Relative Performance and Categorical Coherence:

Equity Rating Outcomes for US Firms, 1995-2007

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Abstract

It is well established that when audiences have difficulty classifying objects, they tend to devalue them. However, difficult to classify objects do receive high valuations, and easy to classify objects can receive low ones. In this paper, I examine one reason this occurs. Rather than examining the entire universe of objects that could be classified, audiences usually focus on a narrower subset of objects and compare within it. I argue that the effect for poor performance is greater for easy to classify objects because the criteria for performance are more standardized, and thus a high evaluation given poor performance is difficult to justify for such objects. Using the set of recommendations on over 5000 publicly traded US stocks issued by equity analysts during the period from 1995 to 2007, I find that lower performance of a stock relative to other stocks already rated by a given analyst is associated with a lower likelihood of a high rating for that stock. This negative effect is increased when a stock has high levels of categorical coherence. In general, the results suggest that the positive effect of categorical coherence, well established in prior literature, is contingent on the relative performance of other objects already rated by a particular evaluator.

It is well established that classification affects market outcomes. Categories are used by audiences to better understand market objects, thus facilitating exchange (Zuckerman 1999, Hsu, Hannan, and Kocak 2009). The fit between an object and the category in which it is placed fundamentally affects the evaluation of the object: difficult to classify objects and those that belong to multiple categories are typically devalued by critics and audiences. Movies without clear genres, stocks without clear comparables, companies with vague descriptions, and eBay auctions with multiple search terms result in lower evaluations than those that are more clearly categorized (Zuckerman 1999, 2004, Hsu 2006, Ruef and Patterson 2009). Such difficulties in classification also result in lower prices for objects—both because audiences value them less and because producers, anticipating audience response, choose lower prices in response to expected quality ratings (Hsu, Hannan, and Koçak 2009, Roberts and Reagans 2009).

However strong the association between difficulty in classification and lower value, and ease of classification and higher value, it is easy to think of exceptions. The iPad, described by Apple only as "a magical and revolutionary product" (Apple 2010) and variously described by others as a competitor to portable DVD players, tablet computers, e-book readers, and audio devices, is sold out in many outlets and enormously popular, garnering strong reviews from influential critics David Pogue and Michael Arrington (Slattery 2010, Arrington 2010). Bristol Myers Squibb, a large pharmaceutical firm, despite being covered by a set of analysts focused solely on pharmaceutical firms, was rated poorly in 2004, even though several of its financial indicators (such as net income) were strong (IBES 2010). Both of these cases could be dismissed as contributing to variance in research that has established mean differences between easily categorized and difficult-to-categorize objects. Yet doing so ignores an opportunity to more carefully examine the process of evaluation, which is often described as a simple ordering and ranking process in which clearly classified objects prevail due to the ability of audience members to more easily understand and evaluate them.

In this paper I focus on the process of evaluation to offer one explanation of why difficult to classify objects could be rated highly, and clearly-classified objects could suffer in evaluation. While audiences do evaluate objects based on the attributes and quality of the object itself, they also compare it to other under consideration (Rosch, 1978, Porac, Ventresca, and Mishina, 2002). That is, evaluations are made as a result of relative judgments on a subset of objects by an audience member, comparing each object under consideration against others on a dimension of performance, rather than absolute comparisons against a set of rules (Markman and Gentner, 1993). Given this, I suggest that poor performance relative to other, already rated objects should be associated with a lower likelihood of a favourable evaluation. I argue that this effect should be magnified to the extent that an object has high categorical coherence, or fit within a given category, because evaluation metrics and standards are easy to apply to coherently classified objects and so poor performance relative to these standards is easier to judge. Thus, the composition of the set of objects considered by an audience member is critical for understanding the resultant evaluations.

