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

Alexander L. Brown, Colin F. Camerer and Dan Lovallo[1]

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[1]Brown: Department of Economics, Texas A&M University, 4228 TAMU, College Station, TX 77843, abrown@econmail.tamu.edu. Camerer: Division for the Humanities and Social Sciences, California Institute of Technology, MC 228-77, Pasadena, CA 91125, camerer@hss.caltech.edu. Lovallo: The University of Sydney Business School, H10 - Storie Dixson Wing Building, The University of Sydney, NSW 2006 Australia, dan.lovallo@sydney.edu.au. We wish to thank audiences at California Institute of Technology (especially David Grether, Stuart McDonald, Tom Palfrey, Charles Plott, Robert Sherman, and Leeat Yariv), audiences at Chicago Graduate School of Business, University of California at Berkeley, Yale Graduate Student Conference on Behavioral Science, 2007 North American Economic Science Association, 2007 Society of Judgement and Decision Making, 2007 Southern Economics Associations, 2010 American Economic Association meetings and the 8th Triennial Invitational Miami Choice Symposium. We thank Esther Hwang, Carmina Clarke, Ferdinand Dubin, Zachary Bethune, Cheng Cheng, Xinrong Li and especially Jonathan Garrity for help with data collection. This paper greatly benefitted from the comments of three anonymous referees.

Abstract

Film studios occasionally withhold movies from critics before their release. These cold openings provide a natural setting to apply laboratory-developed models of limited strategic thinking to the field. In a set of 1303 widely released movies, cold opening is correlated with a 10–30 percent increase in domestic box-office revenue, and a pattern of fan disappointment, consistent with the hypothesis that some moviegoers do not infer low quality from cold opening. While selection and endogeneity may play a role in these regressions, the full pattern of results is consistent with level-k and cognitive hierarchy behavioral-game-theoretic models.

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.[1] In this view, players with private information *can* fool some of the people, some of the time, in contrast to the standard equilibrium result where nobody is fooled.[2] This paper investigates the predictions of these two equilibrium models by exploring a natural setting where producers choose to disclose product quality to consumers.

The setting is Hollywood. Movie studios 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). A few 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, studios 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.

This paper tests this equilibrium prediction by examining the differential box-office revenue of movies that are cold opened versus those screened for critics. If moviegoers make the correct

[1] One class of models of limited strategic thinking assumes there is a hierarchy 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 (See Nagel (1995), Stahl and Wilson (1995), Camerer, Ho and Chong (2004), Crawford and Iriberri (2007), and Crawford, Costa-Gomes and Iriberri (2010)). Another class of models, which apply 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).

[2] See Crawford (2003).

inference there should be no revenue difference between these two classes of movies. If, however, moviegoers fail to make this inference fully—as the cognitive hierarchy, level-k, and cursed models predict—we should see a "cold-opening premium" as cold-opened movies receive higher revenue than their quality dictates.

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). These disclosure games have been extensively studied in economics literature (see Dranove and Jin, 2010, for an exhaustive listing), but this paper provides the first attempt to tie the process of disclosure to models of limited strategic thinking. This paper examines the disclosure process, testing strategic disclosure as a response of producers to the limited strategic thinking of consumers.[3]

Our data show that 11 percent of the movies in our sample are cold opened (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 the quality of movies that are cold opened. We test several alternative explanations, but none can explain the findings as well as limited strategic thinking. If one believes that there is an empirical cold-opening premium, and that the premium is caused by the limited strategic thinking of moviegoers as the cognitive hierarchy, level-k, and cursed models predict, the next question to ask is what level of moviegoer rationality is associated with the premium. Our working paper (Brown, Camerer and Lovallo, 2009) and companion paper (Brown, Camerer and Lovallo, 2011)

[3]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.

both suggest that moviegoers have a level of strategic thinking consistent with that estimated in several experimental studies. This paper specifically addresses only the predictions of the models of bounded and limited rationality in the major motion picture industry and examines which model is more consistent with the general facts of that industry. Brown, Camerer and Lovallo (2011) reports details of the structural model which is beyond the scope of this paper.

The paper is organized as follows: Section 1 describes the equilibrium prediction of the standard model and competing behavioral models. Section 2 describes the data and presents some regression results on the existence and robustness of a box-office premium for movies that are cold opened. Section 3 further examines the robustness of the regression results, examining the premium in box office and domestic DVD markets and using a propensity score matching technique. Section 4 discusses alternative explanations for the cold-opening premium and argues for the explanation of limited strategic thinking. Section 5 concludes and discusses related empirical results on disclosure effects, which are generally consistent with the findings of this paper.

1 Theoretical Predictions

A fully rational analysis, due originally to Grossman (1981) and Milgrom (1981), implies in games of strategic disclosure, all information should be revealed at equilibrium. Thus, 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 studios agree on quality, and firm profits increase in quality. If studios 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. 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 studios 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 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). Dranove and Jin (2010) list (p. 943) these assumptions as:

- "Sellers have complete and private information about their own product quality;"[4]
- "Disclosure is costless;"[5]
- "Monopoly or competitive market with no strategic interaction among competing sellers;"
- "Consumers are willing to pay a positive amount for any enhancement of quality;"
- "The distribution of available quality is public information."[6]

These assumptions generally fit the movie industry reasonably well. Sellers usually know a lot

[4]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).

[5]If disclosure is costly (Viscusi, 1978; Jovanovic, 1982), sellers will only reveal information down to a certain threshold of low quality.

[6]Fishman and Hagerty (2003) assume a portion of consumers are unable to interpret revealed information, but this does not necessarily lead to limited disclosure. 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. The third equilibria is equivalent to the first as consumers can infer low quality products from their firm's lack of disclosure.

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. Disclosure is relatively cheap: The median production budget in our sample is $35 million, the marketing budgets are often comparable in scale (50-100 percent of the production budget), but the costs of arranging screenings for critics (or now, sending DVDs) is on the scale of thousands of dollars. The business is relatively competitive. Nominal ticket prices do not typically depend on quality, but discounting is sometimes limited for popular movies (e.g., passes not accepted) and consumers often "pay" in congestion and queuing costs for popular movies. Quality information is easily found in newspaper and internet sites.

Two of the other assumptions Dranove and Jin (2010) list (p. 943) are not so obviously satisfied:

- "Products are vertically differentiated along a single, well defined dimension of quality;"
- "Consumers are homogeneous."

Moviegoers certainly have different tastes and products are horizontally differentiated. However, our analysis controls for genre effects, and (as we show later) the basic results hold to a surprising degree across different genres in which one might expect differences in perceptions of quality and attention to critic reviews (e.g., horror versus drama).

Dranove and Jin (2010) do not list one implicit assumption, which is relevant to all disclosure models, and is highly relevant to our analysis,

- Consumers know about a firm's decision to disclose.

This assumption is highly suspect in our setting, as surely some moviegoers are not aware whether movies they view have been cold opened. For the first part of the analysis of this paper we will assume all consumers are aware. In Section 4 we will reexamine whether relaxing this assumption might also generate a lack of disclosure and the cold-opening premium found in our data.

This leaves one final assumption, the initial focus of our attention (p. 943):

- "Consumers hold a rational expectation on the quality of nondisclosed products;"

We proceed with the strong maintained hypothesis that complete unravelling should occur in theory, except for the possible violation of the consumer rational expectations assumption. Models of limited strategic thinking provide a precise way to show how this assumption can be violated. The level-k 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 studio anticipates that moviegoers think this way and therefore cold opens all below-average movies, 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 studios who employ various numbers of steps of thinking.[7]

Industry executives and analysts that 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]The model of cursed equilibrium (Eyster and Rabin, 2005) 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 studios 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 studios' information about quality and their cold-opening choice.

For example, Greg Basser, CEO of Village Roadshow Entertainment 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."[8]

To summarize, the standard equilibrium game-theoretic models of Grossman (1981) and Milgrom (1981) suggest that only the worst quality movies should cold open, and there should be no revenue difference between them and movies screened for critics, controlling for quality. Models which include an assumption of limited strategic thinking as well as industry sources suggest that moviegoers do not infer that cold-opened movies have the worst quality. They suggest that movies that have quality greater than the worst possible should also be withheld from critics, and that those movies should receive more revenue than their quality would warrant as moviegoers overestimate their true quality.

The data in the next section generally agrees with the predictions of the models of limited strategic thinking. We find 11 percent of the movies in our sample are cold opened (though that fraction has increased sharply in recent years). Regressions show the cold-opening dummy variable is associated with positive, significant, coefficients, suggesting a 10–30 percent differential increase over similar movies screened for critics. These regressions include several control variables and robustness checks and all are associated with a positive cold-opening coefficient.

[8] Germain, David. 2006. "Studios Shutting out Movie Critics." Associated Press Archive, April 4.

2 Data

The data set is all 1414 movies widely released in their first weekend[9] in the United States (US), over the decade from January 1, 2000 to December 31, 2009.[10]

Critic and moviegoer ratings are both used to measure quality. Metacritic.com ratings are used 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. Because they occur so early in a movie's release, we assume their ratings help determine box-office revenue and not vice versa.

