Quality vs. Variety: Trading Larger Screens for More Shows in the Era of Digital Cinema

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Abstract

Movie exhibitors currently face two forces vying for the limited footprint of their properties. Recent advances have enabled exhibitors to satisfy consumers' long-standing desire for increasingly larger screens. On the other hand, digital technology has reduced the cost of playing the same movie on multiple screens, thereby creating an incentive for screen proliferation to increase the number of show times for a given movie. Increasing the screens also has the added benefit of allowing the exhibitor to expand the number of unique movies screened at a given time. This is fundamentally a tradeoff between quality (larger screen size) and variety (more movies or showings). The goal of this paper is to evaluate consumers' relative valuations of the large screens vs. more shows tradeoff. We use a new data set on movie showings in India at the movie-chain-market-week level to estimate an aggregate discrete-choice demand model providing measures of customer preferences for the number of movie showings and screen size. India provides a valuable setting to study this question because the densely populated cities face substantial space constraints and regional heterogeneity in tastes and languages suggest the option of more shows may be more important in some cities than others. Our findings suggest that regions which are more urban and have a greater share of people with higher education prefer larger screens (quality) while most other regions prefer more showings (variety).

1 Introduction

Providing the variety of products necessary to meet diverse customers' needs often entails sacrifices in quality. For example, Netflix and other movie subscription services aiming to provide a large selection of movies have trouble providing new blockbusters or classics in their lineup. A similar tradeoff between variety and quality arises in movie exhibition. New digital technology enables the same movie to be shown across multiple screens at overlapping times. The quality tradeoff in this case is that exhibitors are considering shrinking screen/auditorium sizes to expand the number of screens and hence potential show times. We consider how consumers tradeoff variety vs. quality in this case of movies where the number of screens vs. the size of each involves a relatively simple tradeoff in how square footage is allocated.

An anecdote from the earliest days of cinema is "the bigger the image, the greater the impact on the viewer".[1] Nevertheless, exhibitors have been shrinking screen sizes as they try to offer a greater variety of movies or greater time flexibility in when a movie is shown. We consider movie exhibitors production of multiplexes in India where recent economic growth is fueling a push toward new theater construction and use of digital technology. The Indian market is insightful to study for three main reasons. First, entrants of new theaters are space constrained by the densely populated cities and therefore cannot afford to build many large screens within a multiplex. Second, there is substantial regional heterogeneity in the breadth of movies watched by the local population suggesting variable preferences for variety. Finally, India is unique in empirically analyzing screen size because customers there are well-versed with the screen size a movie will play in before buying the tickets. Exhibitors often list the screens in which movies will play (see Figure 1 for the choices that come up before a consumer finalizes her theater booking. The movie Terminator Salvation is available in two auditoria - Sathyam and Seasons.) This allows our identification to exploit screen size differences within a theater in addition to the more salient screen size differences across theaters.

[1]Quoted from http://www.imax.com.au/visitor_info/

Figure 1: A consumer can choose both the screen and showtime before booking the movie

Our dataset consists of the number of admits, revenues and number of showings for movies screened between March 2007 and February 2008 at the chain-market-week level. We supplement this data with seat-layout charts, across all theaters in our dataset, which allows us to infer the screen width of each auditorium within a chain. We also use demographic data from the 2001 Census to account for regional heterogeneity.

To analyze the data and evaluate the quality vs. variety tradeoff, we use a demand model similar to that of Davis (2006), who considers whether theater scale choices are optimal. A fundamental difference between our approaches is that he treats the number of screens in a "descriptive" sense by assuming they enter the consumer's utility directly. However, we believe that a consumer's utility is driven by the variety screens can create in terms of the diversity of movies that can be shown or the number of showings of a given movie. Specifically, in regions where customers demand a greater variety of movies, or more showings for a given movie, additional screens will deliver more value than other areas. Furthermore, we compare the value of screens in terms of variety against an explicit opportunity cost: the increase in screen sizes that could have been achieved in place of the extra screen.

Our results indicate that the impact of adding one more show is higher than the impact of increasing screen size. This justifies to some extent the recent shift to multiplexes in India. However, we show that the extent of this impact is market-specific. We find that markets which are more urban and have a higher percentage of people with higher education prefer larger screens.

The empirical literature studying product quality and variety has largely addressed this from the perspective of competition and differentiation (e.g. Draganska, Mazzeo and Seim 2008; Orhun et al 2014; Mazzeo 2003), with little emphasis on consumers' taste for quality and variety. Perhaps closest to our idea of the quality-variety tradeoff is Bohlmann, Golder and Mitra (2002) who theoretically show that pioneers are likely to succeed in markets where consumers' taste for variety is higher than the taste for quality. Our paper contributes to this literature by measuring consumers' preference for quality and variety in a setting where a firm providing one has to necessarily sacrifice the other[2]. Aside from the variety vs. quality tradeoffs, our findings contribute to a growing empirical literature on the movie industry that has covered topics ranging from organizational issues such as movie financing decisions (e.g. Goettler and Leslie, 2005) and contracting (e.g. Gil, 2013) to operational issues such as release and run-length (e.g. Einav, 2007 and Ainslie, Dreze and Zufryden, 2005), pricing (Gil and Hartmann, 2009), and finally post-box office distribution (Mortimer, 2007 and Mortimer 2008). Our analyses is also an input to the determination of the "shelf space" to be allocated in theaters as described by Elberse and Eliashberg (2003). To date this literature has primarily focused on allocating products within this space (e.g. Eliashberg et.al. 2006).

