Watching In the Dark: Limited Strategic Thinking at the Movie Box Office[1]

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Abstract

Film distributors occasionally cold open low quality films, deliberately withholding them from critics before release. For cold openings to be profitable, some portion of the audience must not infer that these movies are of exceptionally low quality. In equilibrium, through an iterative reasoning process, moviegoers should correctly infer quality and a cold opening premium should not exist. Therefore, cold openings provide a natural field setting to test models of limited strategic thinking (cognitive hierarchy and cursed equilibrium) as well as the rational-actor, quantal response equilibrium model. In laboratory experiments, models of limited strategic thinking explain data from a wide variety of games and auctions better than equilibrium predictions. Using a data set of 856 widely released movies, we find that a cold opening produces a significant, 12-15%, increase in domestic box office revenue. Parameter estimates of moviegoers behavior fit those observed in experiments for both the cognitive hierarchy and cursed equilibrium models. Movie distributor behavior better fits the cognitive hierarchy model than the quantal response equilibrium model as well. However, distributors reach levels of iterative sophistication unseen in any experiments. This implies they overestimate the complexity of their consumers and could earn more by increasing the frequency of cold openings.

1 Introduction

The central principle in Bayesian-Nash equilibrium analysis of games with information asymmetry is that players can correctly infer what other players know from observable actions. In contrast, models in which strategic thinking is limited due to cognitive constraints allow the possibility that some players *do not* correctly infer what the actions of other players imply. Models of limited strategic thinking have been shown to explain data from a wide variety of experimental games[1] and auctions[2] better than equilibrium predictions. These models express the idea that those (with asymmetric information) can fool some of the people, some of the time (with the selective disclosure of that information), in contrast to the equilibrium assumption that nobody is ever fooled (see Crawford, 2003).

This paper is the first application of different models of limited strategic thinking,[3] to a novel field setting with private information. The setting is the differential box office earned by movies that are "cold opened," i.e., deliberately unavailable for pre-release review by critics as compared to similar quality movies that received pre-release reviews. In equilibrium, through an iterative reasoning process, moviegoers should correctly infer quality and a cold opening premium should not exist. Therefore, cold openings provide a natural field setting to examine models of limited strategic thinking (cognitive hierarchy and cursed equilibrium) as well as the rational-actor, quantal response equilibrium model. This study estimates behavioral

[1]See Nagel, 1995; Stahl and Wilson, 1995; Camerer, Ho and Chong, 2004; Crawford and Iberri(a), in press.

[2]See Crawford and Iberri(b), in press, and Wang, 2006.

[3]Two unpublished studies using field data and cognitive hierarchy approaches are Östling et al (2007) using Swedish lottery choices and experimental analogues, and Goldfarb and Yang (2007) using estimation of firm adoption of 56K modems. The Östling study compares QRE and cognitive hierarchy approaches but Goldfarb and Yang do not compare to QRE, and neither paper estimates the cursed equilibrium model as we do.

parameters (which ideally include full rationality as a limiting case) to see whether parameters have some stability across economic domains and make interesting predictions about both consumer (moviegoers) and firm (distributors) behavior.

This setting is an example of a more general class of games in which a producer or person that knows something about a product's quality can choose to signal its quality or not. Such games of disclosure have been modeled with various assumptions in the theoretical literature (see Verrecchia, section 3, 2001, and Fishman and Hagerty, 1998 for surveys). Their applications have also been widely discussed. For instance, a car salesman can signal a vehicle's quality by adding a warranty when car quality cannot be directly observed (Grossman, 1981). In online dating, participants can decide whether to post a picture or not (Levitt and Dunbar, 2005). Restaurants can voluntarily post their health ratings when not required to by law (Jin and Leslie, 2003). In politics and law, the analogous situation is when one can choose to answer a direct question about a fact they know, or avoid answering the question (e.g., "pleading the fifth" in legal settings). Additionally, a regulated firm can selectively report information about its industry to regulators (Milgrom, 1981).

The interesting empirical question in these settings is what limitedly-rational consumers, voters, or jurors infer from the reluctance to reveal quality or answer a direct question. when it is easy to do so. Two field studies of consumer quality disclosure found results consistent with the hypothesis that not all consumers fully infer quality information from a failure to disclose, by comparing firm behavior under voluntary and mandatory disclosure.

Mathios (2000) studied nutrition labelling 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 higher-fat dressings fell by about 20%.

Jin and Leslie (2003) studied the effects of a shift from voluntary to mandatory posting of 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.[4].

The behavioral explanation of cold opening of movies is straight forward. Suppose moviegoers prefer to see high-quality movies, but some moviegoers do not pay attention to reviews or do not infer anything negative about the quality of cold opened films (even though unreviewed movies are lower in quality, empirically).[5] If film studios know a film's quality in advance, and believe that critics will judge quality fairly (i.e., independent of the review date), but also understand that some moviegoers will not realize that no review is bad news about quality, they will deliberately keep some mediocre movies from being critically reviewed by opening them cold. The technique has been used in the industry for some time, as Litwak (1986) notes in *Reel Power*,[6]

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

If some moviegoers do not realize that a cold opening is bad news about quality, there will be a cold opening premium: Box office revenues will be higher for movies

[4]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.

[5]Cold-opened movies have an average metacritic rating (0-100) of 22, while all movies have an average rating of 48. See section 2 for an explanation of metacritic ratings.

[6]Some industry members have admitted to press that the decision is strategic: 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)

opened cold (controlling for quality as measured by later critic ratings and other characteristics such as budget, star power, etc. that influence revenue).

On the other hand, a fully rational analysis, due originally to Milgrom (1981), implies no cold opening premium. If moviegoers correctly infer that a cold-opened movie is probably bad news, and form conditional rational expectations given that belief, then there will be no cold opening premium and very few movies will be opened cold. The argument can be illustrated numerically. Suppose movie quality is uniformly distributed from 0 to 100. If distributors cold-open 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 movies with qualities between 26 and 100, and only cold open movies with qualities 25 or below. Those movies would have an expected quality of 12.5; so then it would pay for distributors to screen movies with qualities between 13 and 100. Generally, if the distributors do not screen movies with qualities below q^*, the consumers' conditional expectation if a movie is 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 is that only the worst movies (quality 0) are unscreened.[7]

The rational logic does not appear to jibe with some basic facts about movies. Seven percent of the movies in our sample are opened cold (and that percentage

[7] Their are others models of discretionary disclosure that do not have this full unraveling result. Some models have costly disclosure which cause distributors to only reveal information up to a certain threshold. (Viscusi, 1978; Jovanic, 1982) Other models have sellers uniformed about the quality of their product and can learn it with some probability (Dye, 1985; Jung and Kwon, 1988; and Dye and Sridhar, 1995) or at a cost (Matthews and Postlewaite, 1985; Farrell, 1985; Shavell, 1994). We do not believe either assumption fits this particular industry. Fishman and Hagerty (2003) allow a portion of consumers to be unable to interpret revealed information. They find three main equilibria, one where quality is always revealed, one where it is never revealed, and one where high quality is revealed and low quality is not. However, because there are only two quality levels, in the third equilibrium all quality is also revealed. To our knowledge a proportion of uniformed consumers in the population cannot generate a box office premium or explain that a limited proportion of movies to be cold opened.

has increased in recent years, see figure 7). Furthermore, cold opening appears to generate a box office premium (compared to similar-quality movies that are pre-reviewed). The estimated premium is robust to various specifications and is absent in UK and Mexico grosses (which are almost alwaystypically later than US releases, so that information about movie quality is likely to have leaked out across national borders).[8] The cold-opening box office premium is statistically significant, though not hugely so (probably because cold openings are rare and movie grosses are not very predictable from observed characteristics).

Of course the assumption that we are making is that critic reviews influence moviegoers. Alternatively, it is possible that (i) critics have different sensibilities than moviegoers and have no correlation with actual popularity; or (ii) critics have the same sensibilities, but moviegoers ignore them.

We find a strong correlation between box office revenue and critic rating as well as ex-post moviegoer ratings of movies and critic ratings across genres. With this result and the findings of both Eliashberg and Shugan (1997) and Rienstein and Snyder (2005) (who both studied this very issue) we assume that critics generally have the same quality beliefs as moviegoers. The evidence is weaker that critics influence moviegoers. While survey evidence (Simmons, 1994) suggests one third of moviegoers use critical reviews to make decisions, Eliashberg and Shugan reached no definitive conclusion on this issue and Reinstein and Snyder found evidence that critic ratings matter on certain genres. However, that study only examined the effect of a specific two critics delaying their review. A cold opening delays *all* reviews and thus might have a greater effect. Because this evidence is somewhat inconclusive,

[8]For all practical purposes, there are no cold-opened movies in Mexico or the UK, since only the biggest blockbusters, which are not cold opened in the US, are released simultaneously in those countries.

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.

Assuming moviegoers infer quality from critics, we estimate specific parametric models of the degree of limited strategic thinking. A benchmark equilibrium model is quantal reponse equilibrium (QRE). Two models which allow systematic errors in beliefs about the actions of other players (not allowed by QRE) are cursed equilibrium (Eyster and Rabin, 2005); and a cognitive hierarchy (Camerer, Ho and Chong, 2004). It is important to note that fully rational behavior is a special case of those models, because their behavioral parameters have specific numerical values if players are fully rational. Thus, the model estimation allows a sharp comparison of rational limiting cases and more general behavioral specifications allowing departures from full rationality.

The degree of limited rationality by consumers shown here is not large. Roughly speaking, the estimates suggest about ten times a year a couple of million Americans pay $5-10 in money, and an hour or two in time, to see a movie they would not have seen if they had inferred from the lack of pre-release reviews that the movie was not very good. At the same time, a small synchronized mistake by millions of moviegoers is a multi-million dollar profit opportunity for a small number of movie distributors (Opening cold is estimated to increase total box office revenue by about 15%. In other words if the average cold opened movie makes $20 million in total revenue than the deception of consumers counts for roughly $3 million in additional revenue). This example is a reminder that the industrial organization implications of a behavioral mistake depends on the psychology underlying the mistake and on industrial structure (e.g. Ellison, 2006). Exploiting a small mistake that many agents make can still create a large profit opportunity for a small number of firms, depending on industrial organization, regulation, and other factors.

