Social Influence and Competition Between 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 film and video game product critics. Consistent with prior literature examining stock market analysts, our study suggests that the product critics in our study 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 and video game critics tend to deviate from the reviews of other critics. We examine all movie and video game reviews posted on Metacritic.com for movies released in theaters from 2011 through the middle of 2013 and for video games released from 2011 through the middle of 2014. We attempt to isolate the effect of social influence and competitive forces between critics by comparing the differences between reviews by two critics when their 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 between critics with a critic deviating more when other critic’s reviews are observable. Additionally, we find that the competitive overlap between critics further moderates the treatment effect.
INTRODUCTION

The opinions of information intermediaries—market participants that collect, evaluate, and disseminate information in order to facilitate transactions, often in markets with substantial information asymmetries—guide consumer decisions, and are often used in business and academic research settings as proxies for underlying product quality. To what extent, though, are information intermediaries subject to social influence and competitive forces from other information intermediaries? If they are subject to these forces, how are their published opinions biased as a result? Studies of stock market analysts, often considered prototypical information intermediaries (Zuckerman, 1999), suggest that they do face social influence and competitive pressures that bias their forecasts. Specifically, stock market analysts may over-weight public information at the expense of their own private information (including their personal opinions) and converge on the opinions of other analysts (Bikhchandani & Sharma, 2000; Hong, Kubik, & Solomon, 2000; Kadous, Mercer, & Thayer, 2009).

Unlike financial analysts, however, whose forecasts can eventually be measured against actual ex-post firm performance, many information intermediaries operate in arenas where the information they provide can never—or will never—be evaluated against an objective standard. For example, many product critics offer assessments in markets, such as markets for cultural goods, where value is simply a matter of irreducible taste and the correctness of their opinions cannot be objectively determined. Without an objective standard to provide market discipline (Waguespack, Salomon, & Bae, 2014), instead of converging on the opinions of others, information intermediaries may seek to differentiate. Consequently, in this paper we explore how information intermediaries react to social and competitive forces in markets where quality is
subjective. We pursue this question by examining product reviews by both film and video game critics.

Two opposing pressures likely act on critics as they prepare their reviews: first, product critics may face pressures to conform their assessments to those of other critics in order to ease the cognitive burden inherent in developing an opinion in a subjective context (Festinger, 1954) or to maintain legitimacy with their peers (Zuckerman, 1999); second and simultaneously, as strategic actors, product critics may face pressures to differentiate from each other in order to reduce competition by establishing a niche or securing a unique position in the market (Deephouse, 1999; Greve, 2000). Whereas financial analysts appear to be constrained in their ability to publish bold and divergent forecasts because they risk market discipline if wrong, product critics for whom assessments are substantially a matter of preference or opinion are ostensibly less constrained in expressing deviant opinions and perhaps even experience incentives to differentiate.

The results of our analysis suggest that product critics do indeed react to social influence and competitive pressures, and that, unlike stock market analysts, when a critic has information about the opinions of another critic, the observing critic tends to deviate from the other critic. The propensity to deviate is moderated by the extent to which the two critics are competitors, with critics deviating more as they review more of the same products and critics deviating more when responding to higher status critics. [update with a better discussion of these results.]

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 products 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 natural 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 product critics. We then describe the data and empirical design and present our results. Finally, we discuss the limitations and the contributions of this study to our understanding of social influence and competitive processes, particularly among information intermediaries.

SOCIAL INFLUENCE AND COMPETITION BETWEEN PRODUCT CRITICS

Information intermediaries perform an important function in facilitating and influencing market transactions, particularly in markets that are characterized by limited and asymmetric information. They are, therefore, the subject of much scholarly research in a variety of disciplines that are concerned with how markets function and how value is determined, including economics and finance (Hong, Kubik, & Solomon, 2000; Ottaviani & Sørensen, 2006; Froot, Scharfstein, & Stein, 2012), sociology (Shrum, 1991; Zuckerman, 1999, 2004; Hsu, 2006), marketing (Eliashberg & Shugan, 1997; Chen, Liu, & Zhang, 2012) and management (Rao,
Much of the literature examining information intermediaries focuses on financial analysts, likely because of the importance and broad disciplinary appeal of understanding the market in which they operate, as well as the availability of data on both the analysts’ assessments as well as they companies they follow (for example, Zuckerman, 1999, 2004; and Froot, Scharfstein, & Stein, 2012). Additional research involving information intermediaries explores product critics in a number of industries, [including cuisine, wine, art, theater, books, movies, video games].

