(Z'\xi(\theta_0)\right) = 0, \tag{10}$$

where θ_0 represents the true parameter vector. For a candidate parameter vector, θ, we solve for $\xi(\theta)$ in the usual way. First, we solve for the vector of mean utilities, $\delta_{fht} = x_{fht}\beta + \alpha p_{fht} + \phi_f + \xi_{fht}$, using the market share inversion trick of Berry (1994). Given δ_{fht}, we can then solve directly for ξ_{fht}.

Our second set of moment conditions derives from external information about cinema attendance patterns:[19]

$$g_2(\theta) \equiv E\left(s_{ifht}(\theta) - s^*_{ifht} | i \in \mathcal{D}_m\right) = 0, \qquad m = 1, \ldots, L_m \tag{11}$$

where $s_{ifht}(\theta)$ is the predicted attendance probability of individual i given the parameter vector, θ; s^*_{ifht} is the attendance probability of individual i, obtained from our external source; $\mathcal{D}_m$ is a set of demographic characteristics indexed by m; and expectations are taken with respect to film, cinema, time, and individual characteristics. This set of moment conditions thus places discipline on the model's predicted conditional attendance probabilities of different demographic groups.

Defining $\hat{g}(\theta) = [\hat{g}_1(\theta)\ \ \hat{g}_2(\theta)]'$ as a vector of sample equivalents of our population moment conditions, we can write our GMM estimator as

$$\hat{\theta} = \arg\min_{\theta} G(\theta) = \hat{g}(\theta)'\hat{\Phi}^{-1}\hat{g}(\theta), \tag{12}$$

where $\hat{\Phi}$ is a consistent estimate of $E[g(\theta)g(\theta)']$. Intuitively, the weighting matrix, Φ^{-1} gives less weight to moments with higher variance. Because we include the film fixed

[17] More precisely, we can construct $P(D|L) = P(a, y|L) = P(y|a, L)P(a|L)$, where a and y denote age and income, respectively.

[18] Further details about the estimation procedure are provided in the appendix.

[19] For a detailed discussion of the integration of such moment conditions into estimation see Imbens and Lancaster (1994), and for an early application closely related to our context, see Petrin (2002).

effects, ϕ_f, in equation (1), our GMM estimator does not identify the role of time-invariant film characteristics in consumer choice. Following Nevo (2001), we perform an auxilliary regression to recover these additional parameters.

An important component of the empirical strategy is the choice of instrumental variables. A great deal of intertemporal price variation stems from the common cinema practice of offering ticket prices on Tuesdays. We include a dummy variable for Tuesdays in our instrument set. Average attendance is relatively constant during the week with the exception of Fridays, weekends and opening days. We include dummy variables for Friday, Saturday, Sunday, and opening day in our set of explanatory variables. Effectively then, our maintained assumption is that the choice to offer cheap tickets on Tuesdays instead of Mondays, Wednesdays, or Thursdays, is unrelated to demand conditions. 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; and 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).

For our additional moment conditions, we use information about attendance rates conditional on age and income. In particular, we match attendance rates for the age brackets {15-24}, {25-34}, {35-49}, and $\{\geq 50\}$; and the weekly income brackets $\{< 400\}$, {400-600}, {600-800}, {800-1000}, {1000-1300}, {1300-1600}, {1600-2000}, and $\{\geq 2000\}$, where all figures are in Australian dollars.

We close this section by briefly discussing the nature of variation in our data that identifies our parameter estimates. In principal, we can exploit time-series variation, cross-section variation within the greater Sydney market, and, because consumers face transport costs, some variation between local markets within Sydney. In practice, the variation in price takes a restricted form. The primary source of time-series variation is the common practice of offering cheap Tuesday tickets. There is very little other time-series variation in price, with a small number of small theatres offering cheap tickets on Mondays instead. This time series variation allows identification of the average price sensitivity, α. However, to separately identify heterogeneity in preferences toward price, we need variation in relative prices. For this we rely on cross-section variation in relative prices of similar movies at neighbouring theatres in different areas.

There is sufficient heterogeneity in film offerings in our sample to identify mean preferences towards film characteristics. We need variation in the mix of films to identify heterogeneity in preferences towards film characteristics. In our sample, most new films are introduced simultaneously in many theatres, limiting such heterogeneity. Accordingly, we struggled to separately identify heterogeneity parameters relating to film characteristics. We briefly return to this issue in the discussion of our results.

6 Results

6.1 Multinomial logit model

Before considering the full random coefficients model, we report multinomial logit (MNL) model results. As with our full model, we include film fixed effects in the MNL model rather than time invariant film covariates such as budget, advertising, and reviews. Demographic variables are included as additional product characteristics and are considered as 'distance rings' around each theatre following Davis (2006). For example, our 'Pop[0,5]' variable is the proportion of the total population (approximately 4 million) living within 5 kilometres of theatre h, while 'Pop(5,10]' is the proportion of the population living between 5 and 10 kilometres from theatre h. An example distance ring is provided in Figure 2. Tables 5 and 6 provide first and second stage results, respectively. In both tables, Column 1 reports results with no demographic variables included, while columns 2-4 include, respectively, local population proportion (of total population), within area weighted cinema-age (15-30 year olds) proportions, and within area weighted average median weekly incomes. Column 5 includes all demographics jointly.

For our first stage, price is the dependent variable. Coefficients on excluded instruments are reported in Table 5. Additional (unreported) explanatory variables correspond to the explanatory variables in the second stage (these variables can be seen in Table 6). The first stage results confirm the important role played by our Tuesday indicator variable, and suggest much of the variation in price is explained by our instruments, with the results not sensitive to our specification of demographics. Diagnostic tests support the validity of our instruments.[20]

The second stage results of Table 6 conform largely to a-priori expectations. The coefficient on price is estimated in the region 0.191 to 0.212 in absolute terms.[21] Based on the estimate $\alpha = 0.2$, this (somewhat crudely) implies an average own price elasticity of 2.53 (median 2.70, std. dev. 0.36) using $\eta = -\alpha p_{ht}(1 - s_{fht})$.[22] This magnitude is similar to other (mostly time series) studies which have found elastic own price demand.[23] The time-variant, but theatre specific, film variables relating to 'Opening Day' and (unreported) 'Week of Release' (dummies) display positive and declining (positive) coefficients, respectively, which are highly significant. Consistent with Davis (2006), Einav (2007), and Moul (2007), this suggests consumers prefer to see a film earlier in its run and the opening day provides increased utility. Academy Award nominations are shown to have a positive and highly significant effect on mean utility, but the effect of a win is negative. This is a likely manifestation of the fact that the eventual winners had all spent considerable time

[20] We do not reject the null of over-identification from the Sargan-Hansen test. However, it is well known that this test suffers in large samples and we note that the rejection is also largely attributable to the Tuesday dummy which plays an important role as an instrument.

[21] 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.

[22] See Nevo (2000, p. 552).

[23] For example, Dewenter and Westermann (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. Obviously, however, our daily data are very different to such time-series data.

in cinemas prior to their wins.

Saturday followed by Sunday, followed by Friday are the most popular days, with coefficients relative to a non-Friday weekday numeraire. Public and school holidays also attract moviegoers. Weather also plays a role, with rainy days and cooler days tending to draw larger attendances. Turning to theatre characteristics, we see that location in a shopping centre and the number of cinema screens (at the theatre location) are both associated with greater attendance.

In column 2, the fact that the coefficient of 'Pop[0,5]' is positive and that 'Pop(5,10]' is negative is consistent with travel costs associated with cinema attendance as in Davis (2006). Columns 4 and 5 similarly show that an increase in the proportion of 15-30 year olds, and an increase in median weekly income are both associated with increased attendance, and that when these increase further away (i.e. 5 to 10 kilometres away), the relationship is weaker or even 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.

