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, market expansion.

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 that's 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.[1] The Australian cinema market offers a rare partial exception. For example, in Sydney almost all cinemas offer discounted tickets every Tuesday for the entire day.[2] 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%. We exploit this rare (and arguably exogenous) price variation in the Sydney cinema market to estimate the demand for cinema using a comprehensive data set of daily film revenues for cinemas in the greater Sydney region over the year 2007.

Our first goal is to investigate whether this experiment with discounting has been successful. Has it led to an increase in cinema attendance, or has it simply induced consumers to switch the timing of their attendance? The purpose of discounted pricing is typically to lure consumers into the market and away from competitors. In the case of the Sydney cinema market, discounting is quite well coordinated across cinemas with almost all cinemas engaging in "cheap Tuesday" pricing. In aggregate then, cinemas are likely to benefit only if discounting leads to a market expansion.

To tackle this problem, we consider two alternative market definitions in our demand specification. Our daily market definition includes all films exhibited on a specific day in the choice set of each consumer. An outside good is also available, permitting consumers to opt out of the movie market. Discounting can then lead to substitution away from the outside good or other movies offered on the same day, but not substitution away from movies on other days of the week. By not allowing such temporal substitution, this definition could overstate the market expansion due to cheap Tuesday pricing. Our weekly market definition is designed to address this problem by including all films screening over the week within the choice set of each consumer.[3] Using this definition, we can examine whether discounting has led to substitution away from the outside good or substitution away from other films offered during the week.

[1] Orbach and Einav (2007) 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 (2007) conclude that exhibitors could increase profits if they practiced variable pricing strategies.

[2] 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.

[3] We thank Philip Leslie for suggesting this alternative market definition.

Our second goal is to examine the potential profitability of additional price dispersion. Despite weekly discounting, a remarkable degree of price uniformity remains in the Sydney market. In particular, we observe the two pricing puzzles discussed by Orbach and Einav (2007): 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 uniformly). Armed with our demand estimates, we simulate optimal pricing for different types of films, ranging from a film in the middle of its run to an opening week film to a blockbuster in opening week. This allows us to examine the returns to price adjustments for different categories of films.

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. An additional contribution of our work is then to obtain demand estimates in a setting with substantial price variation. We observe prices that vary by around 30% in every week of the sample for each cinema-film pair. We also make use of 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), 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 preferences for movie offerings, our strategy is based on the empirical model 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 on Tuesdays 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.[4] Under this assumption, an indicator variable for Tuesdays represents a valid instrument for prices.[5] 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

[4]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).

[5]In fact, in estimation we include a 'cheap day' dummy variable as four independent cinemas actually offer a cheap Monday ticket and one cinema offers a cheap Thursday ticket in our sample. Further details are provided in Section 4.

variation in price on Tuesdays. However, we have no reason to suspect demand differs systematically between Mondays, Tuesdays, Wednesdays, and Thursdays. 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.[6] 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-maximising 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.

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 around 2.5 or higher; cross-price elasticities are quite low, leading us to believe that much substitution takes place with the outside good; and there are intuitive relationships between cinema attendance and a range of film-, cinema-, and time-specific characteristics. Both our daily and weekly models suggest that the effect of discounting has been not only a market expansion, but an increase in revenue. Finally, our revenue-maximisation problem is consistent with systematic overpricing for a substantial subset of cinema tickets. For a typical film in our dataset, our demand estimates suggest that a price reduction would raise revenue without stretching screening capacity. However, for a subset of films (such as opening week films with wide release), it is plausible that screening capacity could be constrained in the presence of substantial discounting.[7]

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 modeling demand. Einav (2007) and Moul (2007) both employ nested logit models on weekly revenue data (observed at the national level), exploring seasonality of demand and word-of-mouth

[6] 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.

[7] 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. However, an important complicating factor is the role of 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 exhibition especially pronounced as the two largest theatre circuits (Hoyts and Greater Union) account for more than 77% of sales in our sample.[8] Theatrical distribution is dominated by the six major U.S. based studio distributors who account for 75% of turnover in our sample.[9] 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 895m Australian dollars (A$) 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.[10] 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

[8]In our sample, the Hirfindahl-Hirschmann index is 0.33 for exhibition and 0.11 for distribution.

[9]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.

[10]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.

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 $f \in \{1, \ldots, F_{ht}\}$ at theatre (house) $h \in \{1, \ldots, H_t\}$ on day $t \in \{1, \ldots, T\}$ 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[11]; and x_{fht} is a vector of product characteristics. In particular, x_{fht} includes time-varying film characteristics (e.g. an opening day indicator and week of run indicator variables), theatre characteristics (e.g. number of screens, shopping centre location), and 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 driving distance between consumer i and theatre h. Film-specific fixed effects are captured by ϕ_f. Time-invariant film characteristics (e.g. budget, advertising, reviews, cast, genre) are then recovered in an auxiliary regression in the manner of Nevo (2001). 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[12], 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

[11] 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.

[12] 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.

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 define the scope of the market to be the greater Sydney region within 30km of a cinema, yielding a market size of just over 4 million people.[13] 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. With the majority of new releases occurring on Thursdays, we define a week as the period Thursday to Wednesday. 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. Again, equation (5) can be defined in either the daily or weekly market context.

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.[14] 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

[13] Additional details are contained in Section 4.3.

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

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:

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

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 four alternative definitions of the ownership matrix Ω_t, corresponding to four forms of theatre competition. First, we consider the possibility outlined above 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. Third, we consider market structure at the distributor level by assuming that distributors choose prices to maximise the profits of their basket of exhibited films. That is, $\Omega_t(f, g) = 1$ if films f and g are associated with the same distributor, and 0 otherwise. Finally, we also examine the joint-revenue maximisation problem of the industry by defining Ω_t as a matrix of ones.[15]

[15]It should be noted that in reality, optimal price setting from the exhibitor or distributor perspective

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 cinemas, 13 are owned by Hoyts, 12 by Greater Union, four by Palace, three 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 148,680 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$1,288 (A$569), 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).[16] 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.[17] 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 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*

is likely to be confounded by a number of other considerations beyond the simple ownership structure we have posited. For example, the exhibitor likely considers sales of popcorn, drinks and other snack bar items in her objective function, while the distributor likely considers ancillary (potentially substitute) markets related to DVD/Blu-ray sales or on-demand viewing. In addition, many exhibitors practice more subtle forms of price discrimination with respect to loyalty programs and promotions which would affect optimal price setting behaviour. Also, the repeated interaction between large distributors and exhibitors might impact on the nature of price setting. This last consideration is a potential motivation for our market-level definition of the ownership matrix Ω_t. We are indebted to a referee for drawing our attention to some of these possibilities.

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

[17]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.

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). Review ratings were obtained for 257 out of the total 314 films of the sample.

We 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.[18] 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 a relatively flexible manner by including individual dummy variables for weeks 1-10.[19]

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 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

[18] The full data set actually defines genre over 20 categories. We focus on the largest three. These collectively account for 73% of all observations.