Field applications like these are important in showing whether principles of limited rationality which were inspired and calibrated by experimental data can also explain some basic facts in larger-scale field settings (see Della Vigna, 2007, for many examples). The intent is not to fit three models and "pick a winner". Instead, we want to use all three models to gain insight into this process and show that experimental models can be relevant to empirical data. The strengths and weaknesses of these models indicate our understanding (or lack therof) of the field phenomenon.

The central conclusion here is that some consumers fail to infer that product quality is bad when objective quality reviews are actively avoided or withheld by producers. This possibility could be explored in many other types of markets and settings where the failure to signal quality should itself be informative.

2 Data

The data set contains all 890 movies widely released[9] in the U.S. in their first weekend, over the $6\frac{1}{2}$ year period from January 1, 2000 to June 30, 2006.[10] Metacritic.com ratings are used to measure quality. Metacritic.com quantifies 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 available on Monday for cold opened movies. In this way it is exogenous from

[9]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 expand). 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.

[10]Movies before 2000 are excluded because Metacritic.coms records did not cover every movie from before 2000.

box office revenue measures.[11] A natural question to ask is whether metacritic.com ratings accurately capture the quality of movies. Our analysis indicates they do. Figure 1 indicates, these ratings are highly correlated with the logarithm of total US box office revenue. This result is also found in studies of critic influence (Eliashberg and Shugan, 1997; Reinstein and Snyder, 2005). We also examine the aggregated user ratings on imdb.com, the largest internet site for user movie reviews. We find a high correlation between metacritc scores and imdb user reviews (see Figure 2). The result is not specific to genre, Table 6 indicates this high correlation holds across genres. Metacritic scores align with two clear indicators of movie popularity.

The squares in Figure 1 represent the cold-opened movies in our sample. Notice that no cold opened movie has a metacritic rating higher than 55 with an average rating of 25. Notice also that few movies are actually cold opened: only 62 of the 890 points are squares (7%). However, the graph does not conclusively show whether cold-opened movies do better than non-cold-opened movies because there are other variables that are not included in Figure 1 that correlate with box office revenues (most importantly, the initial number of screens on which the movie is shown).

To determine if a movie was cold opened 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, all of the available sources did not have advance reviews).

[11] Ratings such as the imdb.com user rating are determined by the people who see the movie and who give reviews afterwards. We treat that variable as a measure of popularity, but consider it endogenous to box office.

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 boxofficemojo.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. We averaged this value of star ranking for the top two stars for the week their movie opened. 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.

Two other variables, the average production budget of movies released on the same weekend and the summer dummy variable (whether the movie was released in June, July and August), were calculated from the previous data.

All these variables were used in a regression model to test if movies that are cold opened have significantly greater logged first day, first week and total US box office. Formally, each movie, j, has a Metacritic.com 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.

Table 1 shows summary statistics for all of these variables. The regression model is

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

where y_j is first day, first week 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 "cold" coefficient in the first row of Table 2 shows that cold opening a movie is positively correlated with the logs of first day, first week and total US box office (with the weakest effect on first day box office). These coefficients suggest that cold opening a movie increases revenue from 12-15%.[12][13] Table 3 shows these effects persist when the regressions are run including only the most significant variables (cold dummy, metacritic, theaters, budget, competition, star ranking, sequel or adaptation dummy, and year of release). These simplified specifications show a much more significant effect of cold opening for first weekend and first day box office than the full regressions, and a weaker effect of total box office (which is more consistent with the view that the cold-opening premium is temporary). The coefficients also suggest that cold opening increases movie revenue by roughly the same amount as the previous regressions (14-17%).

It is somewhat surprising that the effect of a cold opening continues after the first weekend when reviewers would have a chance to see and write their review. Our models indicate that the cold opening effect should occur after the first weekend and then dissipate as moviegoers learn the true quality of the cold opened movie. However, a likely alternative explanation is that moviegoers infer quality from other

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

[13] Although we would consider it a regression with endogeneity, these results do not change using imdb.com user ratings instead of metacritic ratings.

moviegoers and the first weekend's revenue is seen as a signal of quality (see De Vany and Walls (1996) for a model with such dynamics). If we run a regression on logged box office revenues after the first weekend (see Table 4), including logged first weekend with our other independent variables, then we find cold has an insignificantly negative effect (-3%, $p \approx 0.5$) after first weekend revenue. There is clear correlation between logged first weekend's box office and the remaining box office as De Vany and Walls also note. Interestingly, first weekend's number of theaters is negative implying that movies with a higher number of opening theaters and identical opening box office (and hence lower return per theater) do worse later.

The main regressions in table 2 give results that one might expect. Higher quality critic ratings on average translate into higher box office — an increase in one meta-critic point increases revenues by 2.1%. Spending an extra million on production budget translates into a 0.3% increase in revenue. The number of theaters opened, which often indicate expectations about movie revenues, have a very large effect. [14] For an increase of 1000 theaters movie revenue increases 86%. The averaged logged star power rankings ($0 = \log(1)$ indicates highest ranked stars, higher numbers indicate lower rankings) have a negative correlation as one would expect. Adaptations and Sequels increase box office by roughly 13%, so it is a smart move by studios to buy the rights to source material or pay extra to make a sequel. A longer opening weekend leads to more revenue in that weekend. Some dummy variables for genre and ratings are significant, implying it is more profitable on average to make movies of certain genres and ratings on average, similar to what has been found in other studies. (e.g. De Vany and Walls, 2002)

[14] Theaters may be a proxy for ad budget as well which may magnify their effect.

2.1 Tests of the Cold Opening Premium

Of course, it is possible that cold opened movies have some other characteristic omitted from the Table 2 regressions that causes these movies to generate apparently greater box office (an omitted variable bias). In this case, our regressions are not capturing the effect of cold opening, but are capturing the effect of an omitted variable that is correlated with cold opening. The most likely omitted variable that could be correlated with the decision to cold open is spending on publicity and advertising.[15] 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., distributors spend more on ads to compensate for missing advance reviews). However, a senior executive at Fox Studios 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 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. Further most rules-of-thumb in the industry suggest advertising budget is a fixed proportion of production budget (Vogel (2007) suggests $\frac{1}{2}$, an executive at Village Roadshow suggested $\frac{2}{3}$). If these rules of thumb are true then our production budget variable could proxy for the effect of advertising.

Another problem is that annoyed critics might 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 studios for making the movie unavailable).[16] In this case,

[15]Unfortunately, we were unable to find advertising budget information for most of the movies in our sample

[16]Litvak (1986) mentions this idea when describing a cold opening.

since we use the critic ratings as an independent variable, if the critic ratings are lower than 'true' quality the cold-opening variable picks up the effect of the gap between 'true' quality and quality as measured from critics. This explanation seems unlikely since critics pride themselves on objectivity. For example, they do not always mention in later reviews that the movie was unavailable in advance.

One test of these explanations looks at the log total box office of the U.K. and Mexico, and log of US video rental data. In these markets, the deception of cold opening should be ineffective 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, so that information about the movie's quality is presumably widely disseminated. Table 5 reports the cold-opening coefficients (from regression of all variables). There is apparently no cold opening premium in these two foreign markets and the rental markets, which works against the hypothesis that the premium is due to an omitted-variable bias.

Another explanation is that moviegoers of cold-opened movies are less sensitive to critic reviews. Then the high turnouts for cold-opened movies have nothing to do with the opening, but just the fact that given identically low critic reviews, cold-opened movies turn out more viewers. This explanation may appear appealing as the correlation of critic reviews and user reviews for cold-opened movies while high (0.4725) is much lower than the correlation of critic reviews and user reviews of non-cold opened movies (0.7536). However, this relationship likely results from the fact that cold-opened movies are on a smaller range of critic ratings ($\bar{x} \approx 22, s^2 \approx 10$). If we restrict non-cold opened movies to those with critic ratings under 40 ($\bar{x} \approx 29, s^2 \approx 7$) we find a similar value for correlation (0.4733).

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 and only 54% of all movies (see Table 6). If fans of these genres have less sensitivity to bad reviews and are more likely to go to a movie that has low critic ratings than fans of other genres (suggested by Reinstein and Snyder) then the cold opening premium could be a result of the selection of cold-opened movies to this genre.[17] Table 6 shows that this is not the case. Throughout genres moviegoers correlation between critic reviews and self-reported reviews are all around 0.75. Further, the cold open premium is positive for all genres (6–21%) except for animated films (which is driven by a single cold-opened movie). The cold-opening premium does not appear to be restricted to particular genres.

Finally, our hypothesis is that limited iterated strategic thinking causes moviegoers to be "tricked," incorrectly overestimating the ex-ante quality of cold opened movies. Since moviegoers presumably go to these movies based on, among other factors, their perception of quality, a greater number of cold-opening moviegoers will have negative impressions of their movie. Using imdb.com user data and the usual independent variables, we find cold-opened movies have a rating 0.4 points (out of 10) lower than non-cold opened movies. The result is highly significant ($p < 0.001$).

In the next section we will develop three 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, that success is another piece of evidence that the premium is not due to an omitted variable.

[17]This explanation would not explain why distributors would withhold bad news in genres where the intended audience is the least receptive to bad news.

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 aggregate box office data, but allow us to estimate behavioral parameters of individual thinking.

Every movie j has specific characteristics X_j and (integer) quality $q_j \in [0, 100]$. We assume that the distributor of movie j and moviegoers both know 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.[18] Below we consider three models of belief formation. One is a standard equilibrium concept and two incorporate forms of limited strategic thinking.

The first assumption is that if a movie is screened to critics, its quality is then known to moviegoers (A1):

Assumption 1 (A1) $E_m[q_j|0, X_j] = q_j$.

To model moviegoing and distributor decisions, we use a quantal response approach in which moviegoers and distributors choose stochastically according to utilities and expected profits. Let's start with moviegoers. Since we have no data on individual choices or demographic market-segment data, we use a representative-agent approach. Assumption (A2) is that moviegoer utility is linear in movie characteristics and expected quality, subtracting the ticket price.