Academic studies on information intermediaries and the markets in which they operate often use aggregated critical evaluations as a (potentially noisy) measure of the underlying characteristics of products in a market. The average review often is taken as evidence of the underlying quality of the product (Waguespack & Sorensen, 2011), while the degree of consensus in reviews, typically measured by the variance in assessments across critics, provides information about either the product—generally the extent to which the product conforms to norms and expectations in the market (Zuckerman, 1999)—or about the market—generally the extent to which market categories themselves are established and legitimized (Reinstein & Snyder, 2005; Hsu, 2006; Hsu, Hannan, & Kocak, 2009).

It is likely, however, that information intermediaries’ assessments are shaped not only by the match between their individual tastes and the underlying attributes of the products they evaluate, but also by the opinions of other information intermediaries. If product critics are indeed biased by other product critics, research 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 they will balance these forces—will they ultimately converge or diverge in their assessments?
We assert that the incentives of information intermediaries, such as stock market analysts, that operate in markets where the value of a product is based on an objective standard (even though the characteristics of the product are only revealed over time or through experience—the market for lemons, for example (Akerlof, 1970)) are different than those of information intermediaries, such as product critics in markets for cultural goods, that operate in markets where the value of a product is inherently subjective and a matter of taste. Moreover, the differences in incentives are likely to change the way information intermediaries respond to social and competitive pressure from other information intermediaries. Our study explores the social influence and competitive pressures among product critics in two settings where product quality is subjective: the film and video game industries. We examine the behaviors of professional critics in each setting, and explore the extent to which we can uncover evidence of social or competitive influence in their published reviews.

**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—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, even though the variance in guesses may be extremely high (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.

**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)).

A product critic, therefore, is likely to face simultaneous pressures to converge and to diverge from the assessments of another critic. Like other market actors, a critic may seek to balance these pressures by strategically differentiating from other critics (Deephouse, 1999; Navis & Glynn, 2011). It could be, therefore, that baseline difference in reviews between two critics, based solely on the underlying differences in tastes and the cognitive burden associated
with generating reviews in arenas where quality is subjective, may be high enough that a critic will, when the opinion of the peer critic is observable, converge on the other’s opinion. Therefore, we hypothesize the following:

**Hypothesis 1a (H1a):** The difference between the assessments of products by two critics will decrease when the assessment of one critic is observable for the other critic.

On the other hand, since product critics operate as market actors, critics may want to augment the difference between their reviews and the reviews of another critic, so a critic will, when the opinion of the other critic is observable, diverge from the other’s opinion. Therefore, we hypothesize the following:

**Hypothesis 1b (H1b):** The difference between the assessments of products by two critics will increase when the assessment of one critic is observable for the other critic.

Because product critics in markets where value is subjective are not subject to the same ex post verification that can be the basis for market discipline against the critic, we expect that on average a product critic will generally diverge from the assessment of another critic.

It is likely that product critics do not respond to social influence and competitive pressures from all other critics equally. They are more likely to be influenced by critics with whom have a higher degree of competitive overlap, including those critics that occupy similar market niches or focus on similar audiences. [Include discussion of salience from social comparison literature and strategic groups]. The increased salience of these other critics should enhance the social influence and competitive pressures and positively moderate the baseline effect, whether toward convergence or divergence.

**Hypothesis 2a (H2a):** The difference between the assessments of products by two critics will decrease more as the competitive overlap between the two critics increases.

**Hypothesis 2b (H2b):** The difference between the assessments of products by two critics will increase more as the competitive overlap between the two critics increases.
EMPIRICAL SETTING AND RESEARCH DESIGN

We test our hypotheses in two empirical settings: reviews by professional critics of theatrically-released films and of video games released for the personal computer and console game segments. Our sample of reviews comes from Metacritic.com—a website that collects reviews for virtually all theatrically released movies and for nearly all videogames that are reviewed in multiple outlets—and includes reviews of 823 movies by 166 film critics between 2011 and mid-2013 and reviews of 460 video games by 177 reviewers between 2011 and mid-2014. Details of our sample selection process, as well as descriptive statistics for the analysis sample, are provided below.

