The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics

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Abstract: There is a substantial theoretical literature on consumer behavior in the presence of experience goods with uncertain quality. In this paper, we study empirically how consumer behavior is influenced by published product reviews. The problem inherent in such studies is that a correlation between good reviews and high demand may be spurious, induced by an underlying correlation with unobserved quality measures. With information on the timing of the reviews by two popular movie critics, Siskel and Ebert, relative to the weekend in which box office revenue is measured, we apply a "differences in differences" approach to circumvent the problem of spurious correlation. We find that positive reviews have a surprisingly large, positive effect on box office revenue.

JEL codes: L82, D83

I Introduction

There is an extensive literature on consumer behavior in the presence of experience goods, the quality of which is uncertain prior to consumption.[1] Economists have considered a variety of mechanisms that transmit information about product quality to consumers.[2] One pervasive mechanism is the publication of experts' product reviews. It is familiar to see books, concerts, movies, plays, restaurants, television shows, and other goods and services in the entertainment industry reviewed by professional critics. Most other experience goods are also critically reviewed, whether in publications devoted to the whole range of consumer products (such as *Consumer Reports*) or to more narrow product classes (such as *PC Magazine* or *Stereo Review*).

Despite the pervasiveness of critical reviews, there is scant empirical evidence concerning their influence on consumer demand. The lack of empirical evidence may be due to an inherent measurement problem: products that receive positive reviews of course tend to be of high quality, and it is difficult to determine whether the review or the quality is responsible for high demand. In formal econometric terms, the coefficient from the regression of demand on reviews will be biased upward due to the omission of quality variables. In principle the bias could be removed by accounting for quality; but quality is hard to measure for any product, especially for products whose quality is uncertain enough to merit critical appraisals. In Eliashberg and Shugan's [1997]

[1] For general discussions, see, for example, Akerlof [1970], Nelson [1970], Smallwood and Conlisk [1979], Hey and McKenna [1981], Wiggins and Lane [1983], Cooper and Ross [1984], Tirole [1988], Laband [1991], and Wolinsky [1995].

[2] Klein and Leffler [1981], Shapiro [1982], Allen [1984], Bowbrick [1992], Png and Reitman [1995], Choi [1998], and Tirole [1998] consider reputation and branding. Cooper and Ross [1985] and Crampes [1991] consider warranties. Vettas [1997] and Vives [1997] consider word of mouth among consumers. Teisl and Roe [1998] and Foreman and Shea [1999] consider audited and unaudited self reports. Sheshinski [1976], Spence [1977], Shavell [1984], Leland [1979] and Shaked and Sutton [1981] consider government policies such as product liability laws and regulation. There is a large literature on strategic signalling through advertising expenditures and price, including Nelson [1974], Schmalensee [1978], Wolinsky [1983], Crèmer [1984], Kihlstrom and Riordan [1984], Farrell [1986], Milgrom and Roberts [1986], Riordan [1986], Bagwell and Riordan [1991], Bagwell and Ramey [1993], Caves and Greene [1996], de Bijl [1997].

terms, the causal effect of reviews on demand holding quality constant is the *influence effect*; the spurious correlation between reviews and demand induced by their mutual correlation with quality is the *prediction effect*.

We propose a novel approach for distinguishing the influence and prediction effects of reviews on demand. The particular case we study is movies, an industry in which demand is readily measured by box office revenue. We consider the reviews of Siskel and Ebert, two movie critics who arguably had the greatest potential for influence through their nationally-syndicated television show. Our approach hinges on the timing of their reviews relative to a movie's release. Reviews that come during a movie's opening weekend can influence box office revenue for the remainder of the opening weekend; such reviews have both an influence and a prediction effect. Reviews that come after a movie's opening weekend cannot influence opening weekend revenue; such reviews have only a prediction effect. By taking a "difference in differences"—the difference between a positive and negative review for movies reviewed during their opening weekends and movies reviewed after—the prediction effect can be purged and the influence effect isolated.

We find that a positive review has surprisingly large and significant influence on opening weekend box office revenue even after purging the prediction effect. This is in contrast with Eliashberg and Shugan [1997], the one previous study of box office revenue that attempts to separate influence from prediction effects. Using a sample of 56 long-running movies released in the early 1990s, the authors regress weekly box office revenue on the movie's percentage of positive reviews for each of the first eight weeks of a movie's run. They find that the percentage of positive reviews is only marginally significant during the first four weeks of the movie's run; the effect becomes larger and more significant during the next four weeks. Based on their maintained assumption that the influence effect declines during a movie's run, the authors conclude that the influence effect cannot be important and must be dominated by the prediction effect. In fact, we also find a similar pattern of increasing correlation between reviews and box office revenue over the course of a movie's run in our data, so cannot dispute their conclusion about the relative importance of the prediction and influence effects. That we still find a positive influence effect on opening weekend revenue may be due to our use of more powerful statistical tests—including over ten times the number of observations and a different measure of reviews (reviews of two influential critics rather than an average of hundreds of critics' reviews)—than Eliashberg and Shugan [1997].

The rest of the literature on the relationship between reviews and box office revenue does not attempt to purge the prediction effect.[3] The studies tend to find a positive effect (Litman [1983]; Wallace, Seigerman, and Holbrook [1993]).

