CONTEMPORARY ECONOMIC POLICY

RATINGS AND REVENUES: EVIDENCE FROM MOVIE RATINGS

CRAIG PALSSON, JOSEPH PRICE and JARED SHORES

Ratings and report cards provide a relatively cheap way to influence consumer and producer decisions. We examine the specific case of movie ratings and find that receiving a mature rating (rated R) reduces a movie's box office revenues by 20%. We focus on the specific role of ratings by constructing a mature content index for each movie and compare movies with similar amounts of mature content, but that received different ratings. We also exploit the fact that the movie rating system places specific guidelines on the number of F-words that are allowed at each content rating. (*JEL* D0, L82)

Ratings play an increasingly important role in people's decisions. Hospital report cards influence where individuals receive health care (Pope 2009), school report cards influence where people with children choose to live (Figlio and Lucas 2004), and hygiene quality ratings influence where people eat out (Jin and Leslie 2003). Even in settings where the ratings (or other types of information about quality) do not influence individual behavior directly, the introduction of the ratings influences the way that producers design their goods (Golan et al. 2001).

In this article, we examine the role that content ratings play in influencing people's decision of which movies to watch in the theater. In this setting, ratings play an important role in allowing consumers to sort into the type of content that they would prefer to watch, and in protecting children from content that may not be appropriate for their age. This second consideration might be particularly important given the potential effects that violent or sexually explicit content might have on children (Anderson and Bushman 2001).

We show that directors have considerable control over the rating that they receive by determining the amount of profanity and in particular the number of F-words they include in the movie. While the Motion Picture Association of America (MPAA) does not release detailed information about their rating criteria, we are able to infer aspects of the criteria using data from ScreenIt.com, which provides a set of ratings for different types of content (including profanity) as well as a count of the number of specific swear words that are used in the movie. We find that profanity is one of the strongest determinants of a movie's rating.

We use these independent measures of the content of a movie to construct a measure of how close to the margin of a particular rating each movie was. This allows us to compare movies that appear to have content that would make them equally likely to receive a particular rating, but for various reasons ended up with different ratings. We find that, among comparable movies that are on the margin of receiving an R-rating, those that actually receive an R-rating end up receiving about 20% less in domestic revenues and are about 10 percentage points more likely to have their revenues fall short of their budget. We are able to confirm these findings both by using a more narrowly defined range of movies that are more similar in content and by employing an instrumental variable (IV) approach. We instrument for a movie's rating using an indicator of whether the movie included three or more F-words.

Palsson: Department of Economics, Brigham Young University, Provo, UT 84602. Phone 801-819-9560, Fax 801-422-0194, E-mail palssonc@byu.edu

Price: Department of Economics, Brigham Young University, Provo, UT 84602. Phone 801-422-5296, Fax 801-422-0194, E-mail joe_price@byu.edu

Shores: Department of Economics, Brigham Young University, Provo, UT 84602. Phone 385-208-3027, Fax 801-422-0194, E-mail jared.shores@gmail.com

ABBREVIATIONS

IV: Instrumental Variable
MPAA: Motion Picture Association of America
MPPDA: Motion Pictures Producers and Distributors of America
OLS: Ordinary Least Squares

Contemporary Economic Policy (ISSN 1465-7287)
Vol. 31, No. 1, January 2013, 13–21
Online Early publication March 28, 2012
doi:10.1111/j.1465-7287.2012.00315.x

I. MOVIE RATINGS

In the early 1920s, Hollywood had a bad string of incidents that provoked public demand for censorship and the cleaning up of the movie industry. In response to the public outcry the Motion Pictures Producers and Distributors of America (MPPDA) formed an association. The leader of this group was the Republican National Committee Chairman, Will Hays. As the new leader of the MPPDA, he drafted what became known as the Hays Code. It outlined strict and specific guidelines as to what was suitable and what was unsuitable for American audiences.

On November 1, 1968, the Hays Code was replaced by the voluntary film rating system, the MPAA. This system gave submitted films a coded rating: G (general audiences, all ages admitted), M (mature audiences, parental guidance suggested but all ages admitted), R (children under 16 not admitted without an adult), and X (no one under the age of 17 admitted). The association later changed M to PG because of common misconceptions that an M was worse than an R-rating. In 1984, the association added the PG-13 and NC-17 categories.