I focus specifically on the role of a particular kind of audience member, the market critic. In most markets, exchange occurs directly between buyers and sellers. However, in some markets information is difficult to obtain, either because of the complicated nature of the objects being exchanged or because the objects themselves are experience goods, such as wine or movies, whose value can be understood only after consumption (Hsu, Roberts and Swaminathan 2009, Zhao 2005). In these markets, market critics perform an important mediating role by providing information that facilitates exchanges between buyers and sellers. I use over 118,000 ratings issued by equity analysts at brokerage firms covering publicly traded

US stocks between the years 1995-2007 as a setting in which to investigate my hypotheses.[1] Equity ratings, along with analyst earnings forecasts, are critical determinants that assist investors in making decisions about buying and selling stocks. As many as fifty analysts may cover a single stock, and while many analysts cover similar portfolios of stocks, few analysts have identical portfolios. This makes it an ideal setting in which to examine evaluations because the portfolios of individual analysts are easily identified. Because of the focus on critics, the results found here should generalize to those settings in which market intermediaries work to interpret and provide information for buyers and sellers. Thus my results are likely to apply to financial markets, movie ratings, product guides and other areas where critics are common.

Results suggest a need to take into account the portfolio considered by a critic, and by extension, the actual process of evaluation. Specifically, I find that lower performance relative to other stocks covered by a given analyst is associated with a lower likelihood of a top rating. This effect is increased when that a stock has high levels of categorical coherence. These results highlight the importance of the relative process of evaluation, but also add insight to the literature on the benefits of categorical coherence. While high levels of categorical coherence increase the likelihood of positive evaluation, poorer relative performance is more detrimental for highly coherent stocks. Thus the benefit of categorical coherence is contingent on the consideration set of a given audience member.

The role of market critics in evaluation. Implicit in many organizational studies of categorization is the idea that classification, and the valuation that ensues, emerges from the entire set of objects in a given universe. Yet in practice, the number of objects to be valued is

[1] Equity analysts technically cover publicly traded firms and make forecasts about the firms' future earnings per share and stock price. However, I use the word stock to avoid confusion with the brokerage firms that employ analysts.

often extraordinarily large—far beyond the capabilities of one individual (Tan and Roberts 2009). The New York Stock Exchange, for example, lists over 3600 stocks (the NASDAQ lists over 2700). In the height of the internet boom, over 400 companies qualified as Internet stocks (Blodget 2004). Because understanding such a vast market is difficult, market critics often emerge to facilitate information flow between producers and audiences. They do so chiefly in two ways: by providing factual information about the objects being covered as well as an evaluation of their performance (Durand, Rao and Monin 2007, Roberts and Reagans 2005).

The information provided by critics matters due in part to the large number of products in many markets combined with limits on time, effort, and cognition on the part of the audience for those products. Most critics only provide detailed information on a selection of the possible product offerings. (Even professional reviewing organizations, such as the Michelin Guide, do not review all possible candidates.) This winnowing from the market at large to a subset of objects to be analyzed means that coverage of any kind is a sign of legitimacy, since it suggests the object is worthy of attention (White and White 1992, Roberts and Reagans 2005, Zuckerman 1999, Shrum 1991). In addition to awareness, critics also provide information about how an object should be viewed—to which it is similar, and what it does (Kennedy 2008, Tan and Roberts 2010).

The evaluative component of a critic's report typically takes the form of a rating or ranking of the object under consideration on some performance dimensions, usually quality, as in consumer products, like wine or movies, but also along other dimensions, such as expected future performance (stocks), default risk (bonds), or mature content (movie ratings).[2] Both positive and negative evaluations significantly affect the success of the covered object (Reinstein

[2] Research suggests several other factors that may affect evaluation, including social and self-interested motivations (e.g. Hayward and Boeker 1998, Rao, Greve and Davis 2004). I control for these alternative explanations.

and Snyder, 2005, Basuroy, Chatterjee, and Ravid 2003, Womack 1996), although this impact may be contingent on the particular market (Berger, Rasmussen and Sorensen, 2010, Shrum 1991). Even if the actual impact on sales may be varied, it is clear that producers strongly believe that critics play an influential role. For example, upon receiving a bad review of his latest book in the influential New York Times Book Review, author Alain de Botton responded to the critic, "You have now killed my book in the United States, nothing short of that. So that's two years of work down the drain in one miserable 900 word review" (Adams 2009).