II Model

Let R_i be the box office revenue for movie $i = 1, \ldots, n$ measured over the time period $[t_i^0, t_i^1]$, for example the opening weekend or the entire run of the movie. Let X_i be a vector of the movie's characteristics that are observable to the econometrician (genre, producer identity, season of release, etc.). The movie may have attributes that raise consumers' expected utility from viewing it which are not included in X_i because they are unobservable to the econometrician, attributes including the quality of the acting, direction, special effects, plot, and marketing efforts.

[3]There are several studies in communications literature (Faber and O'Guinn [1984], Wyatt and Badger [1984, 1987]) that ask questions of focus groups regarding the importance of reviews relative to other ways of generating interest in a movie (advertising, word of mouth, etc.). There is much larger literature that forecasts box office revenue leaving aside critics' reviews, including Anast [1967], Austin [1984], Smith and Smith [1986], Austin and Gordon [1987], Dodds and Holbrook [1988], Prag and Casavant [1994], Sawhney and Eliashberg [1996], De Vany and Walls [1996, 1997], Albert [1998], Neelamegham and Chintagunta [1999].

We will summarize this set of attributes with the single quality variable Q_i^*.

Suppose for simplicity there is a single critic, whose influence we are interested in measuring. The set of movies can be partitioned into three subsets based on the timing of the date the review is published, t_i^c, relative to the period over which revenue is calculated, $[t_i^0, t_i^1]$:

$$\begin{aligned} B &\equiv \{i = 1, \ldots, n \,|\, t_i^c \leq t_i^0\}, \\ D &\equiv \{i = 1, \ldots, n \,|\, t_i^0 < t_i^c < t_i^1\}, \\ A &\equiv \{i = 1, \ldots, n \,|\, t_i^1 \leq t_i^c\}; \end{aligned}$$

in short, B is the set of movies reviewed before, D during, and A after $[t_i^0, t_i^1]$. We will see in Section III that B is too small to be relevant empirically, so we will focus on D and A here. Define the indicator function associated with set $J = D, A$ as follows: $\mathbf{1}_{Ji} \equiv 1$ if $i \in J$ and $\mathbf{1}_{Ji} \equiv 0$ otherwise.

Let C_i be an index of the positiveness of the critic's review. Since movies are an experience good, consumers do not know the quality of a movie before viewing it. Thus, there is a role for C_i to influence consumer demand. A positive review provides an informative signal that the movie is of good quality. For $i \in D$, this information may increase the movie's attendance in the period $[t_i^0, t_i^1]$. Assuming a linear form, the box office revenue equation can be written $R_i = \alpha_D + \beta_D C_i + \delta_D Q_i^* + \epsilon_{Di}$, where α_D, β_D, and δ_D are parameters and ϵ_{Di} is an error term. The influence effect is captured by $\beta_D > 0$. Box office revenue will increase with quality even if consumers are only partially informed about it, implying $\delta_D > 0$. Of course R_i will also depend on X_i, but we have omitted this term from the preceding and subsequent equations for simplicity. There is no loss of generality in omitting X_i from the notation if one thinks of the included variables as representing the residuals that remain after partialling X_i out (see Greene [1990], pp. 181–182). Consumers are assumed to pay attention to reviews because the reviews reflect underlying quality, so a relationship such as $C_i = \gamma_D + \mu_D Q_i^* + \nu_{Di}$ must hold, where γ_D and μ_D are parameters, $\mu_D > 0$, and ν_{Di} is an error term.

Next, consider movies reviewed after the period used to compute box office revenue, so that $i \in A$. This case is similar to the $i \in D$ case discussed in the previous paragraph except that the critic's review cannot have an influence effect. Formally, $R_i = \alpha_A + \delta_A Q_i^* + \epsilon_{Ai}$ and $C_i = \gamma_A + \mu_A Q_i^* + \nu_{Ai}$, where α_A, δ_A, γ_A, and μ_A are parameters; $\delta_A > 0$; $\mu_A > 0$; and ϵ_{Ai} and ν_{Ai} are error terms.

We adopt three assumptions, in which $|J|$ denotes the number of elements in set J and $E[\cdot]$ is the expectations operator.

Assumption 1 *For* $J = D, A$, $E[\epsilon_{Ji}] = E[\nu_{Ji}] = E[\epsilon_{Ji}\nu_{Ji} = E[\epsilon_{Ji}C_i] = E[\epsilon_{Ji}Q_i^*] = E[\nu_{Ji}Q_i^*] = 0$.

Assumption 2 ν_{Di} *and* ν_{Ai} *are identically distributed with variance* σ_ν^2. *For* $J = D, A$, $\alpha_J = \alpha$, $\delta_J \equiv \delta$, $\gamma_J \equiv \gamma$, *and* $\mu_J \equiv \mu$.

Assumption 3 *For* $J = D, A$, $\text{plim}\left[|J|^{-1} \sum_{i \in J} (Q_i^* - \sum_{i \in J} Q_i^*)^2\right] \equiv \Theta_{Q^*}$.

Assumption 1 is the usual assumption about the errors, guaranteeing the model is well specified. Assumptions 2 and 3 rule out selection effects: i.e., the timing of the review is assumed to have no bearing on the quality of the movie nor on the way consumers and critics evaluate quality. The assumptions follow if the process of selecting movies to review is random. We will discuss the effect of relaxing Assumptions 2 and 3 below.