The process for any film to receive an MPAA rating is the same. The producer or director of a movie submits his/her film to the MPAA and pays a scaled fee that is based on the movie's total budget. A review board at the association then watches the film and gives it a rating they believe is appropriate for the film's content. Factors they consider include sex, nudity, violence, language, drug use, and adult topics. Taking specific notes as to their reasoning and rating choice, the group then discusses what rating they believe the film should receive. The final rating is then decided by a majority vote. If the film's producer or director does not like the MPAA's assigned rating, they are allowed to edit and resubmit the film for a re-rating. Because of the cost of re-editing a film, producers and directors are also allowed to appeal the association's rating decision.

Many past studies include the movie's MPAA rating as a control in their examination of other factors that influence movie revenues (Einav 2007; Ravid 1999; Sochay 1994)[1] and all find that R-rated movies have lower average revenues than the movies with lower ratings. Other studies confirm that R-rated movies have lower average revenues, provide a lower return on investment, and are less likely to be financially successful (Austin, Nicolich, and Simonet 1981; De Vany and Walls 2002). This has created an R-rated puzzle in that R-rated movies are less financially successful, but continue to constitute the majority of movies produced in the United States. There have been attempts to try to explain this R-rated puzzle within a rational framework based on concepts of risk aversion by firms or differences in revenues between domestic and international markets (Ravid and Basuroy 2004; Switzer and Lang 2008).

II. DATA

We use data from The Numbers, which provides box office data for all domestically distributed films since 1995. We include in our sample all motion pictures between 1996 and 2009 for which The Numbers provide budget data. It also provides information on each movie's budget, though this information is not publicly available for every movie. In Table 1, we list, for each of the four rating categories,[2] the average domestic revenue, budget, and fraction of movies for which domestic revenue exceeds the budget.

The results in Table 1 show that G films have the highest average revenues ($80 million). PG and PG-13 films have about the same average revenue (around $65 million) and R movies have the lowest average revenue ($35 million). However, nearly each rating has a 55% chance of its theater revenue exceeding its budget. Finally, the number of theaters that show a movie is highly correlated with the film's rating. We find that G, PG, and PG-13 films all have a greater than 90% chance of being qualified as wide release (shown in more than 600 theaters), whereas R films have only a 79% chance.

One of the limitations of the MPAA rating system is that it provides a single measure that combines information about different types of content (sex, violence, profanity, etc.). In 1990, the MPAA started to include rating descriptions for each film so as to provide parents with additional information about reasons a film received a certain rating. Although there is no rubric or scale of reference, the MPAA has adjusted these

1. For a survey of the literature on movie revenues see Hadida (2009) and McKenzie (2012).

2. For our sample, we omit NC-17 and unrated movies. Combined, these two ratings make up only 1% of the box office market share.

TABLE 1
Descriptive Statistics

	G	PG	PG-13	R	All
Budget	52.898 (42.515)	51.890 (43.589)	49.338 (42.647)	29.960 (27.175)	41.299 (38.132)
Average revenue	79.908 (78.106)	69.544 (72.780)	65.513 (75.162)	35.346 (40.689)	53.290 (64.166)
Median revenue	58.522	46.427	39.161	22.702	32.120
Prob(Revenue > Budget)	0.57 (0.50)	0.63 (0.49)	0.54 (0.50)	0.52 (0.50)	0.55 (0.50)
Theaters	2,663 (869)	2,642 (937)	2,412 (934)	1,716 (1,020)	2,145 (1,045)
Content					
Profanity	0.20 (0.45)	1.22 (0.78)	3.01 (1.06)	4.56 (0.91)	3.36 (1.58)
Sex	0.78 (0.79)	1.76 (0.96)	3.17 (1.08)	3.78 (1.25)	3.18 (1.38)
Gore	0.65 (0.55)	1.22 (0.83)	2.10 (1.19)	3.25 (1.59)	2.44 (1.55)
Violence	2.17 (1.00)	2.65 (1.06)	3.36 (1.43)	3.94 (1.41)	3.48 (1.45)
Alcohol	0.65 (0.70)	1.50 (1.13)	2.60 (1.16)	3.01 (1.27)	2.57 (1.33)
F-words	0.00 (0.00)	0.00 (0.07)	0.55 (0.76)	37.86 (48.58)	16.81 (37.16)
N	54	224	668	738	1, 684

