Competition and Influence between Critics

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ABSTRACT

Are information intermediaries subject to competitive pressure and influence from each other? How does this impact their published reviews? Our study provides evidence that film and video game critics, unlike securities analysts whose forecasts tend to converge on those of other analysts, differentiate from each other. Using reviews posted on Metacritic.com for movies and video games, we examine the differences between reviews by critics when they are published on the same day and when one critic publishes a review after the other. Our within-product and within-critic analyses suggest that critics are more negative than they would otherwise be when they can observe the reviews of other critics. This effect is heightened as the competitive overlap between the critics increases.

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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 as proxies for underlying product quality. Information intermediaries themselves, however, compete in a market for information. To what extent, then, are information intermediaries subject to competition and influence from other information intermediaries, and how do these processes impact their published opinions?

If information intermediaries are indeed influenced by other information intermediaries, research on competition and social influence suggests that they face two opposing forces: pressure to converge on the opinions of others and pressure to diverge from the opinions of others. Convergence may ease the cognitive burden inherent in developing opinions in a complex and uncertain context (Festinger, 1954), may help them establish or maintain legitimacy with peers and others (Zuckerman, 1999), and may buffer them against potential negative consequences of differentiating and being wrong (Hong, Kubik, and Solomon, 2000; Scharfstein and Stein, 1990). Differentiating may help them signal a unique identity (Zuckerman, 2015) and reduce competition by allowing them to establish a niche or unique position within the market (Seamans and Zhu, 2013; Wang and Shaver, 2013).

Research on securities analysts, considered a prototypical information intermediary (Zuckerman, 1999), generally finds that they tend to converge on the assessments of other analysts (Hong *et al.*, 2000; Jegadeesh and Kim, 2010; Kadous, Mercer, and Thayer, 2009; Welch, 2000) and multi-point competition between them may reduce the accuracy of their forecasts (Baum, Bowers, and Mohanram, 2015). Research on online consumer reviews suggests that they tend to become more negative over time, potentially in reaction to the reviews of others (Chintagunta, Gopinath, and Venkataraman, 2010; Godes and Silva, 2012;

Kovacs and Sharkey, 2014; Li and Hitt, 2008; Moe and Trusov, 2011). In these prior studies, it is difficult to separate the baseline and unobserved similarities or differences in the strategic actors from any competitive or influence effects. Consequently, accurately estimating the magnitude of any effects, or even whether social influence and competition have any effects, is extremely difficult. It may be the case, for instance, that sets of information intermediaries have a tendency to like or dislike certain products because their underlying tastes are very similar. Underlying unobserved similarities may, therefore, actually be the cause of the effects rather than the social and competitive processes under investigation.

In this paper we attempt to examine the effects of competition and social influence on critical evaluations using variation in the ability of information intermediaries to observe one another's assessments—based on the publication date of the assessments—in order to minimize the impact of unobservable factors in our analysis. Our study explores these social influence and competition using reviews by professional product critics in two settings—the film and video game industries—which provides some confidence that our results are not simply artifacts of a single sample (Goldfarb and King, 2013). Our first set of analyses examines the general trend of reviews of a product over time. Holding the characteristics of products constant, and conducting within-critic analyses, we find that when a critic releases a review later and the reviews of other critics are observable, the review is more negative relative to the other published reviews than when the same critic publishes reviews earlier in the product release cycle. We then construct critic dyads to examine competition and influence between individual critics. We use the differences between the reviews of two critics when the reviews are published simultaneously as a baseline. We then explore how the differences between the two critics diverges from the baseline when one critic in the pair publishes a review after the other and the review of the first is therefore observable. Again, for both film and video games, we find that when the review of another critic is observable, the following critic produces a review that is more negative than we would otherwise expect. The effect is stronger as the number of products that both critics review increases and when the leading critic publishes in an outlet that is the same or higher status as the following critic.

The results of our analyses suggest that product critics do indeed react to competitive pressures. In contrast to prior studies on securities analysts, we find that product critics tend to differentiate in their opinions when the critics have information about the opinions of other critics. This suggests a difference in incentives between securities analysts and product critics, perhaps because analysts operate in a market where their predictions can be evaluated against objective market outcomes and product critics operate in markets where their opinions are subjective and seen as a matter of taste (Waguespack and Salomon, 2015; Zuckerman, 2012). Interestingly, we find little evidence that observability results in an increase in the absolute divergence of reviews, as traditional models of competitive behavior would suggest (see, e.g., Alcácer et al. 2015). Instead, our finding that observing the reviews of others induces critics to produce reviews that are more negative than they would otherwise be is consistent with research on the dynamics of online consumer reviews, though those studies do not address competitive interactions among professional reviewers. Consequently, our study suggests that the published reviews of professional product critics may not accurately reflect the unbiased opinions of the reviewers based solely on the characteristics of the products they review. Instead, the information is potentially biased due to competition and social influence among the critics themselves.

In the next section, we develop our hypotheses regarding the social influence and competitive pressures that information intermediaries face. We then describe our data and empirical design and present our results. Finally, we discuss the contributions of this study to our understanding of social influence and competitive processes among information intermediaries and potential avenues for future research.

INFORMATION INTERMEDIARIES, SOCIAL INFLUENCE, AND COMPETITION

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, consequently, the subject of much scholarly research in a variety of disciplines that are concerned with how markets function and how value is determined. Much of the literature examining information intermediaries focuses on financial analysts, likely because of the importance and broad cross-disciplinary appeal of understanding the financial markets in which they operate, as well as the availability of data on both the analysts' assessments and the companies they follow (e.g., Baum et al., 2015; Hong et al., 2000; Zuckerman, 1999). The role of film critics in the movie industry has also received substantial scholarly attention (e.g., Chen, Liu, & Zhang, 2011; Eliashberg & Shugan, 1997; Hsu, 2006a, 2006b; Wanderer, 1970). Additional research examines product critics in a number of industries, including music (Salganik, Dodds, and Watts, 2006; van Venrooij, 2009), cuisine (Rao, Monin, and Durand, 2003), performing arts (Shrum, 1991; Uzzi and Spiro, 2005), books (Kovacs and Sharkey, 2014; Sun, 2012), and wine (Benjamin and Podolny, 1999; Hsu, Roberts, and Swaminathan, 2012; Malter, 2014; Zhao and Zhou, 2011).

Assessments by Information Intermediaries

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 of product critic reviews is generally taken as a measure of the underlying quality of the product (Sun, 2012; Waguespack and Sorenson, 2011). The degree of consensus in reviews, typically measured by the variance in assessments of a given product across critics, provides information about the product (including an indication of whether the product is general audience or niche product (Sun, 2012) or the extent to which the product conforms to norms and expectations in the market (Hsu, Hannan, and Koçak, 2009; Hsu, 2006a, 2006b; Zuckerman, 1999)) or about the market (generally the extent to which market categories themselves are established and legitimized (Bowers, 2014; Hsu *et al.*, 2012; Mizruchi, Stearns, and Fleischer, 2011; Negro and Leung, 2012)).