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 positive, statistically significant, 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 positive correlation (.75) between metacritic scores and Internet Movie Database (IMDB) user reviews (see Figure 1). The correlation between critic (metacritic) and the moviegoer (IMDB ratings) holds across movies and genres (as shown in Table 7). Metacritic scores therefore correlate with two clear indicators of movie popularity (IMDB reviews and box-office revenue).

[9] We use industry standard definition of a "wide-release," a movie that appears in at least 600 theaters nationwide.

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

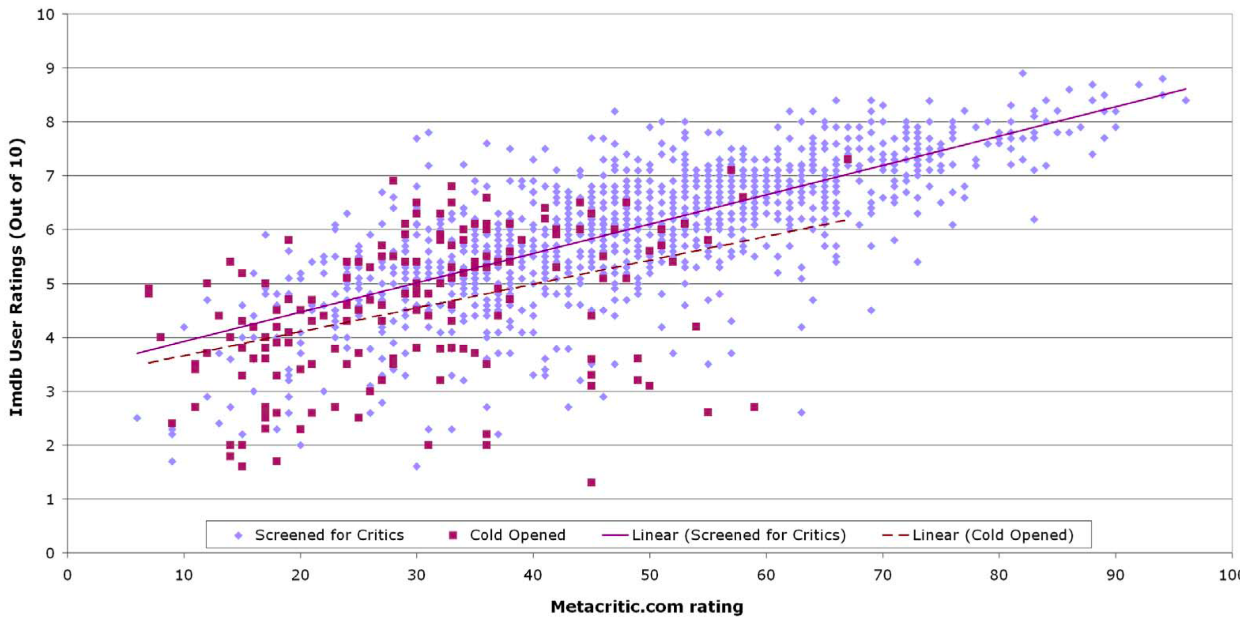

Figure 1: Scatter plot of metacritic.com quality ratings and IMDB user ratings.

The squares in Figure 1 represent the cold-opened movies in our sample. No cold-opened movie has a metacritic rating higher than 67. The average rating for those movies is 30, 17 points below the sample average of 47.

Cold opening, box-office revenues, movie genres and Motion Picture Association of America (MPAA) ratings, production budgets, and star power ratings are collected from various data sources (see the online appendix 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 revenue. The table also shows separate variable means for the cold-opened movies. Those movies are somewhat statistically different in several dimensions—they tend to be smaller in budget and theater coverage, with less well-known stars and over-representing 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

Table 1: Summary statistics for variables. Observations are 1414 for all variables, except there are only 1413 observations for metacritic, 1303 for production budget, 1200 for United Kingdom box office, 1138 for Mexico box office, and 1387 for United States rentals.

variable	mean	median	standard deviation	mean (cold only)
cold opening (1=cold opening)	0.115	0.000	0.319	1.000***
log total box office revenue	3.508	3.578	1.143	2.770***
log 1st weekend box office revenue	2.447	2.503	0.983	1.948***
log total box office revenue per theater	-4.252	-4.203	0.911	-4.849***
log 1st weekend box office revenue per theater	-5.313	-5.316	0.739	-5.671***
log total box office revenue, United Kingdom	0.643	0.907	1.788	-0.114***
log total box office revenue, Mexico	2.951	3.052	1.299	2.379***
log total weekly rental index score, US rentals	5.481	5.653	0.697	5.179***
metacritic rating (out of 100)	46.650	47.000	16.688	30.270***
imdb user rating (out of 10)	5.862	6.000	1.294	4.560***
log theaters released in opening weekend	7.760	7.865	0.383	7.619***
log production budget	3.471	3.516	0.900	2.845***
log advertising expenditures	2.775	2.895	0.655	2.117***
average log competitor budget	3.266	3.390	1.039	2.986***
average log competitor advertising expenditures	2.628	2.769	0.789	2.390***
average log star ranking of lead roles	7.512	6.887	3.562	7.385
summer release (1=opening date is Jun, Jul, or Aug)	0.250	0.000	0.433	0.196*
adaptation or sequel (1=either movie type)	0.612	1.000	0.488	0.693***
days released before Fri (1=Thu, etc.)	0.201	0.000	0.660	0.098***
opening weekend continues after Sunday (1=Mon, 2=Tue, etc.)	0.111	0.000	0.346	0.129
days released earlier in foreign country (in days, 0=US first)	12.679	0.000	87.062	12.742
action or adventure (1=either genre)	0.149	0.000	0.356	0.104*
animated (1=animated genre)	0.065	0.000	0.247	0.012***
comedy (1=comedy genre)	0.361	0.000	0.480	0.301*
documentary (1=documentary genre)	0.007	0.000	0.084	0.018
fantasy or sci-fi (1=either genre)	0.069	0.000	0.254	0.074
supense or horror (1=either genre)	0.179	0.000	0.383	0.448***
year 2001 (1=released in 2001)	0.096	0.000	0.295	0.049***
year 2002 (1=released in 2002)	0.113	0.000	0.317	0.202***
year 2003 (1=released in 2003)	0.118	0.000	0.323	0.209***
year 2004 (1=released in 2004)	0.107	0.000	0.310	0.160*
year 2005 (1=released in 2005)	0.098	0.000	0.297	0.160***
year 2006 (1=released in 2006)	0.113	0.000	0.317	0.202***
year 2007 (1=released in 2007)	0.118	0.000	0.323	0.209***
year 2008 (1=released in 2008)	0.107	0.000	0.310	0.160*
year 2009 (1=released in 2009)	0.098	0.000	0.297	0.160***
PG (1=PG rating)	0.173	0.000	0.379	0.061***
PG-13 (1=PG13 rating)	0.463	0.000	0.499	0.515
R (1=R rating)	0.325	0.000	0.469	0.399***

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

is

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

where y_j is opening weekend or total US box office for movie j in 2005 dollars, standardized using the CPI index (www.bls.gov). Table 2 shows regression results on logged total box-office revenue and logged opening weekend revenue, respectively.

The point of these initial regressions is not to estimate a full model with endogenous studio decisions (we estimate such a model using cursed equilibrium and level-k with quantal response in our working paper, Brown, Camerer and Lovallo, 2009, and cognitive hierarchy in our companion paper, Brown, Camerer and Lovallo, 2011). 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-opening coefficient should be zero.

The cold-opening 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.[11] If the regression model is taken literally, these coefficients suggest that cold opening a movie increases its revenue from 10–30 percent.[12] However, we caution the reader in such an interpretation of these results. Selection and endogeneity no doubt play a part in these regressions. Common sense would tell us that not every movie that is not cold opened (for instance, a critically-acclaimed movie with a high metacritic score) would make more revenue if it were cold opened. Cold-opened movies have

[11]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.

[12]For the average gross of a cold-opened movie, \$25 million, this is roughly \$2.5–7.5 million of box-office revenue.

metacritic scores under 67 and a mean of 30, showing that the positive correlation between cold opening and revenue occurs for low-quality movies. We do not have data for high-quality movies that are cold opened, since studios do not make this choice. Thus movies are not cold opened at random. We account for this selection in section 3 using propensity matching. Additionally, some of the independent variables may have an endogenous relation with cold openings. For instance, the number of theaters a movie is shown is definitely correlated with a studio's expectation of a movie's performance which may affect the decision to cold open. All possible "choice variables," logged marketing expenditures, competitor budget and expenditures, and opening weekend release decisions are omitted in columns 3 and 4. The omission of these variables halves the coefficient of the cold opening variable and reduces its significance for cumulative and weekend box-office revenues. When these regressions are of cumulative and opening weekend revenue per theater (columns 5 and 6), the coefficients increase slightly, and the cold opening variable is significantly positive at the 0.05 level for both measures. These latter regressions suggest that the loss of significance in the previous regressions may have been due to non-cold-opened movies' higher average number of theaters (see table 1). Nonetheless, the lower cold-opening coefficient in these regressions (11–15 vs. 26–34 percent) suggest that we must be careful when interpreting the size of the cold-opening premium. Additionally, the lower significance in columns 3 and 4 suggests we must include a caveat about endogeneity when interpreting these results.

