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Social Influence and Competition among Critics

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Abstract

Movie critics have long been of interest to scholars because of the role they play as information intermediaries in a common market for cultural goods. Movie reviews, particularly when aggregated, are often thought to reflect the underlying quality of the film. Nevertheless, it is likely that critics influence each other, which may lead to bias in their published assessments. These potential social influence and competitive effects among critics have not been systematically studied previously. In a sample of movie reviews for movies released in the United States between 2001 and 2011, we attempt to isolate the social influence and competitive effects by exploring how movie critic reviews systematically change within critic dyads when the critics release their reviews on the same day versus different days, varying the observability of reviews by the critics. Our analysis provides evidence of competitive influence among critics with critics deviating more when other critics? reviews are observables. Additionally, we find that the degree to which critics diverge increases when the consensus about a movie?s quality is high. These findings provide evidence that critics? reviews are biased by the reviews of other crtiics and that information intermediaries, such as movie critics, are susceptible to social influence and competitive effects.

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Social Influence and Competition Among Critics

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ABSTRACT

Are information intermediaries subject to social influence and competitive forces? If so, how do these forces impact the information they provide? We examine these questions in the context of professional journalistic film critics. Consistent with prior literature examining stock market analysts, our study suggests that critics face simultaneous and opposing pressures to converge and diverge. Unlike stock market analysts, who tend to converge on the forecasts of other analysts, our analysis provides evidence that film critics tend to deviate from the reviews of other critics. We examine all movie reviews posted on Metacritic.com for movies released in theaters from the beginning of 2011 through the middle of 2013. We attempt to isolate the effect of social influence and competitive forces among critics by comparing the differences between reviews by two critics when the reviews are released on the same day to the differences between their reviews when the reviews are released on different days. Our analysis provides evidence of competitive influence among critics with critics deviating more when other critics' reviews are observable. Additionally, we find that the degree to which critics diverge increases when the consensus about a movie's quality is high.

INTRODUCTION

Are information intermediaries—market participants that collect, evaluate, and disseminate information in order to facilitate transactions in markets with substantial information asymmetries—subject to social influence and competitive forces? If so, how do these forces impact the information they provide? Studies of stock market analysts, a prototypical example of information intermediaries, have suggested that they do indeed face pressures that bias the information they provide. The incentives for stock market analysts (specifically, the benefits of deviating from the consensus and being right generally do not outweigh the penalties of deviating and being wrong) may lead them to over-weight public information at the expense of their own private information (including personal opinions) and converge on the consensus opinion of other analysts (Bikhchandani & Sharma, 2000; Hong, Kubik, & Solomon, 2000; Kadous, Mercer, & Thayer, 2009).

Unlike stock market analysts, however, whose forecasts can be objectively evaluated ex-post fairly easily, many information intermediaries operate in markets where the information they provide will never—or can never—be evaluated against such an objective standard. For example, reviewers and critics often provide evaluations in markets, such as market for cultural goods, where the value of the goods is subjective or socially constructed and the correctness of the critics' assessments cannot be objectively determined. If these information intermediaries are subject to the same types of social and competitive forces as those that operate on stock market analysts, how does these influences impact their published evaluations.

This study pursues this question in the context of movie reviews by journalistic film critics. We suggest that the degree to which critics converge to or diverge from the assessments of other critics reflects the underlying incentives facing critics. Two potential opposing pressures may act on critics in preparing their reviews: First, critics could face pressures to conform their assessments to those of other critics in order ease the cognitive burden of making their assessments or to gain legitimacy with their peers. Simultaneously, professional critics may also face competitive pressures to differentiate from which other in order to establish a niche or a unique position in the market. The results of our analysis suggest that movie critics do indeed react to social influence and competitive pressures, but, unlike stock market analysts, when critics have information about the opinions of other critics, they tend to deviate from the other critics. This tendency to deviate increases when there is a high degree of consensus about the quality of the film among other critics, which provides additional evidence that critics are motivated by a desire to be unique. Conversely, when critics diverge widely in their assessments of the quality of a film, and consequently there is no unique position in the market, critics tend to converge more than they might otherwise. This behavior suggests that incentives facing movie critics, whose opinions cannot be subject to an objective ex-post, differ from those of stock market analysts.