6.2 Random coefficient model

We present estimates from the full model in Table 7. Column 1 contains our base specification. Relative to this specification, Column 2 replaces a linear specification for week of run with individual week dummies for the first 10 weeks of a movie's run; Column 3 permits consumer heterogeneity with respect to price and the week of run; and Column 4 includes both of these changes.[24] Results for our time-varying characteristics are very similar to our MNL model. Coefficients on our week dummies suggest a linear relationship between week of run and attendance is a reasonable approximation, certainly for the first 8 weeks of a movie's run (which accounts for the majority of our data). The difference between our reported coefficients on the Preview indicator across specifications does not reflect a substantive difference, but a different numeraire: in Columns 1 and 3, the numeraire is effectively a non-preview movie, while in Columns 2 and 4, the numeraire is a movie past week 10 of its run.

Estimates for our time-invariant film variables are extracted from an auxilliary regression of film fixed effect parameters on time invariant characteristics. As we might expect, there is a positive relationship between attendance and a film's budget and advertising spending, while screening a film at a greater number of locations dilutes the audience at any one theatre. Sequels, films with stars, and films attracting favourable reviews are all associated with larger audiences.

Consider next the parameters related to consumer heterogeneity. Recall that travel costs enter with a negative sign. In all specifications, the distance coefficient is highly significant, but estimated to be quite small. Compared to the effect of a one dollar increase in ticket price, travelling an additional kilometre to a movie venue appears a relatively minor imposition. This is consistent with the idea that consumers decide first on the film they intend to see before considering the most appropriate venue.[25] Heterogeneity

[24]The specification in Column 3 permits heterogeneity in linear preferences for week of run, while the specification in Column 4 considers heterogeneity in preferences for films in the first week of their run.

[25]Indeed, according to a Cinema and Video Industry Audience Research survey (conducted by the

in the constant term suggests consumers differ in their propensity to substitute between movies rather than forego movie attendance altogether. In Columns 3 and 4, we permit heterogeneity in preferences towards price and the week of a film's run. For both of these characteristics, we are unable to identify substantial heterogeneity. In all specifications, we also consider the relationship between cinema attendance and local demographic characteristics. In particular, we do not find a consistent relationship between attendance and the local proportion of young adults (those aged 15-30), while we do find a positive relationship between log income and attendance.

We do not take these results to indicate a limited degree of heterogeneity in consumer preferences. Instead, it is likely that limitations in the nature of variation in our data hamper our ability to identify rich substitution patterns. Heterogeneity in movie attendance conditional on product characteristics identifies the random coefficient on the constant, while we need to see variation in relative prices to identify differing preferences towards price. The restrictive nature of price variation in our sample limited our ability to separately identify the mean and variance of preferences for price.[26] Similarly, variation in week of run identifies mean preferences for recent movies, while we need variation in the mix of film vintages to identify heterogeneity in such preferences. With the coordinated release of new films, such variation was limited. Similar arguments pertain to other product characteristics. Finally, with regard to our demographic characteristics, we require variation in attendance rates across cinemas surrounded by local regions exhibiting differing demographic distributions. With a sample of 50 cinemas, we found that our supplementary moment conditions (equation (11)) did much of the work in identifying our age and income parameters, while similar moment conditions were not available to assist in identifying our travel cost parameter.

6.3 Discussion

Elasticities

Tables 8 and 9 present a selection of demand elasticities.[27] In the top panel of Table 8, we show summary information on own-price elasticities by the week of a movie's run. Demand for a movie at a cinema is relatively elastic, with a typical own-price elasticity in excess of 2.5. Because we cannot identify heterogeneity in preferences across week of run, the variation in own-price elasticities stems from changes in the mix of films and cinemas conditional on week. The top panel of Table 9 presents median cross-price elasticities by week of run. The first two rows and columns represent previews and opening days, with the remainder increasing in week of run. Element (j, k) contains the median price elasticity of a film screening in week $j-2$ with respect to the price of a film screening in week $k-2$. As we can see from the diagonal, elasticities tend to fall with week of run as more consumers switch to the outside good.

Cinema Advertising Association) the majority of people decide which film to see in advance of their visit (CAVIAR Consortium, 2000).

[26]For example, we note that, while the random coefficient on price is precisely estimated in Models (3) and (4), this coefficient is quite sensitive to changes in specification. We have omitted other heterogeneity parameters for this reason.

[27]See, for example, Nevo (2000) for details on the calculation of demand elasticities in a similar context.

The bottom panels of Tables 8 and 9 present analogous information indexed by cinema. The bottom panel of Table 8 summarises own-price elasticities by cinema. We see a greater degree of variation in own-price elasticities, reflecting heterogeneity in preferences across cinemas with different locations and local demographic conditions. The bottom panel of Table 9 contains median cross-price elasticities by cinema. Again, the relative lack of variation in elasticities is consistent with anecdotal evidence suggesting consumers often choose a movie before deciding on a venue.

The Tuesday effect: Market expansion or cannibalisation?

The effect of the entry of a new product into a market can be decomposed into a market expansion effect (attracting new customers to the market), a market stealing effect (poaching customers from rival firms), and cannibalisation (diverting customers from one of your existing products to the new product). We could think of the effect of a decrease in price in similar terms.

The major source of price variation in our data set is the discounts offered on films shown on Tuesdays at most theatres. Our daily model, by definition, does not permit substitution across days; the only products in the consumer's choice set are the movies offered on a given day (and the outside good). Hence, when prices are lowered on Tuesdays, the increase in consumption is at the expense of other movies shown on Tuesdays and the outside good. With most movies receiving discounts on Tuesdays, the aggregate effect is a decrease in the market share of the outside good; that is, a market expansion. In practice, some consumers might substitute away from movie consumption on a Wednesday when they decide to see a movie on a Tuesday. By ignoring this, our daily model *overstates* the market expansion effect of a decrease in prices.

In this section, we briefly discuss an alternative market definition. Our weekly model incorporates in the choice set all films at all theatres showing in the week. In principle then, consumers can substitute between movies shown on different days of the week. An extreme version of this is provided by the simple MNL. It is well known that under the MNL, substitution patterns are driven by market shares: consumers substitute to products in proportion to their market share. Let us then compare the daily and weekly implementations of the MNL. Consider the preferences of a consumer contemplating seeing film f shown at theatre h on a Tuesday. In the weekly model, also included in her choice set are film g shown at theatre h on a Tuesday and film g shown at theatre h on a Wednesday. Her substitution patterns to either of these films will be identical because they share the same characteristics (except possibly price) and thus have the same market share. We may suspect that in practice consumers will be more willing to substitute to films screening on the same day. The weekly implementation of the MNL then may *understate* the market expansion effect by imposing too much substitution to films screening on other days.

Ideally, we would like to strike a balance between these two extremes and permit realistic substitution patterns between films screening on different days of the week. One way to do this is to incorporate heterogeneity in preferences across screening times. Because we do not have substantial variation in product characteristics (other than price) over time, we are unable to separately identify such heterogeneity. We therefore take the results from our weekly model to represent an overstatement of the substitution across days of the week.

Results from our weekly market specification are in Table 10. Parameter estimates are very similar to the daily market model. In both specifications, the outside good has a large market share, and the introduction of additional inside goods does not have a large impact on our estimates. However, the weekly model does have different implications once we calculate (unreported) elasticities and revenue-maximising prices. Estimated cross-price elasticities are lower in the weekly model. Effectively, with a larger set of substitute products, the propensity to substitute to any specific one is reduced. At the same time, revenue-maximising prices are higher in the weekly model, because cinemas consider the impact of film prices on movies that they screen on other days. We present additional detail on the results of the revenue-maximisation exercise below.