Under these assumptions, our model can be collapsed into two equations:

$$R_i = \alpha + \beta_D C_i \mathbf{1}_{Di} + \delta Q_i^* + \epsilon_i \tag{1}$$

$$C_i = \gamma + \mu Q_i^* + \nu_i, \tag{2}$$

where $\beta_D > 0$, $\delta > 0$, $\mu > 0$, $\epsilon_i \equiv \epsilon_{Di}\mathbf{1}_{Di} + \epsilon_{Ai}\mathbf{1}_{Ai}$ and $\nu_i \equiv \nu_{Di}\mathbf{1}_{Di} + \nu_{Ai}\mathbf{1}_{Ai}$. The traditional methodology (Eliashberg and Shugan [1997]; Litman [1983]; Wallace, Seigerman, and Holbrook [1993]) can be roughly characterized as regressing R_i on C_i.[4] Letting $\hat{\beta}^1$ be the resulting ordinary least squares (OLS) coefficient on C_i, it can be shown that $\operatorname{plim} \hat{\beta}^1 = K\beta_D + P$, where

$$K \equiv \frac{|D|}{|D| + |A|} \quad \text{and} \quad P \equiv \frac{\delta\mu\Theta_{Q^*}}{\mu^2\Theta_{Q^*} + \sigma_\nu^2}. \tag{3}$$

The traditional methodology provides an inconsistent estimate of the influence effect β_D. There are two sources of bias. The term $P > 0$ captures the upward bias from omitting a variable Q_i^*, which is correlated with C_i by equation (2), from the regression. This is formally what we meant by the prediction effect in the introduction. The second source of bias stems from averaging the influence effect for movies in D, which is positive, with the influence effect for movies in A, which is zero. This will result in a downward bias (note $K < 1$), a bias which increases the greater the proportion of movies in A. It is impossible to tell ex ante if the net effect of the two biases is positive or negative.

A second estimator of the influence effect which one might naively consider would be to take

[4] Other controls X_i are included in the traditional methodology as well, but we can think of equations (1) and (2) as having partialled out X_i as discussed above.

the coefficient from the OLS regression of R_i on C_i for only those observations that have the possibility of an influence effect; i.e., only for $i \in D$. Label this coefficient $\hat{\beta}^2$. It can be shown that plim $\hat{\beta}^2 = \beta_D + P$; so this estimator removes the source of downward bias, K, but retains the positive bias due to the prediction effect, P.

One strategy to reduce the bias due to the prediction effect would be to include observable proxies, Q_i, of true but unobservable quality, Q_i^*. Indeed, proxies such as the number of Academy Award nominations have been included in previous studies (Litman [1983]). As discussed in Judge *et al.* [1985], section 17.3, including proxies will tend to reduce omitted variable bias, though there are exceptions to the rule.

The estimator we will employ in Section V involves the regression of R_i on $\mathbf{1}_{Di}$, $\mathbf{1}_{Ai}$, $C_i\mathbf{1}_{Di}$, and $C_i\mathbf{1}_{Ai}$. For $J = D, A$, let $\hat{\beta}_J$ be the estimated coefficient on $C_i\mathbf{1}_{Ji}$. Since $(\mathbf{1}_{Di}, C_i\mathbf{1}_{Di})$ is orthogonal to $(\mathbf{1}_{Ai}, C_i\mathbf{1}_{Ai})$, $\hat{\beta}_J$ can be equivalently obtained by running a separate regression of R_i on a constant and C_i only for observations $i \in J$, $J = D, A$. This simplifies the calculations of the probablility limits: plim $\hat{\beta}_D = \beta_D + P$ and plim $\hat{\beta}_A = P$. Taken individually, $\hat{\beta}_D$ and $\hat{\beta}_A$ are inconsistent estimates of the influence effect. A consistent estimate of the influence effect can be derived by taking the difference between the coefficients: plim $(\hat{\beta}_D - \hat{\beta}_A) = \beta_D$. We call $\hat{\beta}_D - \hat{\beta}_A$ a "difference in differences" estimator since each of the coefficients $\hat{\beta}_J$, $J = D, A$, is itself the differential effect of a positive (versus a negative) review.

The consistency of our "difference in differences" estimator relies on the same P term appearing in both plim $\hat{\beta}_D$ and plim $\hat{\beta}_A$, which in turn relies on Assumptions 2 and 3. If there are selection effects in violation of the assumptions, our estimator may be inconsistent. For example, suppose that in the absence of an available review, consumers put more weight on other signals of underlying quality; formally, $\delta_D < \delta_A$. Then, using the formula for P in (3), it can be shown that our estimator will understate the influence effect. On the other hand, there are plausible circumstances in which our estimator would be an overestimate. Some anecdotes suggest that movie distributors prevent critics from previewing low quality movies before their release, avoiding negative reviews early in the movie's run, relying on a core of undiscriminating viewers to make up the movie's audience.[5] These undiscriminating viewers may be less sensitive to quality than others, so that $\delta_D > \delta_A$.