An emerging theme in this literature involves attempts to cleanly identifying the causal effects of social phenomena on market outcomes (Mouw, 2006; Malter, 2014). In settings such as these, it is often difficult to separate product attributes and underlying tastes from social signals. Consequently, accurately estimating the magnitude of social influence on evaluation, or even whether social influence has any causal effect, is extremely difficult. It may be the case in our setting, for instance, that sets of critics have a tendency to like or dislike the same movies because their underlying tastes are very similar. Any social influence effect we see, therefore, may be caused by these unobserved similarities rather than the social and competitive processes we seek to uncover. In this paper we will attempt to examine the effects of social influence on critical evaluations using variation in the ability of critics to observe one another's reviews, based on the release date of the reviews, in order to minimize the impact of these unobservable factors in our analysis. Our empirical strategy is explained in more detail in the following sections.

In the next section, we develop our hypotheses regarding the social influence and competitive effects facing moving critics. We then describe the data and empirical design and present our results. Finally, we discuss the limitations of the study and any contributions to our understanding of social influence and competitive processes.

SOCIAL INFLUENCE AND COMPETITION

Movie Critics

Scholars have long been interested in movie critics both because of an inherent fascination with the entertainment and film industry in which they operate and because movie critics are considered a prototypical type of information intermediary operating in a market for cultural and experience goods (Eliashberg & Shugan, 1997; Reinstein & Snyder, 2005). Studies have examined the impact that movie critics' ratings have on the box office performance of films (Elberse & Anand, 2007; King, 2007; Reinstein & Snyder, 2005). They have explored the impact that critics have on moviegoers—the demand side of the market—for example, by investigating whether critics simply forecast which movies moviegoers will see (a predictor role) or actually shape the preferences of the moviegoers (an influencer role) (Eliashberg & Shugan, 1997). They have also explored the impact that critics have on the movie producers—the supply side of the market—for example, by examining how critics help create and establish categories of movies that assist filmmakers in creating movies with a targeted audience in mind (Reinstein & Snyder, 2005).

These prior studies have generally taken critics' reviews as reflecting the underlying attributes of the movies they are reviewing. The aggregation of critics' reviews are taken as a (perhaps noisy) measure of the quality of films in the market (Waguespack & Sorensen, 2011), and the level of consensus in the quality of the movie, often measured by the amount of variance in the reviews, is seen to reflect either the tastes of individual reviewers or the degree to which the movies fall into legitimized categories (Hsu, Hannan, & Kocak, 2009). It is likely, however, that critics' assessments are shaped not only by the match between their individual tastes and the underlying attributes of the movies but also by the opinions of other critics. If critics are indeed biased by other critics, academic literature on social influence and competition suggests that they face two opposing forces: Pressure to converge on the opinions others and pressure to diverge from the opinions of others. Ab initio, it is not clear how critics will balance these forces—will they ultimately converge or diverge in their assessments?

Convergence Pressures

Foundational work in social psychology suggests that assessments can become biased simply by exposure to the assessments of others (Asch, 1951; Festinger, 1954). For example, experiments regarding the "wisdom of the crowds" have shown that the aggregation of naïve and inexperienced assessments can be more accurate than the assessments of experts (Surowiecki, 2005). In a classic example of the wisdom of the crowds—individuals guessing the number of jelly beans in a jar—even though the variance in guesses may be extremely high, it is common for the average to be very close to the actual number of jelly beans in the jar and closer to the actual number than all but a very few of the individual guesses (Treynor, 1987).

The wisdom of the crowds effect, however, relies on the independence of each of the naïve assessments—once the assessors are exposed to perhaps even minor information regarding the judgments of others, their own assessments, and the overall aggregate assessment, is easily biased (Lorenz et al., 2011). In effect, without social influence, the random estimation errors associated with each independent guess tend to cancel each other out. In the presence of social influence, however, assessors anchor on the guesses of others and the estimation errors of the group cease to be random and become correlated across guesses leading to a biased aggregate estimate. Given the right conditions, social influence can bias the expressed opinion of others even when assessing concrete facts (Asch, 1951). The biasing effect of social influence appears to be particularly prevalent as evaluation becomes increasingly subjective or cognitively challenging—such as in markets for cultural goods. Salganik et al. (2006) devised an online experiment to test the effect of social influence in a constructed market for music. Using various experimental manipulations, their study showed that market participants with access to information about the behavior and opinions of others, even if that information did not reflect actual actions but was randomly constructed, were more likely to like songs for which others expressed a preference.

In each case mentioned above, exposure to the opinions of others generally leads to convergence in assessments and opinions. Theoretical work on social influence suggests that there is a "pressure toward uniformity" that accompanies social comparison (Festinger, 1954). This pressure to converge may arise from psychological anchoring processes, an overemphasis of publicly available information from the expressed opinions of others at the expense of private information (Bikhchandani et al., 1992), or a desire to belong to and gain legitimacy within a group (Navis & Glynn, 2011).