In an ideal experiment, we would randomly assign pairs of professional critics to review products and report a numerical score reflecting their assessment. We would then manipulate whether or not a critic within each pair, prior to publishing her review, had access to the evaluations of the product by the other critic in the pair. We do not expect critics to always have the same opinions, so the differences between the reviews of the critics in each pair in instances where the critics were not able to observe the reviews of the other critic (the control condition) capture the unbiased variation in their assessments. The differences between the product reviews in instances where a critic had access to the reviews of the other critic (the treatment condition), however, would include any bias introduced by social comparison and competitive pressures. Therefore, if product critics are impacted by social influence and comparison processes in their reviews, we would anticipate that the difference between the reviews of the critics in each pair would be marginally different in the treatment condition as compared to those in the control condition. By examining the direction and extent of the changes, we would be able to uncover the direction and extent of the bias. Further, by manipulating the characteristics of each of the
critics in the pair to enhance the competitive overlap, we could determine how competition between the two critics moderates the treatment effect.

In reality, reviews are often narratives (as opposed to simply scores) that vary across multiple dimensions, so a simple comparison of the differences between two reviews is difficult. Moreover, some unknown processes (individual choice, editorial decision, product producer influence, or something else) determine both whether a critic reviews a particular product and whether or not the critic has been exposed to information about the product, including other critics’ opinions, prior to publishing the review. Additionally, critics are likely to respond to the totality of observable reviews, rather than solely to the reviews of other specific critics.

[INSERT FIGURES 1 AND 2 ABOUT HERE]

Nevertheless, empirical regularities in the review process in both the film and video game setting allow us to more rigorously explore the social influence and competitive forces operating between critics. First, reviewers display regular patterns in when they file reviews, likely due to the regularity of product release dates (primarily Fridays and Wednesdays) and review publication schedules. Figure 1 shows the review intervals (the number of days between the film release date and each review for the film) for all films in the sample and for reviews published up to two weeks prior to the film release date and up to four weeks after the release date. It is apparent in Figure 1 that reviews have weekly cycles. Most reviews are published on or within a few days prior to the movie release date. A second round of reviews begin appearing in the following week (days one to 7), with later rounds of reviews following at regular intervals. Our interpretation of this figure is that individual reviewers are constrained by both the number of reviews critics are able to produce in a given week and the publication space available, 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 two prominent film critics: Roger Ebert and A.O. Scott. Each critic predominantly publishes shortly before the film release date, and then additional reviews follow at fairly regular weekly intervals for a few weeks thereafter.

[INSERT FIGURES 3 AND 4 ABOUT HERE]

A similar pattern emerges for video games, with a majority of reviews published at the time of product release. Figure 3 shows the review intervals for all video games in the sample. Perhaps because video games are not subject to the same regularity in product release dates, or because of the differences in consumption patterns among video game purchasers, the variance of review intervals is much greater for video game reviews. But again, a regular review interval pattern exists. Figure 4 provides the review intervals for two prominent video game reviewers in our sample, Cheat Code Central and GameSpot, and it is clear that there is substantial variation in when reviewers publish reviews (although the review release pattern is much less regular, perhaps because these reviews are primarily published online and not subject to the same publication schedules and limitations as film critics).

[INSERT FIGURES 5 AND 6 ABOUT HERE]

Perhaps more importantly for our research design, there is substantial variation within each pair of critics on when their reviews are released. Figure 5 provides a histogram of review intervals at the movie and film critic-pair level. Although film critics release their reviews on the same day fairly often, more than half of their reviews are published on different days. Figure 6 shows the variation in review intervals for reviews of the same film by Roger Ebert and A.O. Scott. The panel on the left captures the difference in publication dates for reviews when Ebert is the “lead” and Scott is the “follower.” The panel on the right shows Scott as the lead and
Ebert as the follower. Note that the number of reviews released by the two critics on the same day (0 days between reviews) is the same in both panels.