Our estimator will be consistent in the presence of other selection effects. It might be thought that a correlation between Q_i^* and the timing of the review biases our results. Such a correlation might arise if the average quality of movies reviewed later in their runs is lower than of movies reviewed earlier. In fact, such a correlation does not violate Assumption 3 since the mean is subtracted from each term in the sum Θ_{Q^*}. Hence our estimator would still be consistent. Our results are also consistent in the presence of another selection effect: the mean of box office revenue depending on whether films are reviewed before or after the opening weekend. By including the indicators $\mathbf{1}_{Di}$ and $\mathbf{1}_{Ai}$ in the regression, our method will be consistent even if, in violation of Assumption 2, $\alpha_D \neq \alpha_A$.

A summary of the results of the present section will prove a useful reference in the later empirical work. (1) The traditional methodology produces biased estimates of the influence effect. (2) Under certain maintained assumptions, our "differences in differences" estimator $\hat{\beta}_D - \hat{\beta}_A$ provides a consistent estimate. (3) Adding proxies for unobservable quality will likely have the desirable effect of reducing the upward bias in each individual coefficient $\hat{\beta}_J$, $J = D, A$, and reducing the standard errors of the estimates. (4) Our "difference in differences" estimator

[5] Smith [1998] writes, "Many studios lock [Siskel and Ebert] out of advance screenings and refuse to provide the show's producers with movie clips or trailers, giving up national exposure to avoid receiving [thumbs down]."

does not require such proxies for consistency, however.

III Data

Our study focuses on the influence of two critics, Gene Siskel and Roger Ebert, on opening weekend box office revenue. Siskel and Ebert are ideal candidates for study because they were regarded as the most influential movie critics.[6] Their influence was due in large part to their nationally-syndicated television show (first titled *At the Movies*, later titled *Siskel & Ebert*) in which they each rendered their opinion on about four movies each week, a "thumbs up" for a positive and a "thumbs down" for a negative opinion.

Records were kept on the day movies were reviewed on their television show, allowing us to apply the estimation methodology from the previous section, which relies heavily on the timing of the review relative to the movie's opening weekend. Consider Figure 1. The Friday, Saturday, and Sunday during the first week of a movie's run constitute its opening weekend.[7] For many observations in our data set, the movie was reviewed on Saturday morning during the opening weekend, in which case we set the variable $DURING = 1$.[8] For these observations (identified as belonging to set D in Section II), there is some potential for the review to influence box office for the remainder of the weekend. Even if consumers did not see Siskel and Ebert's television show itself before making their decision, positive reviews were often quoted in the movie's advertisements.

[6]They were ranked among Smith's [1998] list of the 100 most influential people in the history of the movies, the only critics to make the list. Smith writes: "…[their] five-time Emmy Award winning program is aired on 180 of the country's broadcasting stations …reachable through a staggering 95% of all television sets."

[7]In the case of a Monday holiday, the data typically fold the Monday figures into opening weekend.

[8]Siskel and Ebert's television show aired on Sundays in a few markets but aired on Saturdays in most markets including the largest ones (New York, Chicago, Los Angeles, etc.).

Most other movies were not reviewed until the week (or several weeks) after. For these (identified as belonging to set A in Section II) we set *DURING* $= 0$ and set the new variable, *AFTER* $= 1 -$ *DURING*, equal to 1. There is no potential for these reviews to influence opening weekend box office revenue, though there will likely still be a positive correlation between them due to the prediction effect.

A small number of movies were reviewed before the opening weekend (identified as belonging to set B in Section II). We omitted from them from the final data set; pooling them with the *DURING* $= 1$ movies, or indeed treating them as a separate category, did not materially affect the results.

Table 1 lists the main variables we will employ, together with descriptive statistics, and sources.[9] Our box office revenue variables (corresponding to R_i from Section II) are *TOTREV* and *OPENREV*. Our review variables (corresponding to C_i from Section II) are *SISKEL* and *EBERT*. Formal tests in our preliminary work indicated that there was no significant difference between the effects of Siskel's and Ebert's reviews, so we will treat them effectively as a single reviewer who can assign one of three ratings to a movie, ranked in terms of increasing quality: no thumbs up (implying *ONE UP* $= 0$ and *TWO UP* $= 0$), exactly one thumb up (implying *ONE UP* $= 1$ and *TWO UP* $= 0$), or two thumbs up (implying *ONE UP* $= 0$ and *TWO UP* $= 1$). Our dummies for the timing of the review relative to the opening weekend (corresponding to $\mathbf{1}_{Di}$ and $\mathbf{1}_{Ai}$ in Section II) are *DURING* and *AFTER*. Our quality proxies (corresponding to Q_i in Section II) include *MALTIN*, *WEBCOUNT*, and *WEBRATE*.[10] Our other controls (corresponding

[9] The final data set has 609 movie/observations. Merging data from the four sources—the Box Office Guru web site, the Siskel and Ebert web site, the Internet Movie Database web site, and Leonard Maltin's book of reviews (Maltin [1999])—resulted in 806 observations. We dropped 13 that were reviewed on a day other than Saturday, 137 that opened on fewer than 50 screens (indicating a "narrow release strategy" which might confound our results), eight that were reviewed more than 40 days after opening, and 39 which were reviewed before the opening weekend.