Notes: Our sample includes all movies from 1996 to 2009 for which The Numbers has budget data. The budget and revenue numbers are all measured in millions of dollars. Standard deviations are in parentheses. The content measures are from ScreenIt.com and are all measured on a 1–5 scale.

descriptions to fit the specific content of each film. The common descriptors include nudity, language, violence, gore, and drug use. Each of these categories often has further description, such as intense, heavy, or mild. The qualitative nature of these descriptors and their changing nature over time make them difficult to use in an empirical analysis.

Some Websites have begun to provide additional information to parents about movie content. These Websites, such as kidsinmind.com, dove.org, and screenit.com, provide specific ratings for different types of content. We use data from Screen It, an independent organization unaffiliated with any religious or political groups, that provides content ratings for wide-release films. Screen It uses 16 content categories (profanity, sex/nudity, etc.) and assigns one of six ordered ratings—from “none” to “extreme”—to each group. Screen It also provides descriptions of scenes that fit each category, giving users an idea of exactly what the rating signifies. The Screen It data contain reviews for 99% of the movies for which we have revenue and budget data. In Table 1 we provide the average scores and standard deviations for the five content areas we use in our analysis.

Although many of these categories are subjective and may be influenced by the preferences and tastes of the reviewer, profanity is one objective measure of content that is easy to quantify. Screen It provides a list of profanities used in the film along with a frequency count. Since profanity takes many forms, we focus on the four most common swear words. Table 2 uses the full Screen It sample to show the frequency of swear words by rating.

III. CONTENT AND RATINGS

The process by which ratings are assigned to movies is intentionally kept a mystery. In this section, we use data on various content measures to test for patterns in how movie ratings are determined. Since the distribution of scores varies across each of the content measures, we standardize each of these variables to have a mean of 0 and a standard deviation of 1.

In the first column of Table 3, we examine movies that received either a G or PG rating and then examine the characteristics that predict whether a movie received the higher rating of the two (in the subsequent columns we do the same for each of the other adjacent pairs of movie ratings). All of the analysis is based on a logit model, with marginal effects reported in the table. Each regression includes controls for each of the content measures and a linear term for the year the movie was released.

For all three of the rating groups, we find that profanity plays an important role in predicting a movie’s rating. For example, a standard deviation increase in profanity (which is about 1.62 points on the 0–5 scales) increases the

TABLE 2
Incidences of Profanity in Each Rating Category

F-words	G	PG	PG-13	R	S***	G	PG	PG-13	R
0	54	223	375	68	0	54	184	137	55
1		1	243	23	1		21	70	33
2			37	19	2		5	57	32
3			10	14	3		3	60	31
4				26	4		2	43	27
5				12	5		2	32	30
6+			3	576	6+		7	269	530
A**	**G**	**PG**	**PG-13**	**R**	**H*****	**G**	**PG**	**PG-13**	**R**
0	54	164	190	156	0	51	159	417	412
1		12	32	30	1	2	32	64	94
2		11	35	44	2	1	14	37	56
3		13	36	52	3		10	43	36
4		9	44	45	4		5	23	23
5		3	38	52	5		1	16	31
6+		12	293	359	6+		3	68	86

Notes: Data obtained from Screen It for 1996–2009. Budget and revenue information did not affect inclusion in the above tables. We examined more closely the three cases of PG-rated movies in which Screen It reported an F-word. In two cases, the F-word was mouthed rather than spoken, and in the other case, a modified version of the F-word was used. A**, H***, S*** indicate common swear words.