Convergence in assessment has been shown in the experimental settings described above, but also in empirical examinations of real world phenomena. For example, in a number of studies of stock market analyst forecasting behavior, researchers have suggested a tendency for stock market analysts to converge on the consensus forecast of other analysts (Bernhardt et al., 2006; Hong et al., 2000; Kadous et al., 2009; Ramnath et al., 2008). Many of these studies have suggested that this herding behavior leads to suboptimal forecasting behavior since the private information of the individual analysts is not sufficiently weighted.

It could be, therefore, that movie critics will tend to converge in their assessments when they have access to the reviews of other critics. If so, the convergence may be because of anchoring on the prior review, the cognitive burden associated of the assessment, or in order to gain legitimacy with the community of critics. If convergence occurs because of the cognitive burden of reviewing or for legitimacy, we may see the convergence effects increase in situations where these factors are more likely to play a significant role.

Divergence Pressures

Market participants, however, face more than just pressures to conform. Indeed, and consistent with Festinger's (1954) theoretical exploration of social influences, there are situations in which social influence leads to competition or divergence in behavior. Similarly, by changing incentives associated with unique competitive positions, economic models of stock market analyst behaviors have shown that anti-herding—competitive differentiation—is a potential equilibrium outcome (Effinger & Polborn, 2001). These theories of differentiation are consistent with theories of niche market entry that suggest that although isomorphic pressures exist, other pressures may lead to competitive differentiation (Greve, 2000). Additional studies of stock market analysts provide evidence that stock market analysts may in fact differentiate their forecasts from those of other analysts (Bernhardt et al., 2006), particularly when the incentives for conforming change (i.e., career penalties associated with deviating diminish as they gain seniority (Hong et al., 2000) or career prospects increase with nonconforming forecasts (Effinger & Polborn, 2001)).

It could be, therefore, that movie critics will tend to diverge in their assessments when they have access to the reviews of other critics. If so, the divergence may be because of competitive positioning with the critic seeking a unique niche position in the competitive landscape. If divergence occurs because of competitive positioning, we may see the divergence effects increase in situations where niche positions are not already claimed.

Balancing

Overall, critics likely face both pressures to converge and pressures to diverge. Like other market actors, they will balance these pressures based on the incentives they face (Deephouse, 1999; Navis & Glynn, 2011). Their incentives, however, may be different than those faced by stock market analysts. Much of the literature on stock market analysts focuses on the incentives that accompany deviating from consensus and subsequently being wrong, measured concretely by an ex-post comparison of the forecast to the actual realized state of affairs. With their movie reviews, critics are not subject to an ex post objective evaluation of the accuracy of their reviews. Their reviews simply cannot be “wrong” in the same way that stock market analysts’ forecasts can. This should alter the incentives they face to deviate from the consensus and will likely lead critics to differ from stock market analysts in their tendency to converge. Because of this lack of ex post verifiability, our initial position is that critics will, on average, diverge in their assessments of films when presented with information about the opinions of other critics. Therefore, we hypothesize the following:

> **Hypothesis 1 (H1)**: Critics with access to the reviews of other critics will, at the margin, tend to diverge from the consensus assessment in their own reviews more than when they do not have access to the reviews of other critics.

EMPRICAL SETTING AND RESEARCH DESIGN

The empirical setting for this paper is film reviewing by professional critics. We want to know whether these professional critics respond to social and competitive influence. In an ideal experiment, we would gather a large group of critics and a large set of films unfamiliar to the critics, assign each critic to review each movie, and then ask critics to report a numerical score reflecting their assessment. Further, for each movie, we would randomly assign individual critics to either the control group, where movie evaluations are made without awareness of other's opinions, or to the treatment group, where the critics have access to the evaluations of the other critics. Presumably, the control group would provide an independent and unbiased assessment of film quality based solely on the attributes of the movie. If movie critics' reviews are biased by exposure to the reviews of other critics, we would expect the treatment group for each movie to report scores that are marginally different than those of the control group.

Such an experiment would allow us to causally link changes in reviews to the exposure of critics to the reviews of other critics. We could cleanly assess the direction of the effect and estimate its magnitude. Using information on the attributes of the movies, we could also examine how these characteristics impact social and competitive influence in the critic community. For example, are critics in the treatment group more likely to converge toward the control group mean score in their assessments when there is high variation in the scores by critics in the control group (suggesting, perhaps, that the film is more cognitively challenging to evaluate so critics in the treatment group will rely more heavily on signals from the control group critics) or are they more likely to diverge from the control group mean score (suggesting, perhaps, that they are more able to stake out a unique position in the competitive landscape when variation is high)? Conversely, are critics in the control group more likely to converge when there is little variation in the scores by critics in the control group (suggesting, perhaps, conformity to an established category of movie) or are they more likely to diverge (suggesting, perhaps, competitive differentiation)? Similarly, we could assess the impact of other characteristics of the movie on the tendency of critics in the treatment group to change their reviews and begin to understand how critics balance isomorphic and divergent pressures. Random assignment of critics to either the treatment or control groups by movie would help us rule out other alternative explanations for observed patterns in the data.