[INSERT FIGURES 7 AND 8 ABOUT HERE]

Figures 7 and 8 demonstrate that video game review intervals at the pair-level follow the same pattern as movie reviews. Figure 7 shows review intervals for each pair of video game critics in the data. Note that, consistent with the larger variance overall in review publication dates shown in figure 3, the intervals between reviews for each pair of reviewers for a given video game exhibit higher variance than those of film critic reviews. Figure 8 provides an example of the variation in the review intervals for a pair of video game critics, with the left panel capturing cases where Cheat Code Central is the lead and GameSpot is the follower, and the right panel capturing cases where GameSpot is the lead and Cheat Code Central follows.

*Feasible Research Design*

This brings us to a feasible research design for our study. Similar to the ideal experiment outlined above, we exploit variation in the relative review release dates for pairs of critics as a manipulation of the observability of one critic’s review by the other. When critics release their reviews on the same day, we contend that their ability to observe each other’s reviews prior to publishing their own is limited. Thus, comparing the two critics’ reviews in this control condition, we construct the baseline difference between the two. When their reviews are released on different days, the critic who releases the review second (the follower) has the opportunity to observe the review of the other critic. By comparing the two critics’ reviews in this treatment condition, we capture not only the underlying differences in preferences between the two critics, but also any bias introduced by observability. By netting out the baseline
differences between the two reviewers, essentially controlling for unobservable differences in their tastes, we can isolate the treatment effect of observation and begin to quantify the bias introduced into their reviews by social influence and competitive pressures.

Data and Variables

We draw our data on movie and video game reviews from Metacritic.com (Metacritic). We collected all movie reviews and video game reviews posted on Metacritic from its inception through August 22, 2013 for movies and through June 9, 2014 for video games. Metacritic does not attempt to amass the entire universe of critic reviews for each product. Instead, Metacritic collects reviews from a select group of sources that they deem to be high quality. Metacritic converts each review to a 100-point scale (the MC score). Metacritic includes in its 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) and virtually all video games commercially released in the same time period, provided that the game received at least a few reviews in the sources from which Metacritic draws reviews for video games. Although Metacritic collects data on video games released on a number of different platforms, including personal computer games, traditional console video games, as well as handheld devices, we limit the video games included in our sample to those released for personal computers and video game consoles (including Sony’s Playstation 3 and Playstation 4, Microsoft’s Xbox 360 and Xbox One, and Nintendo’s Wii U).

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.
For each product in our sample, our data include the product name and release date. For each review, we have the MC Score assigned to the review by Metacritic, as well as the outlet in which review was published. Until late 2009, Metacritic did not provide any information on the publication date of reviews, and did so only inconsistently through 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 those reviews for which Metacritic has recorded a review date. Additionally, for film reviews, we know the name of the critic that wrote the review. For video games, however, Metacritic does not collect the name of the critic but instead attributes the review to the publication.

We then construct the set of all review dyads for each product. We limit our sample to only those dyads where the critics have reviewed at least 5 of the same products as well as to those dyads where there is variation on observability (the critics have released reviews both on the same day and on different days). Additionally, for convenience in calculation, we restrict the sample of video game reviews to include only those published in an outlet that has at least 20 video game reviews included on Metacritic. We further restrict our sample to reviews that are published within a window around the product release date: for movies, we include reviews published from seven days prior to the product release through 14 days after; and for video games, we expand this window to seven days prior to the product release through 30 days after in order to accommodate the increased variation in video game review intervals. In unreported robustness checks, we relax these sample restrictions without any significant change in results. For movies, our level of analysis is the movie-dyad. For video games, the same game can be released on different platforms, but because of differences in platform characteristics, the game-
play experience can be different and therefore garner different reviews, so our unit of analysis is the game-platform-dyad.

**Variables.** We use two dependent variables in our analysis. *Difference* is calculated as the MC Score of the follower critic minus the MC Score of the lead critic and captures directional differences between the critics’ reviews. *Divergence* variable is the absolute value of the *difference* measure and is designed to capture simply the tendency to diverge or converge rather than any directional effects.