The rest of the paper is organized as follows. The next section outlines the data. Section 3 defines the empirical model and identification. Section 4 provides the model estimates and Section 5 concludes.

2 Data

We use a data set on movie showings in India at the movie-chain-market-week level. Variation in screen size as well as number of shows, necessary to answer our question, is present in our data set. The dataset consists of admits, net collections, shows, occupancy and spans 14 markets, 7 chains, 44 weeks (March 2007 – February 2008) and nearly 600 unique movies.

[2]This ignores costs associated with provision of higher quality and higher variety.

The number of screens specific to a chain in a market was obtained from the chain website. While each chain has only one multiplex in a market, the number of competing chains in each market ranges from two to four.

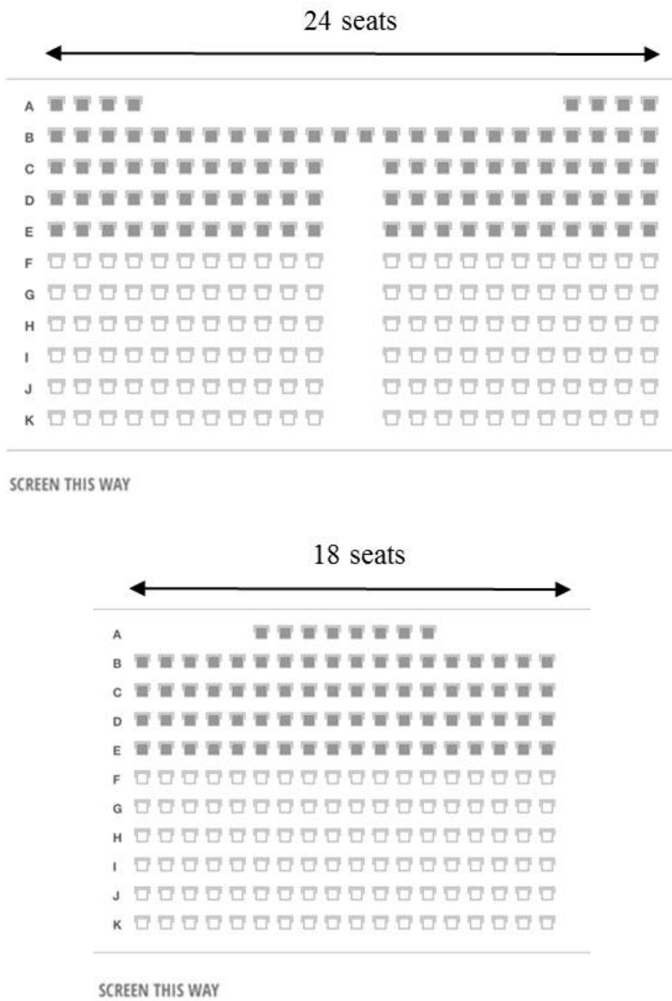
Unlike the US, prices of showings in India vary across markets, chains, movies and time. Weekly price of each movie showing in a chain-market was calculated by dividing the net collections by the total admits.

The number of showings and the occupancy percentage for each movie-chain-market-week combination are available directly from the data. Using the occupancy and admits data, we infer the total seating capacity for each movie showing as:

$$seats_{jclt} = \frac{admits_{jclt}}{occupancy_{jclt} \times shows_{jclt}} \tag{1}$$

Here j indexes movies, c theater-chains, l locations and t the week of the showing.

To map the number of seats to an auditorium's screen width we collect a secondary source of data on each chain's seating configuration for 30 out of the 34 chain-location combinations from the website http://in.bookmyshow.com (the remaining 4 chains are no longer active in the market). in.bookmyshow.com is an online ticket booking portal where consumers can search for movies by chain, location, date and showing. Upon clicking on a particular showing, they are directed to a seat-layout chart and prompted to select their seats and proceed to payment. Using the seat-layout plan provided in this website, we compute the total seating capacity and infer the screen width as the number of seats in the widest row for each auditorium within a chain. Figure 2 shows the layout plan for two auditoria for Chain 5 in Market 4. The first auditorium's seating capacity is 230 seats and it has a wider screen spanning 24 seats, while the second auditorium has a seating capacity of 188 seats and a smaller screen spanning 18 seats. Similarly, Figure 3 shows the layout plan for another chain (Chain 7) in the same market: the first auditorium has a seating capacity of 194 seats and a screen width of 20 seats, while the second auditorium has a capacity of 140 seats and a screen width of 14 seats. This shows that the total seating capacity is a good predictor of screen width not just across auditoria within a chain, but across chains as well.



Source: http://in.bookmyshow.com

Figure 2: Screen size correlates with number of seats

To establish this pattern statistically, we collect this information for every auditorium in every chain-location combination resulting in a total of 122 observations. Figure 4 plots screen width and the total seating capacity across all observations. The plot indicates that the total seating capacity is a good proxy for screen width. A regression of screen width on total seating capacity yields a positive and statistically significant coefficient (Tables 1 and 2). We use the log-log specification (Table 2), because it provides a better fit, to infer the screen width associated with each movie showing in our dataset. Note that when a movie plays on more than one screen, our calculation gives the average screen size the movie played in.