Revenue-maximising prices

In Table 11, we present revenue-maximising prices based on our demand estimates. We present results from both the daily and weekly models. Results are based on a selection of cinemas for screenings taking place on January 4.[28] Recall from the discussion in Section 3.2 that we implicitly impose two main assumptions: cinemas are capacity unconstrained, and concession sales do not enter the profit-maximisation problem. Under these assumptions, and armed with our demand estimates, two features stand out. First, heterogeneity across cinemas in optimal prices is quite limited. This result follows directly from our discussion in Section 6.2, and we again attribute it to lack of variation in our data rather than homogeneity in demand conditions across cinemas. Second, optimal prices are quite low relative to prevailing cinema prices. In light of this result, it is worth briefly interrogating our maintained assumptions.

To investigate the importance of capacity constraints, we focus on a selection of our data for which we have more detailed information. We have session time information for the 13 largest multiplex cinemas in our sample over four complete weeks in April 2007.[29] This dataset comprises 21,206 session times covering 4,821 daily film-at-theatre data points across 41 unique films, and represents approximately 3.3% of our full sample. With screens (seats) ranging from 10 to 17 (1,980 to 4,112), these cinemas are larger than average in our dataset. We note the average seats-per-screen at these 13 locations ranges from 168 to 270, with the average cinema screen among these catering for 217. We calculate average daily capacity for a film-at-theatre by multiplying the average seats-per-screen by the average number of daily screenings-per-film. On average each film screened 4.4 times per day with a standard deviation of 2.48. Naturally, new release and more popular films tend to be allocated a greater number of sessions each day. Restricting attention to opening week films, the average number of daily sessions increased to 5.37. A number of popular films had significantly more screenings than this average. For example, the film *300* occupied 15 sessions per day in its opening week at two locations. Accordingly, we consider further subsets of our data contingent upon national opening week screen count. Conditioning in this manner we observe average (opening week) daily sessions for films

[28]Results are not sensitive to our particular selection of cinemas and date.

[29]Session time information was collected from old newspapers using an optical reader.

opening on more than 200 and 300 screens as 7.38 and 8.95, respectively.[30]

This capacity information is contained in the far right column of Table 12.[31] The remaining columns contain information about actual and simulated attendance for our April selection of cinemas and films. Columns from left to right contain, respectively, information based on actual attendance, model simulated attendance based on actual prices, and model simulated attendances based on cinema-, circuit-, and market-based revenue maximisation. The top (bottom) panel contains information based on our daily (weekly) model. Rows contain information about different cuts of this data: the first row uses this full dataset; the second row restricts attention to films in their opening week; and the next two rows, respectively, further restrict attention to films opening on more than 200 and 300 screens nationally.[32]

The first row ("All Sessions") of each panel suggests that there is substantial excess capacity on average in the data. Further, our model simulations suggest excess capacity for a sizeable selection of screenings even if cinemas were to substantially reduce prices. However, once we restrict our attention to more popular films, capacity constraints start to bind. Taken together, these results paint a picture of an industry with substantial excess capacity for the vast majority of screenings, but with binding capacity constraints for a small selection of screenings.

We are unable to bring direct evidence to our second maintained assumption; that cinema managers do not consider concession sales. If concession sales are positively related to attendance (as we would expect), then our results place an upper bound on optimal prices for the vast majority of sessions which are anticipated to be capacity unconstrained. This suggests non-trivial gains from deviating from the practice of uniform pricing across films.

7 Conclusion

In this paper, we develop a random coefficients discrete choice model of cinema demand using a large sample of daily film-at-theatre box office revenues from the Sydney region over the 365 days of 2007. With price uniformity across film and session a common feature of movie markets, a critical component of our identification strategy derives from the cheap Tuesday ticket prices which characterise the Sydney market.

We find that movie demand is price elastic, with attendance influenced by a number of characteristics which relate to the film, theatre, and timing of consumption. We observe only limited variation in cross-price elasticities between cinemas. This could be an artefact of the nature of variation in our data set, but is also consistent with anecdotal evidence

[30] Across the full sample of 314 films, opening screens above 200 and 300 represent approximately the 75th and 85th percentiles, respectively, of this variable.

[31] We do, of course, realise that cinema operators manage with-in theatre auditoria as well as number of sessions during the course of a film's run but do not attempt to integrate this into our exercise. Given the likely allocation of larger capacity auditoria for new films, this would subsequently increase capacity even further than our estimates.

[32] Note that these sample selections are based only on (a minimal set of) observable information for cinema managers. The week of a film's run is clearly an important determinant of attendance, while the number of opening week screens will be related to the industry's forecast of attendance.

that cinema-goers often prefer an alternate location showing the same film rather than another film at the same cinema. Our elasticity estimates and a revenue-maximisation exercise are consistent with considerable over-pricing for a substantial selection of films. Finally, we consider a variation in our base model in which a market is defined as a week. Our results are suggestive that the common practice of cheap Tuesday cinema prices leads primarily to a market expansion rather than substitution between different days of the week.

Our results imply that cinemas could increase profits by offering more off-peak pricing, and by employing variable film pricing practices. This doesn't necessarily imply that the pricing strategy should be particularly complex—it could be as simple as categorising certain films as 'blockbusters', or offering a 'new release' and 'old release' price contingent upon some (commonly known and pre-specified) week of the run.

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Appendix

In this appendix, we provide additional detail on our demand estimation algorithm. Much of the material is drawn from Berry et al. (1995) and Nevo (2000, 2001), where additional discussion can be found. We break the demand estimation details into several components. We first outline the calculation of the GMM objective function for a given parameter vector. Next, we discuss the gradient of the vector of moment conditions, required both for the application of gradient-based optimisation algorithms, and the calculation of standard errors. We also outline the calculation of the variance-covariance matrix of the objective function.

First, let us briefly introduce some additional notation. Let $J = \sum_{t=1}^{T} \sum_{h=1}^{H_t} F_{ht}$ be the number of observations in the dataset, with $J_t = \sum_{h=1}^{H_t} F_{ht}$ the number pertaining to period t. We define $\mathcal{S}$ to be the $J \times 1$ vector of observed market shares and $\mathcal{S}_{.t}$ the $J_t \times 1$ vector of observed period t market shares. Similarly, $s(x, p, L, \xi; \theta)$ is the $J \times 1$ vector of predicted market shares from our model, and $\tilde{s}(\tau, x, p, L, \xi; \theta)$ is the $J \times NS$ matrix of purchase probabilities of NS simulated individuals drawn from $P^*(L, D, \nu)$. Following Nevo (2001), we partition the parameter vector into two components, $\theta = (\theta_1, \theta_2)$. An important interim step in estimation is the calculation of the vector of mean values, δ. Given $\mathcal{S}$, the parameter vector $\theta_2 = (\lambda, \Pi, \Sigma)$ enters $\delta = \delta(\mathcal{S}, \theta_2)$ in a nonlinear manner. By contrast, the vector $\theta_1 = (\alpha, \beta)$ can be extracted as a linear function of $\delta(\mathcal{S}, \theta_2)$.