[19] Only a very small fraction of films (1.1%) last longer than 10 weeks in our sample.

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.[20] 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.[21]

Our primary revenue data are aggregated across ticket types while our price data are disaggregated by ticket type. We therefore construct daily weighted average prices and admissions by theatre and film. We use supplementary data on revenues for Greater Union (Dataset 3), which is disaggregated by ticket type, to construct weights for different ticket types. We then use these weights to calculate weighted average prices and quantities at the theatre level, aggregated across ticket types.

More precisely, we use the following procedure. We use superscripts to specify datasets and subscripts to indicate the dimension of variation, and abuse our earlier notation slightly.

1. Calculate a set of theatre weights by dividing theatre-specific annual revenue by aggregated annual revenue from our primary dataset, $w_h = R_h^1/R^1$;

2. use these theatre weights and our disaggregated ticket prices to construct weighted average ticket prices by ticket type, $p_{kt} = \sum_h w_h p_{hkt}^2$, where the time subscript indicates intra-weekly variation (e.g. cheap Tuesdays) and k indexes ticket type;

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

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

3. 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, $q_k = R_k^3/p_k$ and weights given by $w_k = q_k/(\sum_k q_k)$;[22]

4. use these weights to construct theatre-specific prices, aggregated across ticket types, $p_{ht} = \sum_k w_k p_{hkt}^1$; and

5. use our constructed weighted average prices and the revenue data to construct admissions (quantity) data, $q_{fht} = R_{fht}^1/p_{ht}$.

Using this method, the weights we apply are 0.56 to the price of an adult ticket, 0.21 to the price of a student ticket, 0.18 to the price of a child ticket, and 0.05 to the price of a pensioner ticket. The 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. Four theatres offer cheap Monday tickets (all owned by Palace) and one theatre offers cheap Thursday tickets (Mt. Victoria Flicks). Of the remaining 45 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

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

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. All distances are calculated as driving distances. 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. In particular, the empirical distribution of age conditional on location, $P(a|L)$, and the empirical distribution of income conditional on age and location, $P(y|a, L)$, are both available from the Census. This allows us to construct $P(D|L) = P(a, y|L) = P(y|a, L)P(a|L)$.

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.[23] 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:[24]

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

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

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

[24]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).

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 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 auxiliary 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 discounted ticket prices on Tuesdays. We include a dummy variable for the cheap ticket day in our instrument set. For most cinemas in our sample the cheap ticket day is a Tuesday, for a small minority of four it is a Monday, and for a single theatre it is a Thursday. 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 principle, 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.

5.1 Identification

Our parameter estimates are identified by 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. Most cinemas offered a fixed menu of prices over our sample, with prices varying by ticket type and day of the week. The primary source of time-series variation is the common practice of offering cheap Tuesday tickets. In addition, a small number of small theatres offered cheap tickets on Mondays instead. Cross-section variation is limited by uniform pricing practices. Cinemas charge the same price for all offerings on a given day. The source of cross-section variation is then price differences across cinemas.

The above price variation is sufficient to identify the average price sensitivity, α. In fact, the depth and regularity of price discounting permits precise estimates of α. However, to separately identify heterogeneity in preferences toward price, we need variation in relative prices. For this we rely on variation in relative prices of similar movies at neighbouring theatres in different areas. The existence of a small number of cinemas offering discounted prices on Mondays aids identification. As we discuss in the next section, we found our estimates of heterogeneity to be sensitive to specification.

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. This variation was somewhat limited, leading to challenges in identifying heterogeneity parameters. Accordingly, we restricted attention to heterogeneity with respect to the week of run of a film. 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 somewhat limited. We briefly return to this issue in the discussion of our results.

Heterogeneity in movie attendance conditional on product characteristics identifies the random coefficient on the constant. 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.

Features of our data also had more fundamental implications for our demand model.

As an alternative to our random coefficients model, we also considered a variety of nested logit models. The nested logit model incorporates heterogeneity by permitting substitution patterns to differ within and between groups. Relative to the MNL model, estimation of the (single-level) nested logit model requires inclusion of an inside share variable as an explanatory variable, where the inside share is the market share of a product within its product grouping. The principal empirical challenge lies with the potential endogeneity of this inside share variable; the inside market share of a product is likely related to unobserved characteristics of the product. Instrumental variables are a common solution; for example, Ho et al. (2012) and Einav (2007) use this strategy to estimate nested logit models in similar contexts. In these settings, the presence of multiple markets is an important element of the instrumental variables strategy. In our setting, we are restricted to a single market, hampering our ability to devise valid instrumental variables. Consequently, we do not present estimates of the nested logit model.[25]

6 Results

Parameter estimates are contained in Tables 5 and 6. Table 5 presents estimates of equation (1), while Table 6 presents the results of an auxiliary regression to recover parameter estimates for time-invariant film characteristics. Columns 1-3 of Table 5 consider our daily market definition, while columns 4-6 relate to our weekly market definition. Columns 1 and 4 present estimates of a simple multi-nomial logit (MNL) model in which our heterogeneity parameters are absent, while the remaining columns present estimates from our random coefficients (RC) model. In our MNL model, demographic variables are included as additional product characteristics and are considered as 'distance rings' around each theatre following Davis (2006). For example, 'Pop[0,5]' and 'Pop(5,10]' measure the proportion of the total population (approximately 4 million) living within 5 kilometres of theatre h, and living between 5 and 10 kilometres from theatre h, respectively. An example distance ring is provided in Figure 2. 'log(Age)[a,b]' and 'log(income)[a,b]' measure the (log) weighted-averages of the median age and median income, respectively, of each collection district within the distance ring [a,b], where weights are population proportion of each collection district within the distance ring. Columns 2 and 5 contain estimates of the RC model where we allow heterogeneity with respect to consumer location, age

[25] Notice that our empirical setting presents different challenges for the nested logit and random coefficients models. In particular, the endogeneity problem that surfaces in the nested logit model is less relevant for the random coefficients model. To see this, compare closely related versions of each model. The nested logit model with two groups consisting of the outside good and all "inside" goods has similar economic implications to the random coefficients model in which consumer heterogeneity is limited to the constant term. Specifically, both models could generate the same substitution patterns. However, the econometric challenges presented by each model are different. In the nested logit model, the nesting parameter which determines substitution patterns is identified by the relationship between the normalised market share of a product and its inside share. Inferring this relationship is complicated by the likely correlation of the inside share with unobserved product characteristics. By contrast, with the random coefficients model, the heterogeneity parameter is determined by the variance in the outside share conditional on product characteristics. The relationship between unobserved product characteristics and the variance in the share of the outside good is likely to be much weaker, and the same endogeneity problem does not arise.

and income, and heterogeneity in preferences for the outside good and attendance in the opening week of a film. In columns 3 and 6, we include, in addition, heterogeneity in preferences over price.