Our primary independent variable of interest is *Observe*, a dummy variable that takes a value of 0 if the two reviews for a product in the dyad were published on the same day and a value of 1 if the reviews were published on different days. Dyad-movie observations where reviews for both critics are published on the same day constitute our control group. Dyad-movie observations where reviews for both critics are published on different days constitute the treatment group.

We also construct two variables as measures of competitive overlap at the pair level. *Review Overlap* is the log of the number of products reviewed by both of the critics within the pair during the 30-day period prior to the focal reviews. This measure is designed to capture the extent to which the product critics operate in the same niche. Similarly, for movie critics, we designate each publication as either national in scope or local. We then construct four dummy variables for each possible combination of national and local for the lead critic and the follower: *national-national*, *national-local*, *local-national*, and *local-local*. [This measure is designed to capture the relative status of each critic in the dyad.]
Additionally, in our analysis we use product fixed effects to control for the time invariant characteristics of the products and ordered pair fixed effects to control for time invariant characteristics of the critic pair.

Movie Critics Analysis

We proceed with our analysis of the movie critic setting. Table 1 reports descriptive statistics for the analysis sample for movie critic pairs.

[INSERT TABLE 1 ABOUT HERE]

Figure 9, a kernel density plot comparing the difference between a pair of critics’ reviews in the control condition to the treatment condition, provides preliminary evidence that social influence and competitive effects between critics impact their reviews. The observe condition curve, drawn in red, shows a slight shift to the left and a slight increase in variance when compared to the non-observe curve in blue. We interpret this figure to mean that the follower critic’s reviews, when able to observe the review of the lead critic, are different than when the follower is not able to observe the lead critic, with the following critic’s reviews being more negative than they would otherwise be. This preliminary evidence for H1b motivates our multivariate analysis of data.

[INSERT FIGURE 9 ABOUT HERE]

Table 2 provides regression results. Models 1A and 1B use the difference as the dependent variable. Model 1A is a simple OLS regression of observe on the difference and the coefficient shows a statistically significant negative effect of observation, suggesting that the follower critic’s reviews are more negative in the observe (treatment) condition, consistent with figure 9. Model 1B, which includes movie and pair fixed effects, yields a similar negative and
statistically significant coefficient. Models 2A and 2B repeat Models 1A and 1B, but with *divergence* as the dependent variable. Model 2A yields a positive and statistically significant coefficient on *observe*, suggesting that in the observe condition, follower critics are likely to diverge further from the lead than they would otherwise. In Model 2B, the coefficient on *observe* is slightly smaller, but still positive and statistically significant at the 95% levels. The results of each of these models provides support for H1b, that social influence and competitive pressures between critics leads a critic to diverge when the assessment of the other critic is observable.

[INSERT TABLE 2 ABOUT HERE]

[Include discussion of analysis of interactions with competitive overlap measures]

[INSERT FIGURE 11 ABOUT HERE]

**Video Game Critics Analysis**

Table 3 reports descriptive statistics for the analysis sample for video game critic pairs.

[INSERT TABLE 3 ABOUT HERE]

Figure 10, a kernel density plot reproducing Figure 9 but for the video game critic pairs, again provides preliminary evidence for social comparison and competitive effects in the video game critic setting. Consistent with Figure 9, the *observe* curve, drawn in red, shifts slightly to the left and shows an increase in variance when compared to the non-observe condition (in blue), suggesting that the follower critic’s reviews are more negative in the observe condition.

Table 4 provides regression results. Models 3A and 3B use the *difference* as the dependent variable. Model 3A shows a statistically significant negative effect of observation, consistent with Figure 9 and Model 1A above. Model 3B, which includes game and pair fixed effects, yields a larger negative and statistically significant coefficient. Models 4A and 4B repeat
use *divergence* as the dependent variable. Model 4A yields a positive and statistically significant coefficient on *observe*, suggesting that in the observe condition, follower critics are likely to diverge further from the lead than they would otherwise. In Model 4B, which includes game and pair fixed effects, the coefficient on *observe* is slightly smaller, but still positive and statistically significant. The results of our analysis of video game critics provide further support for H1b, that social influence and competitive pressures between critics leads a critic to diverge when the assessment of the other critic is observable.