Equity research. The increasing importance of financial markets for firm outcomes has brought renewed attention to brokerage firms in general and equity analysts in particular (e.g. Bradley, Clarke, Lee and Ornthanalai 2010, Benner 2010). Equity analysts function as market critics and are charged with providing information that helps investors and firms with the sales and purchase of stocks (Groysberg 2010). Most investors seek stocks that will appreciate in the future; thus, the work of the analyst is to identify the industries and stocks that will be high performers in terms of future stock price (Michaely and Womack 2005). Analysts provide information that helps investors make sense of complex and often fast changing situations within a particular industry. Simply being covered by an analyst is a signal that a stock is worthy of attention by an investor (Zuckerman 1999, 2004), but the actual research reports analysts generate, which contain an analysis of a stock, a forecast of future earnings, and a recommendation, are intended to guide investor decision-making. In forming their reports, analysts compare a given stock to others that do similar market activities to understand its financial performance, value its assets, analyze its strategy, and predict its future returns (Michaely and Womack 2005).[3]

Evaluation in equity research is done via a rating system—a hierarchical set of categories that allows analysts to rate stocks as above average, average, or below average.[4] While the labels of the categories may be different for different brokerage firms, positive categories generally suggest that stocks are expected to outperform the market and are therefore worth buying by investors, while neutral or negative categories are those that are not expected to perform well compared to other stocks, at least in the short term. Using categories rather than actual rankings requires only that they group stocks with similar prospects together rather than making specific rankings about which stocks are likely to most outperform the market.

Although most stock market movement occurs in response to upgrades or downgrades in ratings, a recommendation in a positive category is extremely desirable for firms. Changes in ratings, downgrades in particular, have been shown to affect trading volumes as well as stock price (Womack, 1996, Lin and McNichols 1998). In addition, covered firms themselves respond to these evaluations in significant ways: one reason firms cited for "de-diversifying" in the 1990s was the failure of analysts to properly understand (and therefore highly value) conglomerate firms (Zuckerman 2000). Anecdotal reports suggest that firms bully analysts who give low or negative ratings, refusing to answer their questions and excluding them from conference calls (Siconofli 1995, Reingold 2006, Kessler 2004).

Brokerage firms generate revenues through commissions earned buying and selling stocks, and, though they do not receive direct compensation via these commissions, analysts

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[3] I follow prior research (Zuckerman 2004, Zuckerman and Rao 2004) in assuming that stocks are grouped when they are "subject to the same set of economic fundamentals" (Zuckerman and Rao 2004, p. 185). Such an assumption is consistent with contemporary accounts of analyst activities (e.g. Reingold 2006, Kessler 2004, Blodget 2006).

[4] While many research papers suggest that all equity rating systems are 3 or 5 category systems, in fact there is great heterogeneity among the systems brokerage firms choose to use, and no legal requirement for one rating system over another. See Fleischer (2009) for a more detailed discussion.

themselves are compensated in relation to market response for the stocks they cover (Groysberg 2008, 2010). Overall, brokerage recommendations skew positively, with most stocks being rated in positive or neutral categories, and fewer being rated sell (Barber, Lehavy, McNichols and Trueman 2006, Dugar and Nathan 1995, Lin and McNichols 1995). This occurs because brokers tend to discontinue stocks with unfavourable future prospects since few investors sell stocks short and are unlikely to buy poor performers (McNichols and O'Brien 1997, Barber et al 2006).[5] Brokerage firms set the rating system for the analysts they employ, but analysts choose the ratings given to individual stocks (e.g. Reingold 2006, Blodget 2006, Kessler 2004).