The coefficients on price suggest that demand is relatively elastic. In the MNL model and the RC model that omits the price heterogeneity term, the price sensitivity parameter is in the vicinity of -0.2 for each specification.[26] This translates to a median film-level own-price elasticity of around 3.34 for the daily RC model (column 2) and 2.45 for the weekly RC model (column 5). This magnitude is similar to other (mostly time series) studies which have found elastic own price demand.[27] Our estimates of mean preferences towards price were sensitive to the inclusion of heterogeneity in price preferences, and this is particularly evident in our daily model estimates of column 3. However, the implied estimates of demand elasticities are somewhat less sensitive. We estimate median film-level own-price elasticities of 3.91 and 1.72 for the daily (column 3) and weekly (column 6) models, respectively. In (unreported) first stage regressions for our MNL model, our cheap ticket indicator variable plays an important role, accounting for much of the variation in price.

We include time-variant theatre-specific film variables relating to previews and opening day sessions, and we include indicator variables (unreported) for each week of the run of a film. Consistent with Davis (2006), Einav (2007), and Moul (2007), consumers prefer to see a film earlier in its run with opening day being particularly attractive. Interest in movie attendance declines approximately linearly with the week of the run, particularly for the first 8 weeks of a movie's run (which accounts for the bulk of our data). The numeraire is a film running beyond week 10 of its release, and the Preview coefficient is consistent with interest similar to a mid-run film. Academy Award nominations have a mixed relationship with attendance, but the effect of a win is estimated to be negative. This is a likely manifestation of the fact that the eventual winners had all spent considerable time in cinemas prior to their wins.[28]

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 movie goers. 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 the MNL model, the fact that the coefficient of 'Pop[0,5]' is substantially greater than that of 'Pop(5,10]' is consistent with travel costs associated with cinema attendance as in Davis (2006). Against a-priori expectations, we see that an increase in the median age increases attendance, and consistent with a-priori expectations an increase in median weekly income is associated with increased attendance, with these relationships being

[26] 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.

[27] 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.

[28] Notice that, while our specification of the dynamic path of attendance is quite flexible, it is still restrictive: we impose the same dynamic pattern of attendance for all firms. Our results suggest that the dynamic path of attendance is different for these successful films.

weaker or even negative at greater distances (i.e. 5 to 10 kilometres away). This suggests that the demographic profile further away from a cinema has little direct bearing on cinema performance. These observations are consistent with the existence of travel costs in cinema attendance.

Table 6 presents coefficient estimates on time-invariant film characteristics. As we might expect, there is a positive relationship between attendance and a film's budget and advertising spending (with the exception of our daily model allowing for price heterogeneity), while screening a film at a greater number of locations dilutes the audience at any one theatre. Sequels, and films attracting favourable reviews are associated with larger audiences. We observe a negative relationship between attendance and the presence of stars in a film. A possible explanation is that the film's budget and advertising already controls for the appeal of marquee cast. Coefficients on our genre and ratings indicator variables suggest that attendance is greater for comedies, action movies, and 'M' and 'PG' rated movies, and is lower for dramas.

Consider next the parameters related to consumer heterogeneity in Table 5. Recall that travel costs enter with a negative sign. In all specifications, the distance coefficient is highly significant, but estimated to be quite small, particularly for the weekly specifications. 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.[29] Heterogeneity in the constant term suggests consumers differ in their propensity to substitute between movies rather than forego movie attendance altogether. Columns 2 and 5 permit heterogeneity in preferences for opening week films, and columns 3 and 6 allow, in addition, heterogeneity in preferences towards price. We observe heterogeneity in preferences for opening offerings. However, for our weekly models, the extent of heterogeneity identified is quite sensitive to specification changes. We also identify heterogeneity in price sensitivity, but we found the magnitude of this parameter to be relatively sensitive in alternative specifications we considered. Finally, in each of these specifications, we also consider the relationship between cinema attendance and local demographic characteristics. 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.

As we presaged in Section 5.1, our empirical setting constrains our ability to identify heterogeneity parameters and this led to sensitivity in our estimates. The restrictive nature of price variation in our sample limited our ability to separately identify the mean and variance of preferences for price.[30] The tendency of cinemas to coordinate the release of new films hampered the identification of the random coefficient on opening week films. Similar considerations led us to rule out more flexible specifications of consumer hetero-

[29]Indeed, according to a Cinema and Video Industry Audience Research survey (conducted by the Cinema Advertising Association) the majority of people decide which film to see in advance of their visit (CAVIAR Consortium, 2000). An additional complication is that some movie goers may see movies near their workplace rather than near their home. We calculate distances relative to the distribution of residential rather than commercial locations.

[30]For example, we note that, while the random coefficient on price is precisely estimated in the models presented, this coefficient is quite sensitive to changes in specification. We have omitted other heterogeneity parameters for this reason.

geneity. For the results that follow, we focus attention on the random coefficients model contained in columns 2 and 5. This specification allows heterogeneity over preferences for opening week attendance but not over price.

6.1 Elasticities

Our demand estimates yield film-level median and mean elasticities of 3.34 and 3.13, respectively, for the daily model, with a standard deviation of 0.45. Elasticities for the weekly model are somewhat lower, with a median, mean, and standard deviation of 2.45, 2.30, and 0.33, respectively. These suggest that film-level demand is relatively elastic. At the market level, estimated elasticities are lower but less than one. We obtain market-level median elasticities for the daily and weekly models of 2.27 and 1.26, respectively.

Tables 7-10 detail a selection of demand elasticities, disaggregated by week of run and by cinema.[31] Table 7 presents summary information on film-level own-price elasticities for the daily and weekly models. The daily (weekly) model is presented in the columns on the left (right). In the top panel, we show elasticities by the week of a movie's run. Our specification allows heterogeneity in preferences for opening week films, but does not admit additional heterogeneity over the life of a film. The variation in own-price elasticities beyond week one of a film then stems from changes in the mix of films and cinemas conditional on week. The bottom panel presents analogous information indexed 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.

Table 8 presents median film-level cross-price elasticities by week of run. Estimates for the daily (weekly) model are presented in the top (bottom) panel. 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 for both market definitions, elasticities tend to fall with week of run as more consumers switch to the outside good. The weekly market definition admits a larger set of substitute products. The propensity to substitute to any specific product is then reduced, leading to lower estimated cross-price elasticities for the weekly model.

Table 9 presents analogous information with cross-price elasticities disaggregated by cinema. Again, we see predominantly lower elasticities in the weekly model, reflecting the greater number of substitute products. The higher estimated travel costs of the daily model are also reflected in the substitution patterns. We observe a greater sensitivity to location in the daily model. In particular, cross-price elasticities for films within the same cinema are markedly higher in the daily model, but not the weekly model.

