To Review or Not to Review? Limited Strategic Thinking at the Movie Box Office

Abstract

Film distributors occasionally withhold movies from critics before their release. Cold openings provide a natural field setting to test models of limited strategic thinking. In a set of 856 widely released movies, cold opening produces a significant 15% increase in domestic box office revenue (though not in foreign markets and DVD sales), consistent with the hypothesis that some moviegoers do not infer low quality from cold opening. Structural parameter estimates indicate 1–2 steps of strategic thinking by moviegoers (comparable to experimental estimates). However, movie studios appear to think moviegoers are sophisticated since only 7% of movies are opened cold.

1 Introduction

The hypothesis that economic agents can correctly infer what other agents know from their actions is a central principle in analysis of games with information asymmetry. A contrasting view is that strategic thinking can be limited by cognitive constraints. In this view, players with private information *can* fool some of the people, some of the time, in contrast to the standard equilibrium assumption that nobody is fooled.[1]

One class of models of limited strategic thinking assumes there is a ‘cognitive hierarchy’ (CH) of levels of steps of thinking. Low-level players do not think strategically, and higher-level players anticipate the behavior of lower-level players correctly. These models have been used to explain experimental data from a wide variety of normal-form games.[2] The many examples studied include both games in which behavior deviates systematically from equilibrium and others in which behavior is surprisingly close to equilibrium even without learning or other equilibrating forces (e.g., Östling et al. 2007). The only applications of these theories to games with private information so far are analyses of auctions.[3] Another class of models, which apply on to private-information games, are models of ‘cursed equilibrium.’ In these models agents ignore the possible link between information and actions of other players to some degree (Eyster and Rabin, 2005).

Models of limited strategic thinking are particularly useful if the same basic principles can apply to many different games, to field data, and to experimental data. This paper explores the generality of these approaches through the first empirical comparison of the CH and cursed equi-

[1] See Crawford (2003).

[2] See Nagel (1995), Stahl and Wilson (1995), Camerer et al. (2004), Crawford and Iriberri (2007a).

[3] See Crawford and Iriberri (2007b) and Wang (2006).

librium model in private-information games using field data.[4] (Full rationality is also part of the comparison since it is a limiting case of both the CH and cursed models.)

The setting is Hollywood. Movie distributors generally show movies to critics well in advance of the release (so that critics' reviews can be published or posted before the movie is shown, and can be quoted in newspaper ads). However, movies are sometimes deliberately made unavailable until after the initial release, a practice sometimes called "cold opening." If moviegoers believe that distributors know their movie's quality (and if some other simplifying assumptions hold), we show in the next section that rational moviegoers should infer that cold opened movies are below average in quality. Anticipating this inference, distributors should only cold open the very worst movies. However, this conclusion requires many steps of iterated reasoning (as well as many simplifying assumptions). So it is an empirical question whether the equilibrium prediction holds. If it does not hold perfectly, it is also an empirical question, whether neoclassical explanations can explain the data or models of limited strategic thinking designed to explain experimental data can fit the distributors' cold opening decisions and the box office response.

This setting is one example of a more general class of disclosure games in which a seller who knows something about a product's quality can choose whether to disclose a signal of its quality or not (see Verrecchia (2001, section 3) and Fishman and Hagerty (2003) for surveys). For instance, a car salesman can signal a vehicle's quality by adding a warranty (Grossman, 1981). A regulated firm can selectively report information about its industry to regulators (Milgrom, 1981).

[4]Three unpublished studies using field data and cognitive hierarchy approaches are Östling et al., (2007) using Swedish lottery choices and experimental analogues, Goldfarb and Yang (2007), using estimation of firm adoption of 56K modems, and Goldfarb and Xiao (2008) using strategic entry of phone companies into new markets. The Östling et al. study compares QRE and cognitive hierarchy approaches but Goldfarb and Yang and Goldfarb and Xiao do not compare to QRE, and none of the papers estimates the cursed equilibrium model as we do since both are modeled as complete information games.

Restaurants can voluntarily post health department ratings even if they aren't required to by law (Jin and Leslie, 2003). HMOs can choose whether to voluntarily disclose quality by submitting to independent accreditation (Jin, 2005). A hedge fund can selectively report past earnings (Malkiel and Saha, 2005). Online daters can decide whether to post a picture or not (Hitsch et al., 2006). Sellers in online auctions can selectively disclose shipping charges (Brown et al., 2007). Colleges can incentivize good (or bad) students to disclose (or not disclose) their SAT scores to US News and World Report (Conlin et al., 2008). In politics and law, the analogous situation is when one can choose to disclose the answer a direct question, or can avoid answering the question (e.g.,"pleading the fifth" in legal settings).

For regulators, what consumers infer from non-disclosure is important for deciding whether disclosure should be voluntary or mandatory. If consumers do not infer that nondisclosure is bad news about quality, an economic argument can be made for mandatory disclosure under some conditions. We return to this topic briefly in the conclusion.

1.1 Basic ideas

A fully rational analysis, due originally to Grossman (1981) and Milgrom (1981), implies that cold opening should not be profitable if some simple assumptions are met. The argument can be illustrated numerically with a highly simplified example. Suppose movie quality is uniformly distributed from 0 to 100, moviegoers and distributors agree on quality, and firm profits increase in quality. If distributors cold open all movies with quality below a cutoff 50, moviegoers with rational expectations will infer that the expected quality of a cold opened movie is 25. But then it would pay to screen all movies with qualities between 26 and 100, and only cold open movies with qualities 25 or below. Generally, if the distributors do not screen movies with qualities below q^*, the consumers' conditional expectation if a movie if unscreened is $q^*/2$, so it pays to screen movies with qualities $q \in (q^*/2, 100]$ rather than quality below q^*. The logical conclusion of iterating this reasoning is that only the worst movies (quality 0) are unscreened. This conclusion is sometimes called "unravelling."

Whether there is complete unraveling, in theory, is sensitive to some of the simplifying assumptions (see Milgrom 2008). If disclosure is costly (Viscusi, 1978; Jovanovic, 1982), sellers will only reveal information down to a certain threshold of low quality.[5] In other cases, sellers may know the quality of their own product with some probability (Dye, 1985; Jung and Kwon, 1988; Shin, 1994; Dye and Sridhar, 1995; Shin, 2003), or can only learn the quality at a cost (Matthews and Postlewaite, 1985; Farrell, 1986; Shavell, 1994). Fishman and Hagerty (2003) assume a portion of consumers are unable to interpret revealed information, but this does not necessarily lead to limited disclosure.[6]

These conditions which may prevent unravelling do not characterize the movie business particularly well. The median production budget in our sample is \$35 million, the marketing budgets are often comparable in scale (50-100% of the production budget), but the costs of arranging screenings for critics (or now, sending DVDs) is on the scale of thousands of dollars. Furthermore, sellers usually know a lot about quality—as judged by likely moviegoers—because movies are almost always screened for test audiences, and learning about quality perceptions from these tests is not costly. Therefore, we proceed with the maintained hypothesis that complete unravelling should

[5]Intuitively, even if low-quality movies below the threshold are pooled in with inferior movies, if disclosure is costly then the penalty from being in the same pool is tolerable if it is below the cost of disclosing.

[6]They find three equilibria—one in which quality is always revealed, one in which it is never revealed, and one in which high quality is revealed and low quality is not.

occur in theory, if distributors and consumers are perfectly rational.

What do models of limited strategic thinking predict? The cognitive hierarchy models proceed through the steps of strategic thinking in the rational unravelling argument, except that they assume that some fraction of moviegoers end their inference process after a small number of steps. For example, a level-0 moviegoer thinks that cold opening decisions are random (they convey no information about quality) and hence infers that the quality of a cold-opened movie is average. A level-1 distributor anticipates that moviegoers think this way and therefore opens all below-average movies cold, and shows all above-average movies to critics. Higher-level thinkers iterate this process. Observed behavior will then be an average of the predicted behaviors at each of these levels weighted by the fraction of moviegoers and distributors who do various numbers of steps of thinking (More details of this model are given in section 4).

The model of cursed equilibrium is similar. It assumes that a fraction of moviegoers form the correct conditional expectation of quality given a cold opening (i.e, those moviegoers act as if they know precisely how distributors map quality into the decision about whether to cold open). The remaining fraction believe—mistakenly—that cold opened movies are random in quality, neglecting the link between distributors' information about quality and their cold opening choice. Note that full rationality is a special case of both models.

Industry executives and analysts who describe the cold opening decision often imply that limited moviegoer rationality justifies a cold opening, because they say that a bad review can hurt more than a non-review does.[7] For example, Greg Basser, CEO of Village Roadshow Entertain-

[7] Another explanation for cold opening is that the movie was not ready to be released to critics, or that the movie contained a surprise that reviewers might spoil (e.g., "Sixth Sense", "Cloverfield", "Blair Witch Project"). In the first case, it is very rare that a film uses this explanation for a cold opening, to our knowledge only one movie ("Doogal") in our dataset has made this claim (Germain, 2006). On the second item, "Sixth Sense", "Cloverfield", and "Blair Witch" were all released to critics. None of the 59 movies that were cold opened in the data sample featured such intense plot

ment Group, told us, "If you screen [a bad movie] for critics all they can do is say something which may prevent someone from going to the movie." As Dennis Rice, the former Disney publicity chief put it, "If we think screenings for the press will help open the movie, we'll do it. If we don't think it'll help... then it may make sense not to screen the movie," (Germain, 2006). Litwak (1986) notes

> "As a courtesy, and to ensure that reviews are ready by the time a film is released, distributors arrange advance screenings for critics. However, if negative reviews are expected, the distributor may decide not to screen a picture, hoping to delay the bad news. (p. 241)"

The data we describe next show that 7% of the movies in our sample are opened cold (though that fraction has increased sharply in recent years). Regressions show that cold opening appears to generate a box office premium (compared to similar-quality movies that are pre-reviewed, and including many other controls), which is consistent with the hypothesis that some consumers are overestimating quality of movies that are opened cold. We apply several mechanical explanations, but none can plausibly explain the findings.

We then fit the two parametric models of limited strategic thinking (described above) to both moviegoer and distributor decisions. The models parameterize the degree of strategic thinking by one parameter, so we can characterize the degree of limited rationality numerically (and also compare the results to experimental estimates). The best-fitting CH model parameters suggest that moviegoers are doing an average of 1.12 steps of thinking, which is lower but roughly comparable to estimates from many experiments (1-2 steps). However, given the box office premium, distributors should be opening many more movies cold. Within the restrictive structure of the CH

twists. Normally, such plot twists are an example of high-quality writing, something which the typical cold-opened movie does not feature. See next section for a description of the quality of cold opened movies.

model, the only possible explanation is that distributors think moviegoers are more sophisticated than they really are, so the distributors' estimated average number of perceived thinking steps is around 8. The mismatch between the degree of strategic thinking of moviegoers and distributors is not typically observed in experimental data. However, keep in mind that experiments rarely use mixtures of populations which are more and less strategically sophisticated, so it is perhaps not surprising that the estimate of distributor strategic thinking is very high, and is much higher than the moviegoer estimates.

The paper is organized as follows: Section 2 discusses the data we use on quality ratings, box-office returns, and control variables, and presents some regression results on the existence and robustness of a box-office premium for movies that are opened cold. Section 3 describes the CH and cursed equilibrium models (including "quantal response equilibrium" (QRE), which is a special case of the cursed model), and section 4 estimates parameters of those models based on distributors' decisions and the box office revenue. Section 5 concludes and discusses related empirical results on disclosure effects, which are generally consistent with ours.

2 Data

The data set is all 890 movies widely released[8] in the U.S. in their first weekend, over the $6\frac{1}{2}$ year period from January 1, 2000 to June 30, 2006.[9]

Critic and moviegoer ratings are both used to measure quality. Metacritic.com ratings are used

[8] Attention is restricted to movies initially released in over 300 theaters. Movies in more limited release have much less box office impact (they are usually art house movies that use a platform strategy of starting on a few screens, then expanding). It is also likely that information about quality leaks out more rapidly for these movies if they later go into wide release, even when they are initially opened cold.

[9] Movies before 2000 are excluded because Metacritic.com's records did not cover every movie from before 2000.

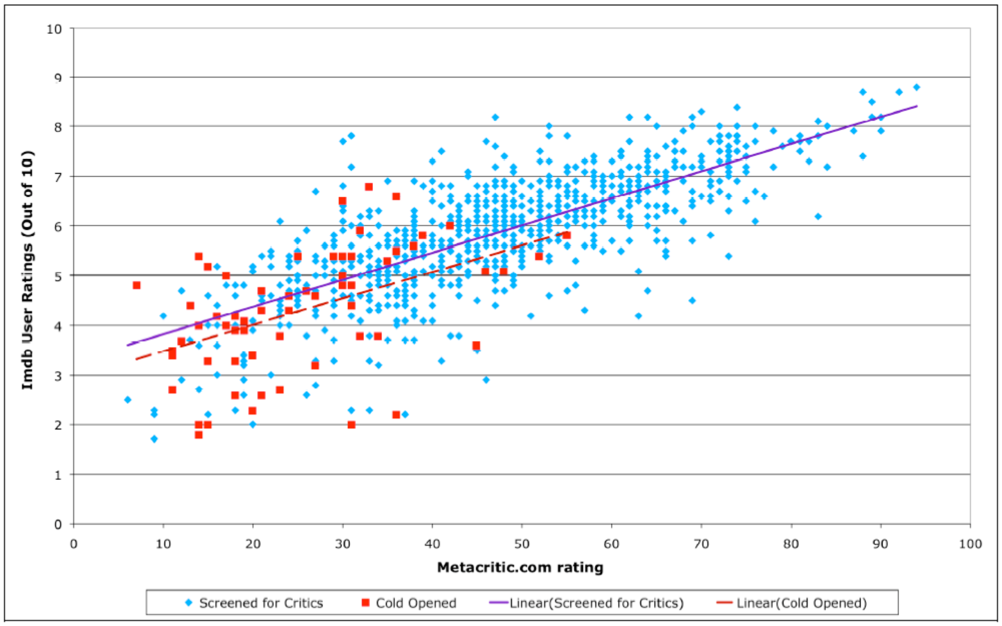

Figure 1: Scatter plot of metacritic.com quality ratings and imdb user ratings

to measure critic ratings. Metacritic.com normalizes and averages ratings from over 30 movie critics from newspapers, magazines, and websites. The metacritic rating is available for all non-cold-opened movies on the day they are released and is available on Monday for cold opened movies. We assume their ratings are generally exogenous from box office revenue measures.