TABLE 3
Relationship between Content and Ratings

	PG vs. G	PG-13 vs. PG	R vs. PG-13
Profanity	0.258** (0.051)	0.200** (0.023)	0.593** (0.038)
Sex	0.039 (0.026)	0.112** (0.019)	0.164** (0.029)
Gore	0.049 (0.037)	0.086** (0.022)	0.314** (0.033)
Violence	0.064* (0.026)	0.078** (0.017)	−0.028 (0.029)
Alcohol	0.012 (0.025)	0.027 (0.014)	0.006 (0.025)
Year	0.006 (0.004)	−0.011** (0.004)	−0.059** (0.006)
N	278	892	1, 406

Notes: The sample includes all movies rated by Screen It from 1996 to 2009. Estimates are marginal effects from a logit model. In each column, the dependent variable is a dummy variable equal to one if the movie received the more mature rating of the two. All covariates are standardized to mean 0 and standard deviation 1. Standard errors are provided in parentheses.
**Statistical significance at 1% level; *statistical significance at 5% level.

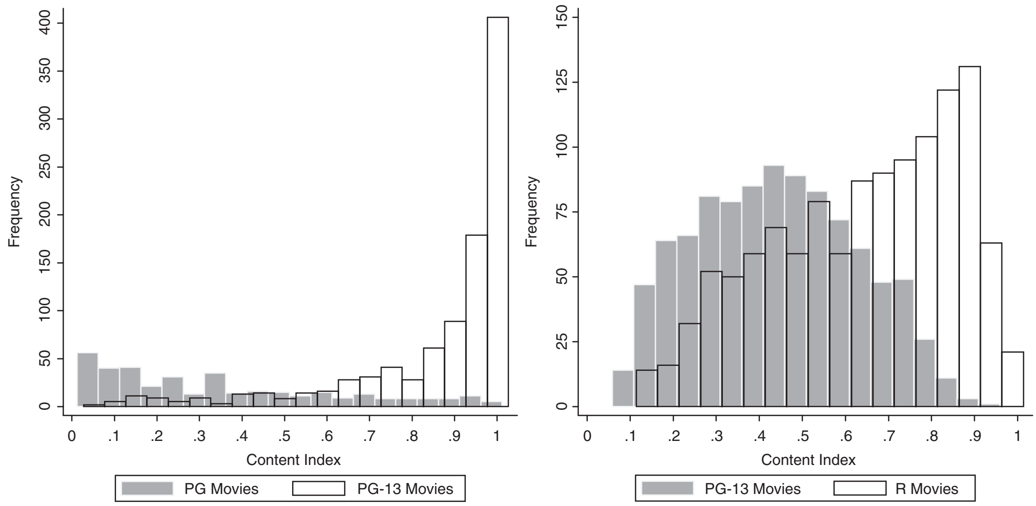
probability of receiving an R-rating by about 59 percentage points (among the movies that are rated R or PG-13). In context, a standard deviation increase in the amount of sex in a movie increases the probability of receiving an R-rating by 16 percentage points.

The coefficient on our linear time trend indicates that there has been a "ratings creep" in the assignment of movies to the PG-13 and R categories. Assuming the way that the content measures have been determined at Screen It has stayed constant over this period, these coefficients indicate that a movie that is on the border of being PG or PG-13 has been 1.5 percentage points *less* likely to get the higher rating each year (controlling for the amount of content in the movie).[3]

We use the coefficients of a similar regression to construct a measure of the underlying content of the movie. For example, among the set of movies that are either PG or PG-13, we can use the estimated coefficients from this regression to find a propensity score (or likelihood) that the movie would be given a rating of PG-13 based on the amount of profanity, sex, violence, gore,

3. These results are robust to including year fixed effects rather than a linear time trend as well as instrumenting to eliminate measurement error using Kids in Mind data.

FIGURE 1
Distribution of Content Index



Notes: The content index is the propensity score from a regression where the higher rating is the dependent variable. We included controls for the different measures of content included in Table 3.

and alcohol use that is included in the movie. This propensity score allows us to identify a set of movies that were very similar in content, but differ in the rating that they actually received. The regression is identical to the model used in Table 3, except instead of the profanity rating we use the number of curse words in the movie minus the number of F-words so that our content index is unrelated to the F-word instrument we use.