Information intermediaries' assessments are not only shaped by the match between their individual information and tastes and the underlying attributes of the products they evaluate but also by the market and social context in which they operate. For example, Vaaler and McNamara (2004) find that turbulence in a credit rating agency's external environment impacts the ratings that the agency issues, with turbulence leading to more negative reviews. Additionally, the status of those associated a product can impact the information that intermediaries provide. Waguespack and Sorenson (2011) find that films from high status directors and producers receive more favorable ratings from the Motion Picture Association of America, an independent content rating agency, controlling for content. Vaaler and McNamara (2004) find that as the relative status of credit rating agencies decline, their ratings of companies become more negative. Kovacs and Sharkey (2014), find that after books win high-status awards, they receive more attention from reviewers, but the reviews are more negative.

Studies showing that product critics respond to social contexts in generating their evaluations suggest that they may also be subject to social influence and competitive forces from other critics. For example, Baum et al. (2015) find evidence that competing stock market analysts will strategically reduce their competitive intensity with rivals as the number of companies that they both simultaneously follow increases. This strategic practice, known as mutual forbearance (Edwards, 1955), leads analysts to exert less effort and produce less accurate forecasts.

If product critics are indeed influenced by other product critics, research on social influence and competition suggests that they face two opposing forces: pressure to converge on the opinions of others and pressure to diverge from the opinions of others. Ab initio, it is not clear whether these forces will ultimately lead them to converge or to differentiate in their assessments.

Convergence Pressures.

Product critics, as social actors engaged in the business of producing evaluations, likely face psychological pressures to conform their opinions to others'. Foundational work in social psychology suggests assessments can become biased simply by exposure to others' assessments (Asch, 1951; Festinger, 1954). For example, experiments on the "wisdom of the crowds," in which the aggregation of naïve and inexperienced assessments are more accurate than the assessments of experts (Surowiecki, 2005), show that the effect is extremely sensitive to bias because of social influence. The wisdom of the crowds effect relies on the independence of each of the naïve assessments; once the assessors are exposed to even minor information regarding the opinions of others, their own assessments anchor on the guesses of others rather than on their independent private beliefs, and the overall aggregate assessment is easily biased (Lorenz *et al.*, 2011). 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 is particularly prevalent as evaluation becomes increasingly subjective or cognitively challenging—such as in markets for cultural goods (Festinger, 1954). Salganik et al. (2006) present results of an online experiment that tests the effect of social influence in a constructed market for music. Using various experimental manipulations, their study shows that market participants with access to information about the behavior and opinions of others, even if that information was randomly constructed, were more disposed to like songs for which others expressed a preference. In experimental manipulations, exposure to the opinions of others generally leads to convergence in assessments and opinions. This "pressure toward uniformity" may arise from psychological anchoring processes (Festinger, 1954: 126), an overemphasis of publicly available information from the expressed opinions of others at the expense of private information (Bikhchandani, Hirshleifer, and Welch, 1992), or a desire to belong to, and gain legitimacy within, a group (Navis and Glynn, 2011).

As strategic actors, product critics are also likely to face pressures to converge on the strategic positions of others. Prior research suggests that strategic similarity increases legitimacy, which in turn facilitates resource acquisition: strategic uncertainty leads to mimetic behavior, as competitors imitate successful strategies (Haveman, 1993), thereby reducing uncertainty (DiMaggio and Powell, 1983) and increasing the possibility for positive resource spillovers (Almeida and Kogut, 1999; Baum and Haveman, 1997). The legitimacy of actors that do not converge on strategic norms may be challenged, reducing their ability to obtain resources from potential exchange partners (DiMaggio and Powell, 1983).

Empirical examinations of stock market analysts commonly show convergence in assessments. 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 or recommendations of other analysts (e.g., Bernhardt et al. 2006, Conrad et al. 2006, Hong et al. 2000, Jegadeesh and Kim 2010, Kadous et al. 2009, Ramnath et al. 2008, Welch 2000). Many of these studies suggest that herding behavior leads to suboptimal outcomes since the private information of individual analysts is not sufficiently weighted.

Divergence Pressures.

Social actors face pressures to diverge from others. Festinger (1954) suggests that there are circumstances where exposure to the opinions of others does not lead to convergence in opinions. For example, if baseline differences between actors are sufficiently large, the basis for comparison between the actors becomes small and social influence pressures may be attenuated. Moreover, when an actor perceives that the underlying differences between that actor and another are consistent with their divergence in opinions, social influence effects between the two may lead to nonconformity and increased divergence in opinions.

Consistent with Festinger's (1954) theoretical propositions on divergence, social science research identifies a number of situations in which actors may seek to diverge from those around them. Individuals may want to distinguish themselves from others who are of low status (DiMaggio and Powell, 1983). They may seek to differentiate themselves from groups that they dislike (Bryson, 1996). They may also seek to differentiate even from similar others simply because they possess a psychological need for uniqueness (Snyder and Fromkin, 1977). Berger and Heath (2008) propose, and find support in a variety of experiments, that "people often diverge to avoid sending undesired identity signals to others" (p. 595). The common theme across this research is that individuals diverge in order to signal a unique identity to others.

In addition to signaling uniqueness, classic strategic competition research suggests that differentiation can reduce competition, which may lead to performance benefits (Barney, 1991; Porter, 1991). Strategic similarities can heighten competition for resources, including from suppliers and customers, and differentiation may occur, then, as competitors reposition or specialize in order to focus on niches with more favorable resource environments (Carroll, 1985). Increased competition in an existing strategic position can drive differentiation as competitors look for new and less contested market opportunities. For example, (Greve, 1996) finds strategic repositioning and differentiation by radio stations when they convert their formats to new music genres. Research also suggests that strategic actors have heterogeneous resources and capabilities, which lead to different returns to given strategic positions for different actors (Barney, 1991). Exploiting the opportunities presented by unique bundles of resources and capabilities may subsequently lead firms to pursue different strategies (Thomas and Weigelt, 2000). Path dependent processes that begin with baseline heterogeneity in resources and capabilities among competitors, therefore, may provide some explanation for increased differentiation in positioning among actors over time.

Optimal Distinctiveness and Strategic Balance.