A natural question to ask is whether metacritic ratings accurately express the quality of movies as perceived by moviegoers and revealed by demand. Our analysis indicates that they do for example, our regressions (discussed later) show a very sharp correlation between critic ratings and box office revenues. This result is also found in other studies of critic influence (Eliashberg and Shugan, 1997; Reinstein and Snyder, 2005).

We also examine the aggregated user ratings on imdb.com, which is the largest internet site for user movie reviews. There is a high correlation (.76) between metacritic scores and imdb user reviews (see Figure 1). The high correlation between critic (metacritic) and the moviegoer (IMDB ratings) holds across movie to genres (as shown in Table 4 below). Metacritic scores therefore correlate with two clear indicators of movie popularity (imdb and box office).[10]

The squares in Figure 1 represent the cold opened movies in our sample. No cold opened movie has a metacritic rating higher than 55, and the average rating for those movies (the total sample average is 48) is 25. There is also an extremely important fact about the comparison between metacritic ratings and ratings by fans who saw the movie and rated it on IMDB. Suppose limited strategic thinking causes some moviegoers to be "tricked" by cold opening (thinking that a lack of a review is not correlated with quality). Those moviegoers will go see cold opened movies based on expectations which are upward biased, and generally be disappointed. Therefore, the IMDB ratings for cold opened movies should be lower, controlling for metacritic rating, than for comparable movies. This effect is in fact evident in the data. Using imdb.com user data and the usual table 2 independent variables, cold opened movies have an average rating which is 0.4 points (out of 10) lower than non-cold opened movies. The result is highly significant ($p < 0.001$).

Cold opening, box office revenues, movie genres and ratings, production budgets, and star power ratings are collected from various data sources (see Appendix A for more details). Table 1 provides summary statistics for all variables. All these variables were used in a regression model to test if movies that are cold opened have significantly greater opening weekend and total US box office. The table also shows separate variable means for the cold opened movies. Those movies are somewhat statistically different in a few dimensions– they tend to be smaller in budget and theater

[10] We are assuming that critic reviews influence moviegoers. Alternatively, critics might correlate with overall popularity (as our previous evidence suggests), but moviegoers ignore them so they have predictive, but not influencing power. Survey evidence suggests one third of moviegoers use critical reviews to make decisions (Simmons, 1994). But the empirical work of Eliashberg and Shugan (1997) finds it impossible to reach a definitive conclusion on this issue, and Reinstein and Snyder (2005) find evidence that critic ratings only matter for specific genres. However, the latter study only examines the effect of two critics (i.e., Siskel and Ebert) delaying their review. A cold opening delays *all* reviews and thus might have a greater effect across genres. Because this evidence is somewhat inconclusive, we will use several different tests to check our hypothesis that it is indeed the cold opening increasing box office and thus the critic reviews (or lack thereof) influencing moviegoers.

variable\regression	mean	median	standard dev	mean (cold only)
cold	0.070	0.000	0.255	1.000*
log total box office revenue (logcubo)	3.443	3.510	1.092	2.615*
log 1st weekend box office revenue (logwkd)	2.354	2.390	0.942	1.756*
metacritic rating (crit)	45.793	46.000	16.813	25.500*
imdb user rating (imdb)	5.762	5.800	1.240	4.312*
theaters opened (in thousands) (thtr)	2.435	2.550	0.787	2.002*
production budget (in millions) (bud)	42.301	33.325	33.470	21.343*
average competitor budget (in millions) (comp)	44.127	36.020	31.080	38.226
average log star ranking (star)	4.645	4.533	1.692	5.381*
summer open (1=Jun, Jul, Aug) (sum)	0.245	0.000	0.430	0.161
sequel or adaptation (1=yes) (sq/adpt)	0.389	0.000	0.488	0.242*
opening days bef fri (1=Thurs, etc.) (beffri)	0.224	0.000	0.658	0.177
opening wkd length (days) (wkdlen)	0.109	0.000	0.336	0.113
early foreign open (days) (forbef)	11.804	0.000	99.724	13.452
action/ adventure (1) (act/adv)	0.164	0.000	0.371	0.081*
animated (1) (ani)	0.060	0.000	0.237	0.016*
comedy (1) (com)	0.380	0.000	0.486	0.371
documentary (1) (doc)	0.006	0.000	0.075	0.000*
fantasy/scifi (1) (fant/sci)	0.062	0.000	0.241	0.065
supense/ horror (1) (susp/hor)	0.157	0.000	0.364	0.403*
year of release (2003=0) (year)	-0.166	0.000	1.902	0.290
PG (1) (pg)	0.158	0.000	0.365	0.032*
PG-13 (1) (pg13)	0.478	0.000	0.500	0.581
R (1) (r)	0.326	0.000	0.469	0.371

*significant mean difference at the 5% level

Table 1: Summary statistics for variables ($N = 890$ except $N = 856$ for production budget).

coverage, with less well-known stars and overrepresenting some genres (suspense/horror).

Each movie, j, has a metacritic.com or IMDB fan rating, q_j, a dummy variable for whether a movie was cold opened, c_j (=1 if cold), and a vector X_j of other variables. The regression model is

$$\log y_j = aX_j + bq_j + dc_j + \epsilon_j \tag{1}$$

where y_j is logged opening weekend or total US box office for movie j in 2003 dollars, standardized using the GDP deflator (`www.bea.gov`). Table 2 shows the regression results.

The point of this initial regression is not to estimate a full model with endogenous distributor decisions (that will be done in Sections 3 and 4). Instead, the regression is simply a way of determining whether there is a difference in the revenue between cold opened and screened movies. Under the standard equilibrium assumption that all quality information of cold opened movies is inferred by logical inference of moviegoers, we should see no difference in revenues, and the cold coefficient should be zero.[11]

The "cold" coefficient in the first row of Table 2 shows that cold opening a movie is positively correlated with the logarithm of opening weekend and total US box office (see Appendix B, Table A.2 for a similar result with opening day data).[12] These coefficients suggest that cold opening a movie increases revenue about 15%.[13] These effects persist when "lean" regressions are run with only the most significant variables included (i.e., cold, metacritic, theaters, budget, competition, star ranking, sequel or adaptation dummy, and year of release). The lean regressions show a more significant effect for opening weekend, than the effect for total box office, presumably because critic reviews of cold opened movies are normally available by the Monday after the opening weekend and they influence total box office.[14]

[11]Alternatively, a switching regression model (similar to Borjas, 1987) for the choice to cold opened could be used to capture the cold opening premium and characterize the decision to cold open. We have instead chosen to describe the industry through a quantal response model (see Section 4)

[12]Note that this relationship is also found between cold opening and opening weekend and total US box office (no logarithm). So this relationship is not just a result of the functional form of the regression.

[13]For the average gross of a cold opened movie, \$20 million, this is roughly \$3 million of box office revenue.

[14]It is somewhat surprising that the effect of a cold opening continues after the first weekend when critical reviews are available. Intuitively, the cold opening effect should occur during the first weekend and then dissipate rapidly as moviegoers learn the true quality of a cold opened movie. An alternative explanation is that moviegoers infer quality from the first weekend's revenue (see De Vany and Walls (1996) for a model with such dynamics). Then the perceived "effect" of a cold opening on post-first-weekend box office includes a secondary result from cold opening affecting the first weekend's box office (as in models of herd behavior or cascades). The data agree with this assessment; if we run a regression on logged box office revenues after the first weekend (see Table A.3), including logged first weekend with our other independent variables, then we find cold has an slightly negative effect (-3%, $p \approx 0.5$; -10%, $p < 0.1$ (lean)) on post-opening-weekend revenue, and a opening weekend is correlated with post-opening-weekend revenue (120%, $p < 0.01$).

independent variable	dependent variable					
	logcubo	logcubo	logcubo	logwkd	logwkd	logwkd
cold	0.153** (0.090)	0.139* (0.088)	0.118* (0.089)	0.147** (0.073)	0.171*** (0.073)	0.143** 0.073
crit	0.021*** (0.001)	0.020*** (0.001)	-	0.013*** (0.001)	0.013*** (0.001)	-
imdb	-	-	0.020*** (0.001)	-	-	0.012*** (0.001)
thtr	0.863*** (0.039)	0.853*** (0.035)	0.863*** (0.035)	0.848*** (0.032)	0.820*** (0.029)	0.825*** (0.029)
bud	0.003*** (0.001)	0.002*** (0.001)	0.003*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
comp	0.022*** (0.001)	0.003*** (0.001)	0.003** (0.001)	0.001** (0.001)	0.001** (0.001)	0.002** (0.001)
star	-0.045** (0.015)	-0.054*** (0.014)	-0.018 (0.014)	-0.029** (0.013)	-0.048*** (0.011)	-0.026** (0.012)
sum	0.052 (0.050)	-	-	0.028 (0.041)	-	-
sq/adpt	0.124*** (0.045)	0.116*** (0.045)	0.160 (0.045)	0.119*** (0.037)	0.111*** (0.037)	0.138*** (0.037)
beffri	0.000 (0.033)	-	-	-0.048* (0.027)	-	-
wkdlen	0.129** (0.063)	-	-	0.175*** (0.051)	-	-
forbef	0.000 (0.000)	-	-	0.000 (0.000)	-	-
act/adv	-0.173** (0.078)	-	-	-0.052 (0.063)	-	-
ani	-0.316** (0.128)	-	-	-0.145 (0.105)	-	-
com	0.032 (0.064)	-	-	0.027 (0.052)	-	-
doc	0.212 (0.362)	-	-	0.267 (0.052)	-	-
fant/sci	-0.175* (0.103)	-	-	0.039 (0.084)	-	-
susp/hor	0.012 (0.078)	-	-	0.040 (0.064)	-	-
year	-0.083*** (0.011)	-0.082*** (0.011)	-0.079*** (0.011)	-0.050*** (0.009)	-0.050*** (0.009)	-0.0476*** (0.009)
pg	-0.182 (0.130)	-	-	-0.034 (0.106)	-	-
pg13	-0.179 (0.136)	-	-	0.100 (0.111)	-	-
r	-0.225 (0.140)	-	-	0.113 (0.114)	-	-
const	0.506** (0.209)	0.433*** (0.134)	0.186* (0.119)	-0.493*** (0.171)	-0.188*** (0.110)	-0.304 (0.119)
R-squared	0.685	0.675	0.671	0.718	0.707	0.700
N	856	856	856	856	856	856
degrees of freedom	21	8	8	21	8	8

*p<0.1, **p<0.05, ***p<0.01

Table 2: Regressions of log box office revenues (in millions)

These results are virtually identical when imdb (fan) ratings are used instead of the metacritic "crit" variable.[15] The coefficients also suggest that cold opening increases movie revenue by roughly the same amount as in the full regressions (14–17%).[16]

The regression coefficients in Table 2 are generally sensible. Higher quality leads to higher box office—an increase in one metacritic point increases revenues by 2.1%. An extra $10 million in production budget is correlated with a 3% increase in revenues. The number of theaters opened, which often indicate expectations about movie revenues, have a very large effect.[17] An increase of 1000 theaters increases revenue by 86%. The averaged logged star power rankings have a negative correlation (higher numbers indicate lower rankings and less revenue). Adaptations and sequels increase box office by roughly 13%, a result which may explain the recent growth in the fraction of movies in this category.

The hypothesis that limited strategic thinking by moviegoers generates the premium suggests that in markets where word-of-mouth information about quality has leaked out, there will be no cold opening premium. One way to test this prediction is to look at the log total box office of the U.K. and Mexico, and log of US video rental data. In these markets, the possible deception of cold opening on strategically naïve moviegoers should be less effective because movies are almost always released in the U.K. and Mexico after the initial U.S. release, and home video rentals are always later than U.S. box office releases. If information about the movie's quality is widely disseminated before these later releases, the cold opening effect should disappear in foreign

[15] For comparability, the imdb ratings were normalized to have the same mean and variance as the metacritic ratings, so that the coefficient estimates can be compared directly.

[16] The p-values on all the cold opening coefficients are based upon one-tailed tests because the hypothesis is that cold opening either increases revenue or has no effect.

[17] Theaters may be a proxy for the omitted variable of advertising budget as well, which magnifies the theater variable effect.

dependent variable	cold opening (dummy) coefficient	std error	t-statistic	one-tailed significance
log total US box office	0.154	0.090	1.710	0.044
log total US rentals	-0.007	0.101	-0.067	-
log UK box office	-0.021	0.231	-0.090	-
log Mexico box office	-0.001	0.150	-0.010	-

Table 3: The cold opening percentage premium (regression coefficient) in non-US box office markets (control variables included, but results not reported).

and rental markets. Table 3 reports the cold-opening coefficients (from a regression including all variables as in Table 2). The coefficients are all slightly negative but insignificant, so there is apparently no cold opening premium in these two foreign markets and the rental markets. The lack of an effect is not due to reduced statistical power because the standard error on the estimate for rental data is about the same as for US box office (.101 versus .090).

2.1 Alternative Explanations of the Cold Opening Premium

The previous section finds a correlation between cold opening and higher box office, but there may be many reasons for that observed cold opening premium. This section explores such possibilities and weights the evidence for and against different explanations.

Note that there are several stylized facts which a good explanation should account for:

1. There is an apparent correlation between cold opening and US box office revenue.

2. The correlation is very similar whether quality ratings are derived from critics (metacritic) or from fans who saw the movie (IMDB).

3. The correlation disappears when the dependent variables are DVD rentals, or UK or Mexico box office revenues.

4. IMBD fan ratings are about .4 points lower (on a 10-point scale) for cold opened movies than for comparable-quality movies that were not cold opened.