The regression coefficients in Table 2 are generally sensible. Higher quality leads to higher box-office revenue—an increase in one metacritic point increases revenue about 1 percent. IMDB ratings appear to have a similar relationship with cumulative box-office revenue, but not weekend box-office revenue. Doubling advertising expenditure increases opening weekend and cumulative box-office revenue by 50 and 70 percent, respectively. Production budget is significantly positive

Table 2: Regressions on logged box-office revenues (in millions). a. In this preferred specification, cold opening is a dummy variable that is 1 for all cold-opened movies. In other specifications, the cold dummy is replaced by interaction terms for cold-opened movies by genre and by year (see the online appendix for complete regression tables). The genre interaction terms are shown in Section 4, Table 7. The cold and year interaction terms are discussed in footnote 14.

dependent variable:	log total box office revenue	log opening weekend box office revenue	log total box office revenue	log opening weekend box office revenue	log total box office revenue per theater	log opening weekend box office revenue per theater
cold opening[a]	0.301*** (0.064)	0.220*** (0.057)	0.152** (0.084)	0.118* (0.076)	0.171*** (0.072)	0.137** (0.063)
metacritic rating	0.011*** (0.002)	0.011*** (0.001)	0.013*** (0.002)	0.011*** (0.002)	0.015*** (0.002)	0.013*** (0.002)
imdb rating	0.082*** (0.023)	-0.009 (0.020)	0.141*** (0.030)	0.040 (0.027)	0.128*** (0.025)	0.027 (0.022)
log theaters opened	1.000*** (0.075)	1.177*** (0.067)	-	-	-	-
log production budget	0.003 (0.029)	0.006 (0.025)	0.489*** (0.031)	0.436*** (0.028)	0.294*** (0.027)	0.241*** (0.023)
log advertising expenditures	0.738*** (0.049)	0.504*** (0.044)	-	-	-	-
average log competitor budget	-0.020 (0.026)	-0.052** (0.023)	-	-	-	-
average log competitor advertising expenditures	-0.039 (0.034)	-0.035 (0.030)	-	-	-	-
average log star ranking of lead roles	-0.014* (0.007)	-0.011* (0.006)	-0.057*** (0.009)	-0.053*** (0.008)	-0.034*** (0.008)	-0.030*** (0.007)
summer release	0.079** (0.039)	0.028 (0.035)	0.064 (0.051)	0.012 (0.046)	0.050 (0.044)	-0.002 (0.038)
adaptation or sequel	0.108*** (0.042)	0.068* (0.037)	0.189*** (0.055)	0.144*** (0.049)	0.151*** (0.047)	0.106*** (0.041)
days released before Friday	0.038 (0.025)	0.015 (0.023)	-	-	-	-
opening weekend continues after Sunday	0.142*** (0.049)	0.124*** (0.043)	-	-	-	-
days released earlier in foreign country	0.000* (0.000)	0.000 (0.000)	-	-	-	-
genre dummy variables included	yes	yes	yes	yes	yes	yes
year dummy variables included	yes	yes	yes	yes	yes	yes
MPAA rating dummy variables included	yes	yes	yes	yes	yes	yes
constant	-6.683*** (0.551)	-8.212*** (0.489)	1.103*** (0.265)	0.466* (0.240)	-6.013*** (0.226)	-6.650*** (0.197)
observations	1303	1303	1303	1303	1303	1303
R^2	0.7074	0.6912	0.4841	0.4345	0.4139	0.3292

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

in regressions that do not involve advertising expenditures. The number of theaters in which the movie opened, which often indicates expectations about movie revenues, has a very large effect. Doubling the number of opening theaters at least doubles the expected weekend and cumulative revenue. The averaged logged star power rankings[13] have a negative correlation (higher numbers indicate lower rankings and less revenue). Adaptations and sequels increase box office by roughly 6–10 percent, a result which may explain the recent growth in the fraction of movies in this category. The year dummy variables show a general decline in real-dollar, box-office revenue in the last decade,[14] consistent with the conventional wisdom in the business.

From a limited strategic thinking point of view, 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). This may explain why movie studios are so quick to run ads claiming to have "the number 1 movie in America" during the second week of their movie's run. This advertising strategy appears to be employed more often than mentioning critical acclaim during the second

[13] See the online appendix for a full description of all variables.

[14] An alternate specification (see the online appendix) with cold$\times$year interaction terms replacing the single cold dummy produces generally similar results. Cold-opened interaction terms for years 2006 and 2008 are significantly positive at the 0.05 level for all regressions with large coefficients (0.3–0.47). The 2002 term has highly negative coefficients $((-0.68)$–$(-0.37))$, which is significantly less than 0 at the 0.05 level in all regressions. Year 2000, 2004, 2005, 2007 and 2009 terms have positive coefficients across all regressions, but most lack significance at the 0.10 level. The 2003 term has negative coefficients across all regressions, but most lack significance at the 0.10 level. The 2001 term is positive and negative for three regressions each.

week of a movie's run. Its effectiveness could be similar to other disclosure studies showing that the influence of quality information depends on whether it is easy to "access and understand, and whether consumers pay attention to disclosure" (Dranove and Jin (2010), p. 954).

Another fact is that reviews for cold-opened movies are typically published, but usually in the Saturday or Monday newspapers (and rarely in a prominent place "above the fold" on the first entertainment page, as popular Friday reviews typically are). It might be that moviegoers with limited attention do not notice those reviews. DellaVigna and Pollet (2009) found a similar effect in the timing of earnings information releases for stocks: Revealing information at times when markets are closed and individuals are not as prepared for news (late in the day on Friday) can delay how quickly the markets respond to that news.

Additionally, during the later part of the data set (2007–2009), several critics began to ignore cold-opened movies (for example, the San Francisco Chronicle stopped reviewing most cold-opened movies around June 2007 after an across-the-board layoff of 25 percent of staff, but the New York and LA Times still do).[15] If critics no longer review cold-opened movies, studios can use cold openings to permanently remove (instead of delay) potential bad reviews from informing moviegoers.[16] In this case, a cold-opening effect due to a moviegoer's failed inference of lack of reviews could persist during the movie's entire run. We suspect this relatively new phenomenon may have contributed to the recent increase in cold openings.

[15]See footnote 14 for a description cold-opening's correlation with box office by year.

[16]Perhaps the most well-known movie critic, Roger Ebert, who writes negative reviews so entertaining that he has published a book of them (Ebert, 2007), rarely reviews any cold-opened movies.

3 Robustness Checks

The hypothesis that limited strategic thinking by moviegoers generates the premium suggests that in markets where quality has leaked out, there will be no cold-opening premium. One way to test this prediction is to look at the logged total box-office revenue of the United Kingdom (UK) and Mexico, and log of US video rental index. 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 UK and Mexico after the initial US release, and home video rentals are always later than US box office releases (although, the lags were greatly reduced over the course of the decade). If information about the movie's quality is widely disseminated before these later releases, the cold-opening effect should disappear in foreign and rental markets.

Table 3 reports the cold-opening coefficients from a regression including all variables as in Table 2. The initial regressions show a cold-opening premium in the UK market, but no such premium once possibly endogenous variables have been removed from the regression. It is interesting to note that the one foreign language market, Mexico, shows the least signs of any cold-opening premium. It may be that UK and US rental markets rely on english-based American reviews to judge quality of their movies, but Mexican moviegoers who likely do not read those reviews infer quality of movies through other means. As discussed above, in recent times, several newspapers have stopped reviewing most cold-opened movies, likely in response to staff reductions. This phenomena may explain the cold opening premium found in other English-speaking markets.