Assumption 2 (A2) $U(X_j, E_m(q_j|c_j, X_j)) = \alpha E_m(q_j|c_j, X_j) + \beta X_j - \hat{t} + \epsilon_j$

[18] 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.

where α and β give the corresponding predictive utility associated with expected quality and other known characteristics of movies. The utility of not going to the movies is defined as zero.[19] 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 $\hat{t}$[20] is

$$p(X_j, E_m(q_j|c_j, X_j)) = \frac{1}{1 + e^{-\lambda_m \left(\alpha E_m(q_j|c_j, X_j) + \beta X_j - \hat{t} + \epsilon_j\right)}}. \tag{2}$$

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. As $\lambda_m \to \infty$, the probability of choosing the option with the highest utility converges to one (best-response).[21]

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 is $R(X_j, E_m(q_j|c_j, X_j)) = N\hat{t}p(X_j, E_m(q_j|c_j, X_j))$. 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 modelled by a stochastic choice function based on a comparison of expected profits from the two decisions. Given assumption (A1), the revenue from screening is $R(X_j, q_j)$ and the revenue from cold opening is $R(X_j, E_m(q_j|1, X_j))$. The probability of a distributor opening the movie cold is therefore given by assumption (A3),

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

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

[21] See Luce (1959), Chen, Friedman, Thisse (1997), McKelvey and Palfrey (1995, 1998).

Assumption 3 (A3) $\pi(X_j, q_j) = 1/\left(1 + \exp\left[-\lambda_d \left[R(X_j, E_m(q_j|1, X_j)) - R(X_j, q_j)\right]\right]\right)$

where λ_d is the sensitivity of distributor responses to expected revenue.[22]

4 Models of Strategic Thinking

The crucial behavioral question is 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 beliefs influence the distributor's cold opening choice probability, $\pi(X_j, q_j)$. This section compares three models of beliefs: Quantal response equilibrium; cursed equilibrium; and a cognitive hierarchy.

Quantal response equilibrium combines the stochastic choice functions described above with the standard equilibrium assumption that agents' beliefs about the behavior of other agents are statistically correct– in this case, moviegoers' beliefs reflect an understanding of the distributors' decisions. The "QR" part of QRE reflects the fact that players do not choose best economic responses all the time, but the "E" part suggests their expectations about other players' behavior are still correct (i.e., they are still in equilibrium).

The cursed equilibrium and cognitive hierarchy approaches allow limits on strategic thinking which are parameterized by a single behavioral parameter. In cursed equilibrium, moviegoers' beliefs about the quality of a cold-opened movie are a χ-weighted average of unconditional overall average quality (with weight χ) and the rationally-expected quality that fully anticipates distributors' decisions (with weight $1 - \chi$). The parameter χ is a measure of the degree of naïveté in the moviegoers'

[22] 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, λ_m and λ_d because the payoffs are on the order of dollar-scale utilities for moviegoers and millions of dollars for distributors.

strategic thinking (i.e. to what extent beliefs about cold-opened movies are biased toward average unconditional quality.[23] In the cognitive hierarchy approach, 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 frequencies of players at different levels in the cognitive hierarchy are characterized by a Poisson distribution with mean level parameter τ. Importantly, both models allow full rationality as a limiting case of their behavioral parameters (full rationality corresponds to $\chi = 0$ or $\tau \to \infty$). Therefore, the data, will indicate the degree of moviegoers rationality.

4.1 Logistic Quantal Response Equilibrium (QRE) Model

In QRE, the moviegoers use Bayes' rule and rational expectations to infer the expected quality of movies that are cold-opened from the distributors actual choice probabilities. That is, $E_m^{qre}(q_j|1, X_j)$, the QRE expectation of moviegoers about the quality of unscreened movies, is

$$\begin{aligned}
E_m^{qre}(q_j|1, X_j) &= \sum_{q=0}^{100} qP\left(q|X_j, 1\right) && \\
&= \frac{\sum_{q=0}^{100} qP(1,X_j,q)}{P(1,X_j)} && \text{(Bayes' rule)} \\
&= \frac{\sum_{q=0}^{100} qP(1,X_j,q)}{\sum_{q=0}^{100} P(1,X_j,q)} && \text{(laws of probability)} \\
&= \frac{\sum_{q=0}^{100} qP(1|X_j,q)P(X_j,q)}{\sum_{q=0}^{100} P(1|X_j,q)P(X_j,q)} && \text{(laws of probability)} \\
&= \frac{\sum_{q=0}^{100} qP(1|X_j,q)P(X_j)P(q)}{\sum_{q=0}^{100} P(1|X_j,q)P(X_j)P(q)} && \text{(independence assumption)} \\
&= \frac{\sum_{q=0}^{100} q\pi(X_j,q)P(q)}{\sum_{q=0}^{100} \pi(X_j,q)P(q)} && \text{(definition in (A3))}
\end{aligned} \tag{3}$$

[23]In some applications χ is more naturally interpreted as a fraction of people who are uninformed or 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 (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 probabiliites.)

Intuitively, for an agent to form an expectation about the quality of a cold opened movie $E_m^{qre}(q_j|1,X_j)$, he 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 it would be of that quality given its characteristics and the fact that a distributor decided to cold open it with probability $P\left(q|1,X_j\right)=\pi(q|1,X_j)$. Using laws of probability, and the assumption that the probability of any movie's quality level $P(q)$ is independent from the probability of it having any other characteristics $P(X_j)$[24] then a cold opened movie's expected quality $E_m^{qre}(q_j|1,X_j)$ only depends on the probability that a distributor would cold-open a movie with such characteristics for any quality $\pi\left(X_j,q\right)$, and the frequency of quality ratings $P(q)$. From this transformation we are able to calculate $E_m^{qre}(q_j|1,X_j)$ if $\pi\left(X_j,q\right)$ is known.

The cold-opening probabilities $\pi(X_j,q)$ depend on estimated revenues from opening the movie cold or screening it (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 is

$$\begin{aligned} R(X_j,E_m(q_j|c_j,X_j)) &= N\hat{t}p(X_j,E_m(q_j|c_j,X_j)) \\ &= N\hat{t}/[1+e^{-\lambda_m\left(\alpha E_m(q_j|c_j,X_j)+\beta X_j-\hat{t}+\epsilon_j\right)}] \end{aligned} \tag{4}$$

Rearranging terms and taking the logarithm yields a specification which is easy to estimate because it is linear in characteristics X_j and expected quality $E_m(q_j|c_j,X_j)$,

$$\log\left(\frac{R(X_j,E_m(q_j|c_j,X_j))}{N\hat{t}-R(X_j,E_m(q_j|c_j,X_j))}\right)=-\lambda_m\left(\alpha E_m(q_j|c_j,X_j)+\beta X_j-\hat{t}+\epsilon_j\right). \tag{5}$$

The QRE is recursive: Moviegoers' beliefs about the quality of cold-opened movies depend on which movies the distributors choose to open cold (through equa-

[24]Table 9 shows the intercorrelation matrix. There is only one variable which has a correlation with quality higher than .15— namely, the budget (r=.27).

tion (3)), and the distributors' choice to open cold depends on moviegoers' beliefs about the quality of cold-opened movies (through assumption (A3)). Because of this recursive structure, we estimate the model using an iterative procedure. The procedure first uses the large number of screened movies (where quality is assumed to be known to moviegoers by (A1)) to estimate regression parameters that forecast revenues conditional on quality in (5). Then 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 decisions best and satisfies the rational expectations property. These inferred expected qualities are then added to qualities of screened movies to re-estimate equation (5) 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 rational-expectations constraint on cold-opened movies (3) is satisfied. Details of the process are given in an Appendix.

Table 7 shows the regression results from nine iterations from this process (which stopped according to the step 6 convergence definition in the Appendix).[25] The r-squared value, 0.683, shows our model has a solid fit with the data. The final log likelihood value, -203.772 implies that the (geometric) mean predicted probability of actual decisions for all movies is 0.79, much better than chance guessing and substantially better than simply guessing that all movies have a cold-opening probability equal to the 93% base rate (which yields a value of -211.62).

Figure 3 shows the predicted probabilities of cold opening by critic quality and actual decision. About half the movies cold-opened (squares) have high predicted

[25]At this point, we have not determined standard errors on any of our parameter estimates through the iteration process. On the next draft of the paper, we intend to use a bootstrap procedure to estimate standard errors for all of our parameters.

probabilities and half have low probabilities. There is a clear relation between quality and the predicted probability of cold opening. The model is on the right track but the correlation is far from perfect. Figure 4 shows the expected quality of each movie given it was cold opened vs the actual quality. Since moviegoers correctly infer expectations in the QRE, about half the cold opened movies have quality less than their actual critic ratings. The low value of λ_d causes a wide variety of expectation values for cold opened movies between 0 and 40.

4.2 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 in which some agents do not seem to infer the private information of others from actions. Their idea is that such an incomplete inference is consistent with agents not appreciating the degree to which other players' actions are conditioned on information.

In our context, for every cold opened movie, all moviegoers believe that the movie has quality equal to some weighted average of the true expected movie quality (given distributor decisions) and the average of all movies. That is,

$$E_m^{ce}(q_j|1) \equiv (1-\chi_m)\, E_m^{re}\,(q|X_j, 1) + \chi_m \bar{q} \tag{6}$$

where $E_m^{re}\,(q|X_j, 1)$ reflects rational expectations about distributor decisions. We use an iterative procedure nearly identical to the one used above to find a best-fitting value of χ_m. The difference in the procedure is that $E_m^{ce}(q_j|1)$ and χ_m are used in forecasting revenue rather than $E_m^{qre}(q_j|1)$, and hence in predicting distributor decisions. If $\chi_m = 0$ this model is equivalent to QRE. The best-fitting value is $\hat{\chi_m} = .369$ however, which indicates a mild degree of curse. That is, moviegoers judge the quality of a cold-opened movie somewhere between its fully-correct expectation of quality and the average quality of all movies, but they are closer to its fully correct expectation.

Since the estimated correct expectation $E_m^{re}(q|X_j,1)$ for cold-opened movies is low ($\overline{E_m(q|1)}$=22), and average overall quality is much higher ($\bar{q} = 48$), cursed moviegoers 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 in the first iteration is $\hat{\chi}_{m1} = .253$. This parameter predicts an average box office premium on logged cumulative box office of 0.025, an increase of 2.52%. This value is lower than 15% estimate determined from our initial regression, but it relies on non-parametric means to estimate box office.

Eyster and Rabin applied their model to experimental data from Forsythe, Isaac and Palfrey (1989) on agents "blind bidding" for objects of unknown value, after the producers of the objects have decided whether to reveal their values. In their estimation, all values of $\chi \in (0,1]$ fit better than the no-curse value $\chi = 0$, and the best-fitting $\chi = .8$. This number is higher than our estimate[26] but both estimates indicate degrees of curse, with agents inferring quality of unknown goods at levels greater than the fully-correct expectation.