5. Cold openings are rare overall, but are increasingly frequent over the years in the sample (as shown in figure 2).

The explanation offered so far is that facts (1) and (2) are due to limited strategic thinking by moviegoers. Fact (3) is explained by quality information coming out after the US release (typically before UK and Mexico release and always before DVD rentals). Fact (4) also follows from moviegoer misperceptions of expected quality which are special to cold-opened movies. Fact (5) requires an explanation based on distributors' beliefs about moviegoer strategic thinking, will be discussed further below, and is the least interesting issue.

Angry critics: One possible explanation is that annoyed critics may give cold-opened movies lower critical ratings than they would have if the movies were screened in advance (perhaps as a way of punishing the distributors for making the movie unavailable).[18] Such an effect would lead to an underestimation of quality of cold opened movies and a positive cold opening coefficient. This explanation seems unlikely a priori since critics pride themselves on objectivity (for example, they rarely mention in late reviews of cold opened movies that the movie was unavailable in advance).[19] Furthermore, this hypothesis cannot explain fact (2), that the cold opening premium on revenues is evident even when IMDB user ratings are used.

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[18]Litwak (1986) mentions this idea when describing a cold opening.

[19]On their TV movie-review show Roger Ebert and Richard Roeper introduced the "Wagging Finger of Shame" awarded to cold opened movies. However, they did not do this to convey negative opinions about particular movies; they did it because they thought that shaming some movies would discourage the practice in general. They discontinued the 'award' when they felt it was not working (Germain, 2006). In one case, Roeper gave a cold-opened movie ("When a Stranger Calls") his video rental recommendation, a recommendation he would not have made if he was intent on being overly negative simply because a movie was cold-opened.

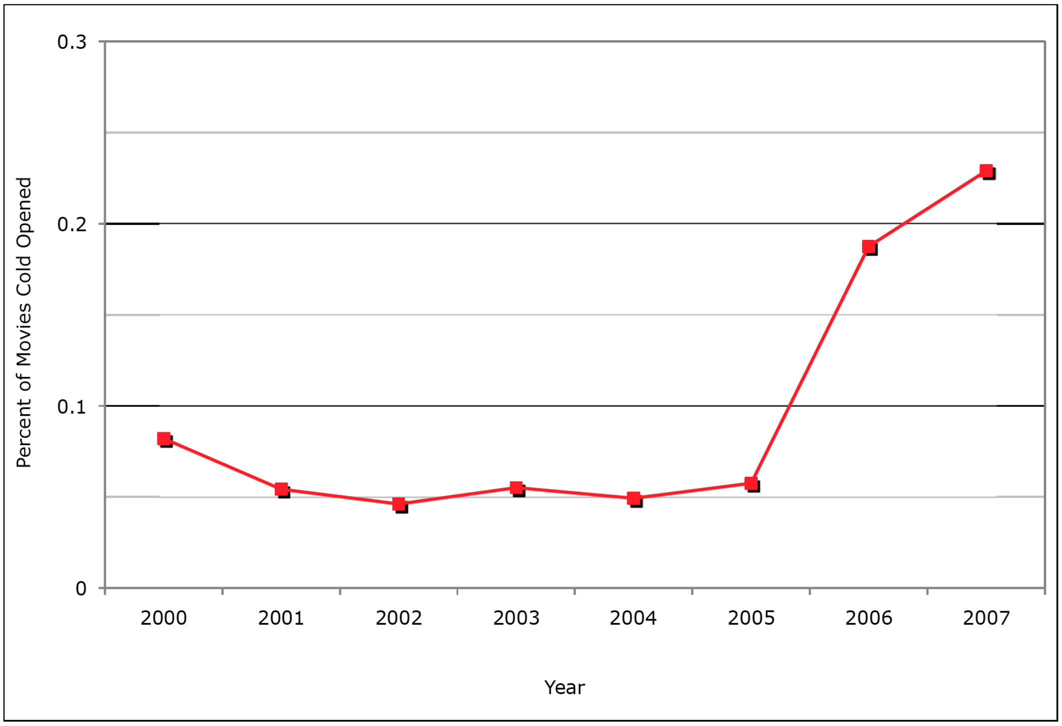

Figure 2: Percent of widely-released movies cold opened by year, 2000–2007

Consumer-critic heterogeneity: The first possibility which springs to mind is that movies which are cold opened are aimed at an audience with tastes which are different than critics' tastes. Indeed, correlation of critic reviews (metacritic) and moviegoer reviews (imdb) for cold-opened movies is high (0.51), but is much lower than the corresponding correlation for non-cold opened movies (0.76). However, this reduced correlation most likely results from the fact that cold-opened movies have a restricted range of critic ratings ($\bar{x} \approx 25, s^2 \approx 11$). If we restrict non-cold opened movies to those with critic ratings under 40 ($\bar{x} \approx 29, s^2 \approx 8$) or above 60 ($\bar{x} \approx 70, s^2 \approx 7$), we find similar values for the correlation (0.51 and 0.53, respectively).

Another way to check whether cold opened movies have any inherent differences in sensitivity to critic ratings is to examine the movies by genre. Comedies and suspense/horror movies account for 80% of cold openings, but only 54% of all movies (see Table 4). If fans of these genres have

Genre	# Movies	# Cold opened	Percent cold opened	Avg weekend Log(BO)	Avg Metacritic score	Avg imdb user rating	Imdb-Meta Correlation	Cold Dummy for Weekend Log(BO)
Act/Adv	143	5	0.03	3.827	48.2	5.91	0.79	0.165
Animated	51	1	0.02	3.949	56.6	6.07	0.85	-0.547
Comedy	322	21	0.07	3.352	42.1	5.41	0.73	0.173
Doc	3	0	0.00	2.351	58.0	5.63	0.87	-
Drama	145	3	0.02	3.240	50.5	6.28	0.69	0.229
Fant/Sci	55	4	0.07	4.120	50.8	6.11	0.88	0.121
Susp/Horr	137	25	0.18	3.334	41.4	5.70	0.74	0.077
Overall	856	59	0.07	3.443	45.8	5.76	0.76	0.155

Table 4: Data separated by movie genre

less sensitivity to bad reviews (suggested by Reinstein and Snyder, 2005), and are more likely to go to a movie that has low critic ratings than fans of other genres, then the cold opening premium could be a result of the selection of cold-opened movies into these genres.[20]

Table 4 shows that this is not the case. Throughout genres, moviegoers' correlation between critic reviews and self-reported reviews are all around 0.75. The cold open premium is positive for all genres (6–21%) except for the genre "animated" which is driven by a single movie, "Doogal."

The cold opening coefficient also does not show any significant interactions with critic or moviegoer ratings or with sequel/adaptations.[21]

Finally, as Table 2 showed, the cold opening effect is approximately the same in magnitude and statistical strength when imdb ratings are used instead of critic ratings. So differences in fan and critic tastes cannot explain the results.

Omitted variable bias: The most obvious alternative rational-choice explanation for the cold opening premium is that cold opened movies have some characteristic omitted from the Table 2

[20]This explanation also would not explain why distributors would be more likely to withhold bad news in genres where the intended audience is the least receptive to bad news.

[21]The interactions with "crit", "imdb", and "sequel/adapt" had coefficients (std. errors) of positive $(0.002\ (0.006)$, $t = 0.42)$, $(0.029\ (0.690)$, $t = 0.04)$ and $(-0.113\ (0.189)$, $t = -0.60.)$

regressions that causes these movies to generate apparently greater box office (a classic omitted variable bias). Based on this omitted-variable explanation, our regressions are not capturing the effect of cold opening; instead, the regressions are capturing the effect of an omitted variable that happens to be correlated with cold opening.

However, all the obvious measurable controls are already included in Table 2. (Appendix B, Table A.4 also shows all correlations and indicates that cold opening is not strongly correlated with any variable except quality.) Since all obvious measurable controls are included, the most likely omitted variable that could be correlated with the decision to cold open is spending on publicity and advertising.[22] Omitting this variable would explain the cold opening premium if revenues increase with spending on advertising, and if advance screening and advertising are substitutes (i.e., if distributors spend more on ads to compensate for cold opening but ad spending is an omitted variable). In our data cold openings are associated with a 10% drop in advertising, however.[23] Furthermore, a senior executive at Fox distributors we interviewed contradicted this notion, suggesting that if anything distributors are *tighter* with their spending on advertising once the decision to cold-open is made (which happens late in the process, after the number of screens and most other variables have been determined). The executive's view was that distributors know cold-opened movies are not very good, and see high levels of ad spending on such movies as throwing good money after a bad movie. The industry also appears to typically set advertising budgets as a fixed proportion of production budgets (Vogel (2007) suggests one-half, an executive at Village Roadshow told us two-thirds). If these rules of thumb are true, then the production budget variable will pick up much

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[22]Unfortunately, we found advertising budgets for only 445 of the 856 movies in our sample, and only 12 of the 59 cold openings.

[23]The result is only based on 12 cold openings and is not significant ($p \approx 0.3$; lean regression $p \approx 0.23$).

of the omitted effect of advertising on the cold opening decision, even if there is any. [24]

Nonetheless, it is of course conceivable that there is some omitted variable which creates a spurious cold opening effect. However, such a variable would have to be highly correlated with cold opening (more highly than the observable variables are), and would also have to be something that the executives we interviewed did not know about or preferred not to discuss. Most importantly, the existence of such a variable cannot account for fact (3), the absence of a cold opening effect in DVD rentals and overseas markets. It also cannot account for the fact (4) that IMBD fans are relatively disappointed by movies that were cold opened (controlling for quality).

Not learning about reviews: The most promising alternative explanation is that not everyone knows whether movies have been cold opened (e.g., it may be costly to find out[25]). Consumers who do not know whether movies were reviewed or not could believe the cold-opened movies have average quality (because they don't know they were unreviewed) and would therefore go to those movies more often than if they made the correct strategic inference.[26]

However, missing information about reviews entirely means that some moviegoers have missing information about *all* critic reviews. Missing information biases the regression coefficient on critic-rated quality toward zero, but does not bias revenues of cold-opened movies upward, compared to revenues from having the same quality movies reviewed.

A simple model will illustrate this point. Suppose that even if a review is available there is a p chance that a moviegoer won't see it (e.g., he glanced at the paper and didn't see a review). Suppose

[24] A regression of production budget on marketing budget, for the 445 movies that we have both types of budget data, has $R^2 = 0.496$, indicating advertising budgets are highly correlated with production budgets.

[25] In the conventional sense, it is not actually "costly" to find out about cold openings. Daily newspapers cost \$1 or less; if there is no review on the day of opening (almost always Friday) then the movie is cold opened.

[26] This example is very similar to having a moviegoers' curse for all movies rather than just the cold opened ones. See section 4.1 for an explanation of the cursed equilibrium model and footnote 35 for more detail.

further that movies have quality uniform in $[0, 1]$ and those with quality below c^* are cold opened. Then if a review is unseen, Bayesian updating implies a belief $\frac{c^*}{c^*+p(1-c^*)}$ that the movie was cold opened (and has conditional expected quality is $c^*/2$); otherwise there was a review which was missed and the conditional expected quality is $(1 + c^*)/2$.[27] However, the unravelling argument still applies to the $1-p$ segment of consumers who either see reviews, or know if they haven't seen a review and draw the conditional inference $(c^*/2)$. Movies with quality $c^* > q > c^*/2$ will then be reviewed and so c^* is reduced to minimal quality.

This simple model does make some predictions, however. First, it predicts that moviegoers will be disappointed in low quality movies and pleasantly surprised by high quality ones, because missed reviews lead to forecasting errors of both types. In our empirical terms, the slope of the regression of IMBD (fan ratings) on critics should be greater than 1 (normalized for scale), but it is not (it is less than one). Second, the model predicts that there should be no difference in IMDB and critic ratings for low-quality movies that are reviewed or cold opened. However, the important fact (4) is that cold opened movies have more fan disappointment (lower IMDB compared to critic rating).

Of course, it is always conceivable that there are other alternative explanations we have not considered or which make sense but cannot be tested with available data. However, the explana-

[27] If a movie is shown for review the expected quality is

$$p\left[\left(\frac{1+c^*}{2}\right)\left(1-\frac{c^*}{c^*+p(1-c^*)}\right)+\left(\frac{c^*}{2}\right)\left(\frac{c^*}{c^*+p(1-c^*)}\right)\right]+(1-p)q. \tag{2}$$

If it is cold opened the expected quality is

$$p\left[\left(\frac{1+c^*}{2}\right)\left(1-\frac{c^*}{c^*+p(1-c^*)}\right)+\left(\frac{c^*}{2}\right)\left(\frac{c^*}{c^*+p(1-c^*)}\right)\right]+(1-p)\frac{c^*}{2}. \tag{3}$$

Note that the first terms of these expressions are exactly the same; they reduce to $p/\left(c^*+p(1-c^*)\right)$ times $(p/2)+c^{*2}(1-p)/2$. However, the second term is $(1-p)q$ for a reviewed movie and $(1-p)(c^*/2)$ for a cold opened movie.

tions considered above are the most plausible and cannot gracefully fit all five stylized facts we have enumerated. Therefore, in the next section we will develop two structural models of strategic thinking by moviegoers and distributors and estimate behavioral parameters which measure the degree of limited strategic thinking for both groups. If some of these models can successfully explain the cold opening premium with similar parameter values to what has been observed in other studies, that result is another piece of evidence that the premium is not due to an omitted variable, but instead reflects some limit on strategic thinking.

3 The General Model

In designing a model of movie viewing and distributor choice, the aim is to create a model that can be analyzed with box office data, but allows estimation of behavioral parameters of individual thinking. The model permits both distributors and moviegoers to be influenced by the choice and cognition of the other side. Recall that the initial regressions in Section 2 were not designed to understand the endogenous choice of distributors to cold open, and the likely reactions of moviegoers, but these behavioral models are.

To fix notation, assume that the distributor of movie j and moviegoers both know movie characteristics X_j. The game form is simple: Distributors observe q_j and then choose whether to open cold ($c_j = 1$) or to screen for critics in advance ($c_j = 0$). Moviegoers form a belief $E_m(q_j|c_j, X_j)$ about a movie that depends on its characteristics X_j and whether it was cold opened c_j.[28] Below we consider two models of belief formation which incorporate different types of limits on strategic

[28]It is not crucial that moviegoers literally know whether a movie has been cold-opened or not (e.g., surveys are likely to show that many moviegoers do not know). The essential assumption for analysis is that beliefs are approximately accurate for pre-reviewed movies and formed based on some different behavioral assumption for cold-opened movies.

thinking. Both include fully rational equilibrium as limiting cases.