Table 10 presents cinema-level cross-price elasticities. Diagonal elements represent own-price elasticities, and off-diagonals contain cross-price elasticities. At the cinema level, demand is still elastic, with own-price elasticities in the vicinity of 3 - 3.5 for most cinemas in the daily model and in the range 2 - 2.5 for most cinemas in the weekly model. This finding is consistent with our conjecture that the daily model may overstate the extent of market expansion due to the daily model not permitting substitution between

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

days—by definition. Once we aggregate to the cinema level, we see noticeable substitution across cinemas. In the daily model, the higher estimated travel cost parameter is again reflected in elasticities that are more sensitive to location.

6.2 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. In this section, we discuss the extent to which our estimates point to a market expansion effect arising from the policy of cheap Tuesday cinema pricing. More pertinently, we are interested in whether discount pricing has led to an expansion in revenues.

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.

Our weekly market definition is designed to overcome this limitation. Our weekly model incorporates in the choice set all films at all theatres showing in the week. Consumers are therefore able to substitute between movies shown on different days of the week. This opens up the possibility that the "cheap Tuesday" policy has led to substitution away from other days in the week. In fact, in this specification, consumers see at most a single movie over the week. That is, any consumer attending a movie on a Tuesday cannot also attend on Wednesday. This specification may therefore also place too much restriction on consumer behaviour. In practice, some consumers who are attracted to cheap Tuesday movies may decide not to visit the cinema on other days in the week, but some consumers may be willing to attend more than once in the week. Consequently, our weekly market definition has the potential to overstate the degree of cannibalisation and/or market stealing.

Because we are unable to account for all of the sources of preference heterogeneity for movies, whether our weekly model overstates or understates the extent of market expansion is ambiguous. In particular, we do not allow for heterogeneity in preference towards the day of screening of a film. To see why this may be important, consider the extreme case provided by the simple MNL with our weekly market definition. 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. 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 implications for our estimates of the market expansion effect are ambiguous, but we have no reason to suspect market expansion is substantially overestimated in our weekly model.[32]

Both our daily and weekly models suggest that the effect of discounting policies on Tuesdays has led to an increase in revenue. Demand elasticities are greater than 1 at the film, cinema, and market level with both market definitions. In both specifications the outside good has a large market share, and much of the substitution is away from the outside good. In the next section, we examine the implications for profit-maximising prices.

6.3 Revenue-maximising prices

In Table 11, we present revenue-maximising prices for a selection of cinemas 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.[33] The first column presents the actual price offered at a specific cinema. The left (right) hand side of the table contains revenue-maximising prices for the daily (weekly) model. Revenue-maximising prices are calculated for a range of ownership structures. Columns (1-4) for each market definition present optimal prices based on cinema-level, circuit-level, distributor-level, and market-level ownership, respectively. In each specification, revenue-maximising prices are below actual prices. Optimal prices are higher for the weekly model, consistent with our lower elasticity estimates for the weekly model. Optimal prices are also higher for more concentrated market structures, with optimal prices under monopoly ownership in the weekly model approaching the observed level of prices. Optimal prices at the circuit level are similar but sometimes higher than at the distributor level, reflecting greater concentration of ownership at the circuit level. Consequently, our results do not suggest a substantial conflict between distributors and exhibitors.

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, 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.[34] 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. The average seats-per-screen at these 13 locations ranges from

[32] A more detailed discussion of this issue is available from the authors on request.

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

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

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 opening on more than 200 and 300 screens as 7.38 and 8.95, respectively, which would be regarded as a large (wide) release in the Australian industry.[35]

This capacity information is contained in the far right column of Table 12.[36] 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-, distributor-, 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.[37]

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.

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

[36]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.

[37]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.

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 an intuitive relationship between attendance and a range of characteristics which relate to the film, theatre, and timing of consumption.

We find that movie demand is price elastic. This suggests that the "cheap Tuesday" discounting experiment has been successful at raising revenue. This conclusion survives several robustness checks. Elasticities are greater than one at the film-, cinema-, and market-level. This result holds both using our daily market definition in which substitution across days of the week is not permitted, and using our weekly market definition in which such substitution is mandated.

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. For example, our simulations suggest mid-run films could be discounted without running into screening capacity constraints.

References

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in equilibrium. *Econometrica*, 63:841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, 25:242–262.

CAVIAR Consortium (2000). CAVIAR 17. Cinema Advertising Association, London.

Dahl, G. and DellaVigna, S. (2009). Does movie violence increase violent crime? *Quarterly Journal of Economics*, 124:677–734.

Davis, P. (2006). Spatial competition in retail markets: Movie theatres. *RAND Journal of Economics*, 37:964–981.

Davis, P. (2010). *Quantitative Techniques for Competition and Antitrust Analysis*. Princeton University Press, Princeton.

De Vany, A. and Walls, W. D. (1996). Bose-Einstein dynamics and adaptive contracting in the motion picture industry. *The Economic Journal*, 106:1493–1514.

Dewenter, R. and Westermann, M. (2005). Cinema demand in Germany. *Journal of Cultural Economics*, 29:213–231.

Einav, L. (2007). Seasonality in the U.S. motion picture industry. *RAND Journal of Economics*, 38:127–145.

Eliashberg, J. and Shugan, S. M. (1997). Film critics: Influencers or predictors? *Journal of Marketing*, 61:68–78.

Greene, W. H. (2008). *Econometric Analysis*. Pearson Prentice Hall, New Jersey, sixth edition.

Ho, K., Ho, J., and Mortimer, J. H. (2012). The use of full-line forcing contracts in the video rental industry. *American Economic Review*, 102:686–719.

Imbens, G. W. and Lancaster, T. (1994). Combining micro and macro data in microeconometric models. *Review of Economic Studies*, 61:655–80.

McKenzie, R. B. (2008). *Why Popcorn Cost So Much at the Movies*. Copernicus, Heidelberg.

Moretti, E. (2011). Social learning and peer effects in consumption: Evidence from movie sales. *Review of Economic Studies*, 78:356–393.

Moul, C. C. (2007). Measuring word-of-mouth's impact on theatrical movie admissions. *Journal of Economics and Management Strategy*, 16:859–892.

Moul, C. C. (2008). Retailer entry conditions and wholesaler conduct: The theatrical distribution of motion pictures. *International Journal of Industrial Organisation*, 26:966–983.

Nevo, A. (2000). A practitioner's guide to estimation of random coefficients logit models of demand. *Journal of Economics and Management Strategy*, 9:513–548.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69:304–342.

Orbach, B. Y. and Einav, L. (2007). Uniform prices for differentiated goods: The case of the movie-theater industry. *International Review of Law and Economics*, 27:129–153.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy*, 110:705–729.

Reinstein, D. A. and Snyder, C. M. (2005). The influence of expert reviews on consumer demand for experience goods: A case study of movie critics. *The Journal of Industrial Economics*, 103:27–51.

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[38]

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

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

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

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

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

[38] 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 auxiliary 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 sampling variance of $\sqrt{N}g(\theta)$ (see, for example, Greene (2008) for additional details).