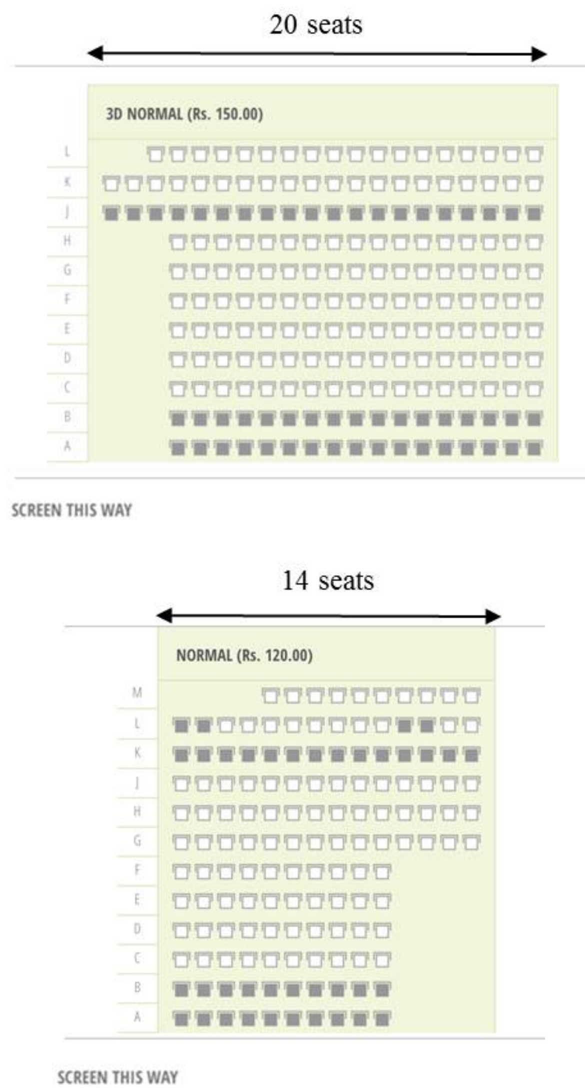


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Figure 3: Seating Configuration: Chain 7, Location 4

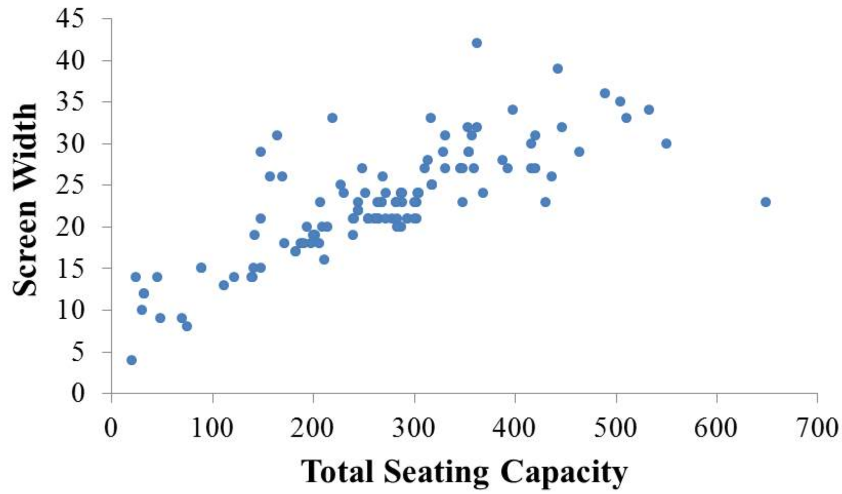

Figure 4: Total Seating Capacity vs. Screen Width

Table 1: Regression Estimates: Screen Width on Total Seating Capacity

Dependent Variable	Screen width	
	coeff	t-stat
Total Seats	0.043	13.81
Constant	11.320	12.31
Adjusted R^2	0.6107	
Observations	122	

Table 2: Regression Estimates: ln(Screen Width) on ln(Total Seating Capacity)

Dependent Variable	ln (Screen width)	
	coeff	t-stat
ln (Total Seats)	0.444	16.98
Constant	0.663	4.62
Adjusted R^2	0.7038	
Observations	122	

Markets were determined mainly by how theaters classified themselves. For example, *PVR - Aurangabad* would belong to the market *Aurangabad*. *Adlabs - Goregaon, Mumbai* and *Adlabs - Mulund, Mumbai* would be treated as belonging to two distinct markets *Goregaon* and *Mulund*. Market shares were computed as admits divided by the population of the market.

As stated in the introduction, a unique feature of the Indian market is that there is likely to be substantial regional heterogeneity in the variety of movies demanded. To account for heterogeneity across locations, we collect demographic information by market from the Indian Census in 2001 available at www. censusindia.gov.in. This includes the percentage of the population that is urban, the percentage of workers in the population, the percentage of people with a graduate education, and the age breakdown. The average, minimum and maximum of these demographic variables across the 14 locations are provided below:

Table 3: Demographics: Summary Statistics

Variable	Description	Mean	Min	Max
Urban	% urban	84%	38%	100%
Educ_graduate	% with graduate degree	6%	1%	12%
Workers_total	% workers	38%	29%	42%
Age_15to59	% in age range 15-59	64%	54%	69%

Movies were classified based on the language of screening. India being a culturally diverse nation, regional movies form a significant portion of the movies being screened. Movies were classified into English (official language), Hindi (national language) and regional (local language of the market). Movies screened in different languages e.g. 'The Fantastic Four' and 'The Fantastic Four (Hindi)' are treated as different movies. This is appropriate as they typically cater to different types of audiences.

Table 4 lists some of the descriptive statistics of the data.