The first assumption is that if a movie is screened to critics, its quality is then known to moviegoers. Quality could be known with noise and all results go through if moviegoers are risk-neutral:

Assumption 1. $E_m[q_j|0, X_j] = q_j$.

To model moviegoing and distributor decisions jointly, we use a quantal response approach in which moviegoers and distributors choose stochastically according to either utilities or expected profits. Since we have no data on individual choices or demographic market-segment data, we use a representative-agent approach to model moviegoers. Assumption 2 is that moviegoer utility is linear in movie characteristics and expected quality, subtracting the ticket price.

Assumption 2. $U(X_j, E_m(q_j|c_j, X_j)) = \alpha E_m(q_j|c_j, X_j) + \beta X_j - \hat{t} + \epsilon_j$

where α and β give the corresponding predictive utility associated with expected quality and other known characteristics of movies. The opportunity utility of not going to the movies is defined as zero.[29] In the quantal response approach, probabilities of making choices depend on their relative utilities. We use a logit specification (e.g., McFadden, 1974). The probability that the representative moviegoer will go to movie j with characteristics X_j and expected quality $E_m(q_j|c_j, X_j)$, at ticket price $\hat{t}$[30] is

$$p(X_j, E_m(q_j|c_j, X_j)) = \frac{1}{1 + e^{-\lambda_m\left(\alpha E_m(q_j|c_j,X_j)+\beta X_j-\hat{t}+\epsilon_j\right)}} \tag{4}$$

[29]This is without loss of generality because a constant term is included in the revenue regression, which in this model is equivalent to the estimated utility of not going to the movie.

[30]The term $\hat{t}$ is the average US ticket price in midyear 2003 (recall box office revenues are in 2003 dollars). For an explanation of why movie ticket prices are not different for different movies see Orbach and Einav (2007) or for a more general explanation, Barro and Romer (1987).

where λ_m is the sensitivity of responses to utility. Higher values of λ_m imply that the higher-utility choice is made more often. At $\lambda_m = 0$, choices are random.[31] As $\lambda_m \to \infty$, the probability of choosing the option with the highest utility converges to one (best-response).[32]

Expected box-office revenues are assumed to equal the probability of attendance by a representative moviegoer, times the population size N and ticket price $\hat{t}$, which yields $R(X_j, E_m(q_j|c_j, X_j)) = N\hat{t}p(X_j, E_m(q_j|c_j, X_j))$. Note that the distributor's choice of c_j is assumed to enter the revenue equation solely through its effect on moviegoer expectations of quality $E_m(q_j|c_j, X_j)$.

The distributor's decision to screen the movie ($c_j = 0$) or open it cold ($c_j = 1$) is also modeled by a stochastic choice function based on a comparison of expected profits from the two decisions. Given assumption 1, the revenue from screening is $R(X_j, q_j)$ and the revenue from cold opening is $R(X_j, E_m(q_j|1, X_j))$. Given the same logit choice specification as for moviegoers, the probability of a distributor opening the movie cold is therefore given by assumption 3,

Assumption 3. $\pi(X_j, q_j) = 1/\left(1 + \exp\left[-\lambda_d\left[R(X_j, E_m(q_j|1, X_j)) - R(X_j, q_j)\right]\right]\right)$

where λ_d is the sensitivity of distributor responses to expected revenue.[33]

The logic of the model and our data (see Section 2 and Table 2) suggest that cold opening most

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[31] This model implies that if $\lambda_m = 0$, the representative moviegoer will attend each movie in its first weekend with .5 probability. While that result may be unappealing, note that a multinomial specification (i.e, if $\lambda_m = 0$, the representative moviegoer will go to the movies with .5 probability and which movie he goes to will depend on its underlying characteristics) would be much more complicated to calculate and also has unappealing results. For instance, movies that open alone each weekend should have much higher box office than those that open when three other movies do (which is generally not true).

Additionally, this point is moot. The later λ_m estimates will be far from 0 (see Table A.5). As it turns out when one looks at equation 8, it is apparent that it would require on average movies to make roughly $800 million in their first weekend to push $\hat{\lambda}_m$ to 0 (because that parameter value suggests half the US population sees the movie). Instead this value can be thought of as an upper bound on movie revenue and a lower bound on rationality.

[32] See Luce and Raiffa (1957), Chen et al. (1997), McKelvey and Palfrey (1995, 1998).

[33] In many previous applications of these games to experimental datasets the response sensitivity parameters λ are the same since game payoffs are on similar payoff scales. We use two separate parameters here for moviegoers and distributors, λ_m and λ_d, because the payoffs are on the order of dollar-scale utilities for moviegoers and millions of dollars for distributors.

strongly affects the first weekend's revenue (which may then affect cumulative revenue). Therefore, we use the first weekend's revenue to calibrate the models' revenue equations and distributor decisions in the next section. Our probability and utility functions given in assumption 2 and equation 4 are based on the moviegoers' behavior in the first weekend.[34]

4 Two Behavioral Models of Limited Strategic Thinking

The crucial behavioral questions are what moviegoers believe about the quality of a movie that is cold-opened—i.e., what is $E_m(q_j|1, X_j)$?—and how those expected beliefs influence the distributor's probability of choosing a cold opening, which is $\pi(X_j, q_j)$.

This section compares two models of beliefs: Cursed equilibrium (Section 4.1), and cognitive hierarchy (Section 4.2). Each model requires that moviegoers and distributors optimize (stochastically) based on their belief about the other's actions, but those beliefs might be limited in strategic sophistication. In this way the model allows the decision of distributors to cold open to be endogenously related to moviegoers' attendance of cold opened movies, which is in turn driven by moviegoers' beliefs about what cold opening implies about quality. This structure represents an improvement on the initial regressions in Section 2), and is a tool for gauging how well behavioral models developed to explain experimental data may work in a field setting.

In cursed equilibrium (Section 4.1), moviegoers' beliefs about the quality of a cold-opened movie are a weighted average of unconditional overall average quality (with weight χ) and the rationally-expected quality that fully anticipates distributors' decisions (with weight $1 - \chi$).[35] The

[34]Results are similar when total box office is used.

[35] It is tempting to interpret χ as a fraction of people who are uninformed about reviews because finding out about reviews is costly (as discussed in section 2.1). This interpretation is not tested by our empirical procedure, because we

parameter χ is a measure of the degree of naïveté in the moviegoers' strategic thinking (i.e., to what extent beliefs about cold-opened movies are biased toward average quality).

In the cognitive hierarchy (CH) approach (Section 4.2), there is a hierarchy of levels of strategic thinking. The lowest-level thinkers do not think strategically at all, and higher-level thinkers best-respond to correctly anticipated choices of lower-level thinkers. For parsimony, the percentages of players at different levels in the cognitive hierarchy are characterized by a Poisson distribution with mean thinking-level parameter τ.

Importantly, both models allow full rationality as a limiting case of their behavioral parameters. Full rationality corresponds to $\chi = 0$ in cursed equilibrium and $\tau \to \infty$ in CH. In the former case, full rationality corresponds to a quantal response equilibrium (McKelvey and Palfrey, 1995, 1998). Therefore, estimates derived from the data will indicate the *degree* of moviegoer rationality as parameterized in these two ways.

4.1 Cursed Equilibrium

Eyster and Rabin (2005) created a model of "cursed equilibrium" to explain stylized facts like the winner's curse in auctions, and other situations where some agents do not seem to infer the private information of other players from those players' actions. Their idea is that such an incomplete inference is consistent with agents not appreciating the degree to which other players' actions are

use the empirical quality-revenue relation for reviewed (i.e., non-cold-opened) movies as an input to then estimate χ. A proper implementation of the theory that some moviegoers don't find out anything about reviews requires inclusion of a parameter measuring the fraction of uninformed moviegoers, which influences both the quality-revenue equation for reviewed movies, and the estimated value of χ (which will mistakenly include that fraction). Such a model is not well-identified without more information of how informed moviegoers are or how many are not thinking strategically, which might be measured directly in surveys or methods to classify people into types. However, in our specific structural framework, box office revenues are not linear in expected beliefs (through assumption 2). So a model in which there are a fraction χ of people who use average quality for cold-opened movies, and a fraction $1-\chi$ who form rational expectations is not exactly equivalent. (The difference is that between a nonlinear probability function of a weighted average and a weighted average of nonlinear probabilities.)

conditioned on information.[36]

In this context, for every cold opened movie, all moviegoers believe that the movie has quality equal to some weighted average of the rational expectation of movie quality (given distributor decisions) and the average of all movies (i.e., ignoring any information conveyed by the cold opening decision). That is,

$$E_m^{ce}(q_j|1) \equiv (1-\chi_m)\, E_m^{re}\left(q|X_j,1\right) + \chi_m \bar{q} \tag{5}$$

where $E_m^{re}\left(q|X_j,1\right)$ reflects rational expectations about distributor decisions.

The rational expectation belief, $E_m^{re}(q_j|1,X_j)$, about the quality of an unscreened movie with characteristics X_j is

$$\begin{aligned}
E_m^{re}(q_j|1,X_j) &= \textstyle\sum_{q=0}^{100} qP\left(q|X_j,1\right) && \\
&= \frac{\sum_{q=0}^{100} qP(1,X_j,q)}{P(1,X_j)} && \text{(Bayes' rule)} \\
&= \frac{\sum_{q=0}^{100} qP(1,X_j,q)}{\sum_{q=0}^{100} P(1,X_j,q)} && \text{(laws of probability)} \\
&= \frac{\sum_{q=0}^{100} qP(1|X_j,q)P(X_j,q)}{\sum_{q=0}^{100} P(1|X_j,q)P(X_j,q)} && \text{(laws of probability)} \\
&= \frac{\sum_{q=0}^{100} qP(1|X_j,q)P(X_j)P(q)}{\sum_{q=0}^{100} P(1|X_j,q)P(X_j)P(q)} && \text{(independence assumption)} \\
&= \frac{\sum_{q=0}^{100} q\pi(X_j,q)P(q)}{\sum_{q=0}^{100} \pi(X_j,q)P(q)} && \text{(definition in (A3)).}
\end{aligned} \tag{6}$$

Intuitively, for agents to form an expectation about the quality of a cold opened movie $E_m^{re}(q_j|1,X_j)$, they must consider all possible levels of quality that a movie *could have* (hence the summations over all integers in [0,100]), and the conditional probability that the movie would be of the hy-

[36]An alternative to the cursed equilibrium model, the analogy-based expectation equilibrium model (Jehiel, 2005; Jehiel and Koessler, 2008) can also model partial sophistication from an equilibrium viewpoint. Because that model is less parsimonious than the cursed equilibrium model, it will not be used in this paper's analysis.

pothesized quality given its characteristics and the fact that a distributor decided to cold open it with probability $P(q|1, X_j)$ (which is equal to $\pi(q|1, X_j)$, the actual probability). This derivation uses the laws of probability, and the crucial assumption that the probability of any movie's quality level, $P(q)$, is independent from the probability of it having any other characteristics $(P(X_j))$,[37] then a cold opened movie's expected quality, $E_m^{qre}(q_j|1, X_j)$, only depends on the joint probability of a distributor cold opening a movie with given characteristics and quality ($\pi(X_j, q)$), and the frequency of quality ratings ($P(q)$). Independence is a helpful simplification because without it, distributor decisions would depend on quality *and* on the entire vector of characteristics, which creates too many decision probabilities to estimate reliably. From this transformation we are able to calculate $E_m^{qre}(q_j|1, X_j)$ if $\pi(X_j, q)$ is known.

The cold opening probabilities $\pi(X_j, q)$ depend on estimated revenues from opening the movie cold or screening it (and revealing its quality, assuming (A1)). We use a transformation, then regression, to estimate the revenue as a function of X_j and q. The revenue equation (defined in previous section) is

$$\begin{aligned} R(X_j, E_m(q_j|c_j, X_j)) &= N\hat{t}p(X_j, E_m(q_j|c_j, X_j)) \\ &= N\hat{t}/\left[1 + e^{-\lambda_m\left(\alpha E_m(q_j|c_j, X_j) + \beta X_j - \hat{t} + \epsilon_j\right)}\right]. \end{aligned} \tag{7}$$

Rearranging terms and taking a logarithm, yields a specification which is easy to estimate because

[37] Appendix B, Table A.4 shows the intercorrelation matrix. There is only one variable which has a correlation with quality higher than .20—namely, the budget ($r = .28$). Therefore, the assumption of independence in (3) is not a bad approximation.

it is linear in characteristics X_j and expected quality $E_m(q_j|c_j, X_j)$,

$$\log\left(\frac{R(X_j, E_m(q_j|c_j, X_j))}{N\hat{t} - R(X_j, E_m(q_j|c_j, X_j))}\right) = -\lambda_m \left(\alpha E_m(q_j|c_j, X_j) + \beta X_j - \hat{t} + \epsilon_j\right). \tag{8}$$

Note that this rational expectation computation is recursive: Moviegoers' beliefs about the quality of cold opened movies depend on which movies the distributors choose to cold open (through equation 6). But the distributors' choice to cold open depends on moviegoers' beliefs about the quality of cold opened movies (through assumption 3).

Because of this recursive structure, we estimate the model using an iterative procedure (see Appendix C for details). The procedure first uses the large number of screened movies (where quality is assumed to be known to moviegoers by (1)) to estimate regression parameters that forecast revenues conditional on quality in (8). Then movie-specific expected qualities for all cold opened movies are imputed using a maximum-likelihood procedure that chooses a distributor response sensitivity λ_d which explains actual distributor decisions best and satisfies the assumption that moviegoers' beliefs are a χ-weighted mixture of rational expectations and naive beliefs (equation 6). These inferred expected qualities are then added to qualities of all movies to re-estimate (8) and the process iterates until parameters converge. Convergence means that parameters have been found such that both the representative moviegoer and the distributors best-respond (stochastically) and the moviegoer rational-expectations constraint on cold-opened movies (6) is satisfied.