In reality, movie reviews are often narratives (as opposed to simply scores or stars) that vary across multiple dimensions, and some unknown processes (individual choice, editorial decision, filmmaker influence, or something else) determine both whether a critic reviews a particular movie and whether or not the critic has been exposed to information about the movie, including other critics' opinions, prior to publishing the review. Nevertheless, empirical regularities in the film review process may allow us to more rigorously explore the social influence and competitive forces operating among the critics.

First, reviewers display regular patterns in when they file reviews, likely due to the regularity of film release dates and publication schedules. Figure 1 reports a histogram of review interval, how many days separate the review date and the film release date, for all movies released on Fridays, the most common day for film releases. It is apparent in Figure 1 that reviews have weekly cycles. Most reviews are published on the day of release (in this case, Friday, or day 0) or the day before (Thursday, or day -1). A second round of reviews begin appearing in the following week (days one to 7), with later rounds on subsequent weekends. Our interpretation of this figure is that individual reviewers are constrained by both time and article space, and therefore there is individual variance on when opinions are revealed. Figure 2 provides some anecdotal evidence for this interpretation by replicating Figure 1 for the review intervals of four prominent critics. Each critic predominantly publishes reviews on the day before the film release (Thursday) or the day of release (Friday), and there is a less marked tendency to file a review before release or one or 2 weeks later.

Additionally, professional critics show considerable variance on film quality assessments. Metacritic.com (MC), a website that aggregates movie reviews and the source of our data on critic reviews, converts each film review narrative into numerical score from 0 ("terrible") to 100 ("excellent"). Figure 3 reports film frequency (histogram – left axis) and score standard deviation (line – right axis) by average Metacritic score (horizontal axis). It is clear in Figure 3 that the consensus opinion is moderately positive for the average movie, and that there is substantial variance at any point in the quality distribution. What is not known is if the review variance is random, if it reflects simply underlying variance in the distribution of reviewer tastes, or if it also reflects social influence or competitive processes.

Empirical Strategy

This brings us to our empirical strategy for this paper. We collected all movie reviews posted on MC through the August 22, 2013 for a total of 135,327 reviews of 6,277 movies. MC does not attempt to amass the entire universe of critic reviews for each movie. Instead, MC collects, by hand, movie reviews from a select group of sources that they deem to be high quality. MC then converts each review to a 100-point scale (the MC score).[1] MC includes in its

[1] If the critic uses a standard scale for rating movies (i.e., a scale from one to ten, zero to four stars, or letter grades), MC uses a mechanical process to convert the critic's scale to MC's 100 point scale. If, instead, the critic simply provides a narrative review, MC assigns a value based on the content of the review, but will adjust the score if the critic disagrees with assigned score.

database virtually every movie theatrically released in the US since the site's inception in 1999 (including limited releases and re-releases, as long as there are reviews published for such movies in at least a few of their pool of publication sources).

Importantly, until late 2009, MC did not provide any information on the publication date of the reviews, and did so only inconsistently through the end of 2010. In order to analyze the effect of social and competitive influences among critics on reviews, observing the timing of review release is critical, so we limit our sample to the reviews for movies included on MC and released from 2011 onward, when the review publication date was consistently recorded. Nevertheless, we had to exclude an additional 24 reviews for 3 movies released in 2011 that did not contain review dates, and another 68 reviews where the critic's name was unavailable, for a final sample of 19,179 reviews for 326 movies by 558 critics from 54 different publications. For each review remaining in our sample, we have the critic name, review date, review publication, MC score, movie title, movie studio, and theatrical release date. In order to analyze the impact of each critic's review on the other reviews in our sample, we create a panel of dyads for each pair of critics who reviewed the same movie ordered by the date each critic's reviews were released. The analysis sample includes 12,821 critic dyads and 193,755 dyad-movie observations.