Figure 1 shows a histogram comparing the propensity scores between PG and PG-13 as well as between PG-13 and R movies. Movies that have a content index near 1 are movies that have content which would have made it extremely likely for them to receive the higher rating, while movies with a content index near 0 have content that would have made it very likely for them to receive the lower rating. In both cases, we see an overlap in our content index between each of the two adjoining ratings, though the overlap of R and PG-13 is much larger than the overlap of PG-13 and PG. These overlapping distributions provide a set of movies that have very similar content but for some reason received different ratings. For example, *The Bourne Ultimatum* (2007) has a content index of 0.416 while *The Matrix* (1999) scored a 0.498, though the former received a PG-13 rating and the latter received an R-rating despite these films containing similar content. We use this type of comparison in the next section to examine the effect of ratings on movie revenues.

To identify the effect of ratings on revenues, we also exploit another interesting pattern in how R-ratings are determined. The results in Table 2 illustrate that the F-word plays a specific role in determining ratings. Movies that have any use of the F-word are automatically rated PG-13 regardless of the other contents in the movie.[4] For R-rated movies, the cutoff appears to be around three F-words. In the analysis that follows in the next section, we exploit the sharp change in ratings when three or more F-words are included in a movie. Since the profanity in a film is not openly advertised, the specific number of F-words in a film should only affect the movie's revenues through the rating that it receives.

IV. RATINGS AND REVENUES

Although past research has measured the differences in revenues across different movie ratings, our primary focus is on the specific effect of the rating separate from the content of the movie. We use the regressions that we estimated

4. We examined more closely the one case of a PG-rated movie in which Screen It reported an F-word. In two cases, the F-word was mouthed rather than spoken, and in the other case a modified version of the F-word was used.

TABLE 4
Effect of Movie Rating on Domestic Revenues (R vs. PG-13)

	Full Sample		**Restricted Sample**	
	OLS	**IV ($f \geq 3$)**	**OLS**	**IV ($f \geq 3$)**
A. Domestic revenues (logged)				
R	−0.301** (0.074)	−0.224* (0.099)	−0.250 (0.130)	−0.210 (0.170)
Content index	0.307 (0.160)	0.221 (0.177)	−0.467 (0.958)	−0.489 (0.960)
Log budget	0.633** (0.029)	0.640** (0.029)	0.798** (0.056)	0.803** (0.058)
Observations	1,406	1,406	378	378
R^2	0.462	0.462	0.553	0.553
B. Domestic revenues > Budget				
R	−0.097** (0.033)	−0.097* (0.045)	−0.069 (0.062)	−0.036 (0.081)
Content index	0.083 (0.073)	0.083 (0.080)	−0.146 (0.454)	−0.165 (0.455)
Log budget	−0.101** (0.013)	−0.101** (0.013)	−0.056* (0.027)	−0.052 (0.027)
Observations	1,406	1,406	378	378
R^2	0.100	0.100	0.128	0.127

Notes: The sample includes all movies between 1996 and 2009 with public access information on the movie's budget and a Screen It review. Each regression includes controls for genre as well as year, season of release, and distributor-fixed effects. The restricted sample includes movies that have a propensity score between 0.4 and 0.6 based on the regression in the third column of Table 3. Standard errors are in parentheses.

**Statistical significance at 1% level; *statistical significance at 5% level.

in Table 3 to assign to each movie a propensity score of how likely it is to receive a particular rating based on the amount of profanity, sex, violence, gore, and alcohol use that it contains. This propensity score aggregates each of the content scores into a single content index. We include the content index in a regression along with the movie's rating and other factors that help predict box office success, such as budget, genre, distributor, the time of year of release, and a linear time trend. We compare movies with similar propensity scores and control for other characteristics, including budget, genre, and year and season of release.

In Table 4, we restrict our sample to all movies that received a PG-13 or R-rating and let the primary independent variable be whether or not the movie received the higher rating (R) and the dependent variable be the log of U.S. revenues.[5] Along with the budget and content index, we control for genre and include year, season of release, and distributor-fixed effects. In the first column, we find that R-rated movies had 30% lower revenue and were 9.7 percentage points less likely to have their domestic revenues exceed their budget.