Actors faced with simultaneous pressures to converge and diverge must balance the two in choosing how to act. Prior literature suggests that there is an ideal level of distinctiveness for an individual, where the individual is similar (but not too similar) and different (but not too different) from other actors in order to appropriately signal both membership and a distinct identity within a group (Chan, Berger, and Van Boven, 2012; Zuckerman, 2015). Successful strategic actors, therefore, balance the two pressures by achieving a level of “optimal distinctiveness” (Brewer, 2003), “legitimate distinctiveness” (Navis and Glynn, 2011), or “strategic differentiation” (Deephouse, 1999). Empirical studies find evidence of this balancing in a number of industries, including the Chinese satellite television industry (Wang and Shaver, 2013), the newspaper classified advertising industry (Seamans and Zhu, 2013), the hotel industry (Baum and Haveman, 1997; Chung and Kalnins, 2001), the automotive industry (Thomas and Weigelt, 2000), and management consulting industry (Semadeni, 2006).

Prior literature suggests that the net impact of the pressures to converge and differentiate, which determines whether actors become more or less similar to others, arises from the incentives inherent in each situation. When dominant competitors enter markets, existing competitors tend to differentiate (Seamans and Zhu, 2013; Wang and Shaver, 2013) in order to decrease competition. In their study of the automobile industry, Thomas and Weigelt (2000) find that existing and established firms in the automotive industry tend to position new products away from their existing products and away from those of rivals. New entrants and foreign manufacturers, however, position new products close to those of rivals in order to gain the benefits of increased legitimacy. Similarly, in an examination of service marks in the managing consulting industry, Semadeni (2006) finds that new and small firms locate nearer to older films, while older firm tend to relocate farther away from others, suggesting that the benefits to these firms of decreased competition outweigh those of legitimacy. Likewise, by changing incentives associated with unique competitive positions of individual financial analysts, economic models suggest that the net effect of social influence and competition may lead to anti-herding when herding might otherwise occur (Bernhardt *et al.*, 2006). Indeed, empirical evidence suggests that differentiation by individual stock market analysts increases as analysts gain seniority (Hong *et al.*, 2000) and when career prospects increase with nonconforming forecasts (Effinger and Polborn, 2001).

We expect that a product critic, therefore, will face simultaneous pressures both to converge and to diverge from the assessments of another critic. It is not obvious, however, if the net effects will be toward convergence or divergence. A product critic may seek legitimacy or to ease the cognitive burden of producing reviews by converging on the opinions of others. Prior research on product critics, including stock market analysts, has suggested that information accuracy is a key dimension on which they compete (Lys and Soo, 1995). In settings where information accuracy cannot be objectively verified, a critic's reputation as an expert may be "based on his ability to justify the merit of the criteria he offers for discriminating value" (Hsu, 2006a: 470). A product critic, therefore, may converge on the observed opinions of another critic in order to enhance legitimacy or to avoid any legitimacy challenges that might accompany divergent opinions. Festinger's (1954) social influence theories suggest that there is a high cognitive burden associated with generating reviews in settings where quality is uncertain or subjective, and this may further lead a critic to converge on the observed opinions of another critic.

On the other hand, the divergence pressures may outweigh convergence pressures. Stock market analysts operate in a setting where the information they provide will ultimately subject to objective verification. The penalties associated with following the opinions of others and being wrong are less severe than those associated with deviating and being wrong, which provides an incentive for analysts to converge (Hong and Kubik, 2003). Other product critics, however, provide information that is essentially subjective and a matter of personal taste. In such settings, they cannot be wrong and are not likely to face the same pressure to converge. Differentiating, therefore, may allow the critic to create a unique identity or to occupy a unique position in the marketplace and thereby garner more attention from resource providers. As a result of this, a critic may, when the opinion of the other critic is observable, diverge from the other's opinion.

Consequently, we present the following competing hypotheses:

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

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

Competitive Overlap.

Consistent with prior literature on social influence and competitive differentiation, we expect that product critics do not respond to social influence and competitive pressures from all other critics equally. Social influence theory suggests that actors are more likely to compare themselves and be influenced by similar others (Festinger, 1954). To the extent we see convergence on the opinions of another critic, we would therefore expect that the convergence effect would be stronger as the similarity between two critics increases. Conversely, optimal distinctiveness theories suggest that actors may also have an incentive to differentiate from similar others in order to establish a distinct identity (Zuckerman, 2015). Similarly, research on competition suggests that as the overlap between two actors increases, the competition for resources intensifies, which increases the likelihood that the actors will differentiate (Seamans and Zhu, 2013; Semadeni, 2006; Wang and Shaver, 2013). Therefore, we would expect that a higher degree of similarity between two critics would enhance the pressures to diverge and lead to increased differences in opinions.

Consequently, we present the following competing hypotheses:

> ***Hypothesis 2a (H2a)****: The similarity between the assessments of products by two critics will increase more as the similarity between the two critics increases.*

> ***Hypothesis 2a (H2b)****: The difference between the assessments of products by two critics will increase more as the similarity between the two critics increases.*

EMPIRICAL STRATEGY

We test our hypotheses in two empirical settings: reviews by professional critics of theatrically-released films and reviews by professional critics of video games released for the personal computer and console game segments. The movie and video game industries provide appropriate settings for our study because they are relatively simple markets with fairly standardized products and there are a large, but still limited, number of critics and publication outlets for their reviews. Product critics in the entertainment industries, like other intermediaries, produce evaluations of another's products in order to guide consumer purchases. We assume that professional critics are motivated by a desire to produce reviews that are deemed uniquely valuable by the public, such that demand for the publications and websites that employ them is increased—a challenging task because critics have limited time to assess the products and because consumer tastes are ex ante uncertain. We therefore surmise that professional critics balance pressures towards uniqueness and conformity with respect to their peers.

In an ideal experiment we would assign professional critics to review products. We would then randomly manipulate whether each critic could observe the opinions of other critics before they delivered their own assessment. Our baseline expectation is that critics come to the reviewing task with different preferences, endowments, capabilities, and target niches, and thus will naturally vary in their evaluations. We would thus expect critics to differ in their opinions even absent social influence effects, and the control "no observation" condition would allow us to establish a baseline level of natural variance on critical opinions. The social influence effect, if any, would be revealed in the difference between reviews where the critic could observe others—the treatment "observation" condition—and the control condition. A natural extension of this mode of inquiry would be manipulating the ability of the focal critic to observe reviews from particular peers as opposed to just the extant global evaluation. In the pairwise analysis, the marginal effect of social influence/competition would again come from comparing paired reviews in the treatment and control conditions. Then, by manipulating the competitive salience across reviewer pairs, we could assess whether competition intensifies or moderates review variance.