Since the principal goal of the analyst is to give insight and make predictions about a given stock, it follows that analysts specialize more or less by industry boundaries, so that they can use common metrics across many stocks that they cover. For example, in airline stocks, valuations are based in part on such features as size and age of fleet, timeliness, and fuel hedging—attributes that would not apply equally even to firms in related industries, such as airplane manufacturing. Because of this specialization in classes of stocks, in aggregate, the analysts' coverage portfolios create a map of the classificatory structure of stocks as characterized by financial markets (Zuckerman 2000, 2004, Boni and Womack 2004). Stocks vary in their categorical coherence, or the level to which they cohere to these generalized asset types or industry categories (Zuckerman 2000). Some stocks, such as GE, sell products in many divergent industry categories, while other stocks, such as Quixote, a manufacturer of automobile air bags, have few direct competitors who are publicly traded. A stock with high coherence is followed by analysts who all follow the same stocks, suggesting a firm with a clear

[5] Certainly some investors, for example, those who are interested in short selling (betting that a stock's price will go down rather than up) make purchase decisions based on negative ratings. Yet these investors make up only a small percentage of any brokerage firm's clients. Even when Merrill Lynch increased its amount of "underperform" ratings, done so in response to hedge fund clients looking for opportunities, they only were 20% of the overall stocks being covered (Martin 2008).

market identity and obvious competitors; a stock with low or no coherence is covered by analysts with few (or no) stocks in common, suggesting a firm with a less clear market identity and fewer obvious competitors.

Analysts who cover the same set of stocks attend to similar information as well as each others' reports and are likely to develop consistent methods for evaluating stocks (Fleischer and Baum 2010, Zuckerman 2004). Thus, in addition to suggesting a set of assets and practices common to all stocks, high levels of categorical coherence imply that there is convergence among analysts about the ways to value the firm's activities and actions, since they are likely directly comparable (Zuckerman 2004). Given a set amount of analyst coverage, a stock with high categorical coherence will trade at a higher value and have less volatility because a general consensus exists about the metrics to use to evaluate the stock's performance (Zuckerman 1999). Conversely, a stock with less categorical coherence is covered by analysts who cover few stocks in common, and thus there is less market level convergence on the set of metrics by which to value the firm (Zuckerman 2004). As a result, trading volumes are more volatile as there are diverging opinions about its future performance, and the stock is likely to trade at a lower price (Zuckerman 1999, 2004).

In addition, high categorical coherence should also be reflected in the recommendations given by equity analysts as well. In general, objects that have a clear identity receive higher valuations. For example, movies with high consistency in genre receive higher evaluations by critics than those that overlap genres (Hsu 2006). Underlying this is the assumption that a clearer identity makes a firm better able to meet the expectations inherent for performance in that particular market: firms that span markets are less likely to be able to effectively target the expectations of consumers and financial markets and so are discounted (Hsu, Hannan and Koçak 2009, Hsu 2006).

Relative Performance. However, critical evaluations inherently take into account not just the performance of the focal object that is the subject of a given review, but the other objects that are similar to it (Zerubavel 1991). Part of the analyst's value occurs in the perspective that he gives on the perspective of the entire portfolio he covers (Reingold 2006). Therefore, an individual stock must be considered in tandem with the other stocks rated by the analyst. Even though the result of an analyst's report is a rating of a single stock, that rating is rarely made in isolation. Since a given analyst looks to sort among the stocks he covers, the performance of a stock may be placed in a higher or lower rating category simply because of the composition of the portfolio of stocks rated by the analyst.

Each rating category binds together a set of stocks that meet similar criteria for a particular rating, while excluding those that are dissimilar. More generally, when multiple items are being evaluated, rather than evaluating each object according to a set of rules, evaluation occurs in comparison to other alternatives (Markman and Gentner 1993).[6] The features that distinguish to occupants of a top category in a rating system become the standards for future evaluation (Schwarz and Bless 1992). When an evaluation is required to be made, individuals compare the object to be evaluated to other objects already rated on these features, looking for differences and relational patterns between the object to be evaluated and those already categorized (Schwarz and Bless 1992, Herr et al 1996, Keller and Aaker 1992).[7] The object's performance relative to these other objects critically affects the evaluation outcome:

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[6] In fact, descriptions of equity rating systems explicitly state that ratings are made in reference to other stocks covered by the analyst or the market at large.