However, the result above only describes what fits box office revenues in the first iteration. If cursed equilibrium requires the moviegoer curse parameter χ_m to be the same as the distributor's estimate of the curse, then iterating the procedures leads to $\chi_m = E_d(\chi_m) = 0$, which is equivalent to the QRE restriction in which there is no curse.[27]

[26] They suggest that the general tendency for players to overbid in auctions (see Kagel 1995) leads to high bids, which in their model can only be explained by a high value of χ.

[27] That is, starting with $E_d(\chi_m) = \chi^m = 0.253$ in the first iteration leads to lower value estimates

The intuition is simple: Given an apparent curse of $\chi_m = .253$, distributors should be cold-opening a lot more movies of low quality than they actually are. Within the simple structure of this model, the only way to explain their anomalous behavior is that they do not believe moviegoers are as cursed as the box office revenue data suggest they are.

4.3 A Cognitive Hierarchy Model

Cognitive hierarchy 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 optimizes against $k-1$ type thinkers.[28] A 0-level thinker, as a moviegoer, does not think about the distributor's actions of cold opening a movie. For any cold-opened movie he judges he infers the movie's quality $E_m^0(q_j|X_j, 1)$ at random[29] by selecting any integer on [0,100] with equal probability. He will go to any movie with probability defined as an analogue of equation (2)

$$p_0\left(X_j, E_m^0(q_j|c_j, X_j)\right) = \sum_{q=0}^{100}(1/101)\frac{1}{1+e^{-\lambda_m\left(\beta X_j+\alpha q-\hat{t}+\epsilon_j\right)}} \tag{7}$$

of λ_d which lead to estimates of $\chi_m = 0$ at the next iteration.

[28]This classification differs from the other version of the cognitive hierarchy model (Camerer et al, 2004) which suggests k level thinkers optimizes against a distribution of $k^* < k$ level thinkers.

[29]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 player 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 Iberri(a), in press). 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.

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,

$$\pi_0(q_j, X_j) = 1/2. \tag{8}$$

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

$$\begin{aligned} E^1_m\left(q|X_j,1\right) &= \frac{\sum_{q=0}^{100} qP\left(q\right)\pi_0\left(q,X_j\right)}{\sum_{q=0}^{100} P\left(q\right)\pi_0\left(q,X_j\right)} \\ &= \frac{\sum_{q=0}^{100} qP\left(q\right)\frac{1}{2}}{\sum_{q=0}^{100} P\left(q\right)\frac{1}{2}} \\ &= \bar{q} \end{aligned} \tag{9}$$

A 1-level distibutor 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 cold-open movie j with probability

$$\pi_1(q_j, X_j) = 1/\left(1 + \exp\left[\lambda_d(\sum_{q=0}^{100}(1/101)R(X_j, q) - R(X_j, q_j))\right]\right). \tag{10}$$

Proceeding inductively, for any strategic level k, the values $E^{k-1}_m(q|1, X_j)$ and $\pi_{k-1}(q_j, X_j)$ are assumed to be known and inform beliefs. Then the k-level moviegoer and distributor have defined strategies

$$\pi_k(q_j, X_j) = 1/\left(1 + \exp\left[\lambda_m(R(X_j, E_{k-1}(q|X_j, 1)) - R(X_j, q_j))\right]\right) \tag{11}$$

and

$$E_k(q|X_j, 1) = \frac{\sum_{q=0}^{100} qP\left(q\right)\pi_{k-1}\left(q,X_j\right)}{\sum_{q=0}^{100} P\left(q\right)\pi_{k-1}\left(q,X_j\right)} \tag{12}$$

which leads to moviegoing probability

$$p_k\left(X_j, E^k_m(q_j|c_j, X_j)\right) = \frac{1}{1 + e^{-\lambda_m\left(\beta X_j + \alpha E^k_m(q_j|c_j,X_j) - \hat{t} + \epsilon_j\right)}} \tag{13}$$

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

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

$$P(x = n|\tau) = \tau^n e^{-\tau}/n!, \tag{14}$$

where τ is the average number of steps of strategic thinking.

As an example, Table 9 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 $\lambda_d = 2.755$, if the distribution of levels is Poisson-distributed.

To determine QRE parameters $\{\lambda_d, \lambda_m\}$ and additional CH parameters $\{\tau_d, \tau_m\}$, we use an iterative procedure for estimating values similar to the QRE procedure. The procedure is easier, however, because level-k player behavior is determined by level-k-1 behavior. So the iteration is a "do loop" conditioned on λ_m, λ_d values, naturally truncated when 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.

Table 7 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 -166.32, which is a significant improvement over the QRE model. The value for λ_d (2.755) is also much greater than for the QRE (0.474), which indicates less noise in the estimated decision process and a better fit. Figure 5 which represents the estimated probability that each movie will be cold-opened, with actual cold-openings plotted in red. The implied line from the scatter plot is much clearer in figure 5 than in figure 3 for the

QRE model. The cold opened movies on average have higher probabilities of being cold opened, so the model fits better. Figure 6 shows the estimated value of the expected quality belief moviegoers would have if each movie had been cold opened. This is almost a constant because of the relatively high λ_d and lower τ_m. Moviegoers expect few cold opening decisions to be the result of quantal response, but they mostly expect distributors to be best responding to 0 or 1 level moviegoers who do not associate quality with movies or the decision to cold open. Note that cold opened movies (red squares) tend to have expected quality above actual quality. This leads to an expected cold-opening box office premium of 8.6‘% (see Table 13, which is still lower than the regression estimate. And screened movies have expected quality below actual quality. Tables 11 and 12 show the sum of squares and log likelihood for the various values of estimates of τ_d and $\{\tau_d, \lambda_d\}$, respectively. Note that the estimated value of $\hat{\tau}^*_m = 3.78$ is in the ballpark[30] of estimates from experimental games (around 1.5) and for the initial week of Swedish LUPI lotteries (2.98, Ostling et al (2007)) and managerial IT decisions (2.67, Goldfarb and Yang, 2007).

4.4 Comparing Distributor Estimation across Models

Tables 13 and 14 compare best-fitting parameter values, log likehoods (for distributor decisions) and sums of squared residuals (for moviegoer decisions). The CH model best predicts the box office revenues of cold-opened movies in terms of deviations from actual data, and the cursed equilibrium model is second best. This is not surprising since both models predict a box office premium. For distributor decisions the cursed model and QRE models perform identically since the best-fitting cursed parameter is zero, so the rational expectations part of the QRE explains behavior

[30] The objective function (sum of squared residuals) is rather flat in the vicinity of the best-fitting τ_m, so values from 2-5 give comparable fits to $\hat{\tau}^*_m = 3.78$. So an *ex ante* prediction based on $\tau = 1.5$ from lab data would forecast reasonably well in this field setting.

pretty well if we must assume the system is in equilibrium. All models are also an improvement over the baseline case which predicts all movies to be cold-opened with the same probability. The CH model improves on the predictions of the other two models. The key to its relative success is that the model estimates a low τ for moviegoers (close to experimental estimates of τ around 1.5-2.5) but the distributor τ_d is much higher. These parameters express the intuition that some moviegoers are easily fooled– they think cold-openings are random– but distributors do not think moviegoers are so easily fooled, which is why so few movies are cold-opened. The CH also predicts the most number of opening decisions correctly because it's high τ_d predicts few movies will be cold opened as a result of deliberate thinking and the higher λ_d predicts few movies will be cold opened as noise.

5 Conclusion

In games in which information can be considered good or bad news, and may be strategically withheld, the only sequential equilibrium involves the information receiver believing all withheld information conveys the worst possible signal, and the information sender choosing to reveal all information (except the worst). However, these equilibria require long chains of iterated strategic thinking. Numerous laboratory experiments have shown in a variety of games that a small number of steps of strategic thinking tends to explain data well, as parameterized by quantal response equilibrium (QRE), cursed equilibrium, and cognitive hierarchy (CH) approaches. Our paper is the first to apply all three models to a naturally-occurring field phenomenon, an example of structural behavioral economics.

Our paper studies a market in which information senders (distributors) are strategically withholding information (the quality of their movie) from information receivers (moviegoers). We find evidence that a Bayesian-Nash equilibrium has not been reached in our data since cold-opened movies do not have the worst possible quality values ($q_j = 0$) *and* there is a "box office premium," for movies that have been cold opened relative to other pre-screened movies of similar characteristics. As an additional test, we find this premium does not exist in foreign or video rental markets, where movies are released after the initial US release and so reviews are widely available.

The QRE and cursed equilibrium models do not do a good job of explaining these facts. The QRE model peroms 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 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 moviegoer perceptions) of distributors to cold-open.

The mismatch of parameter values for moviegoers and distributors suggest that either moviegoers should learn that cold-opened movies are bad, or distributors should learn to cold-open more movies. It does appear that distributors are learning. Figure 7 shows cold opening decisions by year. Near the end of this paper's dataset (January 1, 2006), distributors began to cold open movies with much higher frequency.[31] The models in this paper would suggest distributors have cold opened more movies as a best-response to moviegoer behavior.

There are hints of a difference between consumer and producer strategies in previous studies. With the benefit of this studys results, the somewhat contrary results of Mathios (2000) and Jin and Leslie (2003) make sense. Mathios (2000) found that

[31] Through 2000-2005 distributors cold opened around 5-8% of widely released movies. In 2006 and 2007 distributors cold opened nearly 20% (30/160).

mandatory disclosure was necessary for consumers to buy low-fat salad dressing (i.e. with voluntary disclosure they did not infer what the absence of a "low-fat" label meant). Jin and Leslie (2003) found suggestive evidence that voluntary disclosure of health ratings improved health quality nearly as much as mandatory disclosure, but the data on revenue for non-disclosing restaurants was inconclusive. Given that one choice is a consumer decision (buying salad dressing) and one is a producer decision (improving health quality in a restaurant), we may have more evidence of a different level of iterative thinking by diverse consumers and expert producers. Of course, this is only speculation and more investigation is needed before any conclusions can be drawn from these types of investigations. As noted earlier, there are many markets with asymmetric information in which the failure to reveal information that is often revealed should be informative—if the receiver makes the proper strategic inference. Our approach and some of its technical details could be applied to these markets and other markets with this property.

6 Appendix: Details of iterative estimation procedures

The iterative QRE procedure consists of a number of steps.

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

2. In iteration $i = 1$ only the 791 movies which are screened to critics ($c_j = 0$) are used to estimate revenue equation (4), assuming $N = 300 \times 10^6$ (estimated US population).[32] Using assumption (A1), we substitute the observed q_j 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.[33]

   In later iterations, expected quality values $E^i_m(q_j|c_j, X_j)$ after iteration i will have been computed, and a regression on the full sample can be run.