[10] Based on the work of Litman [1983] and Prag and Casavant [1994], who included Academy Awards as regressors

to X_i in Section II) include *SCREENS* and *FOURDAY* reported in Table 1, as well as dummies for year of release, month of release, genre,[11] and production company.[12]

Table 2 presents correlations among revenue measures, Siskel and Ebert reviews, and other quality proxies. It is tempting to conclude that there is an influence effect from the positive correlation between the reviews. Since both influence and prediction effects are combined in the correlation, such a conclusion would be unwarranted. Indeed, the raw correlation between $\ln($*OPENREV*$)$ and *SISKEL* is higher for movies reviewed after than during the opening weekend (and similarly for the correlation between $\ln($*OPENREV*$)$ and *EBERT*), impossible if the influence effect were the only effect present.

From Table 2 it appears that *WEBCOUNT* and *MALTIN* should serve as good proxies for unobserved quality, *WEBRATE* less so especially if one is concerned with opening weekend box office revenue. The pattern of correlations—higher with $\ln($*TOTREV*$)$ than with $\ln($*OPENREV*$)$—indicates that the critics' reviews are more correlated with revenue later in a movie's run than earlier, consistent with the findings of Eliashberg and Shugan [1997]. *MALTIN* is even more highly correlated with box office revenue than *SISKEL* and *EBERT*, but this is due in part to Maltin's rating scale being more refined than Siskel and Ebert's.

The correlations in the *DURING* row provide ambiguous evidence on the existence of selection

in their revenue equations, we added information on Academy Awards—major awards such as best film, director, actor, and actress, and the other minor awards—to our data set. The data was taken from Maltin [1999]. For brevity, we do not report the regressions we ran including Academy Award variables because all alternative forms of the Academy Award variables we tried were insignificant, and their inclusion/exclusion had no effect on the other coefficients.

[11] Movies are allowed to fall into more than one of our genres, which include adventure, animated, children's, comedy, crime, documentary, drama, fantasy, film noir, horror, musical, mystery, romance, science fiction, thriller, war, and western.

[12] We grouped production companies together with subsidiaries to form nine dummies: Disney (including Buena Vista and Miramax), Sony (including Sony, Columbia, Sony Classics, and TriStar), Fox (including Fox and Fox Searchlight), MGM/UA (including MGM/UA, MGM, Goldwyn, and United Artists), Gramercy, Orion, Universal, Warner Bros. (including Warner Bros., New Line, and Fine Line), and Paramount. The remaining movies were mostly produced by small companies (independents).

effects which might cause our "difference in differences" estimator to be inconsistent. There is essentially no correlation between the revenue measures and *DURING*. On the other hand, certain of the review variables are positively correlated with *DURING*, raising the possibility of selection effects. Because of the importance of the selection issue for the consistency of our estimator, we explore it in more detail in the next section.

IV Evidence on Selection Effects

As noted in Section II, the process by which Siskel and Ebert selected movies to review during their opening weekend rather than after need not have been random for our "difference in differences" estimator to be consistent. It would still be consistent even if quality Q_i^* were on average higher for movies reviewed during opening weekend than those reviewed after, which, by equations (1) and (2), would induce movies reviewed during opening weekend to have higher revenues (R_i) and better critical reviews (C_i) than those reviewed after. Yet evidence of non-random selection cannot be ignored because it casts doubt on Assumption 2, which says that the underlying parameters in the model in (1) and (2) are independent of the timing of the review.

Our personal correspondence with Roger Ebert[13] suggested that the decision to a review a movie during its opening weekend, rather than after, was random in most cases. Siskel and Ebert's general policy was to review a movie during its opening weekend.[14] The most common reason for reviewing a movie after its opening weekend was that it simply did not fit in the

[13]Email correspondence on September 14 and September 17, 2000.

[14]The few cases in which they reviewed a movie before its opening weekend may have involved non-random selection. They sometimes issued early reviews for films which they wanted to boost or for films that were particulary newsworthy. In other cases, the selection process was more random, for example when they issued early reviews to avoid a backlog when a large number of movies were set to be released. In any event, the possible non-random selection of movies to be reviewed prior to opening supports our decision to drop those 39 observations.

previous show. In other cases, they needed to review a backlog of movies accumulated during a hiatus for attending film festivals. It was only rare for a studio not to screen a movie for critics prior to opening, contradicting Smith's [1998] claim referenced in footnote 5 that studios often did this to do this to prevent "two thumbs down" from ruining the movie's opening.

To provide more formal evidence on the randomness of the selection process, we ran a probit of *DURING* on several specifications of revenue and the nature of Siskel and Ebert's reviews, also including the other controls used below in the regressions in Section V. The results are reported in Table 3. Whether the review variables used are *SISKEL* and *EBERT* as in column (1) or *ONE UP* and *TWO UP* as in column (2), there is little explanatory power in the probit. The pseudo R^2, which Judge *et al.* (1985, pp. 777) note can be interpreted as the percentage of the uncertainty in the dependent variable explained by the regressors, is at most 22 percent. The explanatory power does not come from the revenue or Siskel and Ebert review variables: as shown in column (3), the log likelihood and pseudo R^2 remain essentially unchanged if the revenue and review variables are omitted from the regression entirely. Rather, most of the explanatory power comes from variables relating to the release date: *FOURDAY*, year dummies, and month dummies. The coefficients on these variables show that movies were more likely to be reviewed late when there were a large number of releases: during four day holiday weekends, during more recent years, and during the months of January, May, June, August, and December. This is consistent with the claim above that Siskel and Ebert mainly reviewed movies after opening when they had too many movies to review in a given week on their show.