[7] This is similar to the literature on choice (e.g. Payne 1976), where individual choices are shown to be determined in part by the comparison of a potential outcome to other criteria that are salient to an individual. Categorical coherence matters in such situations since it is likely to influence the consideration set from which an individual makes a final choice (Zuckerman 1999). Evaluation is slightly different. First, the consideration set is not freely determined. (The analyses I present are conditional on the analyst's portfolio.) Second, equity analysts are not completing a transaction or making a choice, the subject of prior research. Instead, equity analysts, like all market intermediaries, are creating an evaluative sorting rather than a single preference match. And since this sorting involves a rating system with categories into which multiple stocks can be placed, the process is also akin to sorting tasks rather than a single choice.

poorer the relative performance, the worse the evaluation outcome (Leclerc, Hsee, and Nunes 2005, Hsee, 1996).

Although equity analysts consider many aspects of a firm's activities in evaluating its stock, including net income, market growth, and competitive position (Asquith, Mikhail, and Au 2005, Bradshaw 2004), the critical part of each report is a forecast by the analyst of the firm's projected earnings per share, which is used as the justification for the rating category of an individual stock in 70 to 90 percent of examined earnings reports (Asquith, Mikhail, and Au 2005, Bradshaw 2004). Investors typically wish to buy stocks that have increasing returns, thus earnings per share growth is an important evaluative mechanism that separates potentially high performing stocks from lower ones. Thus, those stocks with high expected earnings per share growth relative to other stocks rated by the analyst should be associated with high ratings. Those stocks that perform poorly relative to others should be less likely to receive a higher rating, because their performance appears less notable compared with other stocks that have already been labelled as attractive to investors.

H1: *The lower the performance of a stock relative to others already rated by a given analyst, the lower the likelihood of a high rating.*

The prior hypothesis suggests that performing poorly relative to other already rated stocks lowers the likelihood of a high rating separate from other factors. However, the level of coherence of the focal stock itself is likely to matter in combination with the relative evaluation. Stocks with high levels of coherence have standardized evaluation methods that determine appropriate business activities (Zuckerman 2004, Tan and Roberts 2010). Performance should be easier to judge for such stocks, since the standards that apply to them are clearer and readily accepted by major stakeholders. Therefore, poor relative performance by highly coherent stocks should be more visible, but also more difficult to justify because of the clarity and consistency of these standards.

Conversely, stocks with lower levels of categorical coherence are those for which there is not a generally accepted set of evaluation mechanisms. Thus, while poor relative performance is visible to the analyst in these cases, the likelihood of downgrade should be less than that for highly coherent stocks because lower coherence stocks are difficult to evaluate and thus unlikely to be highly rated in the first place. Thus, the negative effect of poor performance should be greater to the extent that a stock has high categorical coherence.

H2: The interaction of performance and coherence is negative: the lower the performance of a coherent stock relative to other stocks rated highly, the lower the rating it will receive.

METHOD

Data

I collected data on all analyst recommendations for all US publicly traded firms in Thomson Research's IBES database from the period 1995-2007. These data were then matched to firm level data from the Compustat database and well as data on trading volume and stock-level returns using CRSP. This yielded information on over 250,000 recommendations by over 8,000 named analysts. I augmented this with data from *Institutional Investor* Magazine and the SDC Platinum database on underwriting. I also excluded analysts and brokerage firms following fewer than five stocks, since my hypotheses are conditioned on analysts covering more than a single stock. This resulted in 118,315 recommendations by 4144 analysts over the thirteen year period.[8]

[8] The IBES database records recommendation histories and earnings forecast histories of individual analysts separately. This occurs because analysts often frequently update their forecasts, but update recommendation data less frequently. Therefore I paid careful attention to match the financial information about the firm to the time of the recommendation announcement, using the earnings forecast that occurred either simultaneously with the

Measures

Dependent Variable. *Rating.* Analyst recommendations were coded using the translation ratings supplied by IBES. These ratings are on a scale from 1 to 5, with 1 being a positive recommendation, 3 being a neutral recommendation, and 5 being a negative recommendation. Although brokerage firms may have different category labels for individual rating categories (for example, buy, sell, hold versus market outperform, market perform, and market underperform), the translation ratings allow rating categories to be compared across firms. Interviews with staff members at Thomson Research confirm that the brokerage firms work with Thomson to determine the scaling of their rating system. Thus, one firm with a rating of Buy, Hold, Sell may choose to map its categories to 1, 3, and 5, while another with the same category labels may choose 2, 3, and 5. Because not all firms use all five rating categories, I focused on the top positive rating that a firm could give, since this is the preferred category that covered firms wish to receive and since the top rating has a commensurable meaning across multiple brokerage firms. In subsequent analyses I run regressions among firms using the full range of the rating system.