3. The regression results from step 2 give iteration-i coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ on characteristics X_j and quality, and a response sensitivity $\hat{\lambda}_{m,i}$. From equation (3) we have

$$
\begin{aligned}
&E^{qre}_m(q_j|X_j, 1) = \frac{\sum_{q=0}^{100} q\pi(X_j,q)P(q)}{\sum_{q=0}^{100} \pi(X_j,q)P(q)} \\
&\Rightarrow E^{qre}_m(q_j|X_j, 1) \sum_{q=0}^{100} \pi\left(X_j, q\right) P(q) = \sum_{q=0}^{100} q\pi\left(X_j, q\right) P(q) \\
&\Rightarrow \sum_{q=0}^{100} \pi\left(X_j, q\right) P(q) \left[E^{qre}_m(q_j|X_j, 1) - q\right] = 0 \\
&\Rightarrow \sum_{q=0}^{100} P(q)[E^{qre}_m(q_j|X_j, 1) - q]\times \\
&\left(1 + e^{\lambda_d N\hat{t}\left[\left(1+e^{-\lambda_m\left(\beta X_j+\alpha q_j-\hat{t}+\epsilon_j\right)}\right)^{-1} - \left(1+e^{-\lambda_m\left(\beta X_j+\alpha E^{qre}_m(q_j|X_j,1)-\hat{t}+\epsilon_j\right)}\right)^{-1}\right]}\right)^{-1} = 0
\end{aligned}
\tag{15}
$$

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

[33] 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.

where the last step follows from the definition of $\pi(X_j, q)$ (assumption A3).

All the terms in (6) can be estimated from regression coefficients ($\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\lambda}_{m,i}$ from step 1), fit from the quality distribution $P(q)$ or fixed by assumption ($\hat{t}$, N), except for λ_d and $E_m^{qre}(q_j|X_j, 1)$. 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 (6) for each movie j. Using the fixed λ_d, the estimates of $E_m^{qre}(q_j|X_j, 1)$ for each movie, and regression coefficient parameter estimates from step 1, expected revenue estimates for each movie when they were cold opened ($R(X_j, E_m(q_j|1, X_j))$) or screened to critics ($R(X_j, q_j)$) are calculated. Using the calculated revenue estimates, the predicted iteration-i probability ($\hat{\pi}_i(X_j, q, \lambda_d)$ that each movie j will be cold opened can be computed for the fixed λ_d.

4. Step 3 is performed repeatedly for a grid search over sets of values of $\lambda_d \in A_i$ (where the grid search becomes progressively finer across iterations i).[34] The maximum likelihood estimate $\lambda^*_{d,i}$ is chosen from the set A_i. That value satisfies

$$\begin{aligned} \lambda^*_{d,i} &= \arg\max_{\lambda_d \in A_i} L(\lambda_d) \\ &= \arg\max_{\lambda_d \in A_i} \prod_j \left[\hat{\pi}_i\left(X_j, q_j, \lambda_d\right) c_j \times \left(1 - \hat{\pi}_i\left(X_j, q_j, \lambda_d\right)\right)\left(1 - c_j\right)\right] \quad (16) \end{aligned}$$

where $L(\lambda_d)$ is the joint probability that distributors would choose to screen and cold-open each of the 849 movies in the exact manner they did under the QRE model with parameter λ_d.

5. The value for the maximum likelihood estimator $\lambda^*_{d,i}$ determined from the last step (4) is then used in equation (6) to solve for iteration-i values of

[34] The initial $\lambda_{d,i}$ grid is $A_1 = \{0.05, 0.10, ..., 1\}$. The second grid A_2 takes an interval of values of width .2 in increments of .01 around the maximum likelihood estimate $\lambda^*_{d,1}$. The third grid A_3 takes an interval of values of width .02 in increments of .001 around the maximum likelihood estimate $\lambda^*_{d,2}$.

$E^i_m(q_j|c_j, X_j)$ for each of the 58 cold opened movies using (6). Now we have a full set of quality measures q_j and expected qualities for every movie.

6. The process is stopped when the regression values and parameter estimates $(\lambda^*_d, \lambda^*_m)$ from the current iteration i are all within .001 of those from iteration $i-1$ (i.e., $|\hat{\alpha}_i - \hat{\alpha}_{i-1}| \leq .001$ for all vector elements of α and $|\hat{\beta}_i - \hat{\beta}_{i-1}| \leq .001$ and $|\lambda^*_{d,i} - \lambda^*_{d,i-1}| \leq 0.01$, $|\lambda^*_{m,i} - \lambda^*_{m,i-1}| \leq 0.01$. Otherwise, the process is repeated with the iteration counter increased by one, starting with the regression step 2.

The iterative QR-CH procedure is very similar with small changes.

(a) The iteration counter begins at $i = 1$.

(b) In iteration $i = 1$ only the 791 movies which are screened to critics ($c_j = 0$) are used to estimate revenue equation (4), assuming $N = 300 \times 10^6$ (estimated US population). Using assumption (A1), we substitute the observed q_j 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.

In later iterations, population-averaged expected quality values $E^i_m[E_k(q_j|c_j, X_j)|\tau_d]$ after iteration i will have been computed, and a regression on the full sample can be run.

(c) For a given λ_d and τ_d, we use our estimated values $\hat{\alpha}_i$, $\hat{\beta}_1$, and $\hat{\lambda}_{m,1}$, to estimate $\pi_k(q_j, X_j)$, $E_k(q|X_j, 1)$, and $R(E_k(q|X_j, 1))$ for $k = 0 \ldots m$ using equations 13–16 and 4.[35] Since the probability of a given distributor being level k is $P\left(x = n|_d\right) = \tau^n_d e^{-\tau}/n!$ and the probability of that distributor

[35] We used m=40, because given regular τ values the probability of $k > 40$ is nearly zero.

cold opening given he is level k is $\pi_k(q_j, X_j)$, the total probability that a movie is cold opened is

$$\psi(X_j, q_j, \lambda_d, \tau_d) = \sum_{k=0}^{m} \pi_k(q_j, X_j) \times \tau_d^n e^{-\tau}/n! \tag{17}$$

(d) Step 3 is performed repeatedly for a grid search over sets $A_i \times B_i$ of values of $\lambda_d \in A_i$ and $\tau_d \in B_i$(where the grid search becomes progressively finer across iterations i).[36] The maximum likelihood estimate $\{\lambda^*_{d,i}, \tau^*_{d,i}\}$ is chosen from the set A_i. That value satisfies

$$\begin{aligned} \{\lambda^*_{d,i}, \tau^*_{d,i}\} &= \arg\max_{\{\lambda_d, \tau_d\}} L'(\lambda_d, \tau_d) \\ &= \arg\max_{\{\lambda_d, \tau_d\}} \prod_j \left[\hat{\psi}_i\left(X_j, q_j, \lambda_d\right) c_j \times \left(1 - \hat{\psi}_i\left(X_j, q_j, \lambda_d\right)\right)(1 - c_j)\right] \end{aligned} \tag{18}$$

where $L'(\lambda_d, \tau_d)$ is the joint probability that distributors would choose to screen and cold-open each of the 849 movies in the exact manner they did under the CH model with QR with parameters λ_d and τ_d.

(e) The maximum likelihood value $\lambda^*_{d,i}$ is used to compute the population-averaged expectation for each of the 58 cold opened movies in the sample with

$$E[E_k(q|X_j, 1)|\tau_m] = \sum_{k=0}^{m} \pi_k(q_j, X_j) E_k(q|X_j, 1). \tag{19}$$

The value of τ_m that minimizes the squared residuals in equation (5) is

[36]The initial $\lambda_{d,i}$ grid is $A_1 = \{0.1, 0.2, ..., 3\}$ and $B_1 = \{0.05, 0.1, ..., 10\}$. The second grid A_2 takes an interval of values of width .5 in increments of .01 around the maximum likelihood estimate $\lambda^*_{d,1}$. For grids $i > 3, A_i$ takes an interval of values of width .05 in increments of .001 around the maximum likelihood estimate $\lambda^*_{d,2}$. For grids $i \geq 2, B_i = 8.001, ...9$.

considered the best estimator for this step, that is

$$\tau^*_{m,i} = \arg\min_{\tau_m} \sum_{j:c_j=1} \left(\log\left(\frac{y_j}{N\hat{t} - y_j} \right) - \hat{\lambda}_{m,i} \left(\hat{\alpha}_i E[E_k(q|X_j, 1)|\tau_m] + \hat{\beta}_i X_j - \hat{t} \right) \right)^2 \tag{20}$$

(f) The process is stopped when the regression values and parameter estimates ($\lambda_d, \lambda_m,\ \tau_d$, and τ_m) from the current iteration i are all within .001 of those from iteration $i-1$ (i.e., $|\hat{\alpha}_i - \hat{\alpha}_{i-1}| \leq .001$ for all vector elements of α and $|\hat{\beta}_i - \hat{\beta}_{i-1}| \leq .001$ and $|\hat{\lambda}_{d,i} - \hat{\lambda}_{d,i-1}| \leq 0.01$, $|\hat{\lambda}_{m,i} - \hat{\lambda}_{m,i-1}| \leq 0.01$, $|\hat{\lambda}_{d,i} - \hat{\lambda}_{d,i-1}| \leq 0.01$, $|\hat{\lambda}_{m,i} - \hat{\lambda}_{m,i-1}| \leq 0.01$. Otherwise, the process is repeated with the iteration counter increased by one, starting with the regression step 2.