The one piece of evidence suggesting that observable non-random factors may have had some effect on the timing of Siskel and Ebert's reviews is the significance of *MALTIN*. High-quality movies—as gauged by Maltin's review—tended to be reviewed earlier by Siskel and Ebert. This is an odd result given that quality—gauged by the reviews of Siskel and Ebert themselves—had little effect on the timing of their reviews. In any event, the effect of all observable non-random factors, including *MALTIN*, on *DURING* was not very large: omitting the release-date variables causes the probit's pseudo R^2 to fall to less than eight percent. In sum, there is little evidence of significant selection biases in Siskel and Ebert's decision to review a movie after its opening, much less evidence which would cast doubt on the consistency of our "differences in differences" estimator, which relies on a weaker assumption than random selection.

V Results

The "differences in differences" methodology from Section II called for regressing R_i on $\mathbf{1}_{Di}$, $\mathbf{1}_{Ai}$, $C_i\mathbf{1}_{Di}$, $C_i\mathbf{1}_{Ai}$, and possibly other controls (X_i). Translating these variables into their empirical counterparts, we will regress $\ln(\mathit{OPENREV})$ on *DURING* and *AFTER* dummies, the interaction between these dummies and our review variables *ONE UP* and *TWO UP*, and other controls including *SCREENS*, *FOURDAY*, and dummies for year, month, genre, and production company.

The basic regression is given in the first column of Table 4. The review variables are all positive, with two thumbs up having a larger coefficient than one thumb up, whether interacted with *DURING* or *AFTER*. The coefficient on *DURING* $\times$ *ONE UP* is larger than *AFTER* $\times$ *ONE UP*, and the coefficient on *DURING* $\times$ *TWO UP* is larger than *AFTER* $\times$ *TWO UP*, both results consistent with the existence of a positive influence effect. To gain some understanding of the size of the influence effect and to test its existence formally, some notation is required. Let Δ_k be the difference between the coefficient on *DURING* $\times$ *ONE UP* and *AFTER* $\times$ *ONE UP* for $k = 1$ and *DURING* $\times$ *TWO UP* and *AFTER* $\times$ *TWO UP* for $k = 2$. Then the influence effect, measured as the percentage difference in box office revenue for k thumbs up relative to two thumbs down, can be shown to equal

$$\frac{\exp(\Delta_k) - 1}{\exp(\Delta_k)}. \tag{4}$$

This measure of the influence effect is reported in Table 5. The influence of one thumb up is 14 percent of opening weekend box office revenue, though significant only at the ten-percent level in a one-tailed test.[15] The influence of two thumbs is 18 percent, statistically significant at the five percent level.

The results for the ancillary variables are all in line with the conventional wisdom in the movie industry. The coefficient on *SCREENS* is large and highly significant. The coefficient on *FOURDAY* is positive but not signficant. The seasonal pattern of box office revenue emerges as expected: movies in the spring and fall tend to earn less than summer and winter, with revenues in June and July significantly higher than the rest of the months. Other work, including Radas and Shugan [1998] and Krider and Weinberg [1998] also finds similar strong seasonal patterns.[16] Among genres, animated, children's, documentaries, and film noir earned less than average, while crime, fantasy, romance, and thrillers earned more. Movies from the large studios tended to earn significantly more than from independent studios.

In principle, our "differences in differences" estimator does not require quality proxies for consistency under the maintained assumptions, though adding them should improve the estimator's precision and should reduce any bias in our estimator resulting from violations of our maintained

[15] The standard error of the measure in (4) equals the standard error of Δ_k divided by $\exp(2\Delta_k)$, the adjustment necessary because the influence effect is a nonlinear function of Δ_k (see Section 6.6.2 of Judge *et al.* [1988]).

[16] We abstract from the competitive/strategic aspects of the timing of a movie's release. See de Vany and Walls [1997] and Chisholm [1999] for work along these lines.

assumptions. The regression in column 2 of Table 4 adds the quality proxies *MALTIN* and *WEBCOUNT* to the basic regression in column 1. Both variables have positive and highly significant coefficients.[17] As anticipated in Section II, inclusion of the quality proxies causes the coefficients on the review variables to fall fairly uniformly. Indeed, the coefficients on the review variables interacted with *AFTER* have essentially become zero (or even negative) with the inclusion of the quality proxies, suggesting that the prediction effect has been fully absorbed by the quality proxies. Thus purged of the prediction effect, the coefficients on the review variables interacted with *DURING* essentially reflects only the influence effect. The coefficient on $DURING \times ONE\ UP$ is surprisingly large and significant at better than the one percent level. The coefficient on $DURING \times TWO\ UP$ is larger still. Substituting these results into the formula (4), the influence effect of one thumb up is reported in Table 5 to be 11 percent, although the standard errors on the review variables interacted with *AFTER* are so large that this estimate is only of marginal statistical significance. The influence effect of two thumbs up is 28 percent, significant at better than the one percent level.

To check whether our results were being driven by the presence of outliers, we re-ran the regression in column 2 using Li's [1985] iteratively reweighted least squares procedure, which weights an observation by an inverse function of its residual from the previous iteration. The results from this robust estimation procedure, reported in column 3 of Table 4, are, if anything, stronger than those in column 2.