As a feasible research design, we employ data on reviews from Metacritic.com, a website that aggregates reviews for nearly all theatrically released movies in the United States and for nearly all videogames that are reviewed by multiple publications. As explained in the following section, we collected data on the publication date, critic name, product name, and numerical review score for movies and games. We can thus compare any single review for a single product to all reviews preceding it, allowing us to assess whether reviews vary as a function of available critical opinions. We can also construct critic dyads, looking at differences in numerical scores when the reviews are filed simultaneously (the control condition) as opposed to when one critic follows the other (the treatment condition).

Relative to the ideal experiment, however, an observational study of this sort has several important drawbacks. Most importantly, 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, in the dyadic case, critics are likely to respond to the totality of observable reviews, rather than solely to the reviews of other specific critics.

These drawbacks notwithstanding, we contend that empirical regularities in the review process in both the film and video game setting allow us to rigorously explore social influence and competitive forces operating between critics. Most importantly, nearly all reviewers exhibit variance on the day, relative to the release date of the movie or video game, on which their reviews are published. As a consequence, for any individual or any pair of reviewers, there is natural variance on the ability to observe what others are doing. This contrast is sharpest in the dyadic scenario: when two critics publish reports on the same day, neither is able to observe the other's review, and variance in conclusions cannot reflect social influence. By contrast, when two critics publish on different days, the critic publishing later has the opportunity to adjust his conclusions in response.

In the following section, we describe the data and our analytical results for film and video game reviews.

DATA AND RESULTS

We collected all movie and video games reviews posted on Metacritic.com (hence MC) from its inception through December 31, 2014, a sample which includes 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). The aggregated reviews do not represent the entire universe of critic reviews for each product but rather only those from a select group of sources that MC deems to be high quality. Prior to late 2010, MC did not publish the date on which the review was published. The publication date is central to our empirical strategy for assessing influence via observation, and as such, our sample is limited to the post 2010 period.

Certain empirical regularities in the review process are critical to our research design. First, there are dominant product release patterns in both industries, with 87.6% of movies theatrically released on a Friday, and 75.7% of games digitally released on a Tuesday. Second, and perhaps as a consequence of crowding around product release days, there is seemingly natural variance in when reviews for a given product are published online. Figure 1 shows the review intervals (the number of days between the product release date and each review) for all films and all video games in our analysis sample. In both cases, reviews are most frequently published near the product release date and the frequency then diminishes over time with regular weekly cycles. Video game reviews evidently occur more frequently after the product release date than do those for movies, and they are more dispersed over time. We interpret this figure to mean that individual reviewers are constrained by both the number of reviews they are able to produce in a given week and by the publication space available, and therefore there is individual variance on when opinions are revealed.

[INSERT FIGURE 1 ABOUT HERE]

In addition to review publication date and film release date, several other data items are important. Each review in our analysis sample contains a product name, critic name (for movies only—video game reviews are unattributed), source publication, and review score. Movie name, critic name, and publication date allow us to establish reviewer/product dyads and establish whether the reviews are published on the same day. The review score (the MC score) is assigned by MC and has a 100-point scale, ranging from terrible (0) to excellent (100).[†]

† If the critic uses a standard scale for rating products (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 may adjust the score if the critic disagrees with the assigned score.

Review Analysis

Table 1 presents descriptive statistics for film and video game reviews. To produce the movie sample we selected all reviews published from 2011 through 2014, published from 7 days before to 14 days after the movie's release date, for movies with at least 20 reviews, and from critics with at least 20 total reviews. These sampling criteria result in 16,243 reviews for 556 unique movie titles and 231 unique critics. To produce the game sample, we selected all reviews published from 2011 through 2014 for console games (PC, PlayStation, Wii, Xbox), published from 14 days before to 42 days after the game's release date, for games with more than 40 reviews, and from publications with more than 40 reviews. These sampling criteria result in 22,451 reviews for 407 unique game titles and 176 unique publication sources. Note that unlike it does for movie reviews, MC only lists the name of the source publication and not the individual critic for game reviews.

[INSERT TABLE 1 ABOUT HERE]

Dependent Variables. We use two dependent variables in our review-level analysis. *Score* is the numerical score reported in the review, while *Score Divergence* is the absolute value of the difference between the focal review score and the average score for the product. In comparing across samples, it is evident in Table 1 that game reviews have substantially higher average critical scores and lower variance.

We use two dependent variables in our analysis because it is not clear theoretically whether review deviance is better measured directionally (the direction in which score changes) or as an absolute value (distance from the mean in either direction). A directional measure will miss changes in score variance that occur with equal weight both positively and negatively, while an absolute measure will miss directional shifts where variance in the distribution does not change. We note that the marketing literature tends to use directional measures (e.g., Chen et al. 2011, Godes and Silva 2012, Li and Hitt 2008), while the finance literature tends to use absolute measures (e.g., Hong et al. 2000, Jegadeesh and Kim 2010, Kadous et al. 2009, Welch 2000). We use both in our analyses.

Independent Variables. The two independent variables of interest in the review-level analysis are *Post-Release Review*, which is a dummy variable indicating the review was published after the product release, and *Review Day Interval*, which indicates the precise day relative to the product release date that the review was published. For instance, a *Review Day Interval* of -2 means that the review was published two days before the release, while a 2 means two days after. As suggested by Figure 1, there are some important differences with respect to review timing across the two industries, with video game reviews more likely to occur after the release date and to have greater temporal dispersion than movie reviews.

[INSERT TABLES 2 AND 3 ABOUT HERE]

Results. Tables 2 and 3 report regression results for movie reviews and game reviews, respectively. Each model in Tables 2 and 3 includes fixed effects for *Product* and for *Critic* (based upon website for game reviews), and as such we interpret coefficients of interest as within product and within subject effects. In models 2A and 2B for movie review scores, we find that, controlling for fixed product and critic attributes, review scores decrease *Post-Release* and in a consistent manner over time (as evidenced by the quadratic term for *Review Day Interval*). A similar but more pronounced effect is found for game reviews in models 3A and 3B.

[INSERT FIGURE 2 ABOUT HERE]

The left panel of Figure 2 graphically displays the marginal effect of the quadratic term for *Review Day Interval* for review *Score*. The general downward trend for review score in both movies and games is consistent with prior findings, particularly in the marketing literature, that consumer product review scores decrease over long periods of time (Godes and Silva 2012, Kovacs and Sharkey 2014, Lee et al. 2015, Moe and Trusov 2011). We find that review scores decrease longitudinally, on average, for professional critics, even over relatively short durations. The literature on consumer reviews suggests two primary mechanisms behind the observed negative trend. First, lab studies suggest reviewers who publish negative reviews are seen as more competent and discerning than those who publish positive reviews (Schlosser, 2005). Second, consumers self-select the order in which they consume products, with those who possess a higher probability of liking a product choosing to consume it first, and therefore providing positive reviews early, and those with a lower probability of liking a product choosing to consume it later (potentially based on the early positive reviews), and therefore providing more negative reviews later (Kovacs and Sharkey, 2014; Li and Hitt, 2008). Critic fixed effects give us some confidence that the negative trend we observe does not simply represent a tendency of innately more negative critics to register their opinions later. Models 2C, 2D, 3C, and 3D run the same regressions for *Score Divergence*, and find similar, if somewhat weaker, effects. The right panel on Figure 2 shows those results graphically.