Figure 1: Scatter plot of Metacritic.com Quality Ratings and Log Box Office Revenues

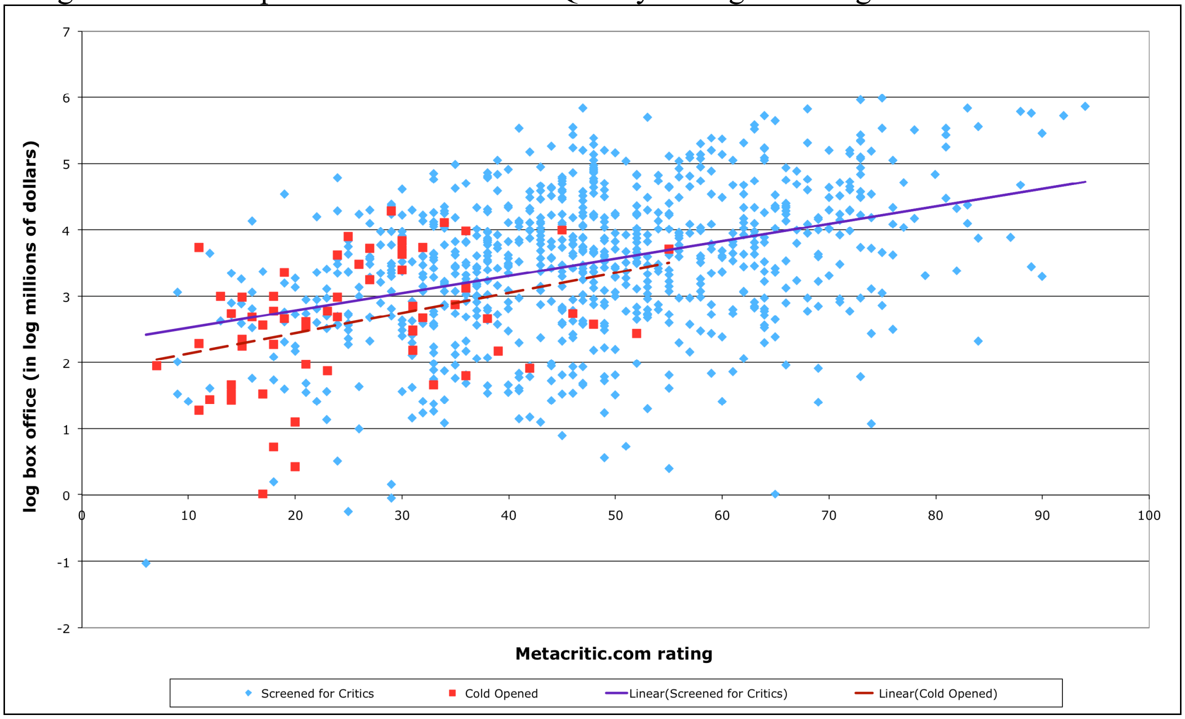

Figure 2: Scatter plot of Metacritic.com Quality Ratings and Imdb User Ratings

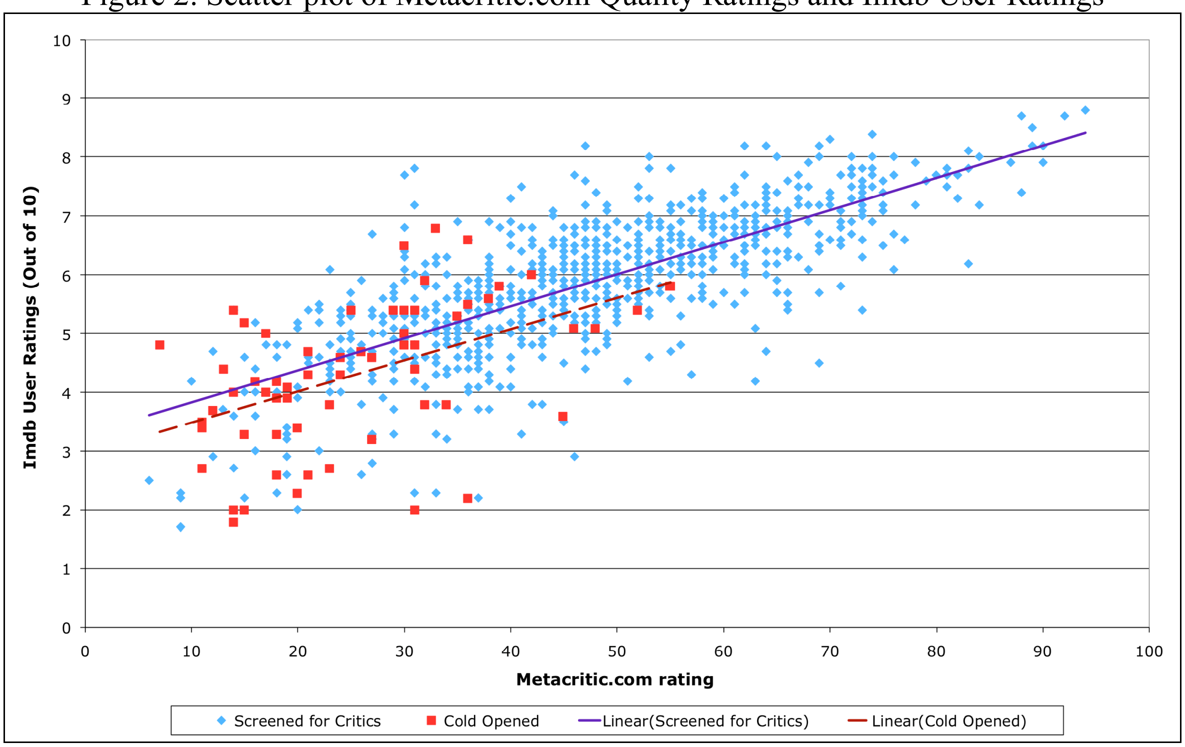

Figure 3: Probability of Movie being Cold Opened in QRE Model by Critic Rating and Actual Decision to Cold Open (λ_d=0.474)

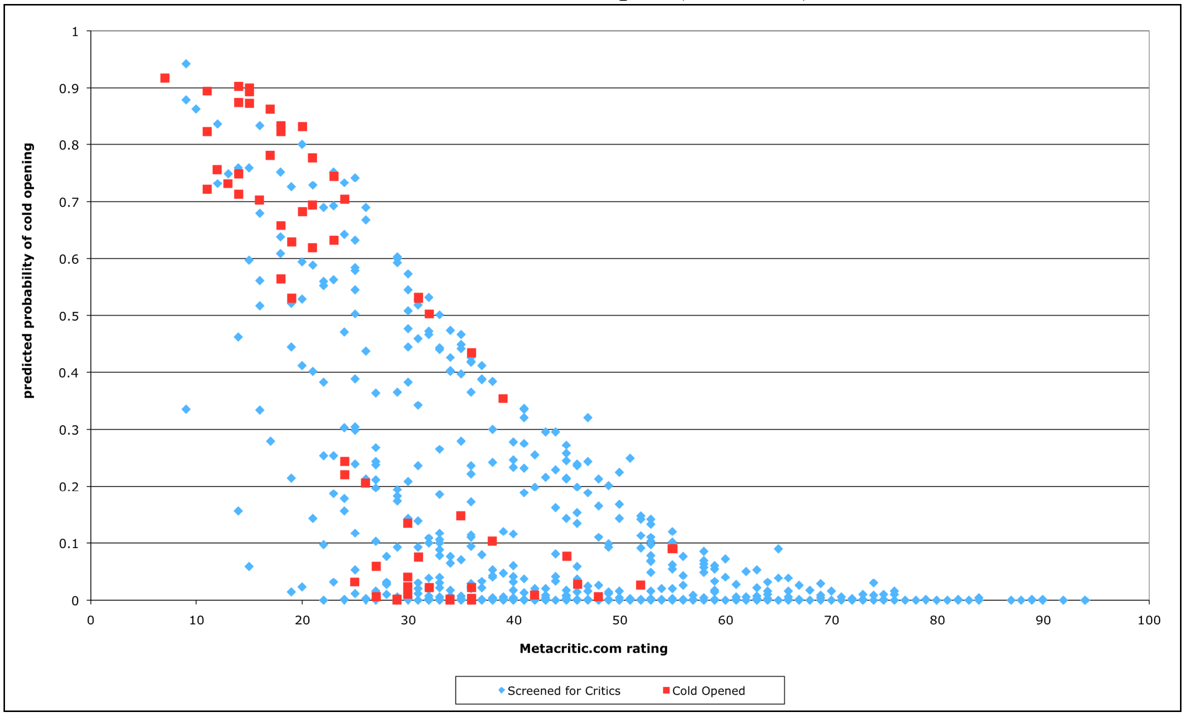

Figure 4: Expected Movie Quality Given it is Cold Opened vs. Actual Quality and Decision to Cold Open in QRE Model by Critic Rating and Actual Decision to Cold Open (λ_d=0.474)

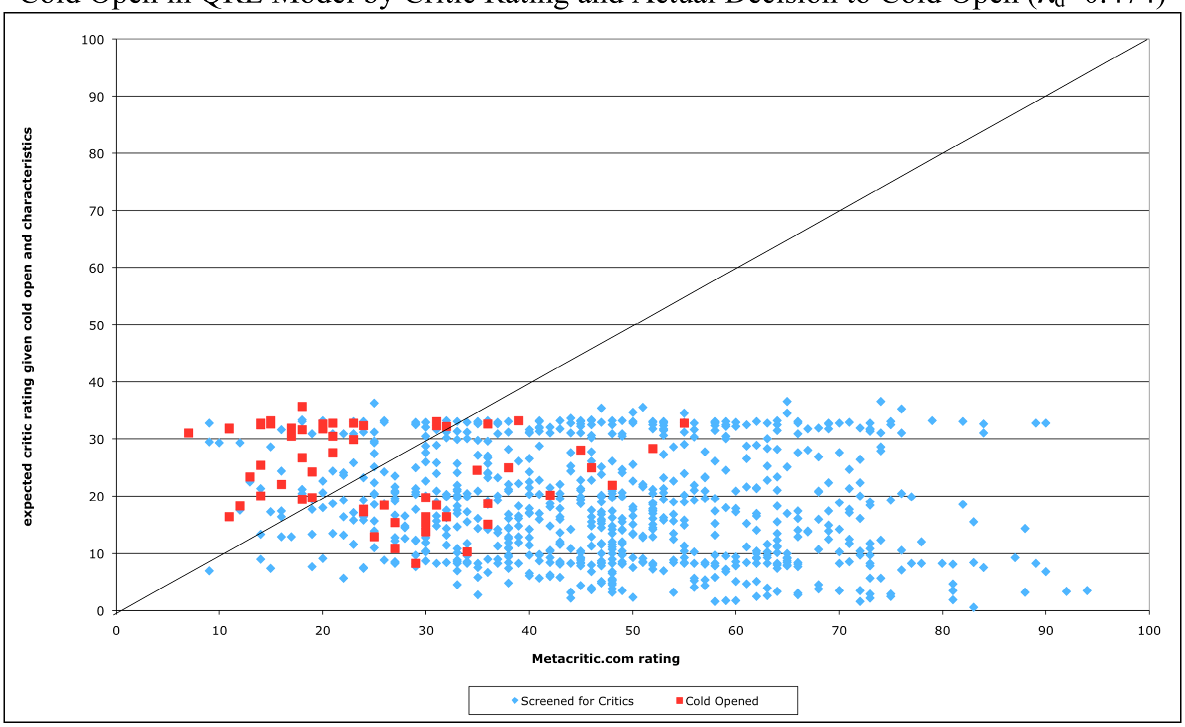

Figure 5: Probability of Movie being Cold Opened in CH model with quantal response by Critic Rating and Actual Decision to Cold Open (λ_d=2.755,τ_d=8.550)