I estimated the likelihood of receiving a brokerage firm's top rating using a conditional logit model with analyst fixed effects, since observations are nonindependent and are grouped by analyst (Long and Freese 2005).[9]

Independent Variables. *Categorical Coherence.* Following Zuckerman 2004, I computed a stock's categorical coherence using a two step process. First, for each quarter of the data, I calculated the proximity of each pair of stocks as the minimum overlap of each pair of analysts for all earnings forecasts issued in the prior twelve months. I used earnings announcements

recommendation or immediately preceding it in time. Doing so reduced the sample when I could not find accurate forecast matches.

[9] Re-estimating the models using stock fixed effects to control for unobserved heterogeneity in stocks produces almost identical results.

rather than recommendations because analysts often keep the same recommendation for many months while making several earnings recommendations. The twelve month window allowed me to include stocks covered by analysts during so-called quiet periods related to underwriting and merger and acquisition activity by the analyst's brokerage firm. Thus, the first quarter 1995 contained all analyst forecasts from January 1, 1994 to December 31, 1994. More formally, proximity is measured as $P_{ij}=\min[(m_{ij}/n_i), (m_{ij}/n_j)]$, where m_{ij} is the number of stocks followed by both i and j, and n_i and n_j are the total number of stocks of each analyst (Zuckerman 2004).

Second, categorical coherence was calculated as $C_f=(\sum_i\sum_{j>i} p_{ij}{*}\ v_{fi}{*}v_{fj})/[I^f(I^f-1)/2])$. I^f is the total number of analysts that follow a given stock. V_{fi} is an indicator variable that is coded as 0 when the two analysts do not cover any stocks in common and 1 otherwise. The categorical coherence variable has the advantage of letting industry groupings be defined solely by the coverage patterns of individual analysts rather than by other industry definitions that may or may not reflect how analysts actually see groupings of stocks.

Relative performance. To measure relative performance, I first calculated the analyst's estimate of the firm's annual earnings per share growth in percentage terms. This was computed by subtracting the analyst's current estimate of the firm's annual earnings per share from the most recent reported earnings per share and then dividing by the reported earnings per share. Thus, the percentage growth is a relative measure that is specific to each analyst, since it is based on his or her estimate. I gathered the analyst's forecasted earnings per share growth for all highly rated stocks for which the analyst had a current forecast to develop the portfolio of earnings per share growth forecasts. I then rank ordered the portfolio, and recorded the focal stock's position within this ranking. The higher the ranking, the worse the position of the stock's forecasted earnings per share growth. Thus, a negative coefficient on the relative performance measure would suggest that a higher ranking is associated with lower likelihood of a top rating.

Control Variables. I controlled for several types of variables that might influence the likelihood of a high rating, including those relating to other analysts, the focal analyst's brokerage firm, and the rated firm (stock) itself.

First, I included two variables that captured the overall levels of forecasted earnings per share in the analyst's top category, since the actual composition may have some influence that would be obscured by a rank ordering. To control for this, I included the mean and variance of the forecasted earnings per share growth for all stocks in the analyst's top category. I also included the raw forecast of actual earnings per share growth made by the analyst.

I included controls for the mean and standard deviation of the ratings of other analysts covering the stock since prior literature has shown that analysts influence each others' ratings (Hayward and Boeker, 1999, Rao, Greve, and Davis 2001). This was calculated by taking the mean and standard deviation, respectively of all outstanding recommendations on a given stock at the time of the focal analyst's recommendation. Since the IBES ratings code the highest rating as a 1, a high mean rating means a low overall evaluation of the stock by other analysts. I also controlled for the number of other analysts covering the stock.