The GMM objective function

Calculating the GMM objective function, $G(\theta)$, involves several steps:

1. given the vector of non-linear parameters, θ_2, and a vector of observed market shares, $\mathcal{S}$, solve for the vector of mean values (defined below) of each product, $\delta(\mathcal{S}, \theta_2)$;

2. given θ_2 and $\delta(\mathcal{S}, \theta_2)$, solve for the vector of linear parameters, θ_1;

3. calculate the moment conditions, $\hat{g}_1(\theta)$ and $\hat{g}_2(\theta)$, and the GMM objective function, $G(\theta)$.

We decompose the indirect utility enjoyed by consumer i by attending film $f \in \{1, \ldots, F_{ht}\}$ at theatre (house) $h \in \{1, \ldots, H_t\}$ on day $t \in \{1, \ldots, T\}$ into three components:

$$u_{ifht} = \delta_{fht} + \mu_{ifht} + \epsilon_{ifht} \tag{13}$$

$$\delta_{fht} = x_{fht}\beta + \alpha p_{fht} + \gamma_f + \xi_{fht} \tag{14}$$

$$\mu_{ifht} = x_{fht} \left(\Pi D_i + \Sigma \nu_i \right) - \lambda d_{ij}, \tag{15}$$

where δ_{fht} is the mean value that is common to all consumers, μ_{ifht} describes how observable (D_i) and unobservable (ν_i) characteristics of consumer i affect her preferences, and ϵ_{ifht} is the familiar type-1 extreme value idiosyncratic unobservable.

Our first exercise is to calculate δ, which is implicitly defined by the relationship

$$s_{.t}(\delta_{.t}, \theta_2) = \mathcal{S}_{.t}. \tag{16}$$

In turn, we calculate the market share vector, s, by aggregating over the individual purchase probabilities of consumers. We simulate NS consumers, with consumer i's characteristics (L_i, D_i, ν_i) drawn from $P^*(L, D, \nu)$. The purchase probabilities of consumer i are given by[33]

$$\tilde{s}_{ifht}(\delta, \theta_2) = \frac{e^{\delta_{fht}+\mu_{ifht}}}{\triangle_{it}}, \qquad \triangle_{it} = 1 + \sum_{l}^{H_t} \sum_{g}^{F_{lt}} e^{\delta_{glt}+\mu_{iglt}}, \tag{17}$$

with the market share vector then determined by

$$s_{fht}(\delta_{.t}, \theta_2) = \frac{1}{NS} \sum_{i}^{NS} \tilde{s}_{ifht}(\delta_{.t}, \theta_2). \tag{18}$$

To solve for the vector of mean values, we exploit the contraction mapping of BLP,

$$\delta_{.t}^{k+1} = \delta_{.t}^{k} + \ln s_{.t}(\delta_{.t}^{k}, \theta_2). \tag{19}$$

Our next step is to solve for the linear parameters, θ_1. These can be obtained from the first order conditions of our GMM objective function,

$$\hat{g}(\theta)' \hat{\Phi}^{-1} \frac{\partial \hat{g}(\theta)}{\partial \theta} = 0. \tag{20}$$

Restrict attention to the linear parameters, θ_1, and note that $\frac{\partial \hat{g}_2(\theta)}{\partial \theta_1} = 0$. Under the assumption that our two sets of moment conditions, $g_1(\theta)$ and $g_2(\theta)$, are independent, we can then write the linear parameters as a function of the mean value vector:

$$\theta_1 = \left(x' Z \hat{\Phi}_{11}^{-1} Z' x \right)^{-1} x' Z \hat{\Phi}_{11}^{-1} Z' \delta(\mathcal{S}, \theta_2), \tag{21}$$

where $\hat{\Phi}_{11}^{-1}$ is a $L_z \times L_z$ partition of the weighting matrix, corresponding to the covariance matrix of the set of moment conditions, $g_1(\theta)$.

Given the vector of mean utilities, $\delta(\mathcal{S}, \theta_2)$, we can use equation (14) to solve for the structural error term, $\xi(\theta)$. Our first set of moment conditions is then given by

$$\hat{g}_1(\theta) = \frac{1}{N} Z' \xi(\theta). \tag{22}$$

Let Υ be a $L_m \times NS$ matrix of inclusion in demographic groups, with typical element $\Upsilon_{im} = 1\{i \in \mathcal{D}_m\}$. Our second set of moment conditions is given by

$$\hat{g}_2(\theta) = \Upsilon \left(\sum_{t=1}^{T} \sum_{h=1}^{H_t} \sum_{f=1}^{F_{ht}} \tilde{s}_{.fht}(\theta)' \right) ./ \left(\sum_{i=1}^{NS} \Upsilon_{i.} \right) - s^*, \tag{23}$$

[33] When we define a market as the set of films screened over a week, we must of course sum over the films shown during the week.

where ./ indicates element-by-element division, and (abusing notation slightly) s^* is a $L_m \times 1$ vector of annual cinema attendance probabilities of each of our demographic groups. Combining the moment conditions, $\hat{g}(\theta) = [\hat{g}_1(\theta)\ \hat{g}_2(\theta)]'$, we can write our objective function for given parameter vector, θ,

$$G(\theta) = \hat{g}(\theta)'\hat{\Phi}^{-1}\hat{g}(\theta), \tag{24}$$

where $\hat{\Phi}$ is a consistent estimate of $E[g(\theta)g(\theta)']$.

Our method for dealing with our film fixed effects follows Nevo (2001). We proceed in two stages. First, we obtain our GMM estimator, $\hat{\theta}$, by minimising $G(\theta)$ using equation (24). This requires removing from x any explanatory variables that are specific to each film and time invariant, and including a set of film indicator variables. We then perform an auxilliary regression of our film-fixed explanatory variables on the estimated fixed effects, yielding

$$\hat{\theta}_1 = \left(X'V_\phi^{-1}X\right)^{-1} X'V_\phi^{-1}\hat{\phi}_f, \tag{25}$$

where X contains the film-specific time-invariant explanatory variables, $\hat{\phi}_f$ is the vector of coefficients on the film-fixed effects, and V_ϕ is the variance-covariance matrix of $\hat{\phi}_f$.

The gradient of the moment vector

The gradient of the moment vector is required for calculation of the variance covariance matrix of the parameter vector, θ, and for the use of gradient based optimisation methods. The gradient is given by

$$\frac{\partial \hat{g}(\theta)}{\partial \theta'} = \left[\frac{\partial \hat{g}_1(\theta)}{\partial \theta'}\quad \frac{\partial \hat{g}_2(\theta)}{\partial \theta'}\right], \tag{26}$$

where the gradient of our first set of moment conditions is

$$\frac{\partial \hat{g}_1(\theta)}{\partial \theta'} = \frac{1}{N}Z'\left[x\quad \frac{\partial \delta(\mathcal{S},\theta_2)}{\partial \theta_2'}\right] \tag{27}$$

and the gradient of our second set of moments is

$$\frac{\partial \hat{g}_2(\theta)}{\partial \theta'} = \left[0\quad \frac{1}{N}\Upsilon\left(\sum_{t=1}^{T}\sum_{h=1}^{H_t}\sum_{f=1}^{F_{ht}}\frac{\partial \tilde{s}_{.fht}(\theta)}{\partial \theta_2'}\right) ./ \left(\sum_{i=1}^{NS}\Upsilon_{i.}\right)\right]. \tag{28}$$

The gradient of the mean value vector, $\frac{\partial \delta(\mathcal{S},\theta_2)}{\partial \theta_2'}$, is obtained implicitly by differentiation of equation (16):

$$\frac{\partial \delta(\mathcal{S},\theta_2)}{\partial \theta_2'} = -\left(\frac{\partial s(\delta,\theta_2)}{\partial \delta}\right)^{-1}\frac{\partial s(\delta,\theta_2)}{\partial \theta_2}. \tag{29}$$