The regression results in Table 3 should also be interpreted carefully. As the number of observations in Table 3 indicate, not all movies are released in other markets. From the 1303 movies observed in Table 2, considerably less have revenue data in the UK (1139), Mexico (1082) and

Table 3: Regressions on logged cumulative box-office revenues in other markets. a. Not all movies were released in other markets. Cold openings make up 138 of 1303 movies in the US market (10.5 percent). They make up 8.6 percent (98/1139) of the UK market, 9.3 percent(101/1082) of the Mexico market, and 10.4 percent of the US video market (134/1283). In both foreign markets, the fraction of cold openings is significantly lower than the US market at the 5 percent level.

dependent variable:	log total box office revenue (United Kingdom)	log total box office revenue (United Kingdom)	log total box office revenue (Mexico)	log total box office revenue (Mexico)	log total weekly rental index (United States)	log total weekly rental index (United States)
cold opening	0.347** (0.166)	0.229* (0.174)	0.074 (0.112)	-0.103 (0.120)	0.079* (0.053)	-0.011 (0.059)
metacritic rating	0.019*** (0.004)	0.019*** (0.004)	0.003 (0.003)	0.003 (0.003)	0.001 (0.001)	0.001 (0.001)
imdb rating	0.145** (0.059)	0.193*** (0.061)	0.006 (0.041)	0.044 (0.043)	0.090*** (0.019)	0.117*** (0.021)
log theaters opened	1.367*** (0.194)	-	1.113*** (0.134)	-	0.529*** (0.062)	-
log production budget	0.273*** (0.072)	0.733*** (0.063)	0.460*** (0.050)	0.808*** (0.046)	0.057** (0.024)	0.286*** (0.022)
log advertising expenditures	0.618*** (0.131)	-	0.498*** (0.089)	-	0.345*** (0.042)	-
average log competitor budget	0.029 (0.062)	-	-0.049 (0.044)	-	0.006 (0.022)	-
average log competitor advertising expenditures	-0.080 (0.080)	-	0.037 (0.056)	-	-0.034 (0.030)	-
average log star ranking of lead roles	-0.069*** (0.017)	-0.105*** (0.018)	-0.035*** (0.012)	-0.059*** (0.013)	-0.015*** (0.006)	-0.036*** (0.006)
summer release	0.057 (0.094)	0.085 (0.097)	0.036 (0.064)	0.058 (0.069)	-0.138*** (0.032)	-0.145*** (0.036)
adaptation or sequel	0.256*** (0.098)	0.306*** (0.103)	0.056 (0.068)	0.097 (0.073)	-0.012 (0.034)	0.019 (0.038)
days released before Friday	-0.019 (0.060)	-	0.020 (0.042)	-	-0.037* (0.021)	-
opening weekend continues after Sunday	0.096 (0.117)	-	-0.077 (0.081)	-	0.037 (0.040)	-
days released earlier in foreign country	0.000 (0.001)	-	0.001*** (0.001)	-	0.000 (0.000)	-
genre dummy variables included	yes	yes	yes	yes	yes	yes
year dummy variables included	yes	yes	yes	yes	yes	yes
MPAA rating dummy variables included	yes	yes	yes	yes	yes	yes
constant	-13.899*** (1.438)	-3.206*** (0.514)	-8.702*** (1.000)	-0.054 (0.362)	-0.378 (0.452)	3.727*** (0.185)
observations[a]	1139	1139	1082	1082	1283	1283
R^2	0.4573	0.385	0.5389	0.4467	0.515	0.384

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

video rental (1283) markets. In all three markets, the percentage of cold-opened movies is lower (significantly so at the 0.05 level in both UK and Mexico), indicating that cold opened movies are less likely to be released in secondary markets. Therefore these regression results (especially the foreign markets) may be distorted by a selection problem.

As mentioned before, the correlation between cold opening and box-office revenue may be misleading in a regression if there is an endogenous relationship between cold opening and one of the other independent variables. One way this might occur is if distributor's choose to cold open at the same time they make a decision about another variable. To examine the relationship between cold opening and the other independent variables, Table 4 shows a logit regression on cold opening with the other independent variables and a shortened regression with only the variables not suspected of being choice variables. The regression shows a few relationships that we suspected: metacritic and IMDB scores are *negatively* correlated with the decision to cold open, meaning that movies that people and critics like are more likely not to be cold opened. Budget and advertising expenditure are negatively correlated with cold opening suggesting that larger scale movies are less likely to be withheld from critics. Some genres cold open more often than others, action/adventure, fantasy/sci-fi and suspense/horror increase the chances that a movie will be cold-opened. The number of theaters in which a movie is shown on opening weekend has a slightly positive relation with cold opening, and PG rating has a slightly negative relationship, but neither effect is as large as in the analysis in table 1. Advertising expenditure is generally negatively correlated with cold opening. As further evidence, Table 5 shows advertising expenditures are about 18 percent less for movies that are cold-opened.

The predictions of the logistic regressions provide a propensity score for each movie in the dataset, a likelihood of its chances of being cold opened given its other characteristics. Using

Table 4: Logistic regression on cold opening of standard independent variables

dependent variable:	cold opening	cold opening
metacritic rating	-0.053***	-0.059***
	(0.014)	(0.013)
imdb rating	-0.784***	-0.841***
	(0.154)	(0.144)
log theaters opened	1.161**	-
	(0.567)	
log production budget	-0.628***	-0.884***
	(0.190)	(0.165)
log advertising expenditures	-1.363***	-
	(0.310)	
average log competitor budget	-0.095	-
	(0.183)	
average log competitor advertising expenditures	0.005	-
	(0.242)	
average log star ranking of lead roles	-0.005	0.003
	(0.056)	(0.054)
summer release	-0.055	-0.021
	(0.318)	(0.305)
adaptation or sequel	-0.954**	-0.928**
	(0.391)	(0.381)
days released before Friday	-0.170	-
	(0.228)	
opening weekend continues after Sunday	0.036	-
	(0.394)	
days released earlier in foreign country	-0.001	-
	(0.002)	
genre dummy variables included	yes	yes
year dummy variables included	yes	yes
MPAA rating dummy variables included	yes	yes
constant	-1.456	4.294***
	(4.148)	(1.547)
observations	1303	1303
log likelihood	-214.740	-226.01

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Table 5: Regression on advertising expenditure of standard independent variables

dependent variable:	log advertising expenditures	log advertising expenditures
cold opening	-0.175*** (0.036)	-0.194*** (0.044)
metacritic rating	0.005*** (0.001)	0.004*** (0.001)
imdb rating	0.065*** (0.013)	0.072*** (0.015)
log theaters opened	0.847*** (0.036)	-
log production budget	0.211*** (0.015)	0.379*** (0.016)
average log competitor budget	0.026* (0.015)	-
average log competitor advertising expenditures	-0.004 (0.020)	-
average log star ranking of lead roles	-0.005 (0.004)	-0.025*** (0.005)
summer release	-0.022 (0.022)	-0.011 (0.027)
adaptation or sequel	0.011 (0.024)	0.044 (0.029)
days released before Friday	0.020 (0.014)	-
opening weekend continues after Sunday	0.062** (0.028)	-
days released earlier in foreign country	0.000 (0.000)	-
genre dummy variables included	yes	yes
year dummy variables included	yes	yes
MPAA rating dummy variables included	yes	yes
constant	-5.001*** (0.282)	1.115*** (0.138)
observations	1303	1303
R^2	0.7077	0.571

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Table 6: Propensity score matching results for logged United States cumulative and weekend box office. Propensity score matching results for logged US cumulative and weekend box office revenues. Cold opening is the treatment variable. The second (rightmost column in Table 4) logit specification is used. All specifications are over the area of common support.

dependent variable	specification	number in treatment group	number in control group	average treatment effect on the treated	standard error	t-statistic
log opening weekend box office revenue	nearest neighbor	138	76	0.191	0.206	0.924
log opening weekend box office revenue	stratification	138	599	0.172	0.102	1.692**
log opening weekend box office revenue	kernel matching	138	599	0.136	0.096	1.421*
log total box office revenue	nearest neighbor	138	76	0.231	0.231	1.001
log total box office revenue	stratification	138	599	0.145	0.122	1.197
log total box office revenue	kernel matching	138	599	0.141	0.126	1.123

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

these values, we can calculate the cold-opening premium weighting more highly the movies that were likely to be cold opened. We can also ignore movies that would never conceivably be cold opened. Recall, the coefficients found in our initial regressions compared cold-opened movies to all movies, including critically acclaimed or blockbuster films which are not ideal comparisons. Table 6 shows the results of three types of propensity score matching for weekend and cumulative US box office data using the logistic specification with possible endogenous variables removed (the rightmost column of Table 4).[17]

The propensity score matching results find cold opening is correlated with a 14–23 percent positive increase in revenue for US opening weekend and cumulative box-office revenues. This

[17] Using the full logit specification leads to propensity score matching results that are more pronounced than Table 6, as cold opening is correlated with a 30-50 percent positive increase in revenue for US opening weekend and cumulative box office.

amount is slightly higher than what is found in the corresponding regressions in Table 2, Columns 3 and 4, though the standard errors are also much greater, which is at least partially due to the reduced sample size in these regressions. Nearest neighbor matching—a technique that matches each cold-opened movie with the regular released movie with the most similar propensity to have been cold opened—finds the highest positive correlation of 19–23 percent, but also has the highest standard error, consistent with its smaller sample size. Other matching techniques that feature more non-cold-opened movies (599 vs. 76), but weigh each film differently, predict a lower value for the cold-opening premium (13–17 percent) and have a higher degree of significance. Taken together, these results suggest that the magnitude of the positive cold-opening premium cannot be reduced by removing larger, blockbuster movies that would never be cold opened from the sample.

4 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 weighs 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) (see Brown, Camerer and Lovallo (2009) for a regression using only IMDB ratings).