We also employ an IV approach in which we exploit the fact that the MPAA has specific guidelines about the number of F-words that are allowed at each movie rating. We instrument for whether a movie receives an R-rating using an indicator variable for whether or not the movie had three or more F-words. This variable is a strong instrument with an F-statistic of over 500 and a partial R^2 of 0.458. For the full sample of movies, our estimates based on this IV approach are very similar to those when we use ordinary least squares (OLS).

These estimates are based on a comparison of all the full set of movies that received either a PG-13 or R-rating. In Figure 1, we show that there are some R-rated movies that include content that makes it very unlikely that they would have been on the margin of receiving a PG-13 rating. Even with a control for the underlying content of the movie, movies with very high (or very low) content index may be a poor comparison group for our analysis. To address this issue, we restrict our analysis to the set of movies that have a content index between 0.4 and 0.6 (about a quarter of our original sample), thus comparing movies with similar amounts of underlying content.[6] We find very similar results as for our full sample when we focus on this more narrowly defined subgroup: the movie that receives the

5. Since we include year fixed effects and use log revenues, the results are the same whether we use inflation adjusted revenues and budgets or not. We use the unadjusted numbers for transparency reasons.

6. Of movies that were re-rated from R to PG-13, the average content index is 0.54. By nature of the change in ratings, these movies represent the margin on which decisions are made, so movies in this neighborhood are likely marginal as well.

TABLE 5
Effect of Movie Rating on Domestic Revenues (PG-13 vs. PG)

	Domestic Revenues (logged)		Domestic Revenues > Budget	
	Full	**Restrict**	**Full**	**Restricted**
PG-13	0.068 (0.113)	0.052 (0.234)	−0.023 (0.057)	−0.010 (0.109)
Content index	−0.262 (0.161)	−1.099 (0.903)	−0.091 (0.082)	−0.264 (0.422)
Log budget	0.700** (0.038)	0.529** (0.108)	−0.075** (0.019)	−0.086 (0.051)
Observations	892	141	892	141
R^2	0.421	0.505	0.064	0.184

Notes: The sample includes all movies between 1996 and 2009 with public access information on the movie's budget and a Screen It review. Each regression includes controls for genre as well as year, season of release, and distributor-fixed effects. The restricted sample includes movies that have a propensity score between 0.3 and 0.7 based on the regression in the second column of Table 3. Standard errors are in parentheses.

**Statistical significance at 1% level.

R-rating will end up with domestic revenues that are 21%–25% lower, and the probability that the domestic revenues will exceed the movie's budget is 3.6–6.9 percentage points lower than if it had received a PG-13 rating, though neither of these results is significant at the 5% level.

In Table 5, we look at the set of movies that received either a PG or PG-13 rating. We use a method similar to the one used in Table 4, but in this case find that, controlling for the underlying content of the movie and other characteristics, there is very little difference in the revenues or likelihood of revenues exceeding the budget for these movies based on their ratings. The coefficients indicate that PG-13 movies receive about 5%–7% greater revenues and are about 1–2 percentage points more likely to have theater revenues greater than the budget, though neither of these differences is statistically significant. We exclude the IV estimates from Table 5 since they provide even less precise estimates than the already imprecise OLS estimates.

One likely explanation for the difference in the effects of the PG-13 rating and the R-rating is that while the PG-13 carries with it the warning, "Parents strongly cautioned—Some material may be inappropriate for children under 13," it does not carry any specific restrictions on entry. R-rated movies require that children under the age of 17 be accompanied by a parent or adult guardian. Another explanation is that individuals place greater weight on the signal provided by an R-rating than a PG-13 rating such that crossing the R-threshold to watch a movie requires a stronger pull than crossing the PG-13 threshold. We also examine another channel through which a movie's rating affects its revenue: the number of theaters in which a film is released. Our regression uses the number of theaters in which a movie was shown in the week of its widest release, typically the first week, as the dependent variable. The results in row A of Table 6 indicate that an R-rating reduces the number of theaters by about 250–360 in the full sample and by 370–380 in the restricted sample. Because theater companies make decisions to host movies based on their belief of how well the movie will do, the number of theaters that take a movie is a proxy for the expected return (Moretti 2011).This suggests that theater owners expect that R-rated movies have a lower expected return than their PG-13 counterparts.