We can simplify the terms on the right as follows:

$$\frac{\partial s_{fht}(\delta,\theta_2)}{\partial\delta_{glt}} = \frac{1}{NS}\sum_{i=1}^{NS}\tilde{s}_{ifht}\left(1\{(f,h)=(g,l)\}-\tilde{s}_{iglt}\right) \tag{30}$$

$$\frac{\partial s_{fht}(\delta,\theta_2)}{\partial\lambda} = \frac{1}{NS}\sum_{i=1}^{NS}\tilde{s}_{ifht}\left(\sum_{l}^{H_t}\sum_{g}^{F_{ht}} d_{il}\tilde{s}_{iglt}-d_{ih}\right) \tag{31}$$

$$\frac{\partial s_{fht}(\delta,\theta_2)}{\partial\sigma_l} = \frac{1}{NS}\sum_{i=1}^{NS}\nu_i^l\tilde{s}_{ifht}\left(x_{fht}^l-\sum_{l}^{H_t}\sum_{g}^{F_{ht}}\tilde{s}_{iglt}x_{glt}^l\right) \tag{32}$$

$$\frac{\partial s_{fht}(\delta,\theta_2)}{\partial\Pi_{ld}} = \frac{1}{NS}\sum_{i=1}^{NS}D_{id}\tilde{s}_{ifht}\left(x_{fht}^l-\sum_{l}^{H_t}\sum_{g}^{F_{ht}}\tilde{s}_{iglt}x_{glt}^l\right), \tag{33}$$

where σ_l is the lth diagonal element of the scaling parameter matrix, Σ; x^l is the lth product characteristic; and Π_{ld} describes the impact of the interaction between demographic characteristic d and the lth product characteristic. The term $\frac{\partial\tilde{s}_{.fht}(\theta)}{\partial\theta_2'}$, required for the gradient of our second condition is implicitly defined above.

The variance-covariance matrix

Defining $\tilde{g}(\theta)=\frac{\partial\hat{g}(\theta)}{\theta'}$, the estimated variance-covariance matrix of the vector of GMM parameter estimates, $\hat{\theta}$, is given by

$$\hat{V}_{GMM}=\frac{1}{N}\left[\tilde{g}(\theta)\hat{\Phi}^{-1}\tilde{g}(\theta)\right]^{-1}\tilde{g}(\theta)\hat{\Phi}^{-1}\hat{A}\hat{\Phi}^{-1}\tilde{g}(\theta)\left[\tilde{g}(\theta)\hat{\Phi}^{-1}\tilde{g}(\theta)\right]^{-1}, \tag{34}$$

where $\hat{A}$ is an estimate of the variance of $\sqrt{N}g(\theta)$. We include variance due to sampling error (see, for example, Greene (2008) for additional details), and due to simulation error (see Berry et al. (1995)).

Table 1: Film Summary Statistics[a]

	Obs.	Mean	Median	Std. Dev.	Min.	Max
Total Box Office[b]	300	3,652	904	6,369	1	35,500
Opening Week Screens	293	107	47	120	1	608
Advertising/Publicity[b]	148	1,175	905	955	489	3,535
Budget[c]	190	41,200	21,500	47,500	30	300,000
Review	257	3.15	3	0.71	1	5

Notes: [a] Source: Nielsen Entertainment Database Inc., the MPDAA, IMDb, and Box Office Mojo (see text for details). [b] Total box office and advertising/publicity are in thousands of AUDs. [c] Budget is in thousands of USDs.

Table 2: Theatre Summary Statistics[a]

	Obs.	Mean	Std. Dev.	Min.	Median	Max
Screens	50	6.78	4.36	1	6.5	17
Seats	50	1,544	1,027	64	1,788	4,112
Ticket Price	50	12.55	1.82	5.82	13.34	14.9
Ticket Price by Day of Week						
Monday	50	12.55	1.76	5.82	13.34	14.79
Tuesday	50	9.73	1.45	5.82	10	14.9
Wednesday	50	12.74	1.67	5.82	13.49	14.9
Thursday	50	12.69	1.81	5.82	13.49	14.9
Friday	50	12.74	1.67	5.82	13.49	14.9
Saturday	50	12.74	1.67	5.82	13.49	14.9
Sunday	50	12.74	1.67	5.82	13.49	14.9

Notes: [a] Reported prices are weighted averages across ticket types. See text for details.

Table 3: Estimated Daily Total Admission, All Cinemas

	Obs.	Mean	Std. Dev.	Min.	Median	Max
All Days						
Monday	53	23,646	20,680	8,907	13,927	97,395
Tuesday	52	47,880	27,865	23,576	36,078	139,873
Wednesday	52	25,721	23,812	9,807	15,526	117,143
Thursday	52	32,683	19,405	13,508	24,222	94,457
Friday	52	45,129	19,119	25,162	38,770	100,748
Saturday	52	66,331	16,416	37,490	61,524	112,604
Sunday	52	53,379	18,447	31,843	47,798	126,985
Total	365	42,059	25,445	8,907	37,490	139,873
Non-Opening Days						
Monday	53	23,099	20,352	8,564	13,778	95,666
Tuesday	52	46,523	28,102	16,700	35,598	139,114
Wednesday	52	22,623	17,443	8,903	15,302	78,683
Thursday	52	20,283	18,479	5,726	13,231	90,848
Friday	52	42,539	18,669	23,437	34,386	97,169
Saturday	52	64,627	16,883	37,289	59,951	111,476
Sunday	52	51,941	18,572	28,880	45,519	123,891
Total	365	38,762	25,498	5,726	34,822	139,114

Table 4: Demographics weighted by Collection District

	Obs.	Mean	Std. Dev.	Min.	Median	Max
Collection District Population	6,587	613	257	0	578	2,765
Minimum Distance to Cinema (kms)	6,587	4.47	5.25	0.02	2.9	29.99
% Aged 15 to 30	6,587	0.23	0.08	0	0.22	1
Median Weekly Income	6,587	568	213	0	536	2,000

Table 5: First Stage Multinomial Logit

	(1)	(2)	(3)	(4)	(5)
Tuesday	-3.328**	-3.329**	-3.330**	-3.328**	-3.330**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Characteristics of Nearest Cinema					
Screens	-0.387**	-0.454**	-0.496**	-0.363**	-0.482**
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Seats	0.001**	0.001**	0.002**	0.001**	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance	0.121**	0.170**	0.159**	0.118**	0.150**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Combined Characteristics of Cinemas within [0,X] kms					
ΣScreens [0,5]	0.074**	0.032**	0.121**	0.012**	0.048**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ΣScreens [0,10]	-0.095**	-0.120**	-0.018**	-0.133**	-0.114**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΣSeats [0,5]	0.000**	0.000**	-0.001**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΣSeats [0,10]	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΣShopping [0,5]	0.800**	0.841**	0.996**	0.919**	0.900**
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)
ΣShopping [0,10]	0.320**	-0.217**	0.396**	0.386**	0.200**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
ΣTheatres [0,5]	0.029**	0.222**	0.190**	-0.230**	-0.098**
	(0.007)	(0.007)	(0.007)	(0.005)	(0.006)
ΣTheatres [0,10]	0.034**	0.209**	0.077**	0.152**	0.227**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Under Identified	37671.4	38804.1	36115.0	39478.7	37751.2
(P-Value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Weakly Identified	23095.1	25156.0	22355.6	25031.2	24357.6
(P-Value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Over Identified	6609.6	5490.0	6286.9	2668.2	3608.6
(P-Value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	145,430	145,430	145,430	145,430	145,430
Partial R^2	0.6314	0.6743	0.6936	0.6805	0.7152
R^2	0.722	0.7594	0.7761	0.7658	0.8069

Notes: Dependent variable is price. All regressions contain all other explanatory variables as reported in Table 6. 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 R^2 refers to the excluded instruments reported in table. R^2 is centred. * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses unless otherwise stated.