At the firm level, I controlled for the size by using the total assets of the firm as recorded in its most recent annual report, since larger firms may attract more analysts and may also have more information available for analysts. Since this variable was highly skewed, I took the natural log. In addition, I controlled for the trading volume of the stock. Since analysts wish to generate commission revenue through their recommendations, stocks with higher trading volume may have different recommendations than other stocks. Following Cooper et al, 2001, I calculated the average trading volume for the period -81 to -41 days from the analyst's recommendation announcement and +41 to +81 days after. Finally, I controlled for the absolute performance of the firm by including its most recent quarterly earnings per share as well as its net income.

Next, I controlled for several characteristics of the analyst covering the firm. Prior research suggests that analysts may face pressure to favorably rate some stocks, but that this pressure is ameliorated to the extent that the analyst has a high reputation in the industry. Therefore, I created a variables based on *Institutional Investor Magazine*'s annual All-Star rankings. These rankings list the top three analysts by industry category and are widely seen by investment professionals as a sign of an analyst's prestige and ability. *Cumulative All Star Years*, captures the number of All Star awards garnered by the analyst. I also created a variable that captures the number of stocks covered by the analyst at the time of the focal recommendation (*Size of analyst's portfolio)*. Finally, I controlled for the analyst's experience level by calculating the number of days since the analyst first covered any stock in the database starting in 1994.[10]

I created a number of brokerage level controls. First, since prior research has suggested that analysts may give higher recommendations to firms when their brokerage firm is an underwriter for that firm, I created an indicator variable *Lead Underwriting* coded 1 if the brokerage firm had been a lead underwriter on the covered firm's stock in the prior year and 0 otherwise. Underwriting data from SDC Platinum was matched to the IBES data using firm names; to be conservative, when it was difficult to tell if the name of the underwriter in SDC Platinum matched the name of the brokerage firm in IBES, I left this as a zero. I also controlled for size of the brokerage firm by using the total number of recommendations outstanding. Last,

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[10] Data constraints prevented me from observing data earlier than 1994; thus the experience variable is left censored. Running the model with an indicator for censored variables and stock fixed effects produces almost the exact same results. In addition, removal of the experience variable does not affect the results.

I created two variables that captured the brokerage firm's rating system. Since analysts do not create their own rating system but instead operate in the confines of a brokerage firm's rating system, I needed to control for the choice of system, since that by definition would affect how a given analyst might rate a particular stock. *Total Brokerage Categories* captures the number of categories in the brokerage firm's rating system, and thus which categories are available to the analyst to use. I also created a variable called *Highest Brokerage Category* that was the number of the highest category used by the brokerage firm in the prior year.

Finally, I controlled for temporal effects using year fixed effects.

Descriptive Statistics

The means, standard deviations, and correlations for all variables are reported in Table 1. On average, analysts cover 14 stocks. The average stock is covered by nearly 11 analysts, who give it an average rating of 2.25. In general, the correlations are unremarkable with a few exceptions. The largest area of concern to the hypothesized variables involves the correlation between the size of the firm (ln(Assets)) and the coherence of the firm, which is correlated at .43 (18.4% shared variance). In addition, size is also correlated with the number of analysts covering the firm (.58, or 33% shared variance). As a result, I computed variance inflation factors for each model, which show a maximum of 1.81, far below the threshold of 10 (Besley, Kuh and Welsch, 1980). In models not reported here, I also computed the effects of each of the variables of concern separately and in various combinations with each other. The signs and significance of the main effects remain the same.

Insert Table 1 Here

RESULTS

Table 2 presents results of conditional logit models on the likelihood of being in a brokerage firm's top positive category. Model 1 reports results of the control variables alone. Models 2 and 3 add the coherence and rank of performance variables separately, and Model 4 presents all main effects. Model 5 includes the main effects and the interaction for the performance variable.

Insert Table 2 about here.