To find the best-fitting χ, the procedure is repeated using a grid-search over values between 0 and 1, and the best-fitting χ is found (using a maximum likelihood criterion over all distributors' release decisions). That is, given the 856 (797 screened, 59 cold) release decisions in our dataset, if distributors were best responding to the a curse of moviegoers (knowing moviegoers characteristics for movies and quantal response parameter λ_m), the maximum likelihood value of that curse is χ^*.

Our best fitting value is $\chi^* = 0$, largely because this value is based on distributors decisions. This is the model's only way of accounting for the two stylized facts– viz., (i) there are few cold openings, but (ii) there is a substantial box office premium. Within the restricted structure of the model, the paucity of cold openings implies χ_d is low (i.e., distributors think moviegoers, have little curse, and hence will believe cold-opened movies are terrible, which is why they open cold so rarely). Given that estimate, the rational expectation of cold-opened movie quality is very low, so to explain the box office premium the weight on the rational expectation term must be low. Note that this is the same as fitting quantal response equilibrium (McKelvey and Palfrey, 1995, 1998).

Table A.5 shows the regression results from six iterations from this process (which stopped according to the step 6 convergence definition in Appendix C). The r-squared value, 0.682, shows our model has a reasonable fit with the data. The final log likelihood value, -205.7 implies that the (geometric) mean correctly-predicted probability of actual decisions for all movies is 0.79. This predicted probability is much better than chance guessing (0.5) but is only a little better than simply guessing that all movies have a cold opening probability equal to the 7% ($= 59/856$) base rate, which yields a log-likelihood value of -211.62, and a mean correctly predicted probability 0.78. Standard error estimates, determined by 100 bootstraps of this process, are shown in Table 8 and will be discussed in Section 4.3.

After calculating $\chi^* = 0$, we calculated an additional parameter for moviegoers, χ_m, given the quantal response parameters λ_m, λ_d and χ^*, based on cold opened movies' first weekend revenues. The best-fitting value is $\widehat{\chi_m} = .922$,[38] indicating a high degree of curse (recall that $\chi_m = 0$ is no

[38]We feel the parameter $\chi^* = 0$ is the true estimate from the cursed equilibrium model. If we began the iterative process with $\chi^* = 0$ it would converge with $\chi^* = 0$, if we began the process with $\chi^* = 0.922$ it would converge with $\chi^* = 0$.

curse). That is, since the estimated correct expectation $E_m^{re}(q|X_j, 1)$ for cold opened movies is low ($\overline{E_m(q|1)}$= 25), and average overall quality is much higher ($\bar{q} = 48$) the representative moviegoer is cursed in believing that quality of a cold opened movie is roughly 46 (=$48\widehat{\chi_m} + 25(1 - \widehat{\chi_m})$), much closer to the average quality of all movies than the actual average quality of cold-opened movies. Cursed moviegoers vastly overestimate the quality of movies that are opened cold.

Since box-office revenues are increasing in quality, the fact that cursed moviegoers overestimate the quality of cold opened movies is consistent with the box office premium found in the basic regressions in Section 2. Indeed, the best-fitting cursed parameter estimate given the expectations found in the previous model, of $\hat{\chi}_{m1} = .922$, predicts an average log box office premium on weekend box office of 0.33 (an increase in revenue of 33%). This value is considerably higher than 15% estimate determined from our initial regression—i.e., it appears that the model implies too *little* rationality of moviegoers, and too large a box office premium compared to the revenue effect from regression (see Appendix B for more detail). However, the curse estimate is close to the value ($\chi = .8$) estimated by Eyster and Rabin on experimental data from Forsythe et al. (1989) on agents' "blind bidding" for objects of unknown value.

4.2 A Cognitive Hierarchy Model

Cognitive hierarchy or level-k models assume the population is composed of individuals that do different numbers of steps of iterative strategic thinking. The lowest level (0-level) thinkers behave heuristically (perhaps randomly) and k level thinkers optimize against $k - 1$ type thinkers.[39] Zero-level thinkers, such as moviegoers, do not think about the distributor's actions of cold opening a

[39]This classification differs from some other versions of the cognitive hierarchy model (Camerer et al., 2004) which suggests k level thinkers optimizes against a distribution of 0,1,...$k - 1$ level thinkers.

movie. For any cold-opened movie they infer the movie's quality $E^0_m(q_j|X_j,1)$ at random[40] by selecting any integer on [0,100] with equal probability. They will go to any movie with probability defined as an analogue of equation (2)

$$p_0\left(X_j, E^0_m(q_j|c_j,X_j)\right) = \sum_{q=0}^{100}(1/101)\frac{1}{1+e^{-\lambda_m\left(\beta X_j+\alpha q-\hat{t}+\epsilon_j\right)}} \tag{9}$$

where $E^0_m(q_j|c_j,X_j) \sim U[0,100]$. Similarly, a 0-level distributor will cold open movies at random, that is,

$$\pi_0(q_j,X_j) = 1/2. \tag{10}$$

A 1-level moviegoer knows 0-level distributors cold open movies at random, and assumes all distributors behave in this manner. For each movie he calculates the expected quality given it has been cold opened as

$$\begin{aligned} E^1_m\left(q|X_j,1\right) &= \frac{\sum_{q=0}^{100} qP\left(q\right)\pi_0\left(q,X_j\right)}{\sum_{q=0}^{100} P\left(q\right)\pi_0\left(q,X_j\right)} \\ &= \frac{\sum_{q=0}^{100} qP\left(q\right)\frac{1}{2}}{\sum_{q=0}^{100} P\left(q\right)\frac{1}{2}} \\ &= \bar{q}. \end{aligned} \tag{11}$$

[40]In many games, assuming that 0-level players choose randomly across possible strategies is a natural starting point. However, the more general interpretation is that 0-level players are simple, or heuristic, rather than random. For example, in "hide-and-seek" games a natural starting point is to choose a "focal" strategy (see Crawford and Iriberri (2007a)). In our game, random choice by moviegoers would mean random attendance at movies. That specification of 0-level play doesn't work well because it generates far too much box office revenue. Another candidate for 0-level moviegoer play is to assume a cold-opened movie has sample-mean quality $\bar{q}$. For technical reasons, that does not work well either. It is admittedly not ideal to have special *ad hoc* assumptions for different games. Eventually we hope there is some theory of 0-level play that maps the game structure and a concept of simplicity or heuristic behavior into 0-level specifications in a parsimonious way.

A 1-level distributor expects all moviegoers to behave like 0-level moviegoers. They will assign quality ratings to cold-opened movies at random from the uniform $U[0,100]$ distribution. The 1-level distributor will therefore cold-open movie j with probability

$$\pi_1(q_j, X_j) = 1/\left(1 + \exp\left[\lambda_d(\sum_{q=0}^{100}(1/101)R(X_j, q) - R(X_j, q_j))\right]\right). \tag{12}$$

Proceeding inductively, for any strategic level k, the values $E_m^{k-1}(q|1, X_j)$ and $\pi_{k-1}(q_j, X_j)$ are computed from response to k-1 level type beliefs and actions. The k-level distributor and moviegoer have probabilities and beliefs

$$\pi_k(q_j, X_j) = 1/\left(1 + \exp\left[\lambda_m(R(X_j, E_{k-1}(q|X_j, 1)) - R(X_j, q_j))\right]\right) \tag{13}$$

and

$$E_k(q|X_j, 1) = \frac{\sum_{q=0}^{100} qP(q)\,\pi_{k-1}(q, X_j)}{\sum_{q=0}^{100} P(q)\,\pi_{k-1}(q, X_j)} \tag{14}$$

which leads to moviegoing probability

$$p_k\left(X_j, E_m^k(q_j|c_j, X_j)\right) = \frac{1}{1 + e^{-\lambda_m\left(\beta X_j + \alpha E_m^k(q_j|c_j, X_j) - \hat{t} + \epsilon_j\right)}} \tag{15}$$

where every level-k distributor and moviegoer is playing a quantal response to the level-k-1 moviegoer and distributor respectively.

As an example, Table 5 shows moviegoer-inferred quality and distributor probability of cold opening for the movie *When a Stranger Calls*, for various levels of thinking and their proportions within the population with $\lambda_d = 7.085$ (a figure estimated from the data, see Table A.6).

k	$E_k(q\|Xj,1)$	$\pi_k(q_j,X_j)$
0	U[0,100]	0.50
1	48.12	1.00
2	40.79	1.00
3	34.28	1.00
4	29.40	1.00
5	24.66	0.94
6	20.97	0.10
7	17.40	0.01
8	14.73	0.00
9	12.20	0.00
10	10.26	0.00

Table 5: Expected quality of *When a Stranger Calls* $(q = 27)$ given it is cold opened by level-k moviegoer and probability it is cold opened by level-k distributor in CH with QR model $(\lambda_d = 7.085)$.

Notice that a 0-level distributor cold opens movies at random. Thus a 1-level moviegoer, optimizing against such distributor, believes that cold opened movies have quality (48.12), the average quality of all movies (see equation 11). Then a 2-level distributor, knows that a 1-level moviegoer's belief in cold opened quality is much higher than actuality ($q = 27$). Since quality is preferred by moviegoers, such distributor is very likely to cold open the movie (he will only release it given a quantal response tremble, which depends on the other characteristics of the movie (X_j)). The same can be said for for all level 1–5 distributors. However if a moviegoer is level 5 or above, he believes a cold opened movie has lower quality than 27, thus distributors who optimize against such moviegoers (levels 6+) are unlikely to cold open a movie of quality 27.

The cognitive hierarchy model of Camerer et al. (2004), based on lots of structurally different experimental games, suggests that the proportion of thinkers in the population is often well approximated by a one-parameter Poisson distribution with mean τ,

$$P\left(x = n|\tau\right) = \tau^n e^{-\tau}/n!, \tag{16}$$

where τ is the average number of steps of strategic thinking.[41]

Since the cognitive hierarchy model is only a partial equilibrium model (i.e., only the highest types have accurate beliefs), it is sensible to the average level of distributor and moviegoer thinking to differ. For this reason we will define two separate τ parameters: τ_m will be the mean number of moviegoer steps of strategic thinking, and τ_d will be the mean number of distributor steps of strategic thinking. The limiting result $\tau_d = \tau_m = \infty$ implies both are best responding to each other and is equivalent to quantal response equilibrium.

To determine QR parameters $\{\lambda_d, \lambda_m\}$ and additional CH parameters $\{\tau_d, \tau_m\}$, we use an iterative procedure for estimating values similar to the cursed equilibrium procedure. The procedure is much easier, however, because level-k player behavior is determined by level-k-1 behavior. The iteration is a "do loop" for specific λ_m, λ_d values, which is truncated at high levels of k ($k > 40$) where the percentage of high level-k players is very small (which depends on τ). Looping through for various λ_m, λ_d makes it easy to then grid-search over the λ values and find best-fitting values of both τ and λ.

Table A.6 shows the results of the iterative process for the CH model with QR. The process stopped after six iterations with a log likelihood value of -166.2, which is a significant improvement over the asymmetric cursed model (-205.7).[42]

Note that in the specification with identical values of mean thinking level τ, the estimated value of $\hat{\tau}_m = \hat{\tau}_d^* = 1.12$. This is lower than in many experimental studies (often 1-2) but is in the

[41] All Poisson distributions are determined by one parameter τ, which is both the mean and variance of the distribution. Thus τ is also the variance of the number of steps of strategic thinking.

[42] The value for λ_d (7.085) is also much greater than for the cursed equilibrium (λ_d=1.345), but this difference reflects an unknown mixture of scale differences and differences in response sensitivity.

model	parameter estimates	mean predicted cold opened weekend box office (N=59)	predicted weekend cold opening premium	(Average squared difference in millions $)$^{1/2}$
QRE	λ_m=1.288	6.73 (0.04)	-5.47% (0.31)	6.00 (0.09)
Cursed Equilibrium	χ_m=0.922, λ_m=1.288	9.46 (0.08)	33.32% (0.80)	3.86 (0.05)
Cognitive Hierarchy k-1	τ_m=1.12, λ_m=1.302	8.96 (0.12)	35.70% (1.20)	5.64 (0.06)
Random	E(q)~U[0,100]	11.44 (0.09)	63.56% (0.83)	5.74 (0.06)
Actual Data	-	20.63 (2.18)	14.70% (7.34)	-

Table 6: Comparison of the three behavioral models for moviegoer predictions with bootstrapped standard errors ($N = 100$). The last column is the square root of the average of the squared difference between actual box office (in millions $) and predicted box office (in millions $).

ballpark,[43] of estimates from experimental games ($\hat{\tau} \approx 1.5$)[44] and for field data the initial week of Swedish LUPI lotteries ($\hat{\tau} = 2.98$, Östling et al., (2007)) and managerial IT decisions ($\hat{\tau} = 2.67$, Goldfarb and Yang (2007)). However, the common-τ estimation implies an average cold opening box office premium of 35.7% (Table 6), which, like the estimate for the cursed model, is positive but is much higher than the regression estimate.

4.3 Comparing Distributor Estimation across Models

Table 8 provides standard error estimates from 100 random bootstraps of the data set for each parameter and each model. These bootstrapped samples are then used to give standard error estimates for comparative statistics between the three models in Tables 6 and 7. Among other things, Table

[43] The objective function (sum of squared residuals) is rather flat in the vicinity of the best-fitting τ_m, so higher values from 2–4 give comparable fits to $\hat{\tau}^*_m = 1.12$. An ex ante prediction based on $\tau = 1.5$ from lab data would forecast reasonably well in this field setting.