Table 1: Film Summary Statistics

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

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

Table 2: Theatre Summary Statistics

	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 by Day of Week[a]						
Monday	50	12.35	1.90	5.82	13.07	14.79
Tuesday	50	9.93	1.63	5.82	10.00	14.90
Wednesday	50	12.74	1.67	5.82	13.49	14.90
Thursday	50	12.69	1.81	5.82	13.49	14.90
Friday	50	12.74	1.67	5.82	13.49	14.90
Saturday	50	12.74	1.67	5.82	13.49	14.90
Sunday	50	12.74	1.67	5.82	13.49	14.90

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

Table 3: Daily Total Admission, All Cinemas

	Obs.	Mean	Std. Dev.	Min.	Median	Max
All Days						
Monday	53	23,584	20,625	8,730	13,914	97,320
Tuesday	52	47,338	27,725	23,348	35,394	138,903
Wednesday	52	25,471	23,749	9,627	15,327	117,070
Thursday	52	32,492	19,349	13,363	24,086	93,970
Friday	52	44,820	19,039	24,855	38,479	100,053
Saturday	52	65,699	16,235	37,333	61,018	111,511
Sunday	52	52,775	18,177	31,543	47,115	124,793
Total	365	41,690	25,243	8,730	37,034	138,903
Non-Opening Days						
Monday	53	23,554	13,914	20,599	8,730	96,894
Tuesday	52	47,191	35,394	27,861	16,566	138,903
Wednesday	52	22,908	15,302	17,388	9,627	78,683
Thursday	52	20,542	13,419	18,392	5,726	90,848
Friday	52	44,476	37,595	19,107	24,249	99,780
Saturday	52	65,661	60,978	16,253	37,289	111,476
Sunday	52	52,758	47,115	18,129	31,543	124,223
Total	365	39,541	35,655	25,611	5,726	138,903

Notes: Daily total admissions are estimates based upon cinema-level weighted average ticket prices. See text for details.

Table 4: Collection District and Demographic Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Median	Max
Collection District Population	6,587	613	256.7	0	578	2,765
Minimum Distance to Cinema (kms)	6,587	4.47	5.25	0.02	2.9	29.99
Median Age[a]	6,587	36.58	5.99	17	36	84
Median Weekly Income[a]	6,587	568.2	213.3	0	536	2,000

Notes: [a] Median age and median incomes are weighted by collection district population.

Table 5: Multinomial Logit and Random Coefficients Model Results

	Daily Model			Weekly Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Price	-0.179**	-0.248**	-1.807**	-0.178**	-0.182**	-0.258**
	(0.004)	(0.004)	(0.016)	(0.004)	(0.004)	(0.004)
Time Variant Film at Theatre Variables						
Preview	1.468**	1.501**	1.992**	1.479**	1.556**	1.916**
	(0.096)	(0.103)	(0.161)	(0.097)	(0.108)	(0.131)
Opening Day	0.190**	0.267**	0.861**	0.189**	0.193**	0.280**
	(0.011)	(0.014)	(0.023)	(0.011)	(0.012)	(0.015)
Oscar Nomination	0.080	0.057	-0.354**	0.065	-0.058	-0.056
	(0.061)	(0.068)	(0.094)	(0.061)	(0.064)	(0.104)
Oscar Award	-0.489**	-0.520**	-0.992**	-0.496**	-0.640**	-0.556*
	(0.197)	(0.211)	(0.247)	(0.197)	(0.200)	(0.268)
Week dummies	Yes	Yes	Yes	Yes	Yes	Yes
Day and Date Variables						
Friday	0.605**	0.792**	1.875**	0.600**	0.585**	0.578**
	(0.007)	(0.008)	(0.032)	(0.007)	(0.007)	(0.008)
Saturday	1.058**	1.420**	3.545**	1.047**	1.015**	1.009**
	(0.008)	(0.011)	(0.034)	(0.008)	(0.009)	(0.009)
Sunday	0.819**	1.078**	2.528**	0.811**	0.787**	0.786**
	(0.008)	(0.010)	(0.034)	(0.008)	(0.008)	(0.009)
Public Holiday	0.403**	0.734**	1.918**	0.406**	0.490**	0.921**
	(0.016)	(0.021)	(0.036)	(0.016)	(0.018)	(0.029)
School Holiday	0.523**	0.656**	1.504**	0.550**	0.906**	1.164**
	(0.017)	(0.019)	(0.030)	(0.017)	(0.019)	(0.027)
Weather						
Rainfall	0.005**	0.007**	0.017**	0.005**	0.006**	0.007**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Max to av. Diff	-0.020**	-0.025**	-0.051**	-0.020**	-0.021**	-0.024**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Theatre Variables						
Shopping Centre	0.270**	0.162**	0.402**	0.269**	0.150**	0.144**
	(0.024)	(0.021)	(0.025)	(0.024)	(0.020)	(0.023)
Cinema Screens	0.102**	0.112**	0.144**	0.102**	0.102**	0.093**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Demographics						
Pop[0,5]	6.081**			6.088**		
	(1.011)			(1.011)		
Pop(5,10]	-0.177			-0.170		
	(0.499)			(0.499)		
log(Age)[0,5]	1.119**			1.123**		
	(0.201)			(0.202)		

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	(1)	(2)	(3)	(4)	(5)	(6)
log(Age)(5,10]	-0.785**			-0.790**		
	(0.181)			(0.181)		
log(Income)[0,5]	0.440**			0.438**		
	(0.074)			(0.074)		
log(Income)(5,10]	0.176**			0.180**		
	(0.070)			(0.070)		
Travel Cost						
Travel Cost		0.129**	0.114**		0.012**	0.044**
		(0.002)	(0.004)		(0.001)	(0.003)
Random Coefficients (Std. Dev.)						
Constant		2.397**	0.282**		0.521**	4.017**
		(0.020)	(0.157)		(0.026)	(0.050)
Price			0.613**			0.143**
			(0.005)			(0.002)
Week		2.543**	2.146**		0.207**	10.161**
		(0.030)	(0.114)		(0.058)	(0.078)
Demographics						
Age*[Constant]		-0.146**	-0.228**		0.134**	-0.067**
		(0.001)	(0.006)		(0.000)	(0.001)
log(Income)*[Constant]		0.308**	0.057**		0.598**	0.355**
		(0.005)	(0.016)		(0.002)	(0.004)
Constant	-32.674**	-24.630**	-19.277**	-32.761**	-39.818**	-33.263**
	(0.191)	(0.256)	(0.294)	(0.191)	(0.211)	(0.266)
N	148,680	148,680	148,680	148,680	148,680	148,680

Notes: MNL models (1) and (4) include distance ring demographic effects; RC models (2) and (5) include linear travel cost, and random coefficients on constant and week; RC models (3) and (6) include linear travel cost and random coefficients on constant, price and week. See text for full specification details. Price is instrumented as discussed in text. All models include film fixed effects. Standard errors clustered at the film and theatre level are in parentheses. * and ** denote two tailed significance at 5% and 1% respectively.