Table 4: Descriptive Statistics

Variable	Description	Mean	Median	Std. Dev
Price (Rs.)	Average weekly price of a movie in Rs.	93	93	37
Screens	Number of screens present in a chain-location	5.16	5	2.37
Screen width	Imputed screen width of a movie screening	22.78	22	4.79
Shows (per week)	Number of showings of a movie	21	14	16
Hindi dummy	The movie's language is Hindi	0.57	1	0.49
English dummy	The movie's language is English	0.32	0	0.46
Observations			9062	

Movies were also distinguished based on their week since release. This weekly distinction among movies is made to capture any demand dampening effects that might be present the further the movie is from its week of release. Moreover any word-of-mouth effects will be picked up by these movie-week fixed effects. Using movie-week fixed-effects rather than movie fixed effects alone will help capture any such patterns in the data that might be missed by not having a dynamic demand specification. A dynamic demand specification would be particularly challenging in this aggregate data analysis. One might be inclined to let the available market shrink over time, but this could not for instance account for customers that want to see the movie multiple times. The potential for word-of-mouth could also greatly complicate the analysis. However, neither of these factors are critical pieces of the analysis because we are not concerned with movie-specific factors.

We now provide preliminary evidence that consumers might value large screens and more shows. A preliminary cut at the data shows that the number of admits increases with increasing screen size (Figure 5) and increasing number of shows (Figure 6). However, there is a potential endogeneity issue here. Chains may screen good movies in larger screens and as demand is likely to be high for good movies, we might wrongly infer that larger screens lead to higher demand if we do not instrument and account for this endogeneity bias. Similarly, good movies may have more shows resulting in an endogeneity bias for shows. Thus, to account for these effects we need instrumental variables. We describe these in the context of our demand equation in Section 3.

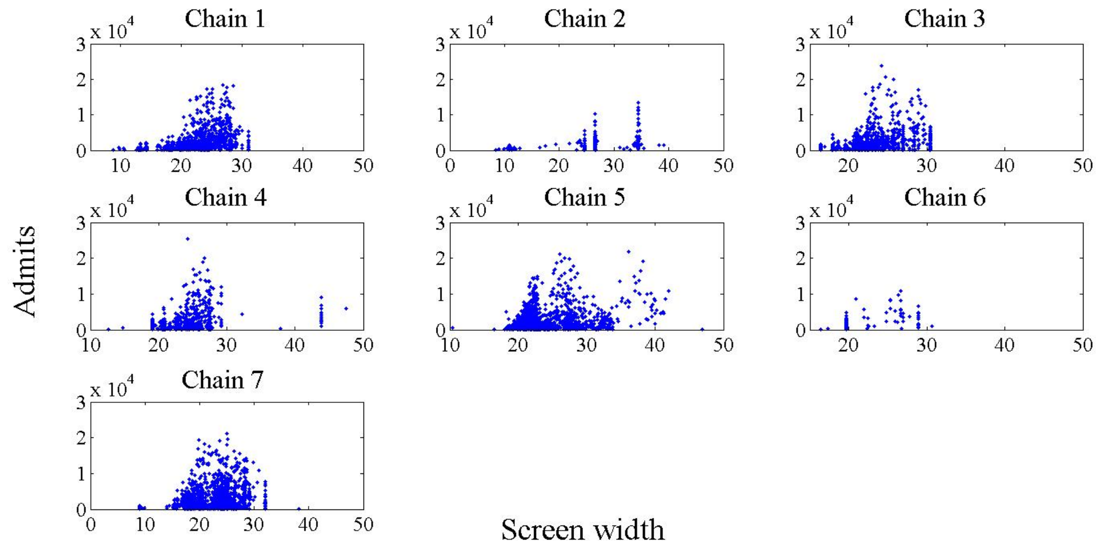

Figure 5: Raw data suggest that demand is positively correlated with screen width

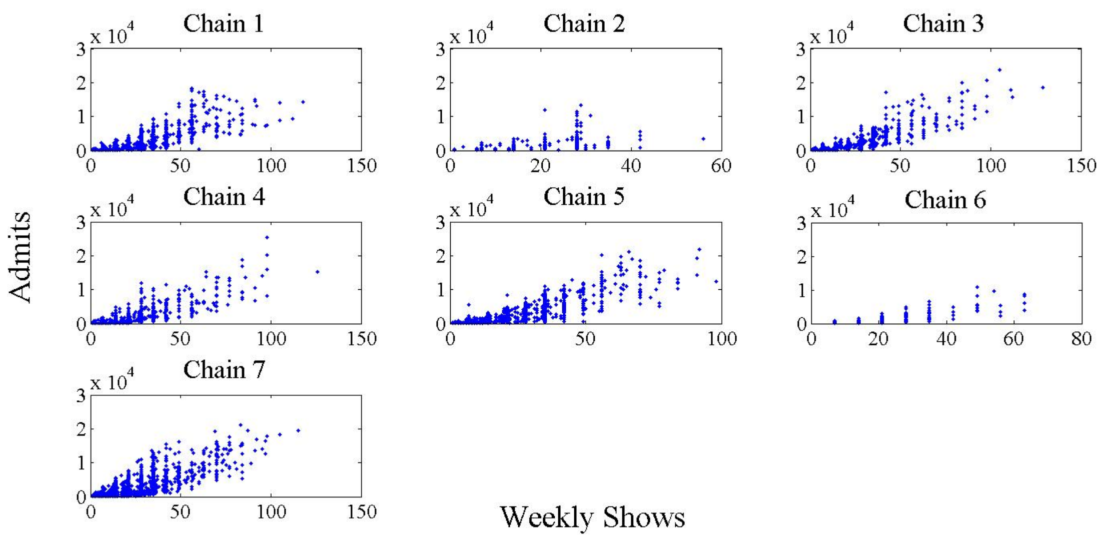

Figure 6: Raw data suggest that demand is positively correlated with number of shows of a movie