[44] Crawford and Iriberri (2007a, 2007b) estimate a level-k model for auctions and hide-and-seek games respectively. They do not use a single Poisson parameter, but most of their classifications are for level 1 thinkers and level 2 second most, which would be most consistent with a Poisson parameter between 1–2.

model	parameter estimates	log likelihood	mean correct (of 856)	standard deviation correct	no. predicted to open cold
QRE	λ_d=1.345	-205.76 (2.16)	737.28 (1.70)	7.37 (0.07)	113.11 (2.10)
Cursed Equilibrium	λ_d=1.345, χ=0	-205.76 (2.16)	737.28 (1.70)	7.37 (0.07)	113.11 (2.10)
Cognitive Hierarchy k-1	l_d=2.755, τ_d=8.550	-166.23 (2.37)	772.22 (0.83)	6.10 (0.03)	61.73 (1.09)
Base Rate	p=59/856	-214.73 (2.21)	740.55 (1.47)	7.41 (0.05)	59.00 (0.85)

Table 7: Predictions of cold opening choices of distributors with bootstrapped standard errors ($N = 100$). Each model provides a probability that a given movie will be cold opened. When compared with actual data, there is a probability that the model would correctly predict all actual decisions correct (log likelihood), an expected number of cold opening decisions the movie would predict correctly (mean correct), and the standard deviation of the number that model would predict correctly.

8 indicates the cognitive hierarchy model with quantal response fits distributor decisions (in terms of log likelihood) significantly better than the other models.

Another thing to note is that most of the cursed model bootstraps have a best-fitting χ value of 0. Thus the initial finding of common moviegoer curse and distributor expectation of moviegoer curse at $\hat{\chi} = 0$ (equivalent to QRE) was not an aberration. However, standard errors indicate that for a few bootstrapped estimates, the best fitting χ was not zero. For χ_m the estimates indicate a high degree of curse with some variation.

Table 6 compares best-fitting parameter values in sums of squared residuals (for moviegoer decisions). The non-equilibrium cursed model predicts the box office revenues of cold opened movies best in terms of deviations from actual data; the cognitive hierarchy model fits second best. This is not surprising since both models predict a box office premium. Even a prediction that moviegoers assume uniformly random quality to cold opened movies (all 0-level thinkers) fits the

	QRE	Cursed Eq	CH with QR
λ_m	1.288 (0.005)	1.288 (0.005)	1.302 (0.004)
λ_d	1.345 (0.018)	1.345 (0.018)	7.085 (30.299)
χ_m	-	0.922 (0.008)	-
χ*	-	0.000 (0.001)	-
τ_{m}	-	-	1.120 (0.121)
τ_d	-	-	8.567 (0.045)
$E_m(q\|Xj,1)$	15.106 (0.315)	15.106 (0.315)	44.666 (0.587)
Log MLE	-205.712 (2.134)	-205.712 (2.134)	-166.232 (2.126)

Table 8: Parameter estimates of models with bootstrapped standard errors ($N = 100$).
Note: χ* denotes result where moviegoers' curse and distributors' beliefs about moviegoers are the same.

data better than the rational alternative, QRE model, which assumes correct expectations for cold opened quality.

For distributor decisions (Table 8) the best fitting equilibrium cursed parameter is zero, so the cursed and rational alternative, QRE models perform identically (because with χ*$= 0$, the models are equivalent). In cursed models, moviegoers and distributors are allowed to have non-Nash expectations, but distributors are required to best respond to them. The results suggest that given distributors must best respond to any degree of moviegoer curse, a model with moviegoers having correct expectations of movie quality fits the data best (that is, no expected moviegoer curse would explain the data better).

The CH model improves a little bit on the predictions of the cursed model. The key to its relative success is that the model estimates a low τ for moviegoers ($\hat{\tau}_m = 1.12$, close to experimental estimates of τ around 1.5–2.5) but the distributor τ_d is much higher (8.5). These parameters express the intuition that some moviegoers are easily fooled—they think cold openings are close to random—but distributors do not think moviegoers are so easily fooled, which is the models way of explaining why so few movies are cold-opened given the box office premium.

The CH model also predicts the most number of opening decisions correctly because its high τ_d predicts very few movies will be cold opened the higher λ_d predicts *some* movies will be cold opened because of noise. The bootstrapped standard errors show these results are reasonably robust and do not depend on only a few data points. Importantly, the bootstrapped standard error around the mean bootstrapped estimate $\tau_m = 1.120$ is 0.121. This estimated τ for moviegoers is less than the average steps of thinking value found in most experiments (1.5), but is not much less. The estimate is also significantly different than random perception of quality $(\tau_d = 0)$ or fully rational perception $(\tau_d \to \infty)$. The large improvement in log likelihood compared to the cursed model also suggests the CH model is a more reasonable overall explanation. All models are also an improvement over the baseline case which predicts that all movies to be cold-opened with the same probability (.07).

Finally, an entirely different explanation for the distributors' behavior is that distributors do not cold open enough because they are optimistic about their movie quality.[45] For example, suppose that they think moviegoers have no curse (i.e., $\chi_d = 0$) but they think their movie's quality is a weighted average of its true quality and the top quality of 100. That is, $E_d(q_j) = 100\zeta_d + q_j(1 - \zeta_d)$. If we use this perceived quality in lieu of the true quality and repeat the analysis, the best-fitting values are $\{\hat{\lambda}_d, \hat{\zeta}_d\} = \{0.183, 0.283\}$. The associated log-likelihood is -175.057, a substantial improvement over the no-optimism ($\tilde{\zeta}_d = 0$) fit of -204.20. So the combination of

[45]We thank Cade Massey for this insightful idea. Optimism has also been studied in economics by Camerer and Lovallo (1999), Brunnermeier and Parker (2005), and Mayraz (2008).

rampant optimism– producers believing that their beloved movies are a quarter of the way from how good they actually are to perfection– along with a faith in moviegoers' rationality, is another way to explain the distributors' reluctance to cold-open movies.

5 Conclusion

In games where information about a single dimension of product quality is known to be good or bad news, and may be strategically disclosed or withheld at no cost, the only equilibrium involves the information receiver believing all withheld information conveys the worst possible news. Then the information sender should always reveal all information (except the worst).

However, this equilibrium reasoning requires many steps of iterated strategic thinking. Numerous laboratory experiments have shown in a variety of games that either noisy responses or a small number of steps of strategic thinking tends to explain data well, as parameterized by cursed equilibrium, and cognitive hierarchy (CH) approaches with stochastic better-response. These models explain both experimental results that are far from equilibrium and other results that are surprisingly close to equilibrium, even in one-shot games (e.g., Goeree and Holt, 2001; Camerer et al., 2004).

This paper is the first to apply both parametrized behavioral models to a naturally occurring field phenomenon, an example of "structural behavioral economics." Field applications like these are important in showing whether principles of limited rationality that were inspired and calibrated by experimental data can also explain some basic facts in larger-scale field settings (see DellaVigna, 2007, for many examples).

We study a market in which information senders (movie distributors) are strategically withholding information (the quality of their movie) from information receivers (moviegoers), by not showing movies to critics in time for reviews to be published before opening weekends. Contrary to the simple Bayesian-Nash equilibrium, there is a "box office premium"—movies that have been cold opened earn more than other pre-screened movies with similar characteristics. Importantly, there is no such premium in foreign or video rental markets, where movies are released after the initial US release (so that reviews are widely available). The disappearance of the premium in rental and overseas markets is consistent with the hypothesis that the premium is due to some moviegoers failing to realize that no advance review is a bad signal about quality. The fact that moviegoer ratings (from imdb) are lower for these movies also suggests moviegoers' overestimated expected quality.

The cursed equilibrium model has difficulty explaining the box office premium (unless the moviegoers' curse and distributors' perceptions are different). Both restricted models perform poorly because moviegoers should correctly anticipate that cold opened movies are of low quality, which is inconsistent with the cold opening box office premium. The CH model with a low number of thinking steps τ_m to represent moviegoer naïveté, and a high τ_d to represent distributor over-sophistication can represent the mismatch of moviegoer perceptions and the reluctance (given expected moviegoer perceptions) of distributors to cold open.

The mismatch of parameter values for moviegoers and distributors suggest that either moviegoers should learn over time that cold opened movies are bad,[46] or distributors should learn to cold

[46] A natural question is how fast consumers will eventually learn that cold opened movies have low quality. Economic intuition and experiments on lemons (e.g. Lynch et al., 2001) suggest consumers will ultimately infer that goods whose quality is not disclosed have low quality. However, movie audiences contain overlapping generations, so that the relevant time frame for learning is the first few years in which teenagers go to the movies. In this time they may only learn, with noise, from a few movies that they hear little about and are disappointed by. So it is conceivable that there is a learning process but it is slow enough within a generation, and does not spill over across generations, to permit the box office premium that we see in the data.

open more movies.

The time trend is consistent with the hypothesis that distributors are learning, because the number of cold opening decisions increase across the years in the sample (Figure 2).[47] The models in this paper suggest that distributors should have cold opened more movies as a best-response to limited strategic thinking by moviegoers. However, this speculation is severely limited by the fact that over the time period we study there are substantial changes in movie economics (a shift from live box office to DVD sales and rental) and information about movie quality (which leaks out in advance more nowadays due to internet sites and blogs).

While the industry studied here, major movie distributors, is quite unique, the main parts of the industry—products of unknown quality and critical review—are found in other industries. For example, another market in which critical valuations are consumed by potential buyers is markets for expensive artworks. Mei and Moses (2005) find that estimates of selling prices, released by auction houses, are upward-biased estimates of later prices, but that investors seem to respond to these prices, as if they do not fully discount the auctioneers' incentives to inflate estimates. Our approach could be utilized to determine the sophistication of these buyers and auctioneers. The applications of this approach are much wider when one considers the similarity between cold opening and the well-studied economic problem of selective disclosure.

Since this setting features producers choosing how much information about a dimension of product quality that consumers value to disclose, it is similar to many other industries that feature selective disclosure. In relation to this literature, our results suggest that some consumers do not perfectly infer low quality from non-disclosure (i.e., from cold opening). Furthermore, the fact that

[47] Through 2000–2005 distributors cold opened around 5–8% of widely released movies. In 2006 and 2007 distributors cold opened 19% (30/160) and 23% (30/131).

IMBD ratings are about 10% lower for movies that are cold opened suggests that consumers make mistakes which they regret. However, these mistakes are small (based on the rating measures) and distributors do disclose information (through reviews) about more than 90% of the movies, so this is a market in which voluntary disclosure is certainly working reasonably well.

Our results are similar to three other sharp field studies of consumer quality disclosure (Mathios, 2000; Jin and Leslie, 2003; Jin, 2005). All three studies are inconsistent with the strong hypothesis that customer strategic thinking leads to complete voluntary disclosure, so that mandatory disclosure will have no effect. Mathios (2000) studied nutrition labeling of salad dressing. Most low-fat dressings (less than 9 grams of fat per serving) were voluntarily labelled for fat content before mandatory disclosure, while only 15% of high-fat dressings were labelled. After mandatory disclosure, the share of the high-fat dressings fell by about 20%. This effect is consistent with the hypothesis that some consumers did not infer that non-labeling implied high fat content, and the mandatory disclosure provided information they had not inferred (but cared about). Jin and Leslie (2003) studied the effects of a shift from voluntary to mandatory posting of standardized health-rating cards in Los Angeles restaurants. They find that mandatory disclosure increases hygiene scores by 5.3%, which is about half a standard deviation of the distribution, and which is modestly significantly higher than under voluntary disclosure.[48] Jin (2005) shows that HMOs do not voluntarily disclose quality (via NCQA accreditation) in markets that are the least competitive. She also finds that HMOs which voluntarily disclose tend to serve areas with large employers, which suggests that HMOs are responding differently when they have more sophisticated customers (be-

[48]Their test probably understates the effects of a shift from voluntary to mandatory disclosure because some of the voluntary-disclosure cities were expected to adopt mandatory disclosure in the near future. Restaurants might have begun complying early during the last parts of the voluntary regime, and earlier than they would have if they did not expect a shift to mandatory disclosure. Since their test understates the change from voluntary to mandatory disclosure, it therefor e overstates the degree of consumer rationality.

cause big firms tend to have more savvy benefits managers) than when they have less sophisticated consumers.

Note, however, that our paper was not designed to pass judgment on the detailed concerns in regulatory debates about disclosure. We simply note that the limits that we infer from consumer (moviegoer) behavior on strategic thinking are comparable to conclusions drawn from the other empirical studies that are more sharply focussed on effects of disclosure changes or choices.

Finally, we note again that there are many markets and political situations with asymmetric information in which the failure to reveal information that could be revealed should be informative, if the receiver makes the proper strategic inference, and yet information is often unrevealed. Our approach could be applied to these situations.

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Appendices: Not for Publication

A Description of Variables

To determine if a movie was cold opened ($c_j = 1$) we examined the dates on three or four major news publications (the Los Angeles Times, New York Times, San Francisco Chronicle, and New York Post). If the dates of reviews in any of these publications were later than the release date we examined the reasoning behind the late reviews. A movie was classified a "cold open" if at least one source stated the movie was not screened for critics before release (in most cases, none of the available sources had advance reviews).

Weekend and total US box office data were obtained from a *FilmSource* database (Nielsen EDI, `www.filmsource.com`). The *FilmSource* database also included the number of theaters that showed a movie during its first weekend, the number of days in the opening weekend, and if the movie was released before Friday (generally only for anticipated blockbusters). *FilmSource* also gave a description of the genre of the movie, its MPAA rating (G, PG, PG-13, R), and whether the movie was adapted from previous source material.

Production budget information came from imdb.com for most movies, and from boxoffice-mojo.com or the-numbers.com for those missing from imdb.com. Budget data were available for 856 of the 890 movies, including 59 or the 62 cold openings (95%). Of this set, 832 movies also had the first day's box office data available on imdb.com including 59 of the 62 cold openings.

The imdb.com database was used to determine the star power rating of each movie's stars. Each week imdb.com determined this value by ranking the number of searches done on the imdb.com site for every person affiliated with movies. The most searched star would have value 1. Since there are over one million stars on imdb.com, we took the natural logarithm of the star ranking to reduce effect of unknown stars with very high numbers. We averaged the logged star ranking for the top two stars for each movie during its opening week.

Three other variables, competition (the average production budget of other movies released on the same opening weekend), the summer dummy variable (whether the movie was released in June, July and August), and the year of release variable (2000=-3, 2001=-2, 2002=-1, 2003=0, 2004=1, 2005=2, 2006=3) were calculated from the previous data.[49]

B Supplemental Tables and Figures

Table A.1 provides a list of each of the 62 cold opened movies in our dataset and date of release. Table A.2 shows the regressions done on logged opening day box office in the full and lean regressions. Table A.3 shows regressions done on logged post-opening-weekend box office in the full and lean regressions including logged opening weekend box office as a regressor. Table A.4 shows the correlations between the regressors in the full regressions done on box office. Table A.5 shows values after each iteration in estimating the cursed parameters with quantal response (QR). Table A.6 shows values after each iteration in estimating the CH parameters with QR.