One potential limitation of these results is that the MPAA allows movie producers to appeal the original rating they receive or to make changes to the movie and have the movie be re-rated. The primary concern is that it might be the case that among movies that are on the border of two ratings, it might be the movies that are expected to have higher revenues that chose to appeal the original decision or make the changes necessary to receive the lower rating. To examine the extent to which this might be a problem in our data we collected data from the MPAA weekly bulletin, which announces the movies which received a rating that week, including those that were appealed or re-rated. Between January1990 and December 2010, the MPAA reported rating 15,663 movies, of which 241 (about 1.55%) received a second look from the ratings committee. Among these movies, there were 80 films that were changed from rated R to rated PG-13 and 7 films that changed from PG-13 to R. For this subset of movies the

TABLE 6
Alternative Specifications (R vs. PG-13)

	Full Sample		Restricted Sample	
Outcomes	**OLS**	**IV($f \geq 3$)**	**OLS**	**IV ($f \geq 3$)**
A. Number of theaters	−360.6* (45.513)	−253.0* (61.676)	−382.0* (78.729)	−372.2* (102.785)
B. Domestic sales (with Rotten Tomatoes rating)	−0.454** (0.070)	−0.407** (0.096)	−0.449** (0.123)	−0.346* (0.165)
Observations	1, 406	1, 406	378	378

Notes: Each cell is a separate regression with the same specification and controls as Table 4 and the number that we report is the coefficient on whether the movie was R-rated or not. The regression in row A contains an additional control for the average Rotten Tomatoes rating received by the movie. The dependent variable in row B is the number of domestic theaters in which the movie has shown. Standard errors in parentheses.

**Statistical significance at 1% level; *statistical significance at 5% level.

average revenue is $32 million and the median is $17 million, well below the average revenue for PG-13 films of $65 million and the median of $39 million. These results suggest that the role of the appeals and re-rating of movies would be only a very minor problem for our analysis.

Another possible limitation to our estimated effects is that, although we can control for several characteristics of the film, we do not include a measure of the quality of the movie. As a final robustness check, we use data from Rotten Tomatoes for most of the films in our sample and re-estimate the results from Table 4, but include an additional control for the fraction of critics that gave the movie a positive review (the most prominently displayed measure of movie quality on the Website). Our estimates of the effect of a movie's ratings on revenues, which we provide in row B of Table 6, are even larger when we control for this measure of quality.

V. CONCLUSION

There is a growing body of evidence documenting the degree to which ratings, rankings, and warning labels influence consumer decisions. This is an encouraging prospect for policy makers who want to influence consumer decisions by providing better information about products. This information can be particularly important for products that could potentially harm certain consumers. Specific forms of information have been designed to protect children from unhealthy foods, registered sex offenders (Pope 2008), prescription drugs with side effects for children (Parkinson et al. 2010), and, in this case, inappropriate media content.

One puzzle that has arisen in response to nutrition labels is that, while the labels seem to have little impact on consumer decisions (Cowburn and Stockley 2005), they do have a large impact on the producer decisions (Caswell and Padberg 1992; Golan et al. 2001). In this article, we document a setting that appears to be the exact opposite. Consumers are more likely to attend lower-rated films, but movie studios continue to produce a large fraction of films with higher ratings.

One possible explanation for the higher number of R-rated movies is that the difference in average revenues that we estimate in this article may differ from the difference in the expected marginal revenue under each of the two ratings. The degree to which marginal revenues will differ from the average revenues is likely to depend on the number of movies of each rating being released during the relevant time period as well as the degree to which consumers are willing to substitute between R and PG-13 movies.