3 Demand for Movies

A consumer is assumed to make a choice of which movie to watch from all movies playing in her market in that week. The choice set as well as the number of choices in the set changes from one week to another. Consumers are influenced in their decisions by the movie, language of the movie (English, Hindi or regional), price, the chain the movie is playing in, the week since the movie was first released, the number of shows of the movie at the chain and the screen size of the particular auditorium the movie is being screened at.

A nested logit demand model is specified with consumer's indirect utility specified by the following equation

$$\begin{aligned} U_{ijclt} = \quad & \alpha_{jt} + \alpha_c + \alpha_l + \alpha_{l,lang} + \beta_p price_{jclt} + \left(\tilde{\beta}_{shows} + \beta^d_{shows}.D_l\right) ln\left(shows_{jclt}\right) \\ & + \left(\tilde{\beta}_{size} + \beta^d_{size}.D_l\right) ln\left(size_{jclt}\right) + \xi_{jclt} + \varepsilon_{ijclt} \end{aligned} \tag{2}$$

where

$j \in \{1, \ldots, J_{lt}\}$ denotes the movies available in location l in week t. Note that a movie playing in one chain is considered as a different choice compared to the same movie playing in another chain.

$c \in \{1, \ldots, C_{lt}\}$ denotes the chains in that location (i.e market). The time subscript allows for new chains to enter the market (observed in the data)

$l \in \{1, \ldots, L\}$ denotes the market and

$t \in \{1, \ldots, T\}$ denotes the week

D_l is the vector of demographics in market l. $\tilde{\beta}_{shows}, \tilde{\beta}_{size}$ is the mean vector of coefficients associated with number of showings and screen size and $\beta^d_{shows}, \beta^d_{size}$ measures the interaction of these coefficients with the demographics.

β_p is the price-sensitivity coefficient. $\alpha_{l,lang}$ measures location l's preference for the language, $lang$ = {Hindi,English,Regional}, of a movie screening. α_c, α_l and α_{jt} are chain, location and movie-week fixed effects. Movie-week fixed effects can be identified as we observe movies across time, chains and locations. As mentioned previously, this weekly distinction among movies is made to help tease out any patterns in the data that might be missed by not having a dynamic demand specification (e.g. demand dampening, word-of mouth effects). ξ_{jclt} is the unobserved (to the researcher) characteristic, e.g. the location-specific quality of a movie in a given week, and ε_{ijclt} is the unobserved individual-specific demand shock.

The choices are partitioned into 2 groups with group 1 consisting of the set of all movies playing in that location that week and group 2 consisting of the outside alternative (see Figure 7).

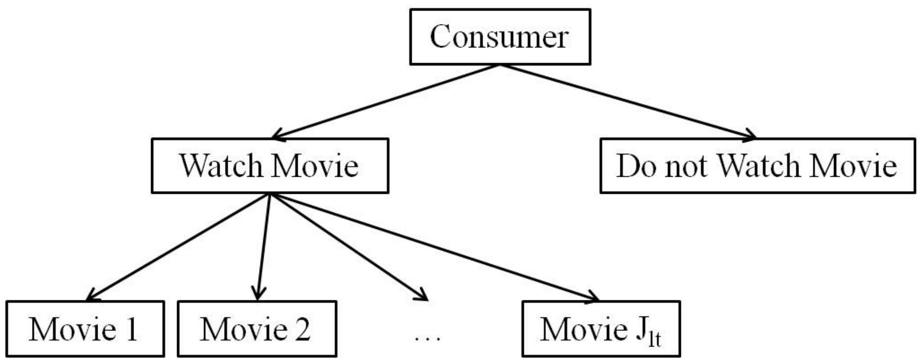

Figure 7: Nested Logit Specification

Following the nested logit formulation, we assume the joint distribution of ε in each market-week as

$$F\left(\varepsilon_0, \varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{J_{lt}}\right) = exp\left(-exp\left(-\varepsilon_0\right) - \left[\sum_{j=1}^{J_{lt}} exp\left(-\rho^{-1}\varepsilon_j\right)\right]^{\rho}\right) \tag{3}$$

The share equation for each movie-chain-market-week is then given by

$$s_{jclt} = \frac{exp\left(\frac{V_{jclt}}{\rho}\right)}{\left(\sum_{k\in J_{lt}} exp\left(\frac{V_{kclt}}{\rho}\right)\right)^{1-\rho}\left(1+\left(\sum_{k\in J_{lt}} exp\left(\frac{V_{kclt}}{\rho}\right)\right)^{\rho}\right)}$$

where $V_{jclt} = U_{ijclt} - \varepsilon_{ijclt}$.

After a few transformations, this translates into the following system of equations

$$ln\left(s_{jclt}\right)-ln\left(s_{0lt}\right)= \alpha_{jt}+\alpha_{c}+\alpha_{l}+\alpha_{l,lang}+\beta_{p}price_{jclt}+\beta_{shows}ln\left(shows_{jclt}\right)+\beta_{size}ln\left(seats_{jclt}\right) +\xi_{jclt}+\left(1-\rho\right)ln\left(\frac{s_{jclt}}{1-s_{0lt}}\right) \tag{4}$$

The standard logit model is obtained when the nesting parameter ρ is 1. When the nesting parameter is 0 there is no substitution between the outside option and the movies nest.