Analysis

Dependent and Independent Variables. The dependent variable is the absolute value of the difference between the MC scores of each critic in each dyad, which measures the divergence between the critic's scores. The primary independent variable of interest is *Observe*, a dummy variable that takes a value of 1 if the two reviews in the dyad were published on the same day and a value of 0 if the reviews were published on different days. Dyad-movie observations where reviews are published on different days, or the *Observe* group, represent the treatment group since the second critic in the dyad to publish a review had, at least, access to the review of the other critic prior to the publication of the second review. Dyad-movie reviews where reviews are published on the same day represent the control group. One assumption underlying any causal interpretation is that the day on which critics reviews are posted within a dyad, and thus a dyad's membership in the treatment or control group for a particular movie, is not driven by the content of the review. Although dyad fixed effects will somewhat mitigate this concern, our assumption is essentially untestable. Another interpretation of any systematic differences between the treatment and control groups could be that critics (or critics' editors, perhaps) elects to publish different (i.e. more negative and more positive) reviews on different days, but does not otherwise respond to the reviews of others.

<u>Control Variables</u>. Since the rate at which critics within dyads review films, dyad fixed effects will not adequately capture differences in experience, so we include as controls the difference between the total number of reviews published by each critic prior to the focal reviews as well as the total number of reviews published by the second critic in the dyad. Similarly, the number of reviews published for a given movie prior to each of the reviews for that movie within a dyad are not constant so dyad fixed effects won't adequately capture these differences. We include as controls the difference between the number of reviews released for a movie prior to each review within the dyad as well as the total number of reviews released for the movie prior to the second critic's review within the dyad.

In order to capture the effect of reviews by other critics on the focal critics within a dyad, we control for the average and standard deviation of scores for a given movie for all reviews released prior to the first critic's review and the average and standard deviation of scores for the movie of all scores released prior to the second critic's review (net of the score of the first critic in the dyad). Control variables in some model specifications include the difference between the total number of reviews published by each critic in the dyad prior to the focal reviews and include that as well as the total number of reviews published by the second critic in the dyad in order to capture any effects from differences in experience levels between the critics. We calculate the difference between the total number of reviews released for a movie prior to each of the reviews in the dyad and include that number and the total number of reviews released for that movie prior to the second review in the dyad in order to capture any effects arising from the .

[INSERT TABLE 1 ABOUT HERE]

Table 1 reports descriptive statistics for our analysis sample. Table 2 presents our initial tests for the existence of social influence and competitive effects among critics using regression analysis. Model 1 reports a simple OLS linear regression model with robust standard errors indicating that reviews in the treatment group do not significantly deviate from those in the control group. Model 2, however, includes fixed effects for the dyad and the movie. With critic fixed effects, the results now provide estimate the difference between the divergence of the critics' scores within dyad when the reviews are released on different days as opposed to when reviews are released on the same day. The coefficient on our treatment variable remains significant and similar in size to that in Model 1. Model 3 includes dyad and movie fixed effects as well as the control variables outlined above, and the coefficient on the treatment variable remains significant and increases to 0.447. These results provide some support for H1, suggesting that in preparing their reviews, critics respond to the reviews of other critics.

[INSERT TABLE 2 ABOUT HERE]

Moderating Effects of Consensus

Our analysis, however, would not be complete without examining potential boundary conditions of social influence and competitive effects. To this end, we explore critic consensus as a moderator and its impact on the treatment effect of releasing reviews on different days. We operationalize consensus as the standard deviation of the MC scores of all reviews released prior to the second critic, excluding the review of the other critic in the dyad. Lower standard deviations indicate that there is a smaller spread between the scores given by the other critics reviewing a given movie and suggest a higher level of consensus among the critics. Higher standard deviations indicate lower levels of consensus. These standard deviations range from 0 to 48.08 with a median of 15.21 and a mean of 15.27.

We included our consensus measure as a control variable in Model 3 of Table 2 and see that it has a negative and significant main effect, suggesting that as the standard deviation increases (consensus is decreasing), the difference between the scores for each critic in the dyad is decreasing. We then interact the consensus measure with the *Observe* treatment variable. The results of this interaction are presented in Model 4 of Table 2. The interaction term is negative and significant, which suggests that higher levels of consensus (measured by lower standard deviation of MC scores) lead to increased divergence when reviews are published on different days. Similarly, with a dyad, when control group consensus is low (measured by higher standard deviation of MC scores), reviews converge more when the reviews are published on different days. Figure 4 presents these results graphically, and includes 95% confidence intervals. Figure 4 also provides a histogram depicting the distribution of the standard deviations of the control group MC scores in the sample and a rug plot indicating the precise location of individual observations (Berry, Golder, & Milton, 2012). Analyzing the figure, we can see that the interaction between the standard deviation of the consensus MC score and the *Observe* variable is significantly different than zero over a substantial portion of the observations in the sample. Instead of lower levels of consensus leading to increased divergence, we see the opposite.