In summary, we find that professional reviews, within product and within critic, for both movies and games become more negative and slightly more clustered over time. These results are suggestive of social influence and competitive mechanisms where pressure to differentiate induces intermediaries to behave differently than they otherwise would. Timing issues are important here, and the precise mechanisms—whether “natural delays” induce observation effects or whether “expected deviance” induces delays in revealing an opinion—are impossible to distinguish in an observational setting. Nonetheless, the results are consistent with findings in the consumer opinion literature and the financial analyst literature, as well as consistent with anecdotal evidence, that peer contagion is a concern amongst professional critics.

A natural extension of the social influence effect is to ask whether critics pay more attention to some peers than others, and we turn to this question in the following section.

Review-Pair Analysis

We next constructed ordered dyads for all critics reviewing each product from the samples used in the review-level analysis above. Conceptually, we treat each pair as comprised of a leading critic (A) and a following critic (B) for a given product (P). We keep any pairs where both reviews occurred on the same day (keep AB_P and BA_P), or where the following critic performs a review one or more days after the lead critic (keep AB_P, drop BA_P). For each ordered pair, we examine how evaluations differ when the critics in the ordered pair publish their evaluations simultaneously compared to when they publish their evaluations sequentially and the following critic can observe the opinion of the leading critic. The 16,243 film reviews in our analysis sample expand to 302,694 leader-follower dyads, and the 22,451 game reviews expand to 730,528 leader-follower dyads. Table 4 presents descriptive statistics at the review-pair level.

[INSERT TABLE 4 ABOUT HERE]

Dependent Variables. We again use two dependent variables in our analysis. *Score Difference* is calculated as the MC Score of the following critic minus the MC Score of the leading critic and captures directional differences between the critics' reviews. *Score Divergence* is the absolute value of the *Score Difference*, and is designed to capture the absolute tendency to diverge or converge rather than directional effects. The average divergence in the movie sample is 17 points, where 20 points is equivalent to a one star difference on a five star scale. The spread is narrower on games, at just under 10 points.

Independent Variables. 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-product observations where reviews for both critics are published on the same day constitute our control group. Dyad-product 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. *Prior Overlap* is the percentage of products reviewed by the following critic in the prior quarter that were also reviewed by the leading critic. 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 source publication as either national or local in scope. We then construct four dummy variables for each possible combination of national and local for the leading critic and the following critic: *national-national*, *national-local*, *local-national*, and *local-local*. This measure is designed to capture the relative status of each critic in the dyad. An equivalent measure of audience aspiration does not, unfortunately, exist in the games setting.

[INSERT TABLES 5 AND 6 ABOUT HERE]

Results. Movie review pair regression results are provided in Table 5, and game review pair results in Table 6. The primary pair level models also include fixed effects for *Critic Pair* and *Product*, and therefore we again interpret the coefficients of interest as within product and within subject-pair effects. All estimations also include fixed effects for *Lead Review Day*, or the day relative to product release when the lead review was published, in order to de-trend simple timing effects related to the likelihood of observation.

Models 5A – 5B and 6A – 6C use *Score Difference* as the dependent variable. In simple estimations (5A and 6A), *Observe* is associated with a more negative following critic review. For movies, the average effect is a modest drop of roughly half of a star, on a five star scale, in one of ten cases for the following critic (-.93 ~= -10/10). For games, the effect is larger, with an expected decrease of half a star in one of three cases for the following critic (-2.98 ~= -10/3). Relative to the average absolute divergence within pair seen in each sample, the average influence of observation on the difference in review scores may seem small, but we regard this as an estimate of the lower bound in that professional reviewers are likely to already have staked out unique positions based on prior historical observations of others. In any case, and again regardless of the precise timing mechanism, there is a distinct difference within critic pairs under the observation and no observation conditions.

[INSERT FIGURE 3 ABOUT HERE]

Models 5B, 6B, and 6C explore whether the size of the *Observe* effects varies as a function of the amount of competitive overlap within the pair. These models drop *Critic Pair* fixed effects in order to examine pair level attributes. The top left panel of Figure 3 is based on model 5B and displays marginal effects for the interaction of *Observe* and the competitive overlap variables on *Score Difference* for movie reviews. In the first panel of Figure 3, it is clear that national/local status matters for social influence. Critics who publish in national publications (national critics) respond to other national critics (point 1), dropping an average of approximately 3 points for reviews when in the *Observe* condition. Critics who publish in local publications (local critics) likewise respond negatively to national critics (point 2), but there is no observable gap when a national critic follows a local critic (point 3), or a local critic follows another local critic (point 4). The top right panel of Figure 3 shows that when the leading critic's opinions are observable, as *Prior Overlap* (the percentage of movies that the following critic reviewed in the prior quarter that were also reviewed by the leading critic) increases, the reviews of the following critic become even more negative. The effect is substantial, with *Score Difference* increasing from roughly -.5 for reviewers with no prior overlap, to roughly -3.5 points for reviewers with identical portfolios.

[INSERT FIGURE 4 ABOUT HERE]

The left panel on Figure 4 examines the interaction effect of *Observe* and *Review Overlap* in reviews by video game critics. Video game reviewing differs in important ways from film reviewing. First, when compared to the film industry, there are relatively low barriers to entry for both game creators, as they can self distribute, and for game reviewers, as MC includes reviews coming from many publications that are purely electronic and have little history. Second, game review websites are not readily classifiable into national and local publications and, indeed, MC includes review summaries for reviews published on websites hosted outside the United States and written in languages besides English. More fluid entry and expanded geographic reach for game reviews likely results in noisier measures of competitive overlap. Perhaps reflecting this, in model 6B we find that the interaction of *Observe* and *Prior Overlap* is positive, indicating that score differences are reduced when overlap is greater. In model 6C, we restrict the sample to observations where both the leading and following publication reviewed 50 or more games in the prior quarter, with the goal of restricting analysis to the most established review websites. The interaction of *Observe* and *Prior Overlap* in model 6C is negative, consistent with that of model 5B for the movie industry. The left panel of Figure 4 shows that in the restricted game review sample, competitive overlap does enhance the negative effect of *Observe* on *Score Difference*, although not as strongly as in the movie setting.