3.1 Endogeneity

Endogeneity can bias the estimates of seats and shows, the main variables of interest, if not accounted for appropriately. Good movies will have more shows and may also be screened in larger screens; these movies will also have high demand. This endogeneity would lead to an upward bias in the estimate for shows and screen size effects. The movie-time fixed effects, α_{jt}, reduce concerns about this bias, but there still could be some local demand shocks for the movies which are correlated with the theater's choice of how many showings or how large a screen to assign. Econometrically, this implies a correlation between ξ_{jclt} and the variables of interest (shows and screen size) chosen at the $jclt$ level. We remove this systematic variation by shifting inference, within movie and time, to cross-chain variation in shows and screen size that is based only on the predetermined chain-location dimensions (number of screens and screen sizes). In other words, by using the predetermined chain-location dimensions as instruments, we remove the variation that is tied directly to how a given movie is matched with the particular number or size of screens in the chain and location.[3]

We instrument for the number showings with the number of available screens at the chain-location. The total number of screens is a good instrument because 1. It is pre-determined

[3] One critique of this approach is that the predicted number of showings is the same for all movies within a chain-location, such that a fixed effect at the chain-location level would remove all variation in this instrument. In the presence of such a fixed effect, an interaction between the instrument and movie characteristics indexed by jt would remove such a concern and predict different numbers of showings across movies within a chain-location.

i.e., theaters cannot adjust the total number of screens in response to demand shocks and 2. It is correlated with the number of shows of a movie at a theater, i.e. a chain with more screens can have more showings. We instrument for the screen size using a summary statistic of the various screen sizes available at the chain-location. Specifically, we use an HHI described in Equation 5 below, that distinguishes between the kinds of screen width present in a given chain. This instrument distinguishes, for example between two theaters with the same total screen width of 50 seat-wide screens, one with one 40-seat wide screen and one 10-seat wide screen and another with two 25-seat wide screens. It removes the endogeneity concerns in much the same way as the number of screens instruments, because it shifts the potential screen size. Both of these instruments are clearly correlated with the observed showings/screen sizes, yet are uncorrelated with the characteristics of any given movie because they were determined well before the observed movies were ever produced.

$$\mathrm{hh}i_c = \sum_{i=1}^{N_c} \left(\frac{screen\ width_i}{\sum_i screen\ width_i} \right)^2 \tag{5}$$

where i refers to an auditorium in chain c which has a total of N auditoria.

Apart from accounting for endogeneity biases in seats and shows, we also have to account for endogeneity that arises from the nesting parameter in Equation 4. A good instrument is one that is unrelated to the share of the movie relative to the outside good but is correlated with the share within the movie nest. Valid instruments include the total number of Hindi (and English) movies playing in that market-week other than the movie under consideration. Einav (2007) uses the total number of movies playing other than the movie under consideration as an instrument and argues that including week- and movie- fixed effects will remove any endogeneity associated with the fact that more movies may be associated with high-demand weeks and that fewer movies may be released along with a high-quality movie respectively. We use all three instruments discussed above to account for endogeneity of the nesting parameter.

Lastly, we instrument for price using the average price of other movies being screened in the particular chain that week.

3.2 Estimation

The estimation recovers β^*, the true parameter vector, that satisfies

$$E\left[\xi\left(\beta^*\right)Z\right]=0$$

This translates to minimizing the GMM objective function

$$\xi\left(\beta\right)^{'}Z\Phi^{-1}Z^{'}\xi\left(\beta\right)$$

where Z is the vector of instruments discussed above. $\xi\left(\beta\right)=Y-X\beta$ where $Y=ln\left(s_{jclt}\right)-ln\left(s_{olt}\right)$ and $X\beta$ is the RHS of Equation 4. Φ is a consistent estimate of $E\left[Z^{'}ww^{'}Z\right]$.

4 Results

Table 5 presents the estimates of the model before[4] and after accounting for the endogeneity bias. As can be seen by the reduction in the magnitude of the shows and seats coefficients, the direction of the endogeneity correction is in line with the potential biases we described above. The coefficients for price, shows and seats coefficients have the intuitive sign and are statistically significant. Chain, market and movie-week fixed effects are included in all specifications.

Specification S1 illustrates the baseline correlation between admits and the variables of interest: shows and screen size. The positive and significant coefficients reaffirm the patterns described in Figures 5 and 6 even after controlling for the price, language of the movie, and chain, location and movie-week effects. Next, in S2, we evaluate whether these relationships

[4]We do not include the nesting parameter in the before estimation as without instrumenting for the nest, this parameter - which is highly correlated with the dependant variable - explains most of the variation in the data.

vary across markets based on demographics. Clearly demographic variables seem to be important. Specification S3 accounts for both the endogeneity in these variables and the potential correlations among options in the choice set via a nested logit. One noticeable change between S3 and S2 is that the sign of the demographic interactions with the shows coefficient reverses. This likely reflects that S2 was picking up correlations between the demands of these demographic groups and the showings. For example, more shows may have been allocated where workers are less likely to go to the movies, but once the endogeneity is accounted for, markets with more workers tend to prefer more showings, all else equal. We also estimated a random coefficients model (Berry, Levinsohn and Pakes 1995, Nevo 2000) that allows for more flexible substitution patterns. However, the estimates of the unobserved heterogeneity were insignificant, leading us to conclude that the nested-logit specification with movie-week fixed-effects is picking up most of the variation in the data. Finally S4 restricts the shows and screen-size coefficients to be positive. The transformation we use for these two variables is:

$$\beta = e^{\widetilde{\beta}+\beta^d(D_l)}$$

where D_l is the vector of demographics in market l, $\widetilde{\beta}$ is the mean vector of coefficients $\beta_{shows}, \beta_{screenwidth}$ and β^d measures the interaction of these coefficients with the demographics. This transformation is done to avoid negative estimates of the screen and shows coefficients at some extreme values of the demographics which arises due to the linear specification.