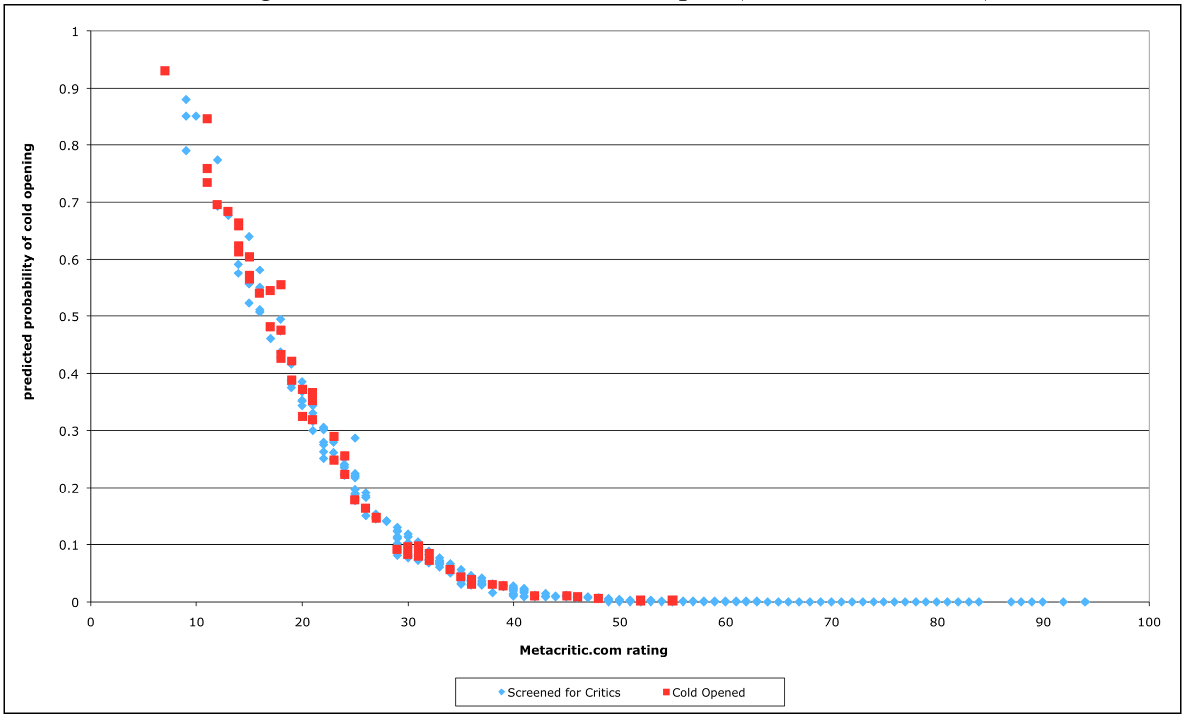

Figure 6: Expected Movie Quality Given it is Cold Opened vs. Actual Quality and Decision to Cold Open in CH Model with QR and Actual Decision to Cold Open (λ_d=2.755,τ_m=8.550)

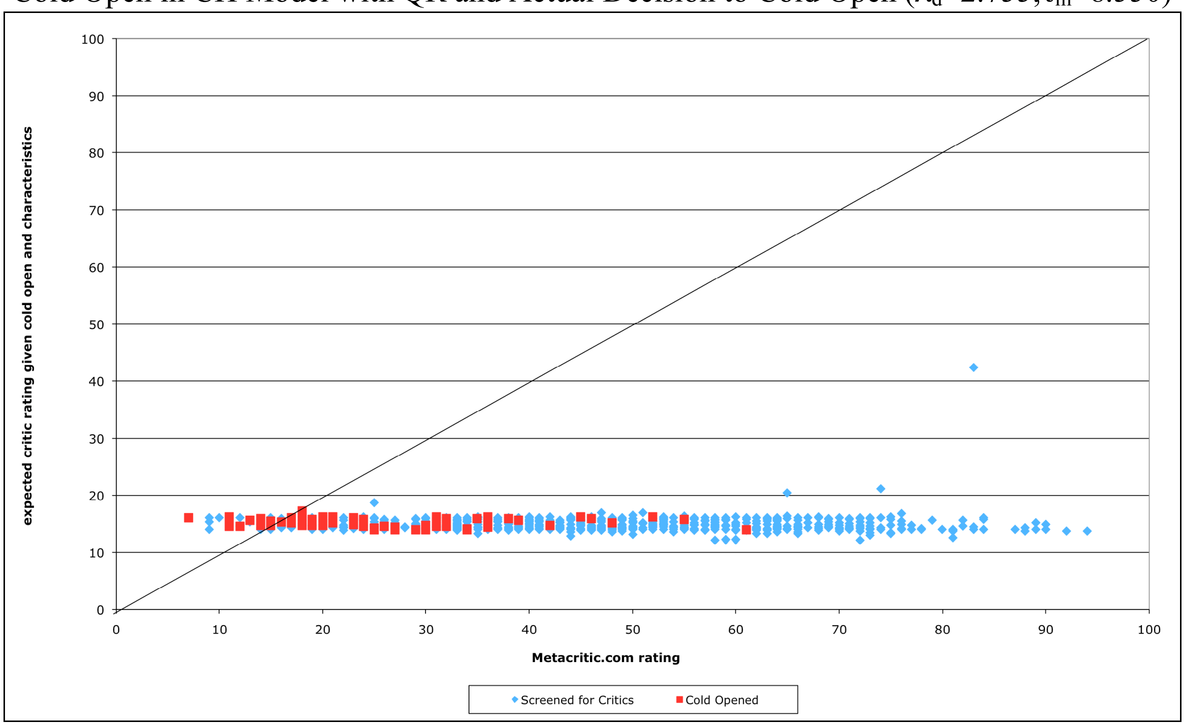

Figure 7: Cold Openings by Year

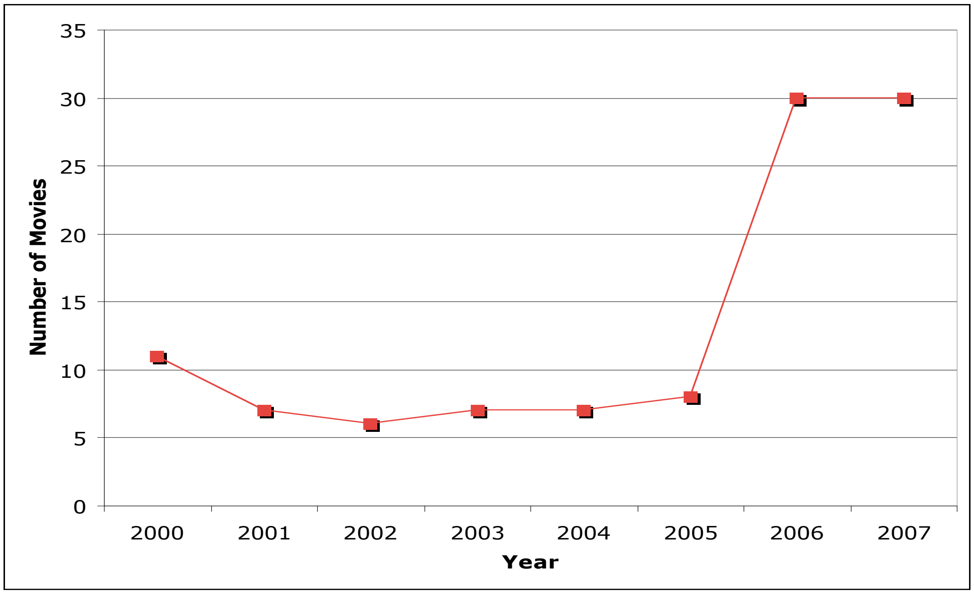

Table 1: Summary Statistics for Variables

variable\regression	mean	median	standard dev
cold	1.242	1.260	0.973
log total box office revenue	3.443	3.510	1.092
log 1st weekend box office revenue	2.354	2.390	0.942
log 1st day box office revenue	1.242	1.260	0.973
metacritic rating	45.793	46.000	16.813
theaters opened (in thousands)	2.435	2.550	0.787
production budget (in millions)	42.299	33.360	33.484
average competitor budget (in millions)	42.061	35.110	27.465
average log star ranking	4.607	4.500	1.672
summer open (1=Jun, Jul, Aug)	0.249	6.130	4.514
sequel or adaptation (1=yes)	0.389	0.000	0.488
opening days bef fri (1=Thurs, etc.)	0.224	0.000	0.658
opening wkd length (days)	0.109	0.000	0.336
early foreign open (days)	11.804	0.000	99.724
action/ adventure (1)	0.164	0.000	0.371
animated (1)	0.060	0.000	0.237
comedy (1)	0.380	0.000	0.486
documentary (1)	0.006	0.000	0.075
fantasy/scifi (1)	0.062	0.000	0.241
supense/ horror (1)	0.157	0.000	0.364
year of release (2003=0)	-0.166	0.000	1.902
PG (1)	0.158	0.000	0.365
PG-13 (1)	0.478	0.000	0.500
R (1)	0.326	0.000	0.469

Note: There are only 856 observations for production budget; all other variables have 890 values.