DISCUSSION AND CONCLUSION

In this paper we explore the social influence and competitive effects operating among film critics. We attempt to detect and measure any systematic bias in the reviews associated with social influence and competitive effects. We develop theoretical arguments for social influence and competitive effects and hypothesize that critics may be incentivized to diverge from the consensus assessments of their peers and that these effects may be greater when critics are reviewing movies that span genres or when there is less consensus about the quality of the film. Using variation in the release dates of movie reviews, we look for evidence of these social influence and competitive effects and find support for the claim that critics diverge in their assessments of films when they are able to observe the reviews of other critics. We also find statistical results consistent with an argument that critics tend to competitively differentiate their reviews from the average control group assessment when control group consensus is high, but tend to converge when the control group consensus is low, which was opposite to our initial hypotheses. Nevertheless, this finding suggests additional support for our general expectation that critics' assessments of products are indeed impacted by the reviews of their peers.

This study has a number of limitations and suggests opportunities for future work. Although we attempt to use natural variation in the review release patterns of critics, the scope of this quasi-experiment, although potentially helpful in limiting alternative explanations, may also limit our ability to detect social influence and competitive effects. We see two primary limitations to our current study. First, it could be that reviews are not exogenously assigned to control group and treatment group. The critics, or perhaps editors at the sources publishing their reviews, could be systematically altering the publication date of reviews based on their content or some other unobserved factor. Although dyad fixed effects may control for some of this tendency, if divergent reviews are released later when it is clear that there is considerable consensus about the movie otherwise, we would observe the same patterns that we find in the data. Additionally, for our data on the review publication date, we rely on information provided on MC. The dates that MC posts as the review dates are actually the dates on which they collect the reviews rather than the actual publication date. Although the site is incentivized to collect reviews as soon as possible following their publication, we do not know if the date provided by MC is the actual publication date or if the reviews were published earlier. At a minimum, some of our observations may be incorrectly classified as belonging to the treatment or control groups. This noise in the data should simply make a statistically significant finding even more difficult to find.

Second, our data and empirical strategy limits us to detecting evidence of social influence only within published reviews. It could be, however, that significant social influence and competitive effects actually occur at a different stage in the process. For example, we do not know where or how the film critics screened movies prior to writing their reviews. Social influence and competition among critics may manifest prior to, during, or immediately following screenings, and we would not be able to detect those effects with our research design.

Future research into the effects of social influence and competition among critics could take advantage of additional data on critics, including information on relative status, geographical location, professional background (journalistic versus film or humanities training, for example), and career history might also provide some insight into the social influence process and boundary conditions for competitive and social influence effects.

We find evidence of competitive effects among critics. Critics tend to diverge when they are able to observe the reviews of other critics. The negative coefficient on the interaction between our treatment variable and the standard deviation of scores as a measure of the level of consensus in the scores provides further evidence of competition among critics suggesting that in situations with high consensus where there is a unique position to be had, critics will deviate from the consensus. Alternatively, when there is little consensus in reviews and therefore little opportunity for a unique voice, critics may actually converge on the reviews of others. This effect is different than that observed among stock market analysts where their deviation from consensus is constrained by the evaluation of their review against an objective standard. This could suggest that in markets for cultural goods, like movies, competitive pressures to differentiate will dominate other convergence pressures. This study is the first step in measuring any bias in movie reviews that social influence and competitive effects introduce.

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TABLE 1 Descriptive Statistics for the Full Sample

Description	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Number of dyad-movie observations	193,755				
Number of dyads	36,151				
Number of reviews	19,179				
Number of movies	326				
Number of critics	558				
Observe (treatment variable)	265,367	.80	.40	0	1
Score difference (independent variable)	265,367	17.15	14.08	0	100
Score difference for *Observe* = 1	211,219	17.19	14.11	0	100
Score difference score for *Observe* = 0	54,148	16.99	13.95	0	100
Average score prior to first reviewer	158,627	63.89	13.98	0	100
Average score prior to second reviewer	189,556	63.81	13.40	0	100
Average standard deviation prior to first	150,435	15.18	5.65	0	48.08
Average standard deviation prior to second	188,373	15.56	4.27	0	51.64
Difference in number of reviews by critics	193,775	65.90	839.25	-2678	2667
Number of reviews of critic 2	193,775	806.13	563.49	1	2688
Difference in number of reviews for movie	193,775	10.32	9.28	0	47
Number of review within movie of critic 2	193,775	19.53	10.48	1	48