Across both specifications S3 and S4, the estimates indicate that more urban areas and markets with a larger share of consumers with higher education prefer wider screens (quality) while markets with a greater share of total workers prefer more shows (variety). The estimates also indicate a nesting parameter significantly different from 1 suggesting that the nested logit model fits the data better than the standard logit model. Appendix A presents the first-stage regression results (for S3) showing the validity of the instruments.

Table 5: Estimates across various specifications

	S1	S2	S3	S4
Instruments	No	No	Yes	Yes
Nest	No	No	Yes	Yes
ln(Shows)	0.992	1.605	-8.183	-10.350
	(84.19)	(9.75)	(-7.01)	(-2.97)
ln(Shows) X Urban		-0.180	1.759	2.742
		(-4.28)	(3.99)	(3.32)
ln(Shows) X Educ_graduate		-1.350	6.146	8.741
		(-6.81)	(2.83)	(3.55)
ln(Shows) X Workers_total		-0.999	17.434	17.434
		(-2.85)	(6.38)	(2.06)
ln(Screen width)	0.767	-5.963	-6.232	-7.972
	(23.30)	(-7.51)	(-2.22)	(-2.69)
ln(Screen width) X Urban		1.198	3.060	3.931
		(5.72)	(4.15)	(2.33)
ln(Screen width) X Educ_graduate		10.939	12.386	10.750
		(10.91)	(3.07)	(2.91)
ln(Screen width) X Workers_total		13.268	9.021	8.553
		(8.01)	(1.58)	(1.69)
Price	-0.0003	0.001	-0.002	-0.003
	(-1.23)	(2.57)	(-3.48)	(-5.55)
Nesting Parameter, rho			0.181	0.256
			(5.50)	(10.53)
Fixed-Effects: Chain, Market, Market-Language, Movie-Week				
Adjusted R^2	0.9344	0.9354	0.9607	N/A
GMM Objective Function			13.5811	16.091

Figure 8 plots the change in willingness to pay , if one more show were added (More shows) or the screen size was widened by an equivalent of five seats (Larger screen). The 1 to 5 ratio reflects the opportunity cost of shows in terms of screen size or vice versa and is derived based on an auditorium being able to provide 5 additional show times and having a width of about 25 seats. In other words, the figure below plots $\frac{\beta}{\beta_p}.\Delta X$ where the baseline X = [ln(Shows),ln(Screen width)] is set to the average shows and screens across all observations in the data. There is clearly heterogeneity across locations in the willingness to pay for both shows and screen size. More importantly, the relative value of adding a show or increasing screen size within a location also varies substantially. Most locations prefer the additional show, however Locations 6 and 11 have a stronger preference for larger screens.

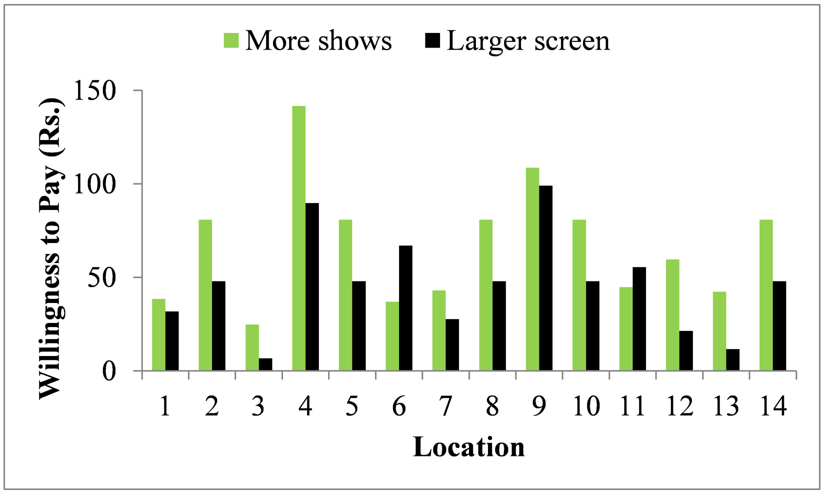

Figure 8: Impact of adding 1 more show or widening the screen by a 4-seat width on consumer's utility by location

As mentioned before, the movie-week fixed effects help us identify patterns that may exist in the data induced by word-of-mouth externalities, demand-dampening dynamic effects etc. Figure 9 shows some relevant interesting patterns that are captured by introducing these movie-week fixed effects. Figure 9 plots, for the movie *Namesake*, the fixed-effects over time since the week of release. As can be seen, demand decreases as the time since release increases. The increase in demand beginning in week 5 may be due to the movie only being retained in locations where it was a hit. The figure also plots these fixed-effects for the movie Blood Diamond which picks up demand as the time to the Oscar nominations announcement nears. The Oscar nominations announcements were released on Jan 23rd 2007, about a month after Blood Diamond's release.