[INSERT FIGURE 5 ABOUT HERE]

The results on *Score Divergence*, the absolute value of *Score Difference*, are less distinct. In model 5C, we find no statistically significant relationship between *Observe* and *Score Divergence*. In model 5D, and as displayed in the bottom panels of Figure 5, there are at best small increases in variance when local critics follow national critics (point 2), and small decreases when nationals follow locals (point 3). In model 6D, for game reviews we find a small increase, with a coefficient roughly 1/9 the size of the coefficient for *Score Difference*, for *Observe*. Notice that this coefficient is positive, indicating an increase in variance in the observation condition, in contrast to the review-level finding for games that variance decreases over product release time. Our explanation for this sign change is that the dyadic analysis can overweight on widely reviewed games with lower within game variance. When we re-run model 6D without game fixed effects, we in fact get a very small positive relationship between *Observe* and *Score Divergence* (note that when dropping game fixed effects for *Score Difference*, the coefficient on *Observe* remains negative and very close in size).

In summary, in the dyadic analysis within reviewing pair and within product we find that there are negative effects on evaluations when a critic can observe the evaluations of a peer, but there are, at most, only very small effects on the absolute score divergence. In other words, when a critic can observe the review of another critic, the critic tends to differentiate reviews by making them more negative than when the critic can't observe the other critic. But, there is little evidence that observing the reviews of another critic causes the critic to increase the absolute amount of difference between the critics. In movies, the differentiation effects increases based on the status distribution between the reviewers and increases as product space overlap increases. In video games, product overlap also magnifies differentiation but only when examining reviews published on websites with the largest presence.

DISCUSSION

In this paper we explore the social influence and competitive effects operating among product critics. We attempt to detect and measure any systematic bias in the reviews associated with these effects. We develop theoretical arguments for convergence and divergence pressures and find evidence that critics in both the movie and video game industries differentiate from the observable assessments of other critics by publishing reviews that are more negative than they otherwise would. There is no evidence, however, that observing the assessments of other critics leads to increased absolute divergence in reviews. We also find that competitive overlap enhances differentiation.

The differentiation we observe contrasts with the herding effect commonly found in analyses of stock market analysts (Hong *et al.*, 2000). It could be that financial analysts, whose forecasts can eventually be objectively measured against actual firm performance, face stiffer penalties if they deviate in their forecasts and are wrong (a mechanism proposed by Bikhchandani and Sharma (2000) to explain the herding of stock market analysts) than information intermediaries who operate in arenas where the information they provide can never—or will never—be evaluated against an objective standard. As Zuckerman (2012) suggests, perhaps the objective standard available in financial forecasting constrains social processes, and the lack of such a standard to provide market discipline (Waguespack and Salomon, 2015) in our context explains why we find that product critics seek to differentiate.

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 are 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 critic and critic-pair fixed effects 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 a particular review is going to be more negative than other reviews by the critic, elects to delay publishing the unusual review, but the critic is not otherwise responding to the reviews of others. Although this suggests a different mechanism than the ones we propose in this paper, systematically withholding divergent opinions also provides evidence of social and competitive processes between product critics.

Our data and empirical strategy also limit our analyses. We can only detect evidence of social influence within published reviews. It could be, however, that significant social influence and competitive effects actually occur at different stages in the reviewing 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. Additionally, since we are primarily interested in how critics influence each other, we use product fixed effects to control for all unchanging characteristics of the product. If we relax our fixed effects, potentially relevant characteristics of the films, but unobservable in our data—including how movies are marketed to and screened for critics, for example—could confound our results. Future research could explore the correlations and interactions between critic characteristics and product characteristics.

In summary, our study provides evidence that peer influence is a concern among professional product critics. In our context, social influence and competitive pressures to differentiate outweigh pressures to converge and lead information intermediaries to behave differently than they otherwise would. Our analyses suggest that critics in the film and video game industries publish reviews that are more negative than they otherwise would when they can observe the opinions of other critics. These results are consistent with the research on consumer opinions, which finds a negative trend in reviews for a product over time (Godes and Silva, 2012; Kovacs and Sharkey, 2014; Lee *et al.*, 2015; Li and Hitt, 2008; Moe and Trusov, 2011; Schlosser, 2005). Our results suggest caution in interpreting product reviews as simply reflecting assessments of the underlying characteristics of the product. Even in settings that employ blind reviewing, including for academic publications, it is critical that reviewers remain unaware not only of the identity of the product producer, but also of the identity and opinions of the other reviewers, in order to minimize bias associated with social comparison and competitive processes.

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Table 1

Review Descriptive Statistics

	Movie Reviews		Game Reviews	
	Mean	S.D.	Mean	S.D.
Score	61.57	20.55	78.42	14.05
Score Divergence	12.00	9.46	7.12	6.42
Post-Release Review	0.17	0.38	0.63	0.48
Review Day Interval	-0.14	3.46	6.91	10.81

16,243 movie reviews posted at Metacritic.com from 2011 – 2014, for reviews published 7 days before to 14 days after the movie theatrical premiere, for movies with 20+ reviews, and for critics with 20+ reviews. 22,451 game reviews posted at Metacritic.com from 2011 – 2014, for reviews published 14 days before to 42 days after the game release date, for games with 40+ reviews, and for publications with 40+ reviews. *Score Divergence* is the absolute value of the difference between the focal *Score* and the mean score for the product. *Post-Release Review* is a dummy variable indicating the review was published after product release. *Review Day Interval* measures the difference, in days, between the review publication date and the product release. For instance, a review published two days before product release has a value of -2 for *Review Day Interval*, while a review published two days after has a value of 2.

Table 2

Movie Reviews- Multivariate Regression Estimates of Review Score and Score Divergence

	Model 2A	Model 2B	Model 2C	Model 2D
	Score		Score Divergence	
Post-Release Review	-0.903*		-0.272	
	(0.37)		(0.22)	
Review Day Interval		-0.171*		-0.100*
		(0.07)		(0.04)
Review Day Interval Squared		0.011		0.006
		(0.01)		(0.00)
Constant	58.980**	58.696**	13.706**	13.548**
	(2.36)	(2.36)	(1.42)	(1.42)
Product Fixed Effects	Y	Y	Y	Y
Critic Fixed Effects	Y	Y	Y	Y
N	16,243	16,243	16,243	16,243
r2	0.459	0.459	0.078	0.079

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

* Standard errors are in parentheses

556 unique titles and 231 unique critics are present in the data.