To check whether our results were being driven by the possible endogeneity of *SCREENS*, we re-ran the regression in column (2) using revenue per screen as the dependent variable rather

[17] We also tried specifications which added *WEBRATE* and various Academy Award variables to the list of quality proxies. These additional variables had little explanatory power and had no impact on the coefficients of the other variables, so we do not report regressions with these additional variables for brevity.

than the revenue level and omitting *SCREENS* from the right-hand side. The results are presented in column 4 of Table 4. The coefficient on *FOURDAY* becomes significant, but otherwise the results are similar to the earlier regression. As shown in Table 5, the influence effect is similar whether measured as a percentage of a movie's revenue level or revenue per screen.

VI Conclusion

To summarize the central results of Table 5, the different specifications consistently show a positive, though marginally significant, influence effect associated with one thumb up. The influence effect associated with two thumbs up is significantly positive, accounting for about twenty percent of first weekend box office revenue.

This is a surprisingly, but not implausibly, large estimate of the influence effect. It is consistent with a survey reported in the *Wall Street Journal*, which found that a third of moviegoers chose a film because of a favorable review, more than half of these because of a review on television (Simmons [1994]). It should also be emphasized that our reduced-form model does not limit the influence effect to the direct influence of a critic on consumers but also includes indirect effects. For example, after a positive review, a movie distributor may choose to redouble its marketing efforts, highlighting the positive review in its advertisements. A positive review may influence one consumer to view the movie, who then influences others to view the movie through word of mouth. The sum of the direct and indirect influence effects, embodied in our estimate, may plausibly be quite high.

Another explanation of our large estimate of the influence effect is that, in violation of maintained Assumptions 2 and 3, there are selection effects which systematically cause certain movies to be reviewed during their opening weekends and others after. The evidence presented in Section IV suggests that selection biases may be present but are probably not large. The evidence is only suggestive since we cannot rule out selection based on variables outside of our data set.

Our results suggest that product reviews can be an important mechanism for transmitting information about goods of uncertain quality. Our results also highlight the possibility that the power to influence consumer demand may be concentrated in a few critics. Reviews can themselves be considered goods of uncertain quality, and it may be natural for critics who have established high-quality reputations to exert the most influence. This raises interesting questions of how reputations may be built, maintained, and—for venal purposes—harvested.

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Table 1: Definitions of Variables and Descriptive Statistics

	Definition	Units	Mean	Standard Deviation	Maximum	Minimum
TOTREV	Total U.S. box office revenue	million 1999 $	30.6	39.6	312.0	0.4
OPENREV	Opening weekend U.S. box office revenue	million 1999 $	6.6	6.9	53.9	0.1
SCREENS	Number of screens exhibiting on opening weekend	thousands	1.49	0.64	3.70	0.05
WEBCOUNT	Number of web site visitors rating movie	thousands	0.93	1.74	15.69	0.01
WEBRATE	Average of web site visitors' quality rating	1-10 scale	6.33	0.91	8.50	2.60
MALTIN	Rating by Leonard Maltin, a popular film critic	1-4 scale	2.29	0.56	3.50	1.00
SISKEL	Gene Siskel positive review ("thumbs up")	dummy	0.32	—	1	0
EBERT	Roger Ebert positive review ("thumbs up")	dummy	0.41	—	1	0
ONE UP	Thumb up by exactly one of S&E	dummy	0.31	—	1	0
TWO UP	Thumbs up by both S&E	dummy	0.21	—	1	0
DURING	Dummy for S&E review during opening weekend	dummy	0.81	—	1	0
AFTER	Dummy for S&E review after opening weekend	dummy	0.19	—	1	0
FOURDAY	Dummy for four day weekend (Monday holiday)	dummy	0.07	—	1	0

Notes: 609 observations. *TOTREV* and *OPENREV* deflated using urban CPI index. *OPENREV* includes Friday, Saturday, and Sunday revenue for all cases except movies opening on four day weekends; these also include Monday revenue. *TOTREV*, *OPENREV and SCREENS* from the Box Office Guru web site (www.boxofficeguru.com). *SISKEL* and *EBERT* from Siskel and Ebert web site (www.tvplex.com/BuenaVista/SiskelandEbert). *WEBCOUNT* and *WEBRATE* from the Internet Movie Database web site (www.imdb.com). *MALTIN* from Maltin [1999]. *DURING* calculated by authors using opening date from the Box Office Guru web site and review date from the Siskel and Ebert web site. The rest of the variables computed by authors. S&E is an abbreviation for Siskel and Ebert.

Table 2: Raw Correlations Among Selected Variables

	ln(*TOTREV*)	ln(*OPENREV*)	*WEBCOUNT*	*WEBRATE*	*MALTIN*	*SISKEL*	*EBERT*
ln(*OPENREV*)	0.95 ***						
WEBCOUNT	0.52 ***	0.49 ***					
WEBRATE	0.12 ***	0.02	0.28 ***				
MALTIN	0.35 ***	0.25 ***	0.31 ***	0.45 ***			
SISKEL	0.16 ***	0.13 ***	0.22 ***	0.26 ***	0.27 ***		
EBERT	0.17 ***	0.09 **	0.21 ***	0.36 ***	0.33 ***	0.35 ***	
DURING	0.04	0.03	0.04	0.19 ***	0.18 ***	0.04	0.08 **

Note: Correlation coefficient significant at the *ten percent level, **five percent level, ***one percent level in a two-tailed test.