TABLE 2 Ordinary least squares regressions

	Model 1	Model 2		Model 3		Model 4	
Observe	0.120	0.172	+	0.447	**	9.640	**
	(0.08)	(0.10)		(0.13)		(0.68)	
Difference in Total # of Reviews between 1 and 2				0.005	**	0.005	**
				(0.00)		(0.00)	
# of Reviews of Reviewer 2				0.000		0.000	
				(0.00)		(0.00)	
Difference in # of Prior Reviews within Movie				0.009		0.010	
				(0.01)		(0.01)	
# of Reviews prior to Second Review within Movie				-0.038	**	-0.048	**
				(0.01)		(0.01)	
Average Movie Score prior to Reviewer 1				0.036	**	0.039	**
				(0.01)		(0.01)	
Standard Deviation of Movie Scores prior to Reviewer 1				-0.162	**	-0.159	**
				(0.01)		(0.01)	
Average of Movie Scores prior to Reviewer 2				0.073	**	0.064	**
				(0.02)		(0.02)	
SD of Movie Scores prior to Reviewer 2				-0.867	**	-0.660	**
				(0.03)		(0.03)	
Observe X Avg Prior to Reviewer 2						-0.025	**
						(0.02)	
Observe X SD Prior to Reviewer 2						-0.483	**
						(0.01)	
Dyad Fixed Effects	N	Y		Y		Y	
Movie Fixed Effects	N	Y		Y		Y	
N	193,775	193,775		150,435		150,435	
R2	0.097	0.097		0.097		0.100	