3. The correlation is far less pronounced in non-US markets, especially the foreign language

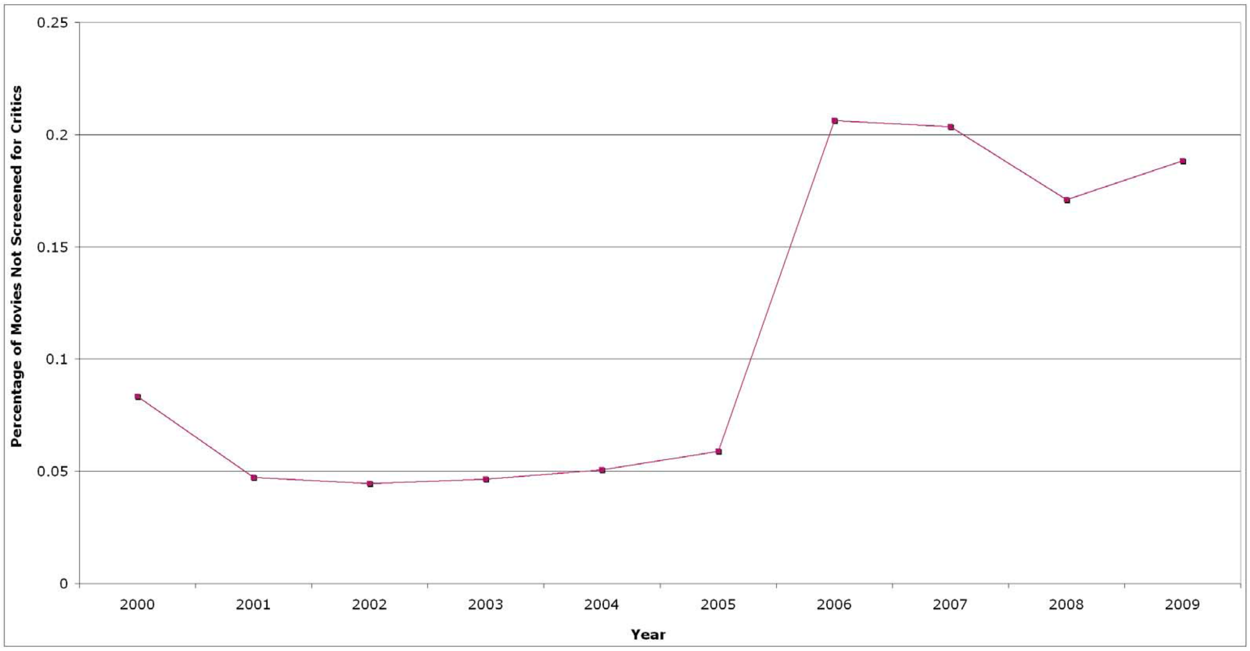

Figure 2: Percent of widely-released movies cold opened by year, 2000–2009

market Mexico.

4. IMDB fan ratings are about 0.5 points lower (on a 10-point scale) for cold-opened movies than for comparable movies that were not cold opened (see the online appendix for the regression).

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

First we will describe the explanation we prefer (in more detail than above). Then we will describe some plausible alternatives and explain which facts they do not fit well. The explanation we prefer is the following: Executives form a judgment, very late in the decision making process, about the fragility of the "buzz" or audience expectations (denoted $E(q_m)$). The judgment comes late because both pre-release buzz and actual quality are not determined until the movie is finished (often after late tweaking in response to test screenings). If the quality perceived by executives, q, is above pre-release buzz ($q > E(q_m)$) they always show the movie to critics. If the perceived quality is below ($q < E(q_m)$) executives decide whether showing the movie to critics will help or hurt. If they judge that audience expectations are fragile, so that having it reviewed will lower expectations, they cold open it. A key ingredient in this story is that executives must think some moviegoers are strategically naïve, in the sense that those moviegoers with expectations ($E(q_m) > q$) will not deduce from the lack of reviews that quality is lower than they think. (Otherwise, the decision to cold open would be tantamount to allowing critics to say the quality is low.)

This possibility has been discussed in the literature on disclosure. In their lengthy review, Dranove and Jin (2010) note that one of the assumptions underlying the standard unravelling theory is that "Consumers hold a rational expectation on the quality of nondisclosed products" and suggest some conditions under which that assumption can fail (p. 952).

This explanation can fit all five stylized facts. The decision to cold open is then associated with a gap between audience expectations and quality. Since box-office revenue is presumably driven by expectations $E(q_m)$, but the regressions use only measures of q, the cold-opening dummy variable captures the expectations gap $E(q_m) - q$ which is positive (fact 1).

The explanation is consistent with (fact 2) since it does not depend on a difference in judged quality between critics and fans who saw the movie (who rate on IMDB).

Since word leaks out about quality from word-of-mouth, the expectation gap is closed over time and so the cold-opening coefficient is smaller (typically closer to zero) in foreign and rental markets (fact 3).

Importantly, IMDB fan ratings for cold-opened movies are about 0.5 ratings points below ratings for screened movies of comparable quality (as judged by critics). IMDB ratings are primarily given by fans who have chosen to see the movie, unlike critic reviews, so they certainly represent a selection of consumers with upward-biased expectations (as well as special tastes). If fans' upward-biased expectations are partly based on strategic naivete (for cold-opened movies), then their actual ratings will be lower than for reviewed movies of comparable quality. Thus, lower IMDB ratings are consistent with the idea that fans are *especially* disappointed in cold-opened movies because of the combined expectation gap and strategic naivete, which cold opening exploits (fact 4).[18]

Finally, we suggest that movie studios might have learned over time that cold opening was often profitable, which accounts for the upward drift in the frequency of cold opening (fact 5; see Figure 2). This fact is the hardest to explain conclusively, however, since there are many changes in the nature of movie marketing and consumption over this time period (chiefly, shorter times in theaters, a rise in DVD sales, and more pre-release information leakage through the internet).

An interesting question is why some movies with comparable characteristics (and critic-rated quality) are cold opened while others are not. There is no publicly observable data on this decision and our vague concept of "fragile buzz" as a key determinant is difficult to measure. Therefore, in order to understand the timing and nature of cold-opening decisions, we collected the best available anecdotal evidence we could find—by conducting interviews with four senior executives in marketing, public relations, distribution and production at three of the four major Hollywood film studios and at a major distributor. We fully understand that economists are often skeptical of survey data. However, the central unanswered questions here are about endogeneity of choice

[18]For an explanatory example, consider the moviegoer who overestimates a movie's quality based on strategic naïveté. Suppose that if he knew the movie's true quality, or knew that it was cold opened and inferred correctly its lower quality, he would not see it in theaters. This type of moviegoer is present in the audience of cold-opened movies but does not go to movies screened for critics. Thus IMDB ratings for cold-opened movies are lower, all else being equal, because these moviegoers bring down their ratings, but not for movies screened for critics. By analogy, imagine an expensive restaurant that posts a menu online but does not list prices. If the highest-priced restaurants withhold prices, and naïve diners do not infer that relation, they will always be complaining about the surprisingly expensive prices at the restaurants they go to that did not post a menu.

variables and what determines cold-opening decisions; asking the people who know the most about those decisions (and sometimes make them, or delegate them) creates data that should be of some value.[19]

Here's what they told us: first, production budgets and personnel are decided early in the process. The number of theaters which agree to show the film is contracted far in advance of any cold-opening decision.[20] Cold-opening decisions are made after distribution contracts have been signed and according to a major distributor and studio executives "are not a part of the contract." There are no contracted decision rights about whether to cold open or not.[21]

The cold-opening decision is almost always made late in the process. After the film is completed, there is often audience surveying and test screenings. As one senior marketing and public relations (PR) veteran put it, "If a movie is not shown to critics, a decision has been made that the film will not be well received by them... After the PR executives have seen the film, if they believe the film will be poorly reviewed, they will have a heart to heart with the marketing execs and filmmakers about the pros and cons of screening for critics."

Our explanation should certainly be treated with caution, however, since it is impossible to rule out the influence of omitted variables that cannot be observed, and our explanation does not account for why the cold-opening effect exists in cumulative box-office revenues when we predict

[19]One concern economists often have is that survey respondents misrepresent their decision making for strategic or image reasons. Keep in mind that these executives are not typically closely involved to the creative process where ego is most involved. They had no problem discussing what they do with low quality movies, and also have no reason to misrepresent the timing of decisions which is relevant for judging endogeneity biases.

[20]In fact, for many years studios used "blind bidding" in which distributors forced theaters to commit to screens before viewing any part of the movie. Since then, 23 states passed laws that distributors must screen their movie for theaters (exhibitors) before negotiating screen commitments (Vogel, 2007).

[21]When asked, "(D)oes the possibility of not showing the movie to critics enter, in any way, in the studios efforts to get theaters to show it?" The replies were a unanimous, "no."

it should only exist during the first weekend.

Next we turn to consideration of other alternative explanations.

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 studios for making the movie unavailable).[22] 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). Furthermore, this hypothesis cannot explain fact (2), that the cold-opening premium on revenues is evident even when IMDB user ratings are used.