[INSERT TABLE 4 ABOUT HERE]

[Include discussion of analysis of interactions with competitive overlap measures]

[INSERT FIGURE 12 ABOUT HERE]

**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 find support for our hypothesis that a critic may be incentivized to diverge from the assessment of another critic in both the movie and video game industries. Additionally, competitive overlap moderates the social influence effects.

One assumption underlying any causal interpretation of our analysis is that the day on which the critics’ reviews are posted, and thus whether reviews of a particular product is categorized as in the control group rather than in the treatment group for the pair, 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 a critic (or the critic’s editors, perhaps), knowing that this particular review is going to be different from other reviews by the critic, elects to delay publishing the unusual review, but the critic is not otherwise responding to the reviews of others. Still, even if this is the case, it demonstrated strategic action on the part of critics.

Additionally, 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.

[Discuss implications and future directions].
REFERENCES


### Table 1

**Descriptive Statistics for Movie Critic Pairs**

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<th>Mean</th>
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<th>Max</th>
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<td>Divergence (absolute difference)</td>
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### Table 2

**Multivariate Regression Estimates of Observability on Difference and Divergence for Movie Critic Pairs**

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<th>Model 2A Divergence</th>
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<td>Intercept</td>
<td>0 (0.08)</td>
<td>3.73 (2.57)</td>
<td>16.988** (0.05)</td>
<td>13.527 (1.63)</td>
</tr>
<tr>
<td>Movie fixed effects</td>
<td>N Y</td>
<td>N Y</td>
<td>N Y</td>
<td>N Y</td>
</tr>
<tr>
<td>Pair fixed effects</td>
<td>N Y</td>
<td>N Y</td>
<td>N Y</td>
<td>N Y</td>
</tr>
<tr>
<td>N</td>
<td>158461</td>
<td>158461</td>
<td>158461</td>
<td>158461</td>
</tr>
<tr>
<td>R2</td>
<td>0.001</td>
<td>0.018</td>
<td>0</td>
<td>0.072</td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01.

* Standard errors are in parentheses
**Table 3**

**Descriptive Statistics for Video Game Critic Pairs**

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference</td>
<td>562287</td>
<td>-1.05</td>
<td>13.67</td>
<td>-88.00</td>
<td>80.00</td>
</tr>
<tr>
<td>Divergence (absolute difference)</td>
<td>562287</td>
<td>10.01</td>
<td>9.37</td>
<td>.00</td>
<td>88.00</td>
</tr>
<tr>
<td>Observe</td>
<td>562287</td>
<td>.73</td>
<td>.44</td>
<td>.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Ln (review overlap)</td>
<td>562287</td>
<td>2.52</td>
<td>.87</td>
<td>.00</td>
<td>4.71</td>
</tr>
</tbody>
</table>

**Table 4**

**Multivariate Regression Estimates of Observability on Difference and Divergence for Video Game Critic Pairs**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 3A Difference</th>
<th>Model 3B Difference</th>
<th>Model 4A Divergence</th>
<th>Model 4B Divergence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observe</td>
<td>-1.428 **</td>
<td>-2.322 **</td>
<td>0.336 **</td>
<td>0.246 **</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0</td>
<td>2.692 **</td>
<td>9.763 **</td>
<td>10.951 **</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.06)</td>
<td>(0.02)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Game fixed effects</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Pair fixed effects</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>562287</td>
<td>562287</td>
<td>562287</td>
<td>562287</td>
</tr>
<tr>
<td>r2</td>
<td>0.002</td>
<td>0.02</td>
<td>0</td>
<td>0.14</td>
</tr>
</tbody>
</table>

* *p < .05; **p < .01.*

* Standard errors are in parentheses
FIGURE 3

Game Review Intervals

Days from Game Release

FIGURE 4

Cheat Code Central
Game Review Intervals

GameSpot
Game Review Intervals

Days from Game Release
FIGURE 11

Reviewing Overlap (ln)

No Observation
Observation

Movie Review Score Difference

Natl-Natl  Natl-Local  Local-Natl  Local-Local

Publication Match (Leader - Follower)

Movie Review Score Divergence

Game Review Score Difference

Game Review Score Divergence

FIGURE 12