Table 6: Second Stage Multinomial Logit

	(1)	(2)	(3)	(4)	(5)
Price	-0.198**	-0.203**	-0.191**	-0.200**	-0.212**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Time Variant Film at Theatre Variables					
Preview	1.466**	1.477**	1.471**	1.509**	1.510**
	(0.044)	(0.043)	(0.044)	(0.043)	(0.043)
Opening Day	0.205**	0.206**	0.193**	0.206**	0.215**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Oscar Nomination	0.096**	0.077**	0.079**	0.104**	0.091**
	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)
Oscar Award	-0.534**	-0.438**	-0.488**	-0.442**	-0.412**
	(0.047)	(0.047)	(0.047)	(0.046)	(0.047)
Week dummies	Yes	Yes	Yes	Yes	Yes
Day and Date Variables					
Friday	0.608**	0.617**	0.602**	0.620**	0.630**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Saturday	1.058**	1.070**	1.055**	1.073**	1.085**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Sunday	0.821**	0.832**	0.817**	0.835**	0.848**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Public Holiday	0.412**	0.421**	0.410**	0.416**	0.429**
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
School Holiday	0.554**	0.545**	0.548**	0.537**	0.534**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Weather					
Rainfall	0.005**	0.005**	0.005**	0.005**	0.005**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Max to av. Diff	-0.020**	-0.020**	-0.020**	-0.020**	-0.020**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Theatre Variables					
Shopping Centre	0.148**	0.175**	0.153**	0.336**	0.346**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Cinema Screens	0.113**	0.107**	0.109**	0.106**	0.105**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Demographics					
Pop[0,5]		6.384**			7.300**
		(0.167)			(0.265)
Pop(5,10]		-0.740**			-0.869**
		(0.076)			(0.086)
Age[0,5]			1.458**		-1.950**
			(0.071)		(0.110)
Age(5,10]			0.478**		-1.036**

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			(0.122)		(0.138)
log(Income)[0,5]				0.914**	0.975**
				(0.021)	(0.022)
log(Income)(5,10]				-0.168**	-0.340**
				(0.025)	(0.027)
N	145,430	145,430	145,430	145,430	145,430
R^2	0.4795	0.4859	0.4828	0.4982	0.5000

Notes: Dependent variable is $(\ln s_{fht} - \ln s_{0t})$. All regressions include Film fixed effects. Price is instrumented as reported in stage 1 results of Table 5. Pop(a,b), Age(a,b), log(Income)(a,b) denote population proportion (of total), weighted average age proportion of 15-30 year olds, and (log) weighted average median weekly income respectively of people living within (a,b) kilometres of theatre h. * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses.

Table 7: Random Coefficients Daily Model

	(1)	(2)	(3)	(4)
Price	-0.206**	-0.200**	-0.246**	-0.318**
	(0.004)	(0.002)	(0.007)	(0.012)
Time Invariant Film Variables				
log(Budget)	0.188**	0.186**	0.188**	0.185**
	(0.005)	(0.005)	(0.005)	(0.005)
log(Adpub)	0.439**	0.455**	0.442**	0.452**
	(0.007)	(0.007)	(0.007)	(0.007)
log(OpWkScrns)	-0.117**	-0.114**	-0.125**	-0.116**
	(0.009)	(0.009)	(0.009)	(0.009)
Star	0.075**	0.082**	0.072**	0.082**
	(0.007)	(0.007)	(0.007)	(0.007)
Sequel	0.176**	0.178**	0.180**	0.177**
	(0.009)	(0.009)	(0.009)	(0.009)
Review	0.222**	0.216**	0.222**	0.215**
	(0.005)	(0.004)	(0.005)	(0.004)
Genre Dummies	Yes	Yes	Yes	Yes
Rating Dummies	Yes	Yes	Yes	Yes
Time Variant Film at Theatre Variables				
Week	-0.353**		-0.353**	
	(0.002)		(0.033)	
Preview	-1.542**	1.478**	-1.541**	1.496**
	(0.033)	(0.044)	(0.033)	(0.044)
Opening Day	0.305**	0.200**	0.303**	0.212**
	(0.017)	(0.017)	(0.017)	(0.018)
Oscar Nomination	0.062**	0.081**	0.066**	0.066**
	(0.026)	(0.024)	(0.026)	(0.024)
Oscar Award	-0.340**	-0.505**	-0.341**	-0.519**
	(0.056)	(0.047)	(0.056)	(0.048)
Week Dummies	No	Yes	No	Yes
Day and Date Variables				
Friday	0.646**	0.623**	0.640**	0.658**
	(0.013)	(0.009)	(0.010)	(0.009)
Saturday	1.142**	1.095**	1.130**	1.173**
	(0.023)	(0.013)	(0.015)	(0.014)
Sunday	0.878**	0.844**	0.870**	0.896**
	(0.017)	(0.010)	(0.011)	(0.011)
Public Holiday	0.485**	0.436**	0.479**	0.492**
	(0.023)	(0.019)	(0.019)	(0.022)
School Holiday	0.573**	0.575**	0.569**	0.606**
	(0.013)	(0.009)	(0.010)	(0.009)
Weather				

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Rainfall	0.005**	0.005**	0.005**	0.006**
	(0.000)	(0.000)	(0.000)	(0.000)
Max to av. Diff	-0.022**	-0.021**	-0.022**	-0.022**
	(0.001)	(0.001)	(0.001)	(0.001)
Theatre Variables				
Shopping Centre	0.164**	0.175**	0.154**	0.179**
	(0.007)	(0.007)	(0.006)	(0.006)
Cinema Screens	0.110**	0.106**	0.109**	0.107**
	(0.001)	(0.001)	(0.001)	(0.001)
Travel Cost				
Travel Cost	0.011**	0.013**	0.010**	0.014**
	(0.000)	(0.000)	(0.000)	(0.000)
Random Coefficients (Std. Dev.)				
Constant	1.453**	0.846**	0.938**	0.903**
	(0.226)	(0.199)	(0.001)	(0.001)
Price			0.067**	0.108**
			(0.001)	(0.006)
Week			0.000	0.005
			(0.158)	(1.531)
Demographics				
Age*[Constant]	-0.382**	-0.214**	0.152**	0.007**
	(0.003)	(0.002)	(0.001)	(0.002)
log(Income)*[Constant]	1.394**	1.617**	1.907**	1.771**
	(0.005)	(0.004)	(0.007)	(0.005)
constant	-28.446**	-32.692**	-31.469**	-33.080**
	(0.088)	(0.086)	(0.088)	(0.087)
N	145,430	145,430	145,430	145,430

Notes: (1) linear week term and random coefficient on constant; (2) weekly dummy variables and random coefficient on constant; (3) linear week term and random coefficient on constant, price and week; (4) weekly dummy variables and random coefficient on constant, price and opening week. See text for full specification details. All models include Film fixed effects. Price is instrumented as reported in stage 1 results of Table 5. * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses.