Table 3

Game Reviews - Multivariate Regression Estimates of Review Score and Score Divergence

	Model 3A	Model 3B	Model 3C	Model3D
	Score		Score Divergence	
Post-Release Review	-2.983**		-0.505**	
	(0.15)		(0.10)	
Review Day Interval		-0.248**		-0.035**
		(0.02)		(0.01)
Review Day Interval Squared		0.004**		0.001**
		(0.00)		(0.00)
Constant	73.812**	73.304**	8.700**	8.549**
	(1.19)	(1.19)	(0.77)	(0.77)
Product Fixed Effects	Y	Y	Y	Y
Critic Fixed Effects	Y	Y	Y	Y
N	22,451	22,451	22,451	22,451
r2	0.586	0.587	0.149	0.149

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

* Standard errors are in parentheses

407 unique titles and 176 unique critics are present in the data.

Table 4

Review-Pair Descriptive Statistics

	Movie Review Pairs		Game Review Pairs	
	Mean	S.D.	Mean	S.D.
Score Difference	-0.11	21.98	-1.10	13.54
Score Divergence (abs diff)	17.02	13.92	9.91	9.29
Observe	0.57	0.50	0.75	0.43
Prior Overlap	0.36	0.22	0.36	0.18
National-National	0.04	0.20		
National-Local	0.18	0.38		
Local-National	0.17	0.38		
Local-Local	0.61	0.49		

Leading/following critic pairs for 16,243 movie reviews posted from 2011 – 2014, and for 22,451 game reviews posted from 2011 – 2014. *Observe* is a dummy variable with a value of 1 if the following critic posts at least 1 day after the leading critic, and a value of 0 if both reviews are published on the same day. *Prior Overlap* measures the percentage of the following critic's reviews in the prior quarter for products that were also reviewed by the leading critic. *National-National* indicates that the leading and following critics' reviews are both from national publications, while *Local-National* indicates the leading critic's review is from a local source while the following critic's review is from a national publication, and so forth.

Table 5

Movie Review-Pairs – Multivariate Regression Estimates of Pairwise Review Score Difference and Divergence

	Model 5A	Model 5B	Model 5C	Model 5D
	Score Difference		Score Divergence (abs diff)	
Observe	-0.934**	-1.428**	-0.019	0.019
	(0.11)	(0.43)	(0.07)	(0.27)
Prior Overlap		-1.272**		-1.602**
		(0.29)		(0.18)
Observe X Prior Overlap		-3.652**		0.003
		(0.37)		(0.23)
National-Local		-0.343		0.386*
		(0.27)		(0.17)
Local-National		0.783**		0.389*
		(0.27)		(0.17)
Local-Local		0.423+		0.696**
		(0.25)		(0.16)
Observe X National-Local		0.844+		-0.463+
		(0.44)		(0.27)
Observe X Local-National		2.689**		0.371
		(0.44)		(0.27)
Observe X Local-Local		2.612**		-0.206
		(0.41)		(0.26)
Constant	0.638	0.339	19.178**	17.317**
	(0.79)	(0.45)	(0.50)	(0.28)
Lead Review Day Fixed Effects	Y	Y	Y	Y
Product Fixed Effects	Y	Y	Y	Y
Critic Pair Fixed Effects	Y	N	Y	N
N	302,694	302,694	302,694	302,694
r2	0.016	0.006	0.066	0.003

+ $p < .1$; * $p < .05$; ** $p < .01$

* Standard errors are in parentheses

Table 6

Game Review-Pairs – Multivariate Regression Estimates of Pairwise Review Score Difference and Divergence

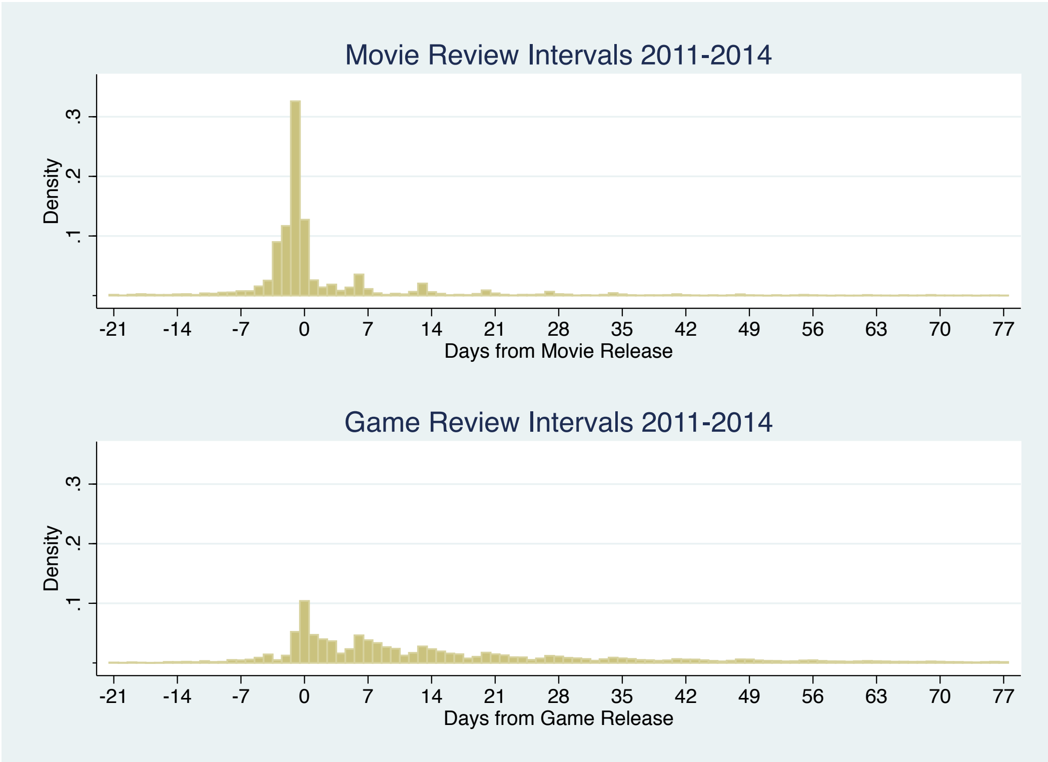
	Model 6A	Model 6B	Model 6C	Model 6D	Model 6E	Model 6F
	Score Difference			Score Divergence		
Observe	-2.320**	-2.164**	-1.299**	0.249**	0.784**	0.451**
	(0.04)	(0.08)	(0.19)	(0.03)	(0.05)	(0.12)
Prior Overlap		-2.001**	-2.957**		-0.717**	-1.127**
		(0.17)	(0.38)		(0.11)	(0.24)
Observe X Prior Overlap		0.563**	-1.181**		-1.100**	-0.282
		(0.20)	(0.44)		(0.13)	(0.28)
Constant	-1.293**	-1.961**	-2.194**	11.503**	8.475**	7.802**
	(0.44)	(0.35)	(0.59)	(0.30)	(0.23)	(0.37)
Lead Review Day FEs	Y	Y	Y	Y	Y	Y
Product FEs	Y	Y	Y	Y	Y	Y
Critic Pair FEs	Y	N	N	Y	N	N
N	730,528	730,528	197,032	730,528	730,528	197,032
r2	0.023	0.006	0.009	0.134	0.002	0.002

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

* Standard errors are in parentheses

Models 6C and 6F restrict analysis to cases where both leading and following review websites have performed 50 or more reviews in the prior quarter.