Consumer-critic heterogeneity: Another possibility is that movies which are cold opened are aimed at an audience with tastes which are different than critics' tastes. Indeed, there is a lower positive correlation of critic reviews (metacritic) and moviegoer reviews (IMDB) for cold-opened movies (0.41), than the corresponding correlation for non-cold-opened movies (0.74). However, this reduced correlation most likely results from the fact that cold-opened movies have a restricted range of critic ratings ($\bar{x} \approx 30, s^2 \approx 12$). 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 ($\bar{x} \approx 70, s \approx 8$), we find similar values for the correlation (0.50 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. Fantasy/science fiction and suspense/horror movies account for 56 percent of cold openings, but only 25 percent of all movies (see Table 7).

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

Table 7: Data separated by movie genre. Regression coefficients are from the Table 2, Column 4 regression with the cold dummy replaced by an interaction term of cold and genre (see the online appendix for a full regression table).

Genre	number of movies	number of cold-opened movies	percent cold opened	average metacritic rating	average imdb rating	imdb-metacritic rating correlation	interaction coefficient coldxgenre, on total box office revenue	interaction coefficient coldxgenre, on opening weekend box office revenue
Action or Adventure	206	17	8.25%	48.379	6.051	0.7767	-0.479***	-0.477***
Animated	85	1	1.18%	57.941	6.307	0.8552	-0.479	-0.429
Comedy	458	36	7.86%	43.480	5.505	0.7293	0.344***	0.297**
Documentary	5	1	20.00%	50.200	4.860	0.7045	1.036	1.326*
Drama	221	6	2.71%	51.869	6.370	0.6577	0.477*	0.366
Fantasy or Sci-fi	95	12	12.63%	50.884	6.255	0.8279	-0.404*	-0.414**
Suspense or Horror	233	65	27.90%	42.691	5.867	0.7585	0.289***	0.251***
Overall	1303	138	10.59%	47.045	5.907	0.7525	0.152**	0.118*

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

If fans of these genres have 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.[23]

Table 7 shows that this is not the case. Throughout genres, moviegoers' correlation between critic reviews and self-reported reviews are all around 0.75. When the regression specifications from Table 2, Columns 3 and 4 are rerun with the cold dummy replaced with specific cold$\times$genre interaction terms, a majority of the dummy variables are positive. It should be noted that many of the genres have very few numbers of cold openings.

Finally, as previously mentioned, 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: Another possible explanation for the cold-opening premium is that cold-

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

opened movies have some characteristic omitted from the Table 2 regressions that causes these movies to generate apparently greater box office. 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.

It is certainly possible that there is such a variable we have not identified. However, all the apparent measurable controls are already included in Table 2. (Table 4 suggests most variables outside of critical acclaim, budget, and genre are not significant in the cold-opening decision.) Of course, it is impossible to prove such variable does not exist. One way to constructively address the challenge of either finding such an omitted variable or justifying why its existence is unlikely is to consider the properties an ideal omitted variable would have (in order to explain the results). Such a variable would need to have the following properties: The variable would have to be highly correlated with cold opening (more highly than the observable variables are). The variable 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 must account for fact (3), the weaker significance absence of a cold-opening effect in DVD rentals and foreign markets. It also must account for the important fact (4) that IMDB fans are relatively disappointed by movies that were cold opened (controlling for quality). The explanation must also explain fact (5), why the number of cold-opened movies has increased over the last decade.

Indeed, an ideal omitted variable would be a source of revenue potential (creating positive cold-opening OLS coefficients and PSM effects) *and* could explain why fans are disappointed in cold-opened movies. The authors of this paper find a model based on high audience expectations and strategic naivete a more plausible explanation for both effects than the existence of this variable, but we leave it to the reader to decide for themselves.

Not learning about reviews: The final explanation we will examine relaxes the assumption that moviegoers are both perfectly informed about movie quality and studios' decision to cold open. Suppose there is a proportion $(0 < a < 1)$ of consumers that are uninformed about a movies quality when it is screened for critics, and a proportion $(0 < b < 1)$ of consumers that are uninformed about a studio's decision to cold-open when a movie is cold-opened. Our analysis has focused on the case where $a = b = 0$, but there are other situations:

1. Equal numbers of moviegoers are uninformed about cold-openings and movie quality ($a = b > 0$).

This first case can be easily described in a simple example where a segment of the population does not observe movie reviews. They do not know movie quality or whether a movie is cold-opened. Studios do not optimize against this segment of the population because these moviegoers will act exactly the same, regardless of whether they release their movie to critics. Thus, studios ignore the uninformed section, and best-respond to the segment of the population that is informed ($1 - a = 1 - b$), and the unraveling result and all of our analysis applies to this segment. If the proportion of uninformed moviegoers are randomly drawn instead of being the same people, this explanation still holds. Thus this case cannot explain the cold-opening premium.

2. A greater number of moviegoers are uninformed about a movie's quality than when it is cold opened ($b > a \geq 0$).

The second case is perhaps the least plausible, but may have the most interesting results. In this case a proportion of the population may be aware a movie is released to critics (or cold-opened) but will not know its quality. This could happen if moviegoers had difficulty interpreting critic reviews or they were very costly to read (given most movie critic reviews involve simple numerical scales available for free on the internet, this assumption seems rather implausible). In such cases, Fishman and Hagerty (2003) show that if this proportion is large enough, a possible result is that no studio would reveal quality. Since 89.5 percent of movies are released to critics, this equilibrium does not characterize our environment very well. Fishman and Hagerty (2003) also note another equilibrium possibility where only high-quality firms reveal product quality, but they concede this equilibrium is equivalent to a fully revealing one because consumers can infer types. Thus, none of these equilibria would fit the data described thus far.

3. A greater number of moviegoers are uninformed about a movie being cold-opened than about its quality ($b > a \geq 0$).

Note that this explanation must involve some type of stochastic process. If one type was always uninformed about cold-openings, but always informed about movie quality, he could rationality infer a cold-opening when he did not possess information about a movie. A more reasonable model would have individuals stochastically uninformed about movies, and when they have no signal they must use Bayesian-Inference to determine if the movie were cold opened or if they have just not received a signal.

In any case, this explanation suggests uninformed consumers, who do not know whether movies were reviewed or not, believe cold-opened movies have average quality (because they don't know if they were reviewed). They then would go to cold-opened movies more often than if they made the correct strategic inference.

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 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 $c^*/\left[c^* + p(1-c^*)\right]$ 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 $(1+c^*)/2$.[24] 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 IMDB (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 reviews relative to all other variables).

Hence all three models of uninformed moviegoers cannot account for a cold-opening premium. However, we have used the assumption that if types are uninformed it is independent of their underlying preferences of movies. With the right interdependence of preferences and uninformed

[24] 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.

consumers, it may be possible to have a cold-opening premium consistent with fully rational agents. We believe there is no plausible way to model this interdependence. The explanation on consumer-critic heterogeneity and the accompanying Table 7 may provide some insight on what interdependences exist among moviegoers with relation to genre.

The explanations considered above are the most plausible and cannot adequately fit all five stylized facts we have enumerated. Nonetheless, we have certainly not shown that the relationship between cold opening and box-office revenue is causal. So readers should interpret our results and conclusion with caution.

5 Conclusion

This paper and others (c.f. Gillen, 2009; Goldfarb and Yang, 2009; Ostling et al., 2011; Goldfarb and Xiao, forthcoming) provide an important test as to 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, 2009, for many examples). We provide the first application of limited strategic thinking models to disclosure games, games where in equilibrium nothing can be gained by the strategic withholding of information. 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. Contrary to the simple Bayesian-Nash equilibrium, our movie-industry-setting features a "cold-opening premium"—movies that have been cold opened earn more than other pre-screened movies with similar characteristics.

While the cold-opening decision may feature some degree of selection and endogeneity—

meaning one should interpret our results with caution—studios cold open more frequently, most likely as response to the perceived increased profitability of cold opening (from 2000-2005 studios cold opened 6 percent of movies; from 2006-2009 they cold opened 19 percent). Those who prefer models with fully rational agents, and dismiss the cold-opening premium, still must explain studio behavior. If the cold-opening premium is not genuine, then studios appear to be making an even greater mistake than moviegoers by cold-opening movies that are above the lowest quality. This non-equilibrium strategy would be costing them millions in box-office revenue rather than small stakes moviegoers would lose by attending the wrong movie.

Assuming the cold-opening premium is real, studio behavior is consistent with the hypothesis that they are learning, because the number of cold-opening decisions increase across the years in the sample (Figure 2). Models of limited strategic thinking would suggest that studios are cold opening more movies as a best-response to limited strategic thinking by moviegoers. Our working paper (Brown, Camerer and Lovallo, 2009) and companion paper (Brown, Camerer and Lovallo, 2011) provide parameterizations of such models.

This examination of disclosure behavior over a ten year period may provide a glimpse of seller behavior in the long run, in an area where "little is known" (Dranove and Jin, 2010, p. 959). It appears when withholding disclosure looks to be profitable, sellers will slowly begin to disclose less often, moving toward a cursed equilibrium (Eyster and Rabin, 2005). Of course this movement is governed by the relative sophistication and experience of film studios (who adjust) and the relative naïveté and inexperience of their primary consumers (who don't). Also, 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 theater box-office revenues to DVD sales and rental) and information about movie quality (which leaks out in advance more recently due to internet sites and blogs).