Table 3: Probit Evidence on Selection Effects

	(1)	(2)	(3)
ln(*OPENREV*)	0.01 (0.14)	0.01 (0.14)	—
SISKEL	0.00 (0.16)	—	—
EBERT	0.09 (0.15)	—	—
ONE UP	—	0.17 (0.16)	—
TWO UP	—	0.04 (0.21)	—
MALTIN	0.43 *** (0.14)	0.44 *** (0.14)	0.45 *** (0.13)
WEBCOUNT	-0.02 (0.06)	-0.01 (0.06)	-0.01 (0.05)
SCREENS	-0.07 (0.21)	-0.07 (0.21)	-0.06 (0.14)
FOURDAY	-0.94 *** (0.26)	-0.94 *** (0.26)	-0.94 *** (0.26)
Constant	0.11 (1.84)	0.10 (1.83)	0.22 (0.53)
Year dummies	34.8 ***	34.5 ***	35.2 ***
Month dummies	36.4 ***	36.3 ***	36.7 ***
Genre dummies	13.9	14.3	13.5
Producer dummies	9.9	10.1	10.0
Log likelihood	-227	-226	-227
Pseudo R^2	0.21	0.22	0.21

Notes: Dependent variable is *DURING*. Regressions involve 573 observations. The sole movie in the documentary genre, the sole movie in the film noir genre, and the 34 movies opening in December had to be dropped since their associated categories were perfect predictors of the dependent variable. White [1980] heteroskedasticity robust standard errors reported in parentheses below coefficient estimates. Entries for dummy variables are F statistics for test of joint significance. Significantly different from zero in a two-tailed test at the *ten percent level, **five percent level, ***one percent level.

Table 4: Determinants of Opening Weekend Box Office Revenue

Dependent Variable:	ln(*OPENREV*)			ln(*OPENREV* ÷*SCREENS*)
Estimation Method:	OLS	OLS	Robust	OLS
	(1)	(2)	(3)	(4)
DURING × *ONE UP*	0.25 ***	0.15 ***	0.16 ***	0.14 ***
	(0.05)	(0.05)	(0.05)	(0.05)
DURING × *TWO UP*	0.41 ***	0.23 ***	0.26 ***	0.21 ***
	(0.06)	(0.06)	(0.06)	(0.07)
AFTER	0.06	0.11 *	0.12 *	0.11
	(0.07)	(0.07)	(0.07)	(0.07)
AFTER × *ONE UP*	0.09	0.04	0.06	0.08
	(0.11)	(0.10)	(0.10)	(0.10)
AFTER × *TWO UP*	0.21	-0.09	-0.09	-0.06
	(0.14)	(0.12)	(0.13)	(0.14)
MALTIN	—	0.21 ***	0.24 ***	0.22 ***
		(0.04)	(0.04)	(0.04)
WEBCOUNT	—	0.09 ***	0.09 ***	0.12 ***
		(0.02)	(0.01)	(0.02)
SCREENS	1.21 ***	1.15 ***	1.15 ***	—
	(0.05)	(0.05)	(0.04)	
FOURDAY	0.07	0.11	0.13	0.18 **
	(0.07)	(0.07)	(0.08)	(0.07)
Constant	12.63 ***	12.27 ***	12.32 ***	6.71 ***
	(0.17)	(0.18)	(0.17)	(0.17)
Year dummies	3.48 ***	3.14 ***	3.23 ***	0.79
Month dummies	3.60 ***	3.71 ***	3.47 ***	3.17 ***
Genre dummies	5.63 ***	4.43 ***	3.71 ***	3.36 ***
Producer dummies	4.48 ***	4.12 ***	4.35 ***	4.24 ***
R^2	0.76	0.80	—	0.44

Notes: Regressions involve 609 observations. Standard errors reported in parentheses below coefficient estimates. For the OLS regressions in (1), (2), and (4), White [1980] heteroskedasticity-robust standard errors are reported. For Li's [1985] iteratively reweighted least squares method in (3), standard errors were calculated according to the formula in Street, Carroll, and Ruppert [1988]. Entries for sets of dummy variables are F statistics for test of joint significance. Significantly different from zero in a two-tailed test at the *ten percent level, **five percent level, ***one percent level.

Table 5: Estimates of the Influence Effect

Regression from Table 3:	As Fraction of *OPENREV* (1)	(2)	(3)	As Fraction of *(OPENREV ÷SCREENS)* (4)
Influence of one thumb up relative to two thumbs down	0.14 *	0.11 *	0.09	0.06
	(0.09)	(0.09)	(0.09)	(0.11)
Influence of two thumbs up relative to two thumbs down	0.18 **	0.28 ***	0.29 ***	0.27 **
	(0.10)	(0.07)	(0.07)	(0.16)

Notes: Calculations as described in text using estimates from corresponding column of Table 3. Standard errors in parentheses. White [1980] heteroskedasticity robust standard errors reported for columns 1, 2, and 4. Significantly different from zero in a one-tailed test at the *ten percent level, **five percent level, ***one percent level.

Figure 1: Timing of Review Relative to Movie's Release