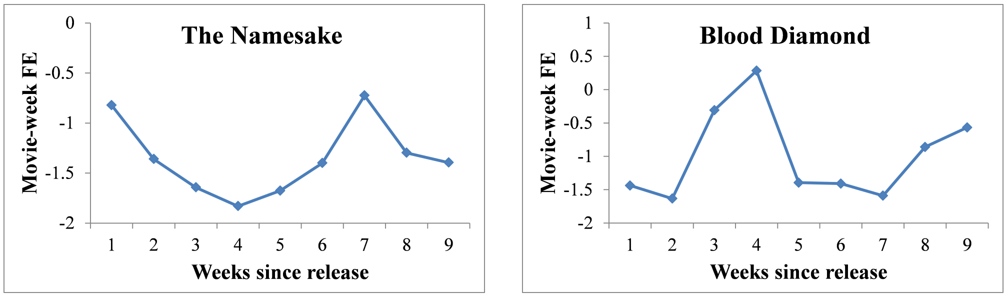

Figure 9: Movie-week fixed effects picking up interesting patterns in the data

5 Conclusion

A demand model providing measures of customer preferences for the number of movie showings and screen size was estimated using a new data set on movie showings in India at the movie-chain-market-week level. The trade-off between large screens and more shows was viewed in the context of the digital era. Digital technology reduces the costs of additional screenings for a given movie, because a digital copy of a movie can be more easily played on multiple screens at the same time. Whether this can help increase revenues depends on how much customers value the additional showings relative to the tradeoff of smaller screen sizes. Consistent with the push toward large multiplexes, we find that additional shows are generally worth the screen size tradeoffs, but that these relative values exhibit significant heterogeneity. Some markets exhibits a higher preference for quality as measured by screen size suggesting marketers need to understand the preferences of their customers before assuming they would prefer variety.

We have only looked at the demand side in this research and answered the question from the perspective of consumer preferences. While solving the supply-side model here is tempting, the integration over all future movie offerings and entry conditions makes it intractable. Managerially, theaters and others firms assessing variety vs. quality tradeoffs can use consumer preference measurements like those we have conducted as an input into their decision-making. Future work would benefit from allowing for the effects of capacity constraints and the associated spillovers between movies.

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A First-Stage Regression

Table 6 presents the first-stage regression results for the main variables of interest - price, ln(Shows), ln(Screen Width) and the nesting parameter - specific to Specification S3. The number of screens in a chain was the instrument for shows. The significant coefficients on screensXhhi indicates that screens and shows are correlated. The overall effect at the average demographic is positive indicating that a chain with more screens (and a higher hhi) has more shows. The instrument for screen size - hhi - is such that it takes on large values when a chain has more variation in screen sizes across its auditoria and also when there are more screens. The overall coefficient on hhi and hhi^2 at the average demographic is significantly negative, indicating that such chains are more likely to screen movies in auditoria with smaller screens. The instrument for the nesting parameter - 1/(No. competing movies) - takes on larger values when there are fewer competing movies playing in the market. A positive coefficient indicates that the inside-nest share of the movie is higher when there are fewer competing movies playing. The average price of other movies playing in a chain that week is positively correlated with the price of the focal movie.

Table 6: First Stage Estimates for Specification S3

	Price	ln (Shows)	ln (Width)	1-ρ
Average Price Other Movies	0.36[a]	-0.001	0.001[a]	0.0001
screens	78.50	1.66	1.72[a]	13.91[a]
screens X Urban	-24.08	-1.44	-1.60[a]	-13.71[a]
screens^2	-49.12	0.14	-0.54[a]	-4.18[a]
screens^2 X Urban	-26.04[a]	0.07	0.04	0.82[a]
screens^2 X Educ_graduate	-45.27[a]	-0.73[a]	-0.45[a]	-4.50[a]
screens^2 X Workers_total	176.83[a]	-0.50	1.22[a]	8.60[a]
hhi	43.44[a]	0.48[a]	0.55[a]	2.19[a]
hhi X Urban	-55.23[a]	-0.35[a]	-0.65[a]	-2.29[a]
hhi X Educ_graduate	246.44[a]	-0.83	-0.27	-0.07
hhi^2	52.92[a]	0.25	0.41[a]	3.33[a]
hhi^2 X Urban	-26.33[a]	-0.25[a]	-0.23[a]	-1.76[a]
hhi^2 X Educ_graduate	-125.48[a]	-0.97[a]	-1.01[a]	-8.65[a]
hhi^2 X Workers_total	-63.13[a]	0.01	-0.42[a]	-3.73[a]
screens X hhi	-60.41[a]	-0.59[a]	-0.53[a]	-3.62[a]
screens X hhi X urban	58.61[a]	0.57[a]	0.51[a]	3.46[a]
screens X hhi X educ_graduate	170.26[a]	1.96[a]	1.85[a]	15.08[a]
screen X regsh	-2.65	-0.06[a]	0.00	0.01
hindish	-9.07	-0.04	-0.07	-0.13
engsh	-11.08	-0.13	-0.01	0.10
obsMarketWeek	-27.03[a]	1.59[a]	-0.07	4.08[a]
Constant	10.23	-3.91[a]	3.20[a]	-7.50[a]
Adjusted R^2	0.7035	0.7835	0.5033	0.8296
F-statistic	13.59	20.21	6.38	26.84