While the industry studied here has some unique features, products with unknown quality and critical expert review are found in other industries.[25] In relation to this literature, our results suggest that some consumers do not correctly infer low quality from non-disclosure (i.e., from cold opening). Furthermore, the fact that IMDB ratings are about 10 percent lower for movies that are cold opened compared to non-cold-opened movies with similar characteristics suggests that consumers make mistakes that they regret. However, these mistakes are small (based on the rating measures) and studios do disclose information for roughly 90% of the movies *(although 80 percent in recent years)*, so this is a market which likely would not be improved greatly through regulated, mandatory disclosure.

Our results are similar to three other field studies of consumer quality disclosure (Mathios, 2000; Jin and Leslie, 2003; Jin, 2005). Mathios (2000) found that mandatory disclosure of fat content on salad dressings reduced market share of the high-fat dressings by about 20 percent. Jin and Leslie (2003) found that mandatory posting of standardized health-rating cards in Los Angeles restaurants increased hygiene scores by 5.3 percent, which is modestly higher than under voluntary disclosure.[26] Jin (2005) shows that HMOs do not voluntarily disclose quality (via National Committee for Quality Assurance (NCQA) accreditation) in markets that are the least competitive, with smaller firms and perhaps less sophisticated benefits managers.

All three studies are inconsistent with the strong hypothesis that customer strategic thinking

[25]For example, another market in which critical valuations are consumed by potential buyers is the market for expensive artwork. 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.

[26]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 therefore overstates the degree of consumer rationality.

leads to complete voluntary disclosure, and that mandatory disclosure will therefore have no effect. Note, however, that our paper was not especially 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 *were* more sharply focussed on effects of disclosure changes or choices. Nonetheless, these results may be most surprising in the film market where consumer search costs are very low.

Finally, we note again that there are many markets and political situations with asymmetric information, in which the failure to reveal information should be informative. However, if the receiver does not make the proper strategic inference, there is great scope for deliberate withholding of information (c.f. Crawford, 2003), which also complicates welfare analysis. In such interactions, self-interest seeking with guile meets strategic naïveté. Models of limited strategic thinking could be applied to settings like these to understand whether people make inferences about undisclosed information in advertising practices, labor markets (e.g., missing years on resumes), and the content of documents which people or organizations should maintain, but which go missing or are mistakenly shredded. In the same vein, to a limited strategic thinker, a phrase like "no comment" in response to a question means nothing, but to an expert strategist it speaks volumes.

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

Alexander L. Brown, Colin F. Camerer and Dan Lovallo

Web Appendix

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 as well as total box office data for international markets for movies from January 2000-June 2006 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. After June 2006 these values were obtained from the pro service of imdb.com and boxofficemojo.com. All rental numbers were obtained from these two sites.

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 1313 of the 1414 movies, including 138 or the 163 cold openings (85%).

The pro version of 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 the 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 dummy variables were calculated from the previous data. Interaction terms were calculated by multiplying one dummy variable by another.

Advertising expenditures were obtained from the ad$ spender print resources for advertising before 2007, and from the ad$ spender database for advertising after 2007.

CPI data was obtained for the US from the Bureau of Labor Statistics. Daily historical exchange rate data from finance.yahoo.com.

B List of cold-opened movies included in our dataset

Table A.1 provides a list of each of the 138 cold-opened movies in our dataset and date of release.

Movie Title	date of release (United States)	Movie Title	date of release (United States)
Armored	12/4/2009	Saw III	10/27/2006
Saw VI	10/23/2009	One Night with the King	10/13/2006
The Stepfather (2009)	10/16/2009	The Marine	10/13/2006
Pandorum	9/25/2009	The Grudge 2	10/13/2006
Surrogates	9/25/2009	The Texas Chainsaw Massacre: The Beginning	10/6/2006
Tyler Perry's I Can Do Bad All By Myself	9/11/2009	The Covenant	9/8/2006
Sorority Row	9/11/2009	Crank	9/1/2006
Halloween II (2009)	8/28/2009	The Wicker Man	9/1/2006
The Final Destination	8/28/2009	Snakes on a Plane	8/18/2006
G.I. Joe: The Rise of Cobra	8/7/2009	Pulse	8/11/2006
Aliens in the Attic	7/31/2009	Zoom	8/11/2006
Obsessed	4/24/2009	See No Evil	5/19/2006
Crank: High Voltage	4/17/2009	Silent Hill	4/21/2006
Dragonball Evolution	4/10/2009	Phat Girlz	4/7/2006
12 Rounds	3/27/2009	Benchwarmers, The	4/7/2006
Street Fighter: The Legend of Chun-Li	2/27/2009	Larry the Cable Guy: Healt..	3/24/2006
Underworld: Rise of the Lycans	1/23/2009	Stay Alive	3/24/2006
My Bloody Valentine 3-D	1/16/2009	Ultraviolet	3/3/2006
The Unborn (2009)	1/9/2009	Madea's Family Reunion	2/24/2006
The Haunting of Molly Hartley	10/31/2008	Doogal	2/24/2006
Saw V	10/24/2008	Date Movie	2/17/2006
Quarantine	10/10/2008	When a Stranger Calls	2/3/2006
An American Carol	10/3/2008	Big Momma's House 2	1/27/2006
Fireproof	9/26/2008	Underworld: Evolution	1/20/2006
My Best Friend's Girl	9/19/2008	BloodRayne	1/6/2006
Tyler Perry's The Family That Preys	9/12/2008	Hostel	1/6/2006
Bangkok Dangerous	9/5/2008	Aeon Flux	12/2/2005
College	8/29/2008	Fog, The	10/14/2005
Disaster Movie	8/29/2008	Cry Wolf	9/16/2005
Babylon A.D.	8/29/2008	King's Ransom	4/22/2005
Mirrors	8/15/2008	Man of the House	2/25/2005
Prom Night (2008)	4/11/2008	Cursed	2/25/2005
The Ruins	4/4/2008	Boogeyman	2/4/2005
Superhero Movie	3/28/2008	Darkness	12/25/2004
Tyler Perry's Meet the Browns	3/21/2008	Seed of Chucky	11/12/2004
Doomsday	3/14/2008	The Cookout	9/3/2004
Witless Protection	2/22/2008	Paparazzi	9/3/2004
Step Up 2 the Streets	2/14/2008	Exorcist: The Beginning	8/20/2004
Hannah Montana/Miley Cyrus… Concert Tour	2/1/2008	Alien vs. Predator	8/13/2004
The Eye	2/1/2008	My Baby's Daddy	1/9/2004
Meet the Spartans	1/25/2008	House of the Dead	10/10/2003
In the Name of the King: A Dungeon Siege Tale	1/11/2008	The Order	9/5/2003
One Missed Call	1/4/2008	Marci X	8/22/2003
Aliens Vs. Predator - Requiem	12/25/2007	My Boss's Daughter	8/22/2003
Awake	11/30/2007	From Justin to Kelly	6/20/2003
Saw IV	10/26/2007	Wrong Turn	5/30/2003
Tyler Perry's Why Did I Get Married?	10/12/2007	They	11/27/2002
Resident Evil: Extinction	9/21/2007	Extreme Ops	11/27/2002
Dragon Wars	9/14/2007	Trapped	9/20/2002
Halloween (2007)	8/31/2007	Adventures of Pluto Nash	8/16/2002
WAR	8/24/2007	Halloween: Resurrection	7/12/2002
The Last Legion	8/17/2007	Kung Pow: Enter the Fist	1/25/2002
Who's Your Caddy?	7/27/2007	The Wash	11/14/2001
I Know Who Killed Me	7/27/2007	Glitter	9/21/2001
Captivity	7/13/2007	Soul Survivors	9/7/2001
Hostel Part II	6/8/2007	Get Over It	3/9/2001
The Invisible	4/27/2007	Valentine	2/2/2001
Slow Burn	4/13/2007	Sugar and Spice	1/26/2001
Redline	4/13/2007	Dracula (2000)	12/22/2000
The Hills Have Eyes 2	3/23/2007	Dude, Where's My Car?	12/15/2000
Dead Silence	3/16/2007	Get Carter	10/6/2000
The Abandoned	2/23/2007	Highlander: Endgame	9/1/2000
Ghost Rider	2/16/2007	The Art of War	8/25/2000
Tyler Perry's Daddy's Little Girls	2/14/2007	Autumn in New York	8/11/2000
The Messengers	2/2/2007	The In Crowd	7/19/2000
Epic Movie	1/26/2007	Screwed	5/12/2000
Black Christmas (2006)	12/25/2006	3 Strikes	3/1/2000
National Lampoon's Van Wilder: The Rise of Taj	12/1/2006	Down to You	1/21/2000
The Return	11/10/2006	Supernova	1/14/2000