Table 8: Own-Price Elasticities

	Obs.	Mean	Median	Std. Dev.
Week/Day of Run				
Preview	1,466	-2.641	-2.721	0.232
Opening Day	4,542	-2.602	-2.701	0.298
Week 1	29,678	-2.515	-2.701	0.365
Week 2	29,041	-2.525	-2.701	0.364
Week 3	25,100	-2.529	-2.701	0.362
Week 4	20,340	-2.530	-2.701	0.366
Week 5	14,669	-2.534	-2.701	0.362
Week 6	9,964	-2.546	-2.701	0.352
Week 7	6,436	-2.545	-2.719	0.358
Week 8	3,907	-2.553	-2.719	0.352
Cinema				
George St.	4,781	-2.689	-2.811	0.289
Bondi Jn.	4,281	-2.643	-2.749	0.260
Broadway	5,497	-2.619	-2.719	0.249
Campbelltown	3,830	-2.627	-2.730	0.253
Blacktown	4,248	-2.603	-2.701	0.242
Warringah	3,950	-2.636	-2.740	0.257
Fox Studios	4,777	-2.553	-2.641	0.221
Newtown	2,317	-2.343	-2.430	0.216
Academy	900	-2.828	-2.983	0.379
Cremorne	3,609	-2.648	-2.719	0.178

Notes: Own price elasticities derive from model (2) as reported in Table 7.

Table 9: Cross-Price Elasticities

		1	2	3	4	5	6	7	8	9	10
Week/Day of Run											
Preview	1	**0.000132**	0.000148	0.000386	0.000266	0.000191	0.000167	0.000155	0.000166	0.000106	0.000117
Opening Day	2	0.000162	**0.000232**	0.000253	0.000162	0.000126	0.000098	0.000079	0.000065	0.000056	0.000041
Week 1	3	0.000136	0.000240	**0.000272**	0.000194	0.000146	0.000119	0.000100	0.000082	0.000069	0.000062
Week 2	4	0.000135	0.000229	0.000274	**0.000233**	0.000149	0.000117	0.000101	0.000088	0.000072	0.000062
Week 3	5	0.000139	0.000241	0.000277	0.000212	**0.000170**	0.000115	0.000101	0.000083	0.000076	0.000065
Week 4	6	0.000138	0.000240	0.000274	0.000212	0.000148	**0.000136**	0.000090	0.000084	0.000069	0.000061
Week 5	7	0.000113	0.000222	0.000265	0.000209	0.000157	0.000105	**0.000124**	0.000072	0.000078	0.000058
Week 6	8	0.000124	0.000243	0.000286	0.000207	0.000149	0.000127	0.000084	**0.000106**	0.000065	0.000074
Week 7	9	0.000127	0.000218	0.000252	0.000197	0.000167	0.000116	0.000115	0.000069	**0.000074**	0.000056
Week 8	10	0.000137	0.000229	0.000261	0.000184	0.000144	0.000119	0.000101	0.000104	0.000066	**0.000061**
Cinema											
George St.	1	**0.000259**	0.000320	0.000249	0.000184	0.000157	0.000205	0.000153	0.000173	0.000217	0.000062
Bondi Jn.	2	0.000293	**0.000276**	0.000242	0.000187	0.000153	0.000196	0.000151	0.000171	0.000219	0.000064
Broadway	3	0.000289	0.000312	**0.000212**	0.000185	0.000151	0.000187	0.000148	0.000169	0.000221	0.000062
Campbelltown	4	0.000256	0.000280	0.000216	**0.000150**	0.000149	0.000177	0.000133	0.000149	0.000188	0.000055
Blacktown	5	0.000261	0.000283	0.000216	0.000177	**0.000124**	0.000168	0.000133	0.000152	0.000199	0.000056
Warringah	6	0.000303	0.000333	0.000248	0.000193	0.000158	**0.000165**	0.000153	0.000172	0.000233	0.000063
Fox Studios	7	0.000294	0.000324	0.000244	0.000191	0.000155	0.000196	**0.000133**	0.000172	0.000225	0.000063
Newtown	8	0.000286	0.000311	0.000235	0.000186	0.000154	0.000194	0.000148	**0.000123**	0.000224	0.000064
Academy	9	0.000288	0.000312	0.000245	0.000182	0.000153	0.000198	0.000152	0.000172	**0.000052**	0.000066
Cremorne	10	0.000297	0.000333	0.000250	0.000195	0.000161	0.000209	0.000155	0.000173	0.000226	**0.000157**

Notes: Cross price elasticities derive from model (2) as reported in Table 7. Cell entries i, j , where i indexes row and j column, give the percent change in market share of i with a one-percent change in price of j . Each entry represents the median of the elasticities.

Table 10: Random Coefficients Weekly Model

	(1)	(2)	(3)	(4)
Price	-0.194**	-0.193**	-0.197**	-0.246**
	(0.002)	(0.002)	(0.005)	(0.008)
Time Invariant Film Variables				
log(Budget)	0.185**	0.184**	0.189**	0.180**
	(0.005)	(0.005)	(0.005)	(0.005)
log(Adpub)	0.444**	0.452**	0.468**	0.472**
	(0.007)	(0.007)	(0.007)	(0.007)
log(OpWkScrns)	-0.127**	-0.107**	-0.148**	-0.127**
	(0.009)	(0.009)	(0.009)	(0.009)
Star	0.080**	0.088**	0.081**	0.085**
	(0.007)	(0.007)	(0.007)	(0.007)
Sequel	0.176**	0.176**	0.182**	0.186**
	(0.009)	(0.009)	(0.009)	(0.009)
Review	0.226**	0.218**	0.212**	0.209**
	(0.005)	(0.004)	(0.005)	(0.005)
Genre Dummies	Yes	Yes	Yes	Yes
Rating Dummies	Yes	Yes	Yes	Yes
Time Variant Film at Theatre Variables				
Week	-0.355**		-0.354**	
	(0.002)		(0.002)	
Preview	-1.542**	1.491**	-1.543**	1.511**
	(0.032)	(0.044)	(0.059)	(0.045)
Opening Day	0.289**	0.195**	0.288**	0.194**
	(0.017)	(0.017)	(0.029)	(0.021)
Oscar Nomination	0.012**	0.036**	0.013**	0.008**
	(0.027)	(0.024)	(0.027)	(0.029)
Oscar Award	-0.374**	-0.554**	-0.375**	-0.574**
	(0.056)	(0.047)	(0.056)	(0.047)
Week Dummies	No	Yes	No	Yes
Day and Date Variables				
Friday	0.605**	0.599**	0.604**	0.597**
	(0.008)	(0.008)	(0.008)	(0.008)
Saturday	1.047**	1.039**	1.047**	1.036**
	(0.007)	(0.007)	(0.008)	(0.008)
Sunday	0.814**	0.806**	0.814**	0.802**
	(0.007)	(0.007)	(0.007)	(0.008)
Public Holiday	0.434**	0.409**	0.434**	0.417**
	(0.018)	(0.017)	(0.018)	(0.025)
School Holiday	0.665**	0.665**	0.665**	0.731**
	(0.018)	(0.013)	(0.020)	(0.030)
Weather				

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Rainfall	0.005**	0.005**	0.005**	0.005**
	(0.000)	(0.000)	(0.000)	(0.000)
Max to av. Diff	-0.023**	-0.022**	-0.023**	-0.023**
	(0.001)	(0.001)	(0.001)	(0.001)
Theatre Variables				
Shopping Centre	0.141**	0.149**	0.139**	0.157**
	(0.006)	(0.006)	(0.006)	(0.006)
Cinema Screens	0.108**	0.108**	0.108**	0.106**
	(0.001)	(0.001)	(0.001)	(0.001)
Travel Cost				
Travel Cost	0.011**	0.008**	0.011**	0.012**
	(0.000)	(0.000)	(0.000)	(0.000)
Random Coefficients (Std. Dev.)				
Constant	0.323**	0.174**	0.393**	0.253**
	(0.413)	(0.452)	(0.000)	(0.000)
Price			0.022**	0.082**
			(0.001)	(0.004)
Week			0.008	0.003
			(0.417)	(4.474)
Demographics				
Age*[Constant]	-0.240**	-0.086**	-0.242**	-0.101**
	(0.001)	(0.001)	(0.001)	(0.001)
log(Income)*[Constant]	1.660**	1.430**	1.616**	1.536**
	(0.004)	(0.003)	(0.003)	(0.002)
constant	-29.451**	-31.135**	-29.386**	-31.544**
	(0.088)	(0.087)	(0.088)	(0.088)
N	145,430	145,430	145,430	145,430

Notes: (1) linear week term and random coefficient on constant; (2) weekly dummy variables and random coefficient on constant; (3) linear week term and random coefficient on constant, price and week; (4) weekly dummy variables and random coefficient on constant, price and opening week. See text for full specification details. All models include Film fixed effects. Price is instrumented as reported in stage 1 results of Table 5. * and ** denote two tailed significance at 5% and 1% respectively. Standard errors are in parentheses.