Tables A.7 and A.8 show the sum of squares and log likelihood for the various values of estimates of τ_d and $\{\tau_d, \lambda_d\}$, respectively.

[49]The regressions had similar results when dummy variables for year were used instead of one year variable.

Movie Title	US release date
See No Evil	5/19/2006
Silent Hill	4/21/2006
Phat Girlz	4/7/2006
The Benchwarmers	4/7/2006
Stay Alive	3/24/2006
Larry the Cable Guy: Health Inspector	3/24/2006
Ultraviolet	3/3/2006
Madea's Family Reunion	2/24/2006
Doogal	2/24/2006
Date Movie	2/17/2006
When a Stranger Calls	2/3/2006
Big Momma's House 2	1/27/2006
Underworld: Evolution	1/20/2006
Grandma's Boy	1/6/2006
Hostel	1/6/2006
BloodRayne	1/6/2006
Aeon Flux	12/2/2005
In The Mix	11/23/2005
The Fog	10/14/2005
Cry Wolf	9/16/2005
King's Ransom	4/22/2005
Man of the House	2/25/2005
Cursed	2/25/2005
Boogeyman	2/4/2005
Darkness	12/25/2004
Seed of Chucky	11/12/2004
Paparazzi	9/3/2004
The Cookout	9/3/2004
Exorcist: The Beginning	8/20/2004
Alien vs. Predator	8/13/2004
My Baby's Daddy	1/9/2004
House of the Dead	10/10/2003
The Order	9/5/2003
My Boss's Daughter	8/22/2003
Marci X	8/22/2003
From Justin to Kelly	6/20/2003
Wrong Turn	5/30/2003
House of 1000 Corpses	4/11/2003
Extreme Ops	11/27/2002
Wes Craven Presents: They	11/27/2002
Trapped	9/20/2002
The Adventures of Pluto Nash	8/16/2002
Halloween: Resurrection	7/12/2002
Kung Pow: Enter the Fist	1/25/2002
The Wash	11/14/2001
Extreme Days	9/28/2001
Glitter	9/21/2001
Soul Survivors	9/7/2001
Get Over It	3/9/2001
Valentine	2/2/2001
Sugar & Spice	1/26/2001
Wes Craven Presents Dracula	12/22/2000
Dude, Where's My Car?	12/15/2000
Get Carter	10/6/2000
Highlander: Endgame	9/1/2000
The Art of War	8/25/2000
Autumn in New York	8/11/2000
The In Crowd	7/19/2000
Screwed	5/12/2000
3 Strikes	3/1/2000
Down to You	1/21/2000
Supernova	1/14/2000

Table A.1: List of Cold Opened Movies

variable\regression	log 1st day	log 1st day
cold	0.119* (0.083)	0.153** (0.086)
crit	0.012*** (0.001)	0.010*** (0.001)
thtr	0.875*** (0.037)	0.822*** (0.035)
bud	0.002*** (0.001)	0.001* (0.001)
comp	0.015** (0.001)	0.001 (0.001)
star	-0.026* (0.015)	-0.066*** (0.014)
sum	0.101** (0.046)	-
sq/adpt	0.139*** (0.043)	0.097** (0.044)
beffri	0.000 (0.000)	-
wkdlen	-0.001 (0.059)	-
beffor	0.000 (0.000)	-
act/adv	0.082 (0.073)	-
ani	-0.264** (0.120)	-
com	0.021 (0.061)	-
doc	0.493 (0.334)	-
fant/sci	0.131 (0.096)	-
susp/hor	0.035 (0.074)	-
year	-0.041*** 0.011	-0.037*** (0.011)
pg	-0.105 (0.130)	-
pg13	0.376*** (0.127)	-
r	0.384*** (0.130)	-
const	-1.843*** (0.196)	-1.10*** (0.134)
R-squared	0.670	0.622
N	833	833
degrees of freedom	21	8
*p<0.1, **p<0.05, ***p<0.01		

Table A.2: Regressions of log opening day revenues (in millions)

variable\regression	log post-opening weekend	log post-opening weekend
log rwkd	1.210*** (0.024)	1.177*** (0.026)
cold	-0.035 (0.051)	-0.091* (0.054)
crit	0.009*** (0.001)	0.009*** (0.001)
thtr	-0.134*** (0.030)	-0.076** (0.030)
bud	1.21*** (0.001)	0.000 (0.001)
comp	0.001*** (0.000)	0.002*** (0.000)
star	-0.016* (0.009)	-0.001 (0.009)
sum	0.035 (0.028)	-
sq/adpt	-0.020 (0.026)	-0.013 (0.028)
beffri	0.087*** (0.019)	-
wkdlen	-0.121*** (0.036)	-
beffor	0.000 (0.000)	-
act/adv	-0.166*** (0.044)	-
ani	-0.238*** (0.073)	-
com	0.001 (0.036)	-
doc	-0.197 (0.206)	-
fant/sci	-0.329*** (0.059)	-
susp/hor	-0.048 (0.044)	-
year	-0.042*** (0.007)	-0.041*** (0.007)
pg	-0.201*** (0.074)	-
pg13	-0.427*** (0.077)	-
r	-0.52*** (0.079)	-
const	0.556*** (0.119)	-0.060 (0.026)
R-squared	0.916	0.899
N	856	833
degrees of freedom	21	8
*p<0.1, **p<0.05, ***p<0.01		

Table A.3: Regressions of log box office revenues after first weekend (in millions)

	Cold	crit	theater s	rBud	Actor 1	Actor 2	Hol	adapt or seq	BefFri	Wkd Len	Before Foreign	Act/ Adv	Ani- mated	Com- edy	Docu- mentary	Fant/ Sci	Susp/ Horr	YEAR	PG	PG-13	R
Cold	1.00	-0.33	-0.15	-0.17	-0.06	0.12	-0.05	-0.08	-0.03	0.01	0.01	-0.06	-0.05	-0.01	-0.02	0.00	0.20	0.07	-0.11	0.06	0.03
crit	-0.33	1.00	0.16	0.28	0.10	-0.11	0.04	0.13	0.12	0.00	0.04	0.06	0.16	-0.18	0.04	0.08	-0.12	0.12	0.04	-0.06	-0.01
theaters	-0.15	0.16	1.00	0.58	0.07	-0.38	0.11	0.26	0.07	0.02	-0.12	0.22	0.16	-0.11	-0.10	0.19	-0.03	0.15	0.17	0.10	-0.28
rBud	-0.17	0.28	0.58	1.00	0.12	-0.40	0.14	0.24	0.19	0.04	-0.08	0.32	0.09	-0.26	-0.07	0.28	-0.16	0.01	0.05	0.11	-0.16
Actor 1	-0.06	0.10	0.07	0.12	1.00	-0.05	0.15	0.05	0.11	0.05	0.01	0.01	0.06	0.06	-0.01	0.00	-0.08	-0.01	0.10	0.02	-0.11
Actor 2	0.12	-0.11	-0.38	-0.40	-0.05	1.00	-0.06	-0.09	-0.05	0.01	0.10	-0.15	0.25	0.03	0.17	-0.11	0.00	0.02	0.17	-0.17	-0.03
Hol	-0.05	0.04	0.11	0.14	0.15	-0.06	1.00	0.04	0.08	-0.11	0.01	0.06	0.00	0.02	0.06	0.06	-0.03	-0.02	0.04	0.06	-0.10
adapt or seq	-0.08	0.13	0.26	0.24	0.05	-0.09	0.04	1.00	0.13	0.02	-0.05	0.11	0.05	-0.16	-0.05	0.14	0.02	0.10	0.09	-0.04	-0.05
BefFri	-0.03	0.12	0.07	0.19	0.11	-0.05	0.08	0.13	1.00	0.09	-0.05	0.01	0.05	-0.02	0.04	0.07	-0.09	-0.03	0.02	-0.02	-0.02
WkdLen	0.01	0.00	0.02	0.04	0.05	0.01	-0.11	0.02	0.09	1.00	-0.03	-0.01	0.02	-0.02	-0.02	0.03	-0.05	-0.03	0.01	0.04	-0.06
ForBef	0.01	0.04	-0.12	-0.08	0.01	0.10	0.01	-0.05	-0.05	-0.03	1.00	0.09	-0.01	-0.07	-0.01	-0.01	0.03	-0.02	-0.02	-0.04	0.05
Act/Adv	-0.06	0.06	0.22	0.32	0.01	-0.15	0.06	0.11	0.01	-0.01	0.09	1.00	-0.11	-0.35	-0.03	-0.12	-0.20	0.04	-0.07	0.09	-0.01
Animated	-0.05	0.16	0.16	0.09	0.06	0.25	0.00	0.05	0.05	0.02	-0.01	-0.11	1.00	-0.20	-0.01	-0.07	-0.11	0.00	0.24	-0.23	-0.18
Comedy	-0.01	-0.18	-0.11	-0.26	0.06	0.03	0.02	-0.16	-0.02	-0.02	-0.07	-0.35	-0.20	1.00	-0.05	-0.20	-0.34	-0.02	0.05	0.14	-0.16
Documentary	-0.02	0.04	-0.10	-0.07	-0.01	0.17	0.06	-0.05	0.04	-0.02	-0.01	-0.03	-0.01	-0.05	1.00	-0.02	-0.03	0.04	-0.03	-0.02	0.04
Fant/Sci	0.00	0.08	0.19	0.28	0.00	-0.11	0.06	0.14	0.07	0.03	-0.01	-0.12	-0.07	-0.20	-0.02	1.00	-0.11	0.00	0.11	0.04	-0.11
Susp/Horr	0.20	-0.12	-0.03	-0.16	-0.08	0.00	-0.03	0.02	-0.09	-0.05	0.03	-0.20	-0.11	-0.34	-0.03	-0.11	1.00	0.04	-0.19	-0.10	0.28
YEAR	0.07	0.12	0.15	0.01	-0.01	0.02	-0.02	0.10	-0.03	-0.03	-0.02	0.04	0.00	-0.02	0.04	0.00	0.04	1.00	0.09	0.02	-0.10
PG	-0.11	0.04	0.17	0.05	0.10	0.17	0.04	0.09	0.02	0.01	-0.02	-0.07	0.24	0.05	-0.03	0.11	-0.19	0.09	1.00	-0.41	-0.30
PG-13	0.06	-0.06	0.10	0.11	0.02	-0.17	0.06	-0.04	-0.02	0.04	-0.04	0.09	-0.23	0.14	-0.02	0.04	-0.10	0.02	-0.41	1.00	-0.66
R	0.03	-0.01	-0.28	-0.16	-0.11	-0.03	-0.10	-0.05	-0.02	-0.06	0.05	-0.01	-0.18	-0.16	0.04	-0.11	0.28	-0.10	-0.30	-0.66	1.00

Table A.4: Correlation between variables

variable\iteration	1st	2nd	3rd	4th	5th	6th
λ_m	1.285	1.290	1.282	1.291	1.288	1.288
crit	0.017	0.016	0.015	0.016	0.016	0.016
thtr	0.001	0.001	0.001	0.001	0.001	0.001
bud	0.003	0.003	0.003	0.003	0.003	0.003
comp	0.002	0.002	0.002	0.002	0.002	0.002
star	-0.041	-0.036	-0.037	-0.037	-0.037	-0.037
sum	0.057	0.040	0.035	0.037	0.036	0.036
sq/adpt	0.101	0.105	0.101	0.105	0.102	0.102
beffri	0.001	0.001	0.007	0.004	0.007	0.007
wkdlen	0.101	0.100	0.097	0.099	0.098	0.098
beffor	0.000	0.000	0.000	0.000	0.000	0.000
act/adv	-0.140	-0.151	-0.153	-0.148	-0.149	-0.149
ani	-0.247	-0.236	-0.232	-0.234	-0.233	-0.233
com	0.023	0.022	0.014	0.022	0.018	0.018
doc	0.211	0.193	0.197	0.196	0.196	0.196
fant/sci	-0.140	-0.120	-0.121	-0.119	-0.120	-0.120
susp/hor	0.001	0.025	0.042	0.028	0.037	0.037
year	-0.073	-0.062	-0.061	-0.064	-0.063	-0.063
pg	-0.151	-0.141	-0.142	-0.141	-0.142	-0.142
pg13	-0.165	-0.124	-0.122	-0.126	-0.123	-0.123
r	-0.205	-0.164	-0.170	-0.166	-0.169	-0.169
R-squared	0.683	0.682	0.678	0.682	0.681	0.682
N	797	856	856	856	856	856
degrees of freedom	20	20	20	20	20	20
λ_d	1.478	1.356	1.367	1.350	1.345	-
χ	0.000	0.000	0.000	0.000	0.000	-
log likelihood	-191.308	-198.569	-196.965	-203.406	-205.712	-
Mean $E_m(q\|Xj,1)$ for λ_d	14.159	13.264	14.894	15.319	15.106	-

Table A.5: The iterative estimation process for the cursed equilibrium model with quantal response

variable\iteration	1st	2nd	3rd	4th	5th
λ_m	1.285	1.302	1.302	1.302	1.302
crit	0.017	0.017	0.017	0.017	0.017
thtr	0.001	0.001	0.001	0.001	0.001
bud	0.003	0.003	0.003	0.003	0.003
comp	0.002	0.002	0.002	0.002	0.002
star	-0.041	-0.039	-0.039	-0.039	-0.039
sum	0.057	0.036	0.037	0.037	0.037
sq/adpt	0.101	0.107	0.108	0.108	0.108
beffri	0.001	0.000	0.000	0.000	0.000
wkdlen	0.101	0.095	0.095	0.095	0.095
beffor	0.000	0.000	0.000	0.000	0.000
act/adv	-0.140	-0.154	-0.155	-0.155	-0.155
ani	-0.247	-0.253	-0.254	-0.254	-0.254
com	0.023	0.016	0.016	0.016	0.016
doc	0.211	0.226	0.228	0.228	0.228
fant/sci	-0.140	-0.152	-0.153	-0.153	-0.154
susp/hor	0.001	-0.016	-0.018	-0.018	-0.018
year	-0.073	-0.066	-0.066	-0.066	-0.066
pg	-0.151	-0.139	-0.139	-0.139	-0.139
pg13	-0.165	-0.148	-0.149	-0.149	-0.149
r	-0.205	-0.177	-0.177	-0.177	-0.177
R-squared	0.683	0.682	0.674	0.682	0.682
N	797	856	856	856	856
degrees of freedom	20	20	20	20	20
λ_d	6.816	7.136	7.090	7.085	-
τ_d	8.567	8.550	8.554	8.554	-
log likelihood	-166.424	-166.226	-166.231	-166.232	-
τ_m	1.26	1.15	1.13	1.12	-
Mean $E_m(q\|Xj,1)$ for τ_m, λ_d	44.666	45.254	45.359	45.412	-