FIGURE 1

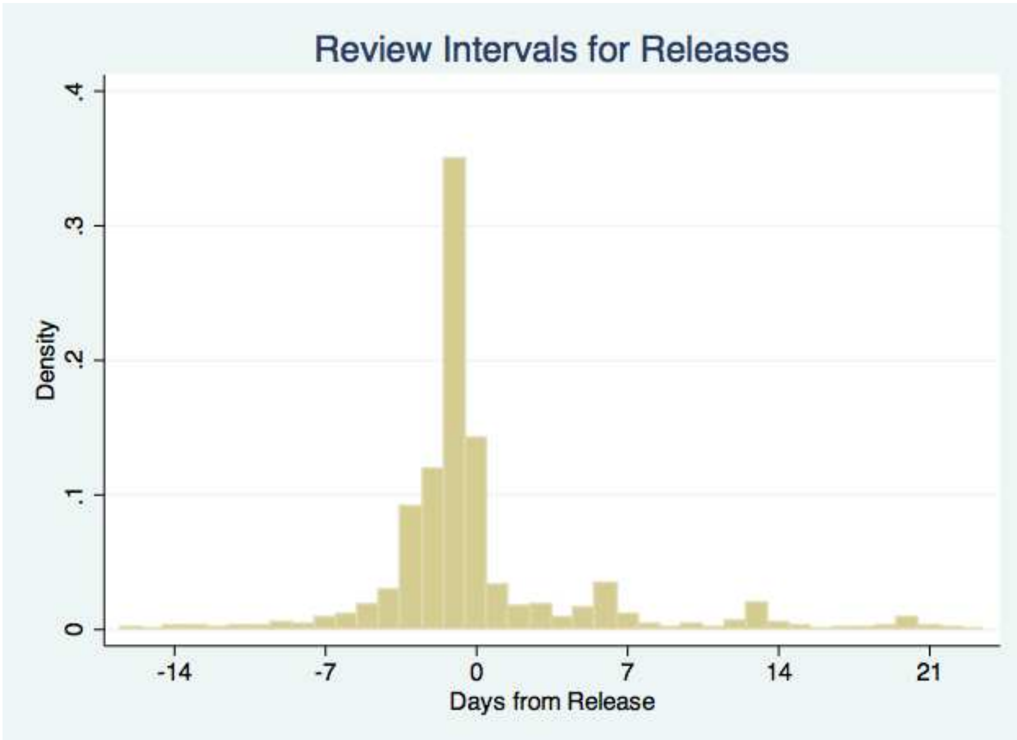

FIGURE 2

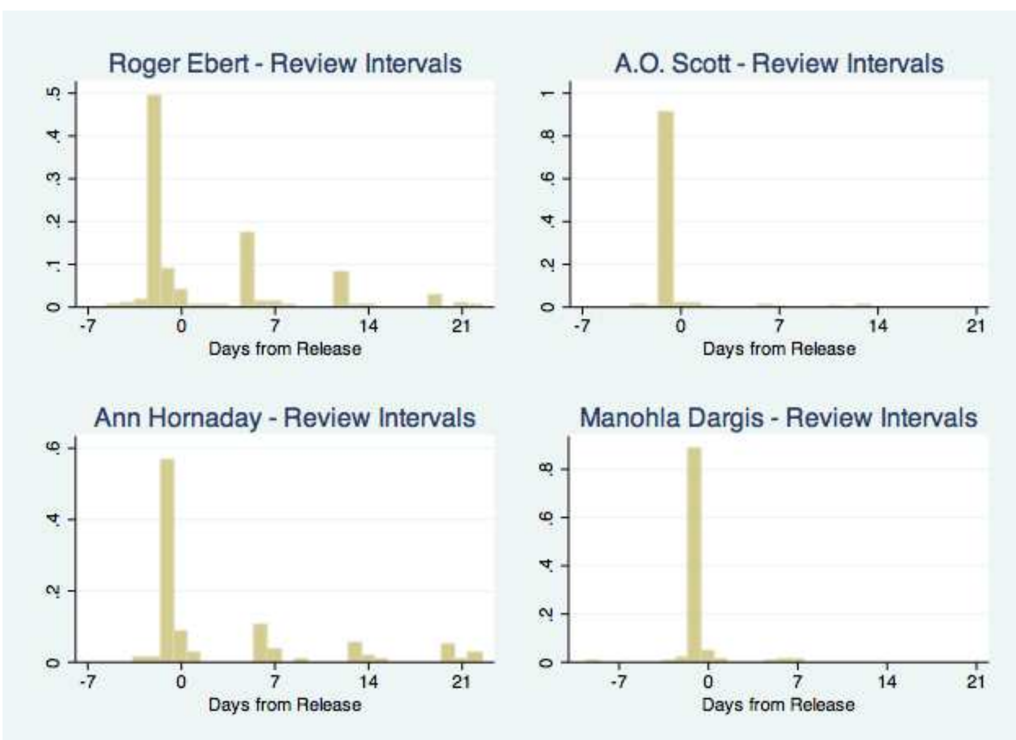

FIGURE 3

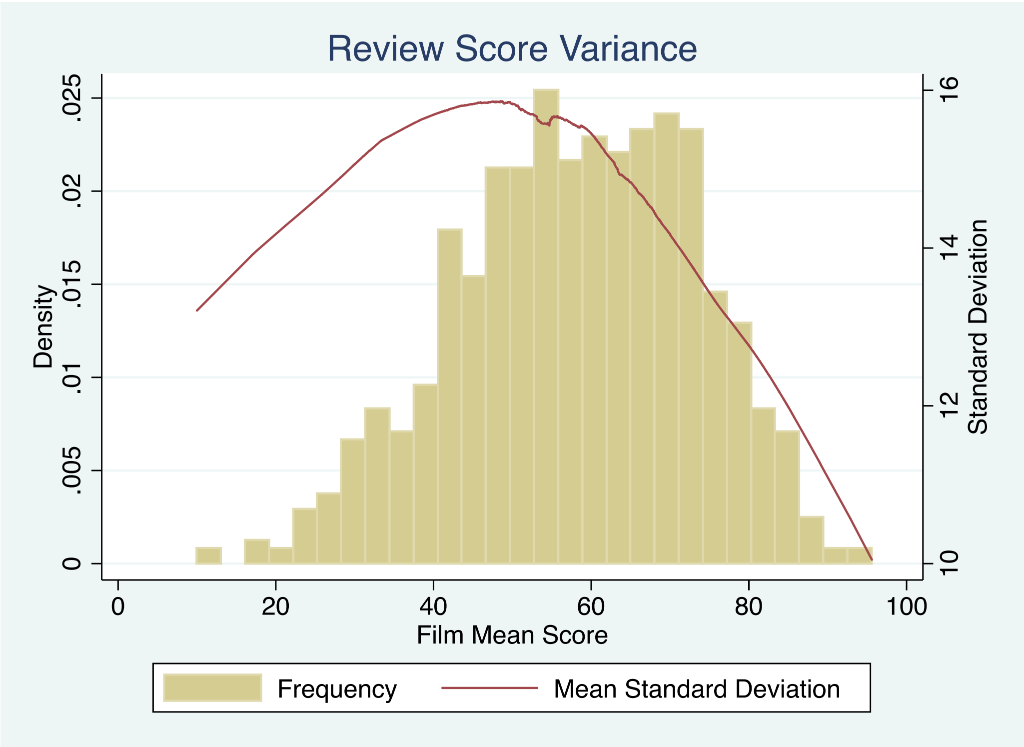

FIGURE 4