Table 6: Film Fixed Effects on Time Invariant Covariates

	Daily Model			Weekly Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Time Invariant Film Variables						
log(Budget)	0.738**	0.738**	1.127**	0.749**	0.732**	0.840**
	(0.009)	(0.012)	(0.014)	(0.009)	(0.010)	(0.013)
log(Adpub)	0.134**	0.169**	-0.010	0.132**	0.269**	0.356**
	(0.010)	(0.014)	(0.016)	(0.010)	(0.010)	(0.013)
log(OpWkScrns)	-0.242**	-0.257**	-0.501**	-0.247**	-0.369**	-0.439**
	(0.011)	(0.016)	(0.017)	(0.011)	(0.011)	(0.015)
Star	-0.481**	-0.492**	-1.284**	-0.494**	-0.453**	-0.452**
	(0.017)	(0.023)	(0.024)	(0.017)	(0.019)	(0.024)
Sequel	0.193**	0.289**	0.103**	0.195**	0.278**	0.385**
	(0.025)	(0.032)	(0.036)	(0.025)	(0.026)	(0.033)
Review	0.267**	0.288**	0.444**	0.267**	0.299**	0.258**
	(0.012)	(0.016)	(0.018)	(0.012)	(0.014)	(0.017)
Action	0.127**	0.123**	0.393**	0.126**	0.108**	0.202**
	(0.025)	(0.031)	(0.035)	(0.025)	(0.026)	(0.033)
Comedy	0.479**	0.633**	1.304**	0.478**	0.475**	0.509**
	(0.023)	(0.029)	(0.029)	(0.023)	(0.025)	(0.031)
Drama	-0.356**	-0.380**	-0.893**	-0.364**	-0.388**	-0.618**
	(0.023)	(0.030)	(0.032)	(0.023)	(0.026)	(0.032)
M	0.467**	0.437**	0.767**	0.475**	0.452**	0.263**
	(0.030)	(0.039)	(0.046)	(0.030)	(0.031)	(0.040)
MA15+	-0.039	0.179**	-0.051	-0.052	-0.008	-0.055
	(0.033)	(0.044)	(0.048)	(0.033)	(0.036)	(0.045)
PG	0.500**	0.612**	1.151**	0.513**	0.543**	0.597**
	(0.031)	(0.042)	(0.048)	(0.031)	(0.032)	(0.041)
R18+	0.343**	0.365**	0.266**	0.344**	0.346**	0.132
	(0.063)	(0.072)	(0.083)	(0.063)	(0.066)	(0.080)
N	122	122	122	122	122	122

Notes: Estimates derive from auxiliary regression of film fixed effects (derived from models (1)-(6) reported in Table 5) on time-invariant film covariates where the complete set of film covariates is observed. From the full set of 314 film fixed effects, the complete set of covariates is observed for 122 films.

Table 7: Own-Price Elasticities

		Daily Model			Weekly Model		
	Obs	Mean	Median	SD	Mean	Median	SD
Week/Day of Run							
Preview	1,508	-3.272	-3.371	0.288	-2.398	-2.471	0.211
Opening Day	4,618	-3.194	-3.323	0.365	-2.363	-2.450	0.268
Week 1	30,317	-3.087	-3.290	0.450	-2.284	-2.449	0.330
Week 2	29,641	-3.126	-3.345	0.450	-2.293	-2.450	0.329
Week 3	25,595	-3.133	-3.346	0.448	-2.296	-2.450	0.328
Week 4	20,768	-3.134	-3.346	0.452	-2.297	-2.450	0.331
Week 5	14,977	-3.141	-3.346	0.448	-2.301	-2.450	0.328
Week 6	10,219	-3.157	-3.363	0.435	-2.312	-2.466	0.319
Week 7	6,613	-3.156	-3.366	0.443	-2.312	-2.466	0.325
Week 8	4,005	-3.166	-3.367	0.435	-2.319	-2.466	0.318
Cinema							
George St.	6,036	-3.331	-3.480	0.351	-2.445	-2.550	0.256
Bondi Jn.	4,281	-3.267	-3.402	0.322	-2.397	-2.493	0.236
Broadway	5,497	-3.239	-3.366	0.308	-2.375	-2.466	0.226
Campbelltown	3,975	-3.229	-3.374	0.317	-2.382	-2.476	0.230
Blacktown	4,248	-3.220	-3.344	0.300	-2.361	-2.450	0.220
Warringah	3,950	-3.232	-3.376	0.322	-2.391	-2.485	0.233
Fox Studios	4,786	-3.157	-3.271	0.274	-2.314	-2.396	0.201
Newtown	2,317	-2.900	-3.008	0.268	-2.125	-2.204	0.196
Academy	921	-3.499	-3.692	0.469	-2.565	-2.705	0.344
Cremorne	3,609	-3.273	-3.365	0.220	-2.402	-2.466	0.161

Notes: Own price elasticities derive from models (2) and (5) as reported in Table 5.

Table 8: Cross-Price Elasticities by Week of Run (Film Level)

	1	2	3	4	5	6	7	8	9	10
Daily Model										
1. Preview	0.000413	0.000278	0.000701	0.000802	0.000559	0.000476	0.000444	0.000477	0.000321	0.000376
2. Opening Day	0.000177	0.003786	0.003887	0.000213	0.000162	0.000122	0.000106	0.000077	0.000076	0.000059
3. Week 1	0.000150	0.003678	0.004129	0.000243	0.000179	0.000143	0.000125	0.000093	0.000090	0.000080
4. Week 2	0.000377	0.000478	0.000529	0.000561	0.000363	0.000283	0.000250	0.000215	0.000179	0.000171
5. Week 3	0.000391	0.000494	0.000539	0.000525	0.000405	0.000283	0.000250	0.000200	0.000187	0.000176
6. Week 4	0.000391	0.000477	0.000519	0.000529	0.000366	0.000321	0.000224	0.000210	0.000168	0.000164
7. Week 5	0.000329	0.000480	0.000521	0.000526	0.000391	0.000259	0.000293	0.000175	0.000198	0.000157
8. Week 6	0.000374	0.000485	0.000541	0.000514	0.000369	0.000319	0.000211	0.000244	0.000170	0.000192
9. Week 7	0.000390	0.000519	0.000556	0.000512	0.000417	0.000284	0.000298	0.000175	0.000173	0.000167
10. Week 8	0.000433	0.000518	0.000541	0.000524	0.000391	0.000317	0.000263	0.000272	0.000188	0.000159
Weekly Model										
1. Preview	0.000168	0.000274	0.000333	0.000243	0.000167	0.000142	0.000132	0.000123	0.000093	0.000098
2. Opening Day	0.000161	0.000277	0.000329	0.000233	0.000175	0.000142	0.000121	0.000095	0.000086	0.000077
3. Week 1	0.000159	0.000271	0.000321	0.000231	0.000171	0.000141	0.000121	0.000095	0.000086	0.000077
4. Week 2	0.000160	0.000269	0.000325	0.000267	0.000180	0.000142	0.000128	0.000105	0.000091	0.000081
5. Week 3	0.000166	0.000279	0.000325	0.000253	0.000201	0.000139	0.000124	0.000098	0.000094	0.000083
6. Week 4	0.000166	0.000278	0.000320	0.000250	0.000177	0.000163	0.000112	0.000098	0.000088	0.000079
7. Week 5	0.000139	0.000266	0.000315	0.000251	0.000191	0.000131	0.000151	0.000088	0.000093	0.000076
8. Week 6	0.000136	0.000281	0.000327	0.000240	0.000172	0.000147	0.000103	0.000119	0.000082	0.000085
9. Week 7	0.000160	0.000268	0.000309	0.000246	0.000206	0.000146	0.000143	0.000088	0.000096	0.000074
10. Week 8	0.000161	0.000286	0.000318	0.000235	0.000179	0.000150	0.000130	0.000120	0.000085	0.000083