Table A.1: List of cold openings

C Additional Regressions

Table A.2 and A.3 report alternate specifications of the regressions in Table 2 where the cold dummy is replaced by cold and year interaction dummy variables and cold and genre interaction dummy variables. Both specifications are discussed in Sections 2 and 4. Table A.4 shows the results of a regression on IMDB user ratings of the standard regression variables. Cold openings are correlated with a 0.5–0.6 point drop in the ten point user rating.

dependent variable:	log total box office revenue	log opening weekend box office revenue	log total box office revenue	log opening weekend box office revenue	log total box office revenue per theater	log opening weekend box office revenue per theater
year 2000 cold opening	0.223	0.143	0.203	0.124	0.252	0.173
	0.190	0.169	0.251	0.227	0.215	0.187
year 2001 cold opening	0.293	0.195	-0.313	-0.390*	0.003	-0.074
	0.254	0.225	0.332	0.301	0.284	0.248
year 2002 cold opening	-0.442**	-0.371**	-0.679**	-0.597**	-0.599**	-0.517**
	0.252	0.224	0.332	0.300	0.284	0.247
year 2003 cold opening	-0.012	-0.079	-0.514*	-0.543**	-0.279	-0.308
	0.254	0.226	0.336	0.304	0.287	0.250
year 2004 cold opening	0.654***	0.563***	0.373	0.342	0.436**	0.405**
	0.235	0.209	0.309	0.280	0.264	0.230
year 2005 cold opening	0.119	0.039	0.066	0.040	0.020	-0.006
	0.234	0.208	0.310	0.280	0.265	0.231
year 2006 cold opening	0.472***	0.347***	0.499***	0.428***	0.416***	0.345***
	0.130	0.116	0.171	0.155	0.146	0.128
year 2007 cold opening	0.392***	0.317***	0.051	0.052	0.125	0.126
	0.142	0.126	0.187	0.169	0.160	0.139
year 2008 cold opening	0.410***	0.298***	0.413**	0.343**	0.378***	0.308**
	0.139	0.123	0.183	0.165	0.156	0.136
year 2009 cold opening	0.201*	0.160	0.083	0.099	0.034	0.050
	0.153	0.136	0.202	0.182	0.173	0.150
metacritic rating	0.011***	0.011***	0.013***	0.011***	0.014***	0.013***
	0.002	0.001	0.002	0.002	0.002	0.002
imdb rating	0.086***	-0.005	0.144***	0.041	0.131***	0.029
	0.023	0.020	0.030	0.027	0.025	0.022
log theaters opened	0.990***	1.168***	-	-	-	-
	0.075	0.067				
log production budget	0.008	0.010	0.493***	0.440***	0.298***	0.244***
	0.029	0.026	0.031	0.028	0.027	0.023
log advertising expenditures	0.740***	0.506***	-	-	-	-
	0.049	0.044				
average log competitor budget	-0.017	-0.050**	-	-	-	-
	0.026	0.023				
average log competitor advertising expenditures	-0.039	-0.036	-	-	-	-
	0.034	0.030				
average log star ranking of lead roles	-0.013*	-0.011*	-0.056***	-0.053***	-0.033***	-0.030***
	0.007	0.006	0.009	0.008	0.008	0.007
summer release	0.082**	0.030	0.073	0.019	0.057	0.003
	0.039	0.035	0.051	0.046	0.044	0.038
adaptation or sequel	0.104**	0.063*	0.183***	0.138***	0.146***	0.101**
	0.042	0.037	0.055	0.049	0.047	0.041
days released before Friday	0.043*	0.019	-	-	-	-
	0.025	0.023				
opening weekend continues after Sunday	0.134***	0.117***	-	-	-	-
	0.049	0.043				
days released earlier in foreign country	0.000*	0.000*	-	-	-	-
	0.000	0.000				
genre dummy variables included	yes	yes	yes	yes	yes	yes
year dummy variables included	yes	yes	yes	yes	yes	yes
MPAA rating dummy variables included	yes	yes	yes	yes	yes	yes
constant	-6.647***	-8.168***	1.071***	0.446*	-6.049***	-6.674***
	0.553	0.491	0.265	0.240	0.227	0.198
observations	1303	1303	1303	1303	1303	1303
R^2	0.7113	0.6949	0.4921	0.4436	0.4219	0.3385

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Table A.2: Regressions on logged box office revenues (in millions) with cold and year interaction variables.

dependent variable:	log total box office revenue	log opening weekend box office revenue	log total box office revenue	log opening weekend box office revenue	log total box office revenue per theater	log opening weekend box office revenue per theater
action or adventure genre cold opening	0.046 0.158	-0.077 0.140	-0.479*** 0.206	-0.477*** 0.186	-0.354** 0.175	-0.352** 0.152
animated genre cold opening	-0.428 0.607	-0.449 0.537	-0.479 0.802	-0.429 0.725	-0.486 0.684	-0.436 0.594
comedy genre cold opening	0.379*** 0.110	0.313*** 0.098	0.344*** 0.146	0.297** 0.132	0.338*** 0.124	0.292*** 0.108
documentary genre cold opening	1.742*** 0.681	2.202*** 0.602	1.036 0.893	1.326* 0.807	1.921*** 0.762	2.212*** 0.662
drama genre cold opening	0.842*** 0.250	0.677*** 0.221	0.477* 0.329	0.366 0.297	0.617** 0.281	0.506** 0.244
fantasy or science fiction genre cold opening	-0.021 0.190	-0.157 0.168	-0.404* 0.248	-0.414** 0.224	-0.331* 0.211	-0.341** 0.183
suspense or horror genre cold opening	0.305*** 0.091	0.238*** 0.080	0.289*** 0.120	0.251*** 0.108	0.253*** 0.102	0.214*** 0.089
metacritic rating	0.011*** 0.002	0.010*** 0.001	0.013*** 0.002	0.011*** 0.002	0.014*** 0.002	0.012*** 0.002
imdb rating	0.087*** 0.023	0.000 0.020	0.146*** 0.030	0.046* 0.027	0.136*** 0.025	0.035 0.022
log theaters opened	1.026*** 0.075	1.209*** 0.067	-	-	-	-
log production budget	0.010 0.029	0.015 0.025	0.494*** 0.031	0.441*** 0.028	0.299*** 0.027	0.245*** 0.023
log advertising expenditures	0.716*** 0.049	0.476*** 0.044	-	-	-	-
average log competitor budget	-0.024 0.026	-0.055** 0.023	-	-	-	-
average log competitor advertising expenditures	-0.033 0.034	-0.031 0.030	-	-	-	-
average log star ranking of lead roles	-0.011 0.007	-0.009 0.006	-0.055*** 0.009	-0.051*** 0.008	-0.031*** 0.008	-0.028*** 0.007
summer release	0.080** 0.039	0.030 0.035	0.065 0.051	0.013 0.046	0.053 0.043	0.001 0.038
adaptation or sequel	0.108*** 0.041	0.068* 0.037	0.189*** 0.054	0.145*** 0.049	0.151*** 0.046	0.107*** 0.040
days released before Friday	0.036 0.025	0.013 0.022	-	-	-	-
opening weekend continues after Sunday	0.147*** 0.048	0.130*** 0.043	-	-	-	-
days released earlier in foreign country	0.000* 0.000	0.000 0.000	-	-	-	-
genre dummy variables included	yes	yes	yes	yes	yes	yes
year dummy variables included	yes	yes	yes	yes	yes	yes
MPAA rating dummy variables included	yes	yes	yes	yes	yes	yes
constant	-6.647*** 0.553	-8.168*** 0.491	1.071*** 0.265	0.446* 0.240	-6.049*** 0.227	-6.674*** 0.198
observations	1303	1303	1303	1303	1303	1303
R^2	0.7113	0.6949	0.4921	0.4436	0.4219	0.3385

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Table A.3: Regressions on logged box office revenues (in millions) with cold and genre interaction variables

dependent variable:	imdb rating	imdb rating
cold opening	-0.515*** (0.078)	-0.595*** (0.078)
metacritic rating	0.047*** (0.001)	0.050*** (0.001)
log theaters opened	-0.124 (0.092)	-
log production budget	-0.028 (0.035)	0.048 (0.030)
log advertising expenditures	0.302*** (0.060)	-
average log competitor budget	-0.046 (0.032)	-
average log competitor advertising expenditures	0.032 (0.042)	-
average log star ranking of lead roles	-0.051*** (0.008)	-0.055*** (0.008)
summer release	-0.154*** (0.048)	-0.155*** (0.048)
adaptation or sequel	-0.156*** (0.051)	-0.158*** (0.051)
days released before Friday	-0.025 (0.031)	-
opening weekend continues after Sunday	-0.126** (0.060)	-
days released earlier in foreign country	0.001*** (0.000)	-
genre dummy variables included	yes	yes
year dummy variables included	yes	yes
MPAA rating dummy variables included	yes	yes
constant	4.106*** (0.666)	3.599*** (0.228)
observations	1303	1303
R^2	0.6722	0.6599

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Table A.4: Regression on IMDB user ratings