Future research could combine the insights from this article about the effects of ratings with the structural approach that has been used to examine the relationship between release date and revenue (Einav 2007, 2010; Krider and Weinberg 1998). Einav (2007) notes that since there is virtually no price competition between movies in theaters, the one short-run margin on which movies can compete is their release date. Our results suggest that, for some movies, another margin on which movies can compete is by editing the content slightly to obtain a different rating. It is likely that a structural model that jointly estimates both of these decisions could provide insight into the marginal revenue implications of both release date and rating.

REFERENCES

Anderson, C., and B. Bushman. "Effects of Violent Video Games on Aggressive Behavior, Aggressive Cognition, Aggressive Affect, Physiological Arousal, and Prosocial Behavior: A Meta-Analytic Review of the Scientific Literature." *Psychological Science*, 12, 2001, 353–9.

Austin, B., M. Nicolich, and T. Simonet. "MPAA Ratings and the Box Office: Some Tantalizing Statistics." *Film Quarterly*, 35, 1981, 28–30.

Caswell, J., and D. Padberg. "Toward a More Comprehensive Theory of Food Labels." *American Journal of Agricultural Economics,* 74(2), 1992, 460–68.

Cowburn, G., and L. Stockley. "Consumer Understanding and Use of Nutrition Labelling: A Systematic Review." *Public Health Nutrition*, 8, 2005, 21–8.

De Vany, A., and W. D. Walls. "Does Hollywood Make Too Many R-Rated Movies? Risk, Stochastic Dominance, and the Illusion of Expectation." *The Journal of Business*, 75(3), 2002, 425–51.

Einav, L. "Seasonality in the U.S. Motion Picture Industry." *The RAND Journal of Economics,* 38(1), 2007, 127–45.

———. "Not All Rivals Look Alike: Estimating an Equilibrium Model of the Release Date Timing Game." *Economic Inquiry*, 48(2), 2010, 369–90.

Figlio, D., and M. Lucas. "What's in a Grade? School Report Cards and the Housing Market." *American Economic Review*, 94(3), 2004, 591–604.

Golan, E., F. Kuchler, L. Mitchell, C. Greene, and A. Jessup. "Economics of Food Labeling." *Journal of Consumer Policy,* 24(2), 2001, 117–84.

Hadida, A. L. "Motion Picture Performance: A Review and Research Agenda." *International Journal of Management Reviews*, 11(3), 2009, 297–335.

Jin, G. Z., and P. Leslie. "The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards." *Quarterly Journal of Economics*, 118(2), 2003, 409–51.

Krider, R., and C. Weinberg. "Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game." *Journal of Marketing Research*, 35(1), 1998, 1–15.

McKenzie, J. "The Economics of Movies: A Literature Survey." *Journal of Economic Surveys*, 26(1), 2012, 42–70.

Moretti, E. "Social Learning and Peer Effects in Consumption: Evidence from Movie Sales." *Review of Economic Studies*, 78, 2011, 356–93.

Parkinson, K., J. Price, K. Simon, and S. Tennyson. "The Influence of FDA Advisory Information and Black Box Warnings on Individual Use of Prescription Antidepressants." Working Paper, Cornell University, 2010.

Pope, D. "Reacting to Rankings: Evidence from 'America's Best Hospitals'." *Journal of Health Economics*, 28(6), 2009, 1154–65.

Pope, J. "Fear of Crime and Housing Prices: Household Reactions to Sex Offender Registries." *Journal of Urban Economics*, 64, 2008, 601–14.

Ravid, S. A. "Information, Blockbusters, and Stars: A Study of the Film Industry." *The Journal of Business*, 72(4), 1999, 463–92.

Ravid, S. A., and S. Basuroy. "Managerial Objectives, the R-Rating Puzzle, and the Production of Violent Films." *The Journal of Business*, 77(S2), 2004, S155–92.

Sochay, S. "Predicting the Performance of Motion Pictures." *Journal of Media Economics*, 7(4), 1994, 1–20.

Switzer, D., and D. Lang. "Does Sex Sell? A Look at the Effects of Sex and Violence on Motion Picture Revenues." Working Paper 2005–08, Saint Cloud State University, Department of Economics, revised March 2008.