Notes: Cross price elasticities derive from models (2) and (5) as reported in Table 5. 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 9: Cross-Price Elasticities by Cinema (Film Level)

	1	2	3	4	5	6	7	8	9	10
Daily Model										
1. George St.	0.002004	0.002246	0.001810	0.000034	0.000132	0.002725	0.001211	0.001665	0.001630	0.000447
2. Bondi Jn.	0.002133	0.001949	0.001680	0.000032	0.000115	0.002256	0.001104	0.001668	0.001416	0.000510
3. Broadway	0.002159	0.002129	0.001506	0.000040	0.000132	0.002181	0.001145	0.001647	0.001411	0.000656
4. Campbelltown	0.000046	0.000046	0.000044	0.003270	0.000064	0.000016	0.000033	0.000038	0.000019	0.000060
5. Blacktown	0.000247	0.000224	0.000205	0.000095	0.000696	0.000162	0.000140	0.000180	0.000167	0.000555
6. Warringah	0.003510	0.003153	0.002428	0.000015	0.000121	0.008669	0.001374	0.002847	0.004477	0.002113
7. Fox Studios	0.002183	0.002414	0.001707	0.000032	0.000112	0.002622	0.001124	0.001726	0.001558	0.000672
8. Newtown	0.001988	0.001992	0.001588	0.000044	0.000130	0.001740	0.000746	0.001524	0.001171	0.001242
9. Academy	0.002140	0.002170	0.001727	0.000035	0.000122	0.002673	0.001121	0.000420	0.001578	0.000263
10. Cremorne	0.002571	0.002408	0.001950	0.000023	0.000156	0.005724	0.001152	0.002046	0.002339	-0.000005
Weekly Model										
1. George St.	0.000323	0.000362	0.000279	0.000227	0.000187	0.000224	0.000172	0.000203	0.000250	0.000194
2. Bondi Jn.	0.000337	0.000359	0.000278	0.000230	0.000191	0.000220	0.000171	0.000198	0.000255	0.000195
3. Broadway	0.000335	0.000364	0.000272	0.000229	0.000190	0.000216	0.000169	0.000199	0.000257	0.000194
4. Campbelltown	0.000322	0.000351	0.000268	0.000236	0.000194	0.000211	0.000162	0.000189	0.000242	0.000184
5. Blacktown	0.000322	0.000347	0.000263	0.000227	0.000185	0.000206	0.000159	0.000188	0.000244	0.000184
6. Warringah	0.000340	0.000368	0.000276	0.000228	0.000193	0.000211	0.000169	0.000195	0.000257	0.000194
7. Fox Studios	0.000339	0.000370	0.000279	0.000231	0.000192	0.000222	0.000168	0.000200	0.000259	0.000195
8. Newtown	0.000334	0.000362	0.000273	0.000231	0.000193	0.000222	0.000169	0.000184	0.000256	0.000192
9. Academy	0.000330	0.000353	0.000276	0.000222	0.000186	0.000223	0.000170	0.000198	0.000208	0.000192
10. Cremorne	0.000333	0.000366	0.000278	0.000230	0.000195	0.000231	0.000171	0.000195	0.000253	0.000189

Notes: Cross price elasticities derive from models (2) and (5) as reported in Table 5. 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: Cross-Price Elasticities by Cinema (Cinema Level)

	1	2	3	4	5	6	7	8	9	10
Daily Model										
1. George St.	-3.368187	0.069190	0.066112	0.008034	0.006657	0.080975	0.040610	0.012018	0.006310	0.033386
2. Bondi Jn.	0.095124	-3.327461	0.058108	0.006391	0.005115	0.065113	0.037192	0.010880	0.006132	0.029639
3. Broadway	0.097894	0.060934	-3.301929	0.010105	0.007110	0.063319	0.035443	0.011565	0.005874	0.027766
4. Campbelltown	0.015591	0.008500	0.013008	-3.169197	0.023900	0.000592	0.005193	0.002041	0.000244	0.000922
5. Blacktown	0.016250	0.008968	0.011595	0.032016	-3.297852	0.004154	0.005213	0.001991	0.000713	0.003021
6. Warringah	0.187646	0.104629	0.099427	0.000718	0.003878	-3.076050	0.069407	0.015131	0.009785	0.080700
7. Fox Studios	0.104572	0.068946	0.063763	0.007432	0.005684	0.077193	-3.222685	0.011264	0.006150	0.032105
8. Newtown	0.079199	0.048234	0.049967	0.006817	0.005222	0.042285	0.028186	-2.995928	0.005861	0.021350
9. Academy	0.087644	0.058814	0.056579	0.001624	0.004132	0.059799	0.034558	0.012340	-3.686736	0.027508
10. Cremorne	0.127760	0.076244	0.072116	0.001950	0.004899	0.141992	0.047827	0.012078	0.007150	-3.305150
Weekly Model										
1. George St.	-2.464277	0.061374	0.055934	0.037604	0.034652	0.033676	0.035011	0.013474	0.006801	0.024095
2. Bondi Jn.	0.086290	-2.431593	0.056449	0.037608	0.034642	0.033934	0.035128	0.013588	0.006826	0.024151
3. Broadway	0.085892	0.061581	-2.410617	0.037647	0.034645	0.033702	0.034982	0.013529	0.006790	0.023994
4. Campbelltown	0.081624	0.058066	0.053207	-2.436776	0.034442	0.031756	0.033232	0.012888	0.006416	0.022838
5. Blacktown	0.081557	0.058105	0.053243	0.037398	-2.415351	0.032085	0.033243	0.012829	0.006407	0.022930
6. Warringah	0.085276	0.060914	0.055583	0.036916	0.034298	-2.451404	0.034544	0.013344	0.006697	0.023926
7. Fox Studios	0.086378	0.061960	0.056140	0.037566	0.034616	0.033981	-2.360810	0.013583	0.006830	0.024117
8. Newtown	0.085629	0.061608	0.056545	0.037802	0.034730	0.033720	0.035130	-2.190355	0.006785	0.023898
9. Academy	0.085883	0.062169	0.056755	0.037658	0.034712	0.034059	0.035415	0.013595	-2.698693	0.024055
10. Cremorne	0.085234	0.060853	0.055883	0.037216	0.034346	0.033664	0.034774	0.013331	0.006750	-2.442678