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

variable\regression	log total US BO	log 1st wkend BO	log 1st day BO
cold	0.154**	0.147**	0.119*
metacritic rating	0.021***	0.013***	0.012***
theaters opened (in thousands)	0.864***	0.848***	0.875***
production budget (in millions)	0.003***	0.002***	0.002***
average competitor budget (in millions)	0.022***	0.001**	0.002**
average log star ranking	-0.045**	-0.029**	-0.026**
summer open (1=Jun, Jul, Aug)	0.052*	0.028	0.139**
sequel or adaptation (1=yes)	0.124***	0.119***	-0.222***
opening days bef fri (1=Thurs, etc.)	0.000	-0.048*	-0.212
opening wkd length (days)	0.129**	0.175***	0.001
early foreign open (days)	0.000	0.000	0.000
action/ adventure (1)	-0.173**	-0.052	-0.082
animated (1)	-0.316**	-0.145	-0.264
comedy (1)	0.032	0.027	0.021
documentary (1)	0.212	0.267	0.493
fantasy/scifi (1)	-0.175*	0.039	0.131
supense/ horror (1)	0.0124783	0.040	0.035
year of release (2003=0)	-0.083***	-0.050***	-0.041***
PG (1)	-0.182	-0.034	0.105
PG-13 (1)	-0.179	0.100	0.376***
R (1)	-0.225	0.113	0.384***
constant	0.506**	-0.493***	-1.843***
R-squared	0.677	0.718	0.662
N	856	856	832
degrees of freedom	21	21	21

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

Table 3: Simplified Regressions of log box office revenues (in millions)

variable\regression	log total US BO	log 1st wkend BO	log 1st day BO
cold	0.140*	0.171***	0.153**
metacritic rating	0.020***	0.013***	0.01***
theaters opened (in thousands)	0.853***	0.001***	0.823***
production budget (in millions)	0.002***	0.002***	0.001**
average competitor budget (in millions)	0.003***	0.001*	0.001
average log star ranking	-0.054***	-0.048***	-0.066***
sequel or adaptation (1=yes)	0.116***	0.111***	0.097**
year of release (2003=0)	-0.082***	-0.050*	-0.037***
constant	0.433***	-0.18847	-1.10***
R-squared	0.672	0.707	0.622
N	856	856	833
degrees of freedom	21	21	21

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

Table 4: Regressions of log box office revenues after first weekend (in millions)

variable\regression	log total US BO
cold	-0.035
metacritic rating	0.009***
log 1st wkend box office (in millions)	1.210***
theaters opened (thousands)	-0.134***
production budget (in millions)	0.001
1st actor log star ranking	0.001
2nd actor log star ranking	-0.016
holiday open (1=holiday)	0.035
sequel or adaptation (1)	-0.020
opening days bef fri (+1=Thurs, etc.)	0.087
opening wkd length (days)	-0.121
early foreign open (days)	0.000
action/ adventure (1)	-0.166
animated (1)	-0.238
comedy (1)	0.001
documentary (1)	-0.197
fantasy/scifi (1)	-0.329
supense/ horror (1)	-0.048
year of release (2003=0)	-0.042
PG	-0.201
PG-13	-0.427
R	-0.520
constant	0.55642
R-squared	0.914
N	849
degrees of freedom	22

Table 5: The Cold Opening Coefficient in non-US Box Office Markets

	cold opening (dummy)			
dependent variable	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 6: Data Separated by Genre

Genre	# Movies	Cold Opens	Percent	Avg Log(BO)	Avg Metacritic	Avg imdb user rating	Imdb-Meta Correlation	Cold Dummy
Act/Adv	143	5	0.03	3.827	48.238	5.911	0.7928	0.09
Animated	51	1	0.02	3.949	56.627	6.071	0.8456	-0.79
Comedy	322	21	0.07	3.352	42.096	5.413	0.7321	0.18
Doc	3	0	0.00	2.351	58.000	5.633	0.8663	
Drama	145	3	0.02	3.240	50.510	6.275	0.6866	0.18
Fant/Sci	55	4	0.07	4.120	50.764	6.115	0.8771	0.20
Susp/Horr	137	25	0.18	3.334	41.401	5.698	0.7368	0.06
Overall	856	59	0.07	3.443	45.793	5.762	0.7641	0.15

Table 7: The Iterative Estimation Process for the QRE Model

variable\iteration	1st	2nd	8th	9th
λ_m	1.285	1.287	1.292	1.292
metacritic rating	0.017	0.016	0.016	0.016
theaters opened (in thousands)	0.001	0.001	0.001	0.001
production budget (in millions)	0.003	0.003	0.003	0.003
average competitor budget (in millions)	0.002	0.002	0.002	0.002
average log star ranking	-0.041	-0.037	-0.038	-0.038
summer open (1=Jun, Jul, Aug)	0.057	0.036	0.037	0.037
sequel or adaptation (1=yes)	0.101	0.104	0.107	0.107
opening days bef fri (1=Thurs, etc.)	0.001	0.002	0.001	0.001
opening wkd length (days)	0.101	0.102	0.102	0.102
early foreign open (days)	0.000	0.000	0.000	0.000
action/ adventure (1)	-0.140	-0.147	-0.149	-0.149
animated (1)	-0.247	-0.229	-0.234	-0.234
comedy (1)	0.023	0.021	0.021	0.021
documentary (1)	0.211	0.192	0.201	0.201
fantasy/scifi (1)	-0.140	-0.112	-0.117	-0.117
supense/ horror (1)	0.001	0.031	0.025	0.025
year of release (2003=0)	-0.073	-0.062	-0.063	-0.063
PG (1)	-0.151	-0.143	-0.142	-0.142
PG-13 (1)	-0.165	-0.122	-0.124	-0.124
R (1)	-0.205	-0.163	-0.164	-0.164
R-squared	0.683	0.682	0.683	0.683
N	791	856	856	856
degrees of freedom	20	20	20	20
Mean E(q|Xj,cj=1)	15.442	17.259	18.331	18.302
λ_d	0.604	0.525	0.473	0.474
log likelihood	-196.530	-204.228	-203.771	-203.772

Table 8: The Iterative Estimation Process for the QRE Model with CH

variable\iteration	1st	2nd	3rd	4th	5th	6th
λ_m	1.285	1.299	1.299	1.299	1.299	1.299
metacritic rating	0.017	0.017	0.017	0.017	0.017	0.017
theaters opened (thousands)	0.001	0.001	0.001	0.001	0.001	0.001
production budget (in millions)	0.003	0.003	0.003	0.003	0.003	0.003
1st actor log star ranking	0.002	0.002	0.002	0.002	0.002	0.002
2nd actor log star ranking	-0.041	-0.037	-0.037	-0.037	-0.037	-0.037
holiday open (1=holiday)	0.057	0.034	0.034	0.034	0.034	0.034
adaptation or sequel (1)	0.101	0.103	0.103	0.103	0.103	0.103
opening days bef fri (+1=Thurs, etc.)	0.001	0.002	0.002	0.002	0.002	0.002
opening wkd length (days)	0.101	0.098	0.098	0.098	0.098	0.098
early foreign open (days)	0.000	0.000	0.000	0.000	0.000	0.000
action/ adventure (1)	-0.140	-0.141	-0.140	-0.140	-0.140	-0.140
animated (1)	-0.247	-0.239	-0.239	-0.238	-0.239	-0.239
comedy (1)	0.023	0.026	0.026	0.026	0.026	0.026
documentary (1)	0.211	0.195	0.194	0.194	0.194	0.194
fantasy/scifi (1)	-0.140	-0.125	-0.124	-0.124	-0.124	-0.124
supense/ horror (1)	0.001	0.020	0.021	0.021	0.021	0.021
year of release (2003=0)	-0.073	-0.064	-0.064	-0.064	-0.064	-0.064
PG	-0.151	-0.140	-0.140	-0.140	-0.140	-0.140
PG-13	-0.165	-0.134	-0.134	-0.134	-0.134	-0.134
R	-0.205	-0.172	-0.172	-0.172	-0.172	-0.172
R-squared	0.683	0.679	0.685	0.685	0.685	0.685
N	791	856	856	856	856	856
degrees of freedom	20	20	20	20	20	20
τ_d	8.622	8.549	8.550	8.550	8.550	8.550
λ_d	2.381	2.862	2.804	2.764	2.755	2.755
log likelihood	-166.249	-166.329	-166.308	-166.307	-166.307	-166.307
τ_m	3.66	3.76	3.78	3.78	3.78	3.78
Mean $E_m(q\|Xj,1)$ for τ_m, λ_d	32.008	31.510	31.421	31.425	31.426	31.426

Table 10: Cognitive Hierarchy Expected Quality Rating of Cold Opened Movie by level-k Moviegoer for "When a Stranger Calls" for λ_d=2.755

k	$E_k(q\|Xj,1)$	$\pi_k(q_j,X_j)$
0	U[0,100]	0.50
1	48.12	1.00
2	40.81	1.00
3	34.26	0.40
4	29.40	0.00
5	24.62	0.00
6	20.92	0.00
7	17.22	0.00
8	14.37	0.00
9	11.59	0.00
10	9.50	0.00

Table 11: Moviegoer Cognitive Hierarchy Estimation for λ_d=2.755

τ_m	$(\text{Average SSR})^{1/2}$
0	15.71
1	14.19
2	12.59
3	11.73
3.78*	11.56
4	11.58
5	11.80
6	12.17
7	12.57
8	12.96
9	13.33
10	13.67

Table 12: Distributor Cognitive Hierarchy Estimation on QRE

$\tau_d \backslash \lambda_d$	0	1	2	2.755*	3
0	-593.33	-593.33	-593.33	-593.33	-593.33
2	-593.33	-791.02	-805.12	-809.17	-810.09
4	-593.33	-441.29	-440.89	-440.79	-440.84
6	-593.33	-244.40	-231.34	-227.79	-227.19
8	-593.33	-180.51	-169.69	-168.12	-167.96
8.550*	-593.33	-174.93	-166.84	**-166.32**	-166.37
10	-593.33	-173.55	-175.95	-178.89	-179.59
12	-593.33	-188.98	-212.43	-221.39	-223.21

Table 13: Comparison of the Three Models for Moviegoer Predictions

model	parameter estimates	mean predicted cold-opened box office (N=59)	predicted cold opening premium	(Average SSR)$^{1/2}$
QRE	λ_m= 1.292	18.52	-7.31%	13.80
Cursed Equilibrium	χ_m=0.253, λm=1.292	20.49	2.52%	12.52
Cognitive Hierarchy k-1	τ_m=3.78, λm=1.299	22.16	8.61%	12.00
Random	U[0,100]	36.22	42.57%	29.99

Table 14: Predictions of Cold Opening Choices of Distributors

model	parameter estimates	log likelihood	mean correct (of 856)	standard deviation	no. predicted to open cold
QRE	λ_d= 0.474	-202.18	751.32	6.89	98.89
Cursed Equilibrium	λ_d=0.474, χ_d=0	-202.18	751.32	6.89	98.89
Cognitive Hierarchy k-1	λ_d=2.755, τ_d=8.550	-166.32	772.49	6.09	60.43
Base Rate	p=59/856	-211.62	740.92	14.92	58.00