Table A.6: The iterative estimation process for the CH model with quantal response

τ_m	$(\text{Average SSR})^{1/2}$
0	5.14
1.12*	5.08
2	5.08
4	5.14
6	5.35
8	5.59
10	5.81

Table A.7: Average squared difference between predicted and actual weekend revenues (in $) for all cold openings $(N = 59)$ by moviegoer sophistication in CH model with QR $(\lambda_d = 7.085)$

$\tau_d \backslash \lambda_d$	0	3	6	7.085*	9
0	-593.33	-593.33	-593.33	-593.33	-593.33
2	-593.33	-783.20	-798.29	-800.62	-803.45
4	-593.33	-441.44	-438.66	-438.31	-438.17
6	-593.33	-248.56	-230.67	-228.38	-226.32
8	-593.33	-183.70	-169.26	-168.39	-167.89
8.567*	-593.33	-177.43	-166.43	**-166.23**	-166.44
10	-593.33	-173.94	-175.62	-177.55	-179.92

Table A.8: Log likelihood for all distributor release decisions $(N = 856)$ in CH model with QR by distributor sophistication

C Details of Iterative Estimation Procedures (QRE, Cursed, CH)

This section provides the general iterative procedure for obtaining estimates for the relevant parameters of the QRE, cursed and CH models.

1. The iteration counter begins at $i = 1$.

2. The coefficients in equation 8 are estimated using a linear regression,

$$\log\left(\frac{y_j}{N\hat{t} - y_j}\right) = (-\lambda_m \alpha) E_m(q_j|c_j, X_j) - (\lambda_m \beta) X_j - (\lambda_m)\hat{t} - (\lambda_m)\epsilon_j \tag{17}$$

   assuming $N = 300 \times 10^6$ and $\hat{t} = 5.34$.[50] In iteration $i = 1$ only the 797 movies which are screened to critics ($c_j = 0$) are used. Using assumption 1, the observed q_j is substituted for the unobserved expectation $E_m(q_j|0, X_j)$ for these movies. Then all the independent and dependent variables are measured and we can estimate the regression easily.[51] In later iterations, expected quality values $\left(E^{qre}_{m_i}(q_j|c_j, X_j),\ E^{ce}_{m_i}(q_j|c_j, X_j), \text{ or } E^{ch}_{m_i}[E_k(q_j|c_j, X_j)|\tau_d]\right)$ after iteration i will have been computed, and a regression on the full sample can be run.

3. Since simply using $\hat{R}(X_j, E_m(q_j|c_j, X_j)) = N\hat{t}\left(1 + \exp[\widehat{\lambda_m \alpha} E_m(q_j|c_j, X_j) + \widehat{\lambda_m \beta} X_j + \widehat{\lambda_m}\hat{t}]\right)$ to estimate $R(X_j, E_m(q_j|c_j, X_j)$ would produce biased estimates, non-parametric kernel regression techniques are used. A consistent Gaussian kernel regression is used to estimate

[50] Results are highly similar for $N = 100 \times 10^6$, 200×10^6, and $\hat{t} = 5.34$.

[51] A crucial maintained assumption below is that the coefficient on expected quality, α, in determining moviegoer attendance, and hence revenue, is the same for known-quality (screened) and unknown-quality (cold opened) movies.

revenue from the parameter estimates from equation 17.

$$
\begin{aligned}
\hat{R}(X_j, E_m(q_j|c_j, X_j)) &= \hat{m}\left(-\lambda_m(\alpha E_m(q_j|c_j, X_j) + \beta X_j - \hat{t})\right) \\
&= \frac{\sum_{l\in J_i} K_h(g(j) - g(l))y_l}{\sum_{l\in J_i} K_h(g(j) - g(l))}
\end{aligned} \tag{18}
$$

where $g(j) = -\widehat{\lambda_m}\left(\hat{\alpha}E_m(q_j|c_j, X_j) + \hat{\beta}X_j - \hat{t}\right)$, and K is the Gaussian kernel, $K_h(x) = h\frac{1}{\sqrt{2\pi}}e^{\frac{x}{2h}}$, with bandwidth, $h = 0.9w\|J_i\|^{-1/5}$ where $w = \min(s_y, IQR_y/1.34)$ (from Silverman, 1986) and J_i is the current iteration's set of movies (with length 797 for iteration 1, 856 thereafter).

4. The regression results from step 2 give iteration-i coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ and a response sensitivity $\hat{\lambda}_{m,i}$. Step 3 gives estimated revenue equation $\hat{R}_i$ from these parameters for different values of X_j and q_j. From equation (3) we have

$$
\begin{aligned}
& E_m^{qre}(q_j|X_j, 1) = \tfrac{\sum_{q=0}^{100} q\pi(X_j,q)P(q)}{\sum_{q=0}^{100} \pi(X_j,q)P(q)} \\
& \Rightarrow E_m^{qre}(q_j|X_j, 1)\sum_{q=0}^{100} \pi\left(X_j, q\right)P(q) = \sum_{q=0}^{100} q\pi\left(X_j, q\right)P(q) \\
& \Rightarrow \sum_{q=0}^{100} \pi\left(X_j, q\right)P(q)\left[E_m^{qre}(q_j|X_j, 1) - q\right] = 0 \\
& \Rightarrow \tfrac{\sum_{q=0}^{100} P(q)[E_m^{qre}(q_j|X_j,1)-q]}{1+\exp\left(\lambda_d\left(\hat{R}\left(X_j, E_m^{qre}(q_j|X_j,1)\right)-\hat{R}(X_j,q_j)\right)\right)} = 0
\end{aligned} \tag{19}
$$

where the last step follows from the definition of $\pi(X_j, q)$ (assumption 3). All the terms in 19 can be estimated from regression coefficients ($\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\lambda}_{m,i}$ from step 2), determined from the revenue equation $\hat{R}_i$ (from step 3), fit from the quality distribution $P(q)$, or fixed by assumption ($\hat{t}$, N), except for λ_d and $E_{m_i}^{qre}(q_j|X_j, 1)$. To create an iteration of estimates of $E_m^{qre}(q_j|X_j, 1)\ \forall j$ we fix a value of λ_d and solve 19 for each movie j. Next, using fixed λ_d, and newly calculated estimates of $E^{qre}_{m_i}(q_j|X_j, 1)$ for each movie, along with the estimated parameters in step 2 and revenue equations in step 3, the predicted iteration-i probability $(\hat{\pi}_i(X_j, q_j, \lambda_d))$ that each movie j will be cold opened can be computed from assumption 3.

Additionally, in the cursed procedure: For any fixed χ_d, the newly calculated estimates of $E^{qre}_{m}(q_j|X_j, 1)$ (see above equation 19) for each movie can be converted to $E^{ce}_{m}(q_j|X_j, 1)$, by equation 5. With those values, along with the estimated parameters in step 2 and revenue equations in step 3, the predicted iteration-i probability ($\hat{\pi}_i(X_j, q_j, \lambda_d)$ that each movie j will be cold opened can be computed from assumption 3 *for each value of* χ_d.

The CH procedure obtains the probabilities that each movie is cold opened differently:

For a given λ_d and τ_d, we use our estimated values $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\lambda}_{m,i}$, and estimated revenue equation $\hat{R}_i$ to estimate $\pi_{ki}(q_j, X_j)$, $E_{ki}(q|X_j, 1)$, and $\hat{R}_i(E_k(q|X_j, 1))$ for $k = 0 \ldots \bar{k}$ using equations 11–14.[52] Since the probability of a given distributor being level k is $P\left(x = n|_d\right) = \tau_d^n e^{-\tau}/n!$ and the probability of that distributor cold opening given he is level k is $\pi_k(q_j, X_j)$, the total probability that a movie is cold opened is

$$\hat{\pi}_i(X_j, q_j, \lambda_d, \tau_d) = \sum_{k=0}^{\bar{k}} \pi_k(q_j, X_j) \times \tau_d^n e^{-\tau}/n! \tag{20}$$

5. Step 4 is performed repeatedly for a grid search over sets of values of $\lambda_d \in A_i$ (or $(\lambda_d, \chi_d) \in \{A_i, B\}$, $(\lambda_d, \tau_d) \in \{A_i, B_i\}$), where the grid search becomes progressively finer across iterations i.[53]

[52] We used $\bar{k} = 40$, because given regular τ values the probability of $k > 40$ is nearly zero.

[53] The initial $\lambda_{d,i}$ grid is $A_1 = \{1, 1.25, ..., 2\}$. The second grid A_2 takes an interval of values in increments of .1

The maximum likelihood estimate ω ($\lambda^*_{d,i}$, (λ^*_d, χ^*_d), or (λ^*_d, τ_d)) is chosen from the set Ω_i (A_i, $\{A_i, B\}$, or $\{A_i, B_i\}$).[54] That value satisfies

$$
\begin{aligned}
\omega^*_i &= \underset{\omega\in\Omega_i}{\operatorname{argmax}} L(\omega) \\
&= \underset{\omega_i\in\Omega_i}{\operatorname{argmax}} \prod_j \left[\hat{\pi}_i\left(X_j, q_j, \omega\right) c_j \times \left(1 - \hat{\pi}_i\left(X_j, q_j, \omega\right)\right)\left(1 - c_j\right)\right] \qquad (21)
\end{aligned}
$$

where $L(\omega)$ is the joint probability that distributors would choose to screen and cold open each of the 856 movies in the exact manner they did under the QRE (or cursed, CH) model with parameter(s) ω.[55]

6. The value for the maximum likelihood parameter $\lambda^*_{d,i}$ determined from the last step 8 is then used in equation 19 to solve for iteration-i values of $E^{qre}_{m_i}(q_j|c_j, X_j)$ for each of the 59 cold opened movies.

   For the CH procedure: The maximum likelihood value $\lambda^*_{d,i}$ is used to compute the population-averaged expectation for each of the 59 cold opened movies in the sample with

$$
E[E_k(q|X_j, 1)|\tau_m] = \sum_{k=0}^{\bar{m}} \pi_k(q_j, X_j) E_k(q|X_j, 1). \qquad (22)
$$

around the maximum likelihood estimate $\lambda^*_{d,1}$. The next grids A_i take on values of values of width .05, 0.01, 0.005, and 0.001 around the maximum likelihood estimate $\lambda^*_{d,i-1}$.

For cursed: The initial $\lambda_{d,i}$ grid is $A_1 = \{1, 1.25, ...2\}$. The second grid A_2 takes an interval of values in increments of .1 around the maximum likelihood estimate $\lambda^*_{d,1}$. The next grids A_i take on values of values of width .05, 0.01, 0.005 and 0.001, around the maximum likelihood estimate $\lambda^*_{d,i-1}$. The grid for χ_d, B is always {0,0.005,...1}.

For CH: The initial $\lambda_{d,i}$ grid is $A_1 = \{1, 2, ..., 10\}$ and $\tau_{d,i}$ grid is $B_1 = \{0.05, 0.1, ..., 10\}$. The second grid A_2 takes an interval of values in increments of .1 around the maximum likelihood estimate $\lambda^*_{d,1}$. The next grids A_i take on values of values of width .05, 0.01, 0.005 and 0.001, around the maximum likelihood estimate $\lambda^*_{d,i-1}$. For grids $i \geq 2, B_i = 8.001, ...9$.

[54] In the early steps of iteration (i.e., steps 1–3) this value is determined by interpolating inside the grid to achieve more decimal precision.

[55] This process takes roughly 15 minutes (8 minutes for CH) for each λ_d on a single PC running Mathematica 5.2.

The value of τ_m that minimizes the squared residuals in equation 8 is considered the best estimator for this step, that is

$$\tau_{m,i}^* = \underset{\tau_m}{\operatorname{argmin}} \sum_{j:c_j=1} \left(\hat{R}_i \left(X_j, E\left[\left(E_k(q|X_j,1)|\tau_m\right]\right) - y_j\right)^2 \tag{23}$$

where $\hat{R}_i(...)$ is estimated from the kernel estimation 17 in step 2.

Now we have a full set of quality measures q_j and expected qualities for every movie.

7. The process is stopped when the regression values and parameter estimates (λ_m^*, ω_m^*) from the current iteration i are all within .001 of those from iteration $i-1$. Otherwise, the process is repeated with the iteration counter increased by one, starting with the regression step 2. *For the cursed procedure:* When the process converges, a new value χ_m is calculated to minimize the sum of squares between predicted and actual values over all cold openings. That value is determined by

$$\chi_m^* = \underset{\chi_m}{\operatorname{argmin}} \sum_{j:c_j=1} \left(\hat{R}\left(X_j, (1-\chi_m)\, E_m^{re*}\left(q|X_j,1\right) + \chi_m \bar{q}\right) - y_j\right)^2 \tag{24}$$

where $\hat{R}(...)$ is the last estimate done in step 3.

8. The process is repeated 100 more times with different bootstrapped data sets. A bootstrapped data set is created by randomly sampling with replacement from the 856 movies in the original data set. Parameter estimates are obtained by repeating steps 1–7. Standard errors (see Table 8) are calculated by taking the standard deviation of these 100 parameter estimates.[56]

[56]Depending on the bootstrap and number of iterations, the process for a single bootstrap takes 2–6 hours for QRE (2–6 for cursed, 2–12 for CH) on a single PC running Mathematica 5.2