Table 11: Observed and Optimal Prices for Selected Cinemas

Cinema	Observed Price	Daily Model (1)	Daily Model (2)	Daily Model (3)	Weekly Model (1)	Weekly Model (2)	Weekly Model (3)
George St.	14.042	5.079	5.689	6.463	5.389	6.790	9.397
Bondi Jn.	13.730	5.059	5.691	6.470	5.340	6.790	9.398
Broadway	13.582	5.049	5.425	6.459	5.326	6.273	9.395
Campbelltown	13.633	5.041	5.636	6.344	5.289	6.771	9.318
Blacktown	13.489	5.032	5.403	6.372	5.269	6.268	9.346
Warringah	13.685	5.046	5.430	6.476	5.298	6.274	9.402
Fox Studios	13.193	5.023	5.426	6.465	5.274	6.273	9.396
Newtown	12.135	5.005	5.016	6.452	5.217	5.250	9.391
Academy Twin	14.897	5.003	5.033	6.466	5.210	5.318	9.397
Cremorne	13.582	5.021	5.112	6.474	5.266	5.494	9.402

Notes: All optimal prices derive from model (2) as reported in Tables 7 and 10, respectively. Optimal prices reported in (1), (2) and (3) refer to different hypothetical cinema ownership arrangements. Specifically, (1) cinema-level ownership, (2) circuit-level ownership, and (3) market-level ownership. Actual ownership and number of screens as follows: George St., Greater Union, 17; Bondi Junction, Greater Union, 11; Campbelltown, Greater Union, 11; Blacktown, Hoyts, 12; Warringah, Hoyts, 9; Fox Studios, Hoyts, 12; Newtown, Dendy, 4; Academy Twin, Palace, 2; Cremorne Orpheum, independent, 6.

Table 12: Observed and Implied Daily Film-at-Theatre Demand

	Data	Model	Optimal Price (1)	Optimal Price (2)	Optimal Price (3)	Capacity
Daily Model						
All Sessions	142	145	613	573	516	957
Opening Week	253	256	1,065	993	893	1,168
Opening Week (Screens > 200)	387	390	1,621	1,511	1,359	1,605
Opening Week (Screens > 300)	548	550	2,278	2,126	1,907	1,947
Weekly Model						
All Sessions	142	145	414	365	300	957
Opening Week	253	256	723	638	524	1,168
Opening Week (Screens > 200)	387	391	1,104	975	800	1,605
Opening Week (Screens > 300)	548	552	1,568	1,388	1,138	1,947

Notes: All estimates derived from model (2) as reported in Tables 7 and 10, respectively. Optimal prices reported in (1), (2) and (3) refer to different hypothetical cinema ownership arrangements. Specifically, (1) cinema-level ownership, (2) circuit-level ownership, and (3) market-level ownership. Calculation of capacity information is discussed in text.

Figure 1: Cinema Locations

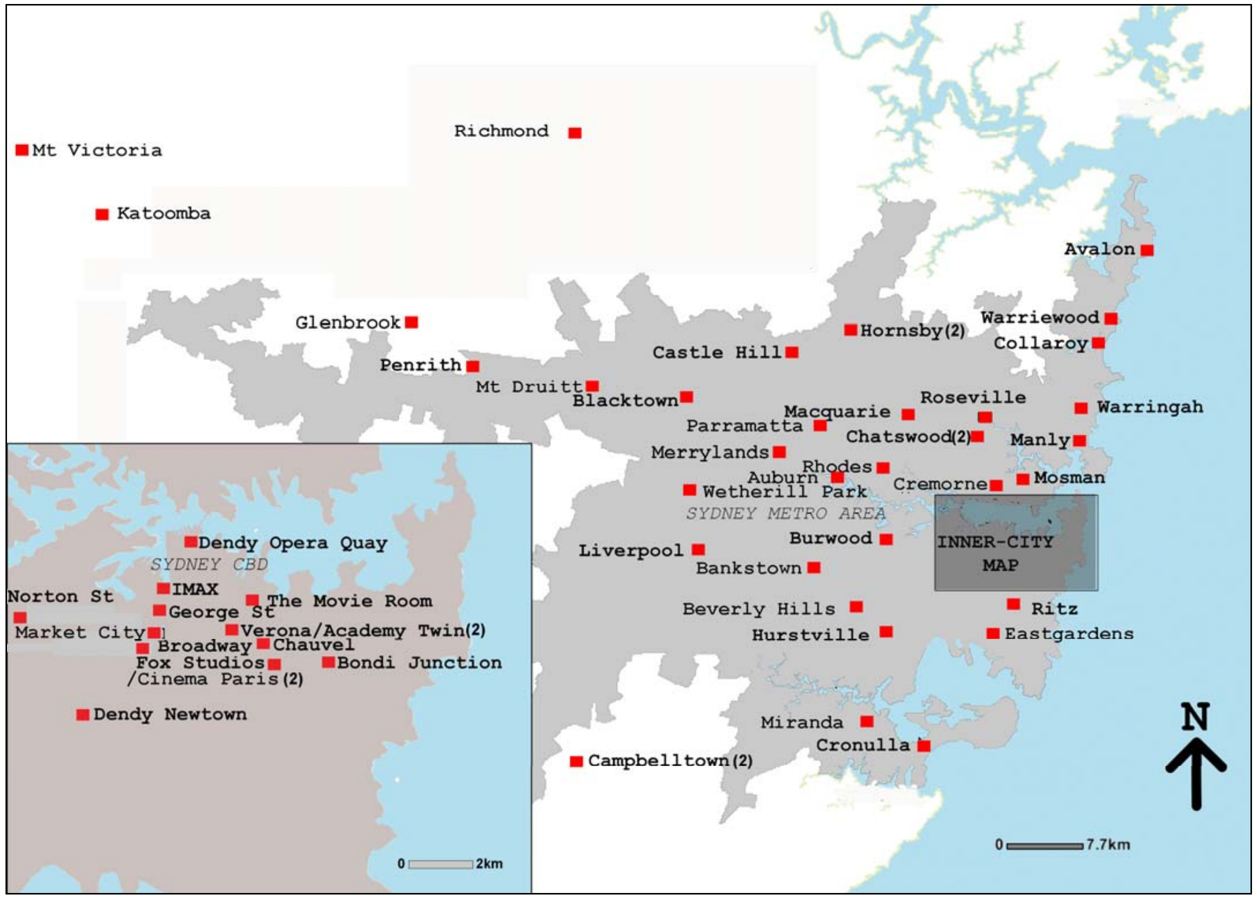

Figure 2: Collection Districts