Notes: Cross price elasticities derive from models (2) and (5) as reported in Table 5. 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 11: Observed and Optimal Prices for Selected Cinemas

	Observed	Daily Model				Weekly Model			
	Price	Median Optimal Price				Median Optimal Price			
Cinema		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
George St.	14.042	4.259	5.135	4.509	7.194	5.748	7.511	6.405	12.471
Bondi Junction	13.730	4.256	5.103	4.489	7.068	5.682	7.515	6.410	12.490
Broadway	13.582	4.174	4.672	4.512	7.117	5.661	6.840	6.407	12.464
Campbelltown	13.633	5.485	5.778	4.532	6.357	5.632	7.466	6.385	12.269
Blacktown	13.489	4.235	4.917	4.481	6.451	5.607	6.813	6.384	12.264
Warringah	13.489	4.152	4.755	4.203	7.407	5.612	6.835	6.249	12.417
Fox Studios	13.193	4.127	4.708	4.496	7.186	5.610	6.845	6.409	12.492
Newtown Dendy	12.135	4.064	4.093	4.356	7.030	5.543	5.587	6.068	12.462
Academy Twin	14.897	4.059	4.169	4.137	7.171	5.534	5.671	5.662	12.477
Cremorne Orpheum	13.582	4.146	4.285	4.462	7.660	5.592	5.901	6.068	12.446

Notes: Daily and weekly estimates derive from models (2) and (5), respectively, as reported in Table 5. Optimal prices reported in (1), (2), (3) and (4) refer to different hypothetical cinema ownership arrangements. Specifically, (1) cinema-level ownership, (2) circuit-level ownership, (3) distributor-level ownership, and (4) 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)	(2)	(3)	(4)	Capacity
Daily Model							
All Sessions	144	144	605	539	595	438	957
Opening Week	261	256	789	675	732	494	1,168
Opening Week (Screens > 200)	413	403	1,240	1,061	1,091	779	1,605
Opening Week (Screens > 300)	586	567	1,755	1,509	1,495	1,107	1,947
Weekly Model							
All Sessions	144	145	279	241	268	175	957
Opening Week	261	263	495	425	463	308	1,168
Opening Week (Screens > 200)	413	412	773	663	695	480	1,605
Opening Week (Screens > 300)	586	585	1,085	931	962	672	1,947

Notes: Daily and weekly estimates derive from models (2) and (5), respectively, as reported in Table 5. Optimal prices reported in (1), (2), (3) and (4) refer to different hypothetical cinema ownership arrangements. Specifically, (1) cinema-level ownership, (2) circuit-level ownership, (3) distributor-level ownership, and (4) market-level ownership. Calculation of capacity information is discussed in text.

Figure 1: Cinema Locations

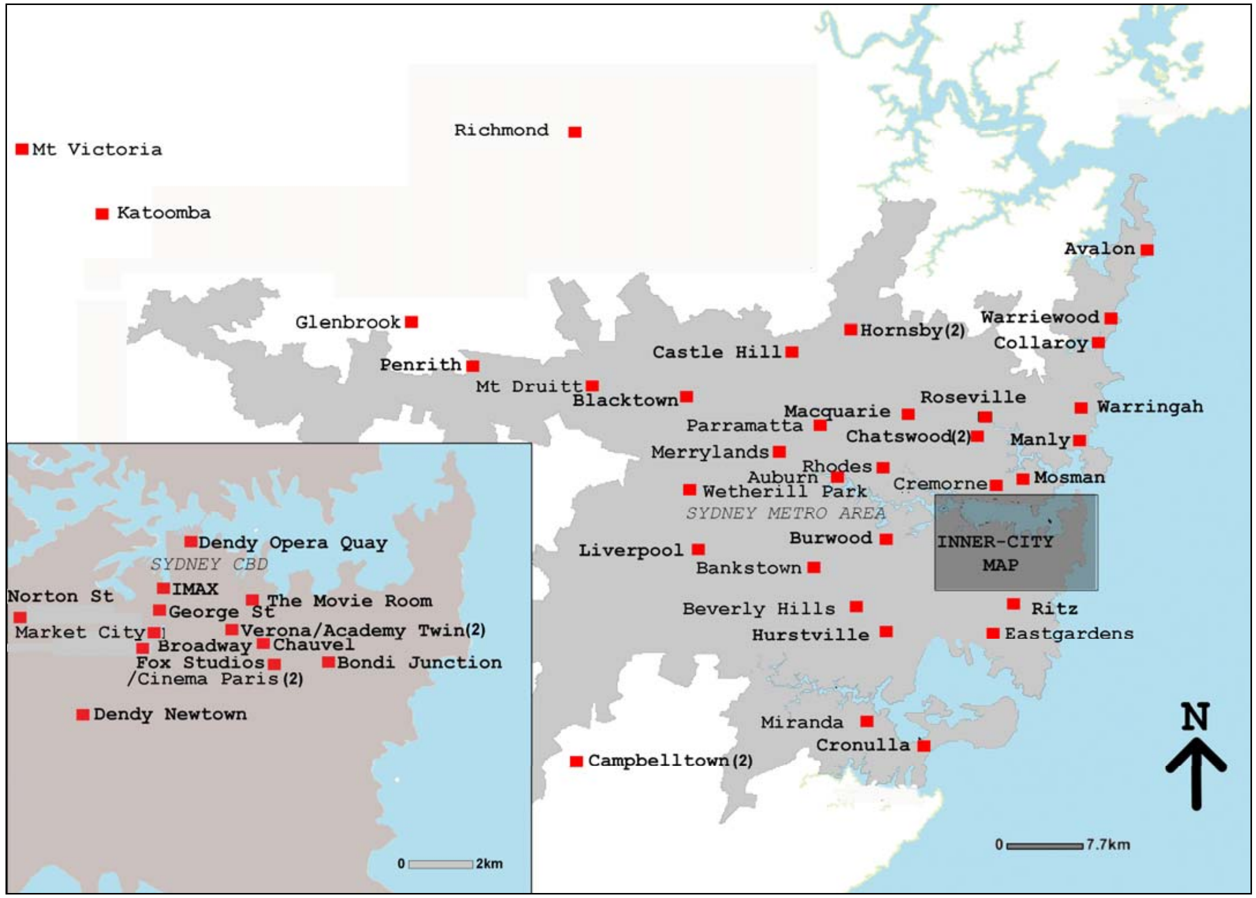

Figure 2: Collection Districts