FIGURE 1



Distribution of review intervals—days before or after product release—for all reviews posted on Metacritic.com for movies and video games released from 2011 to 2014. 90% of movies are released on Friday, 8% on Wednesday, with the remainder distributed among the other days of the week. 39% of movie reviews are posted on a Thursday, and roughly 15% are posted, each day, on Wednesday, Saturday and Sunday. 53% of games are released on Tuesdays, followed by 12% to 14% each on Wednesday, Thursday and Friday. Game reviews are posted relatively equally throughout weekdays, with 15% to 21% per day, and are sparse on weekends, at 4% to 6% each day.

FIGURE 2

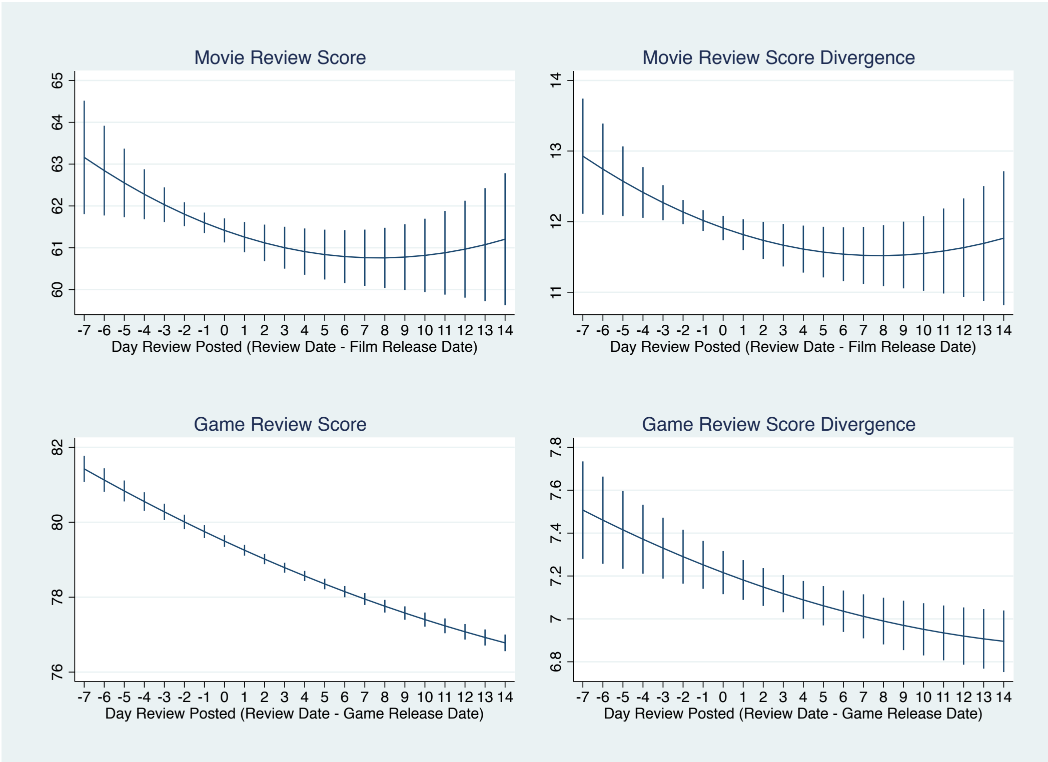


FIGURE 3

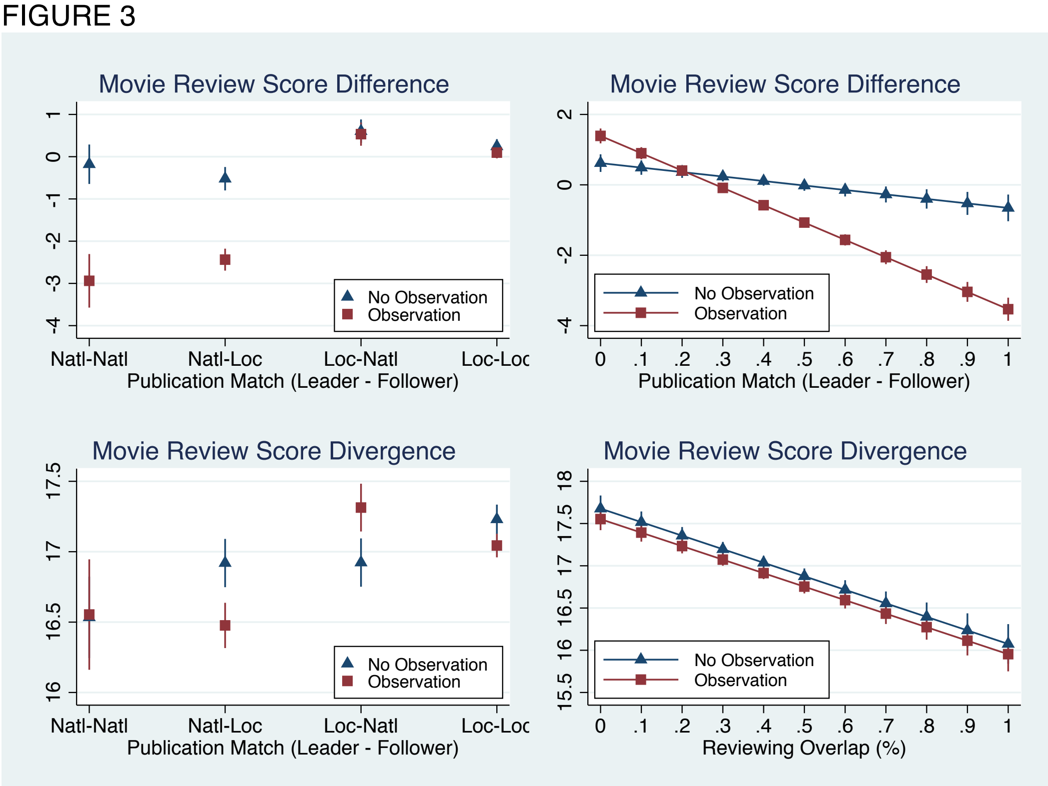


FIGURE 4

Game Review Score Difference
2
0
-2
-4
No Observation
Observation
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
Reviewing Overlap (%)
Game Review Score Divergence
10
9.5
9
8.5
8
No Observation
Observation
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
Reviewing Overlap (%)