In Model 1, consistent with prior literature, the coefficient of the average recommendation is significant and negative, suggesting that the likelihood of a top recommendation is less when the mean recommendation of analysts is unfavorable (in this case, a high value for the mean recommendation, since a score of 1 is the most favorable score possible). In addition, larger firms and firms with a high net income are more likely to receive top ratings. As well, consistent with prior work, analysts whose brokerage firms are the lead underwriter on the stock are more likely to give that stock a high rating, while those with Institutional All-Star status are less likely to give top ratings (Hayward and Boeker 1999). These control variables remain significant in all models.

Model 2 adds the variable for categorical coherence. As in prior literature, this variable is significant and positive, suggesting that a more coherent classification is associated with a higher likelihood of a top rating.

Model 3 presents the main effect for relative performance. Consistent with hypothesis 1, the coefficient is significant and negative. In Model 4, this effect remains when the coherence variable is returned to the model. In Model 5, the interaction term is significant and negative, although the main effect for rank of performance becomes positive and nonsignificant. Figure 1 shows the coefficient of the interaction term in graphical form for model 5.[11] It suggests that a

[11] The axis for rank of performance ranges from 0 to 30. However, the range was quite high, with a maximum of 90 stocks in an analyst's top category. Although such analysts are unusual, I felt there was no obvious reason to exclude them from the analysis. However, in results not reported here, I reran the models using only observations that ranged between +/- 1 and then 2 standard deviations from the mean rank (highest rank of 12). The results are much stronger, and the predicted likelihoods suggest a stronger discount for high coherent but low performing firms.

stock with high categorical coherence has the greatest likelihood of a top rating when its performance is high relative to other stocks already rated. When the categorical coherence of a stock is high, but its performance is lower than the other already rated stocks, its likelihood of a high rating is in fact slightly lower than a high performing stock with low categorical coherence. The graphs suggest an interesting juxtaposition: stocks with low categorical coherence do benefit from high performance, but only very slightly. Conversely, stocks with high categorical coherence are associated with a very high likelihood of a top rating, but the penalty for poor performance appears to be much larger.

Insert Figure 1 about here.

While the interaction is negative and significant, suggesting support of Hypothesis 2, according to the conditional logit, some care is needed to interpret the significance of interaction effects in logistic models, since the interaction may not be significant over all values of the two interacted variable (Ai and Norton 2003). As a result, I did several post-hoc tests to ensure the significance of the interaction. First, a likelihood ratio test on the full model with the interaction effect from a model in with only the main effects suggests that the interaction effect is significant ($p<.0001$) (Long and Freese 2005). Additionally, I ran the same model using generalized least squares with analyst fixed effects, where the interaction effects may be interpreted in a more straightforward manner. The interaction term was significant and negative, as in the prior model, and both main effects were significant and in the same direction as the conditional logit model. 93.4% of the predicted values were within range.

In addition, I also ran two models (not reported) that use the entire range of possible ratings as the dependent variable (1-5). I reverse coded the dependent variable so that a high (positive) recommendation is associated with a high value. In the first model, an ordered logit, the significance of the main effects and interaction for categorical coherence are almost identical to those presented in Table 2. A generalized linear model with analyst fixed effects also produced similar results to Table 2. Both of these models have limitations. Since not all firms use all possible categories, an ordered logit specification is not technically correct, since all stocks should have the potential to be rated in all possible categories. While the generalized least squares model relaxes this requirement, it does have the disadvantage that it does not take into account the ordered, categorical nature of the dependent variable and instead treats it as continuous.

One possible concern could be that rating behavior is path dependent, and that rating outcomes are a function of the analyst's prior ratings rather than the current rating. I ran additional models using a lagged dependent variable to control for prior rating behavior on this stock. Results were similar to the models without the lagged dependent variable.

An additional concern involves the use of the top rating category as the comparative performance category. Since prior research suggested a process by which the focal stock should be compared against other, highly rated stocks to see the effect of its relative performance on the rating, I rank ordered only the top category. However, it is possible that this effect may occur for any category, not just the top one. I reran the models using the lower categories and found no significant effect. Overall, the results of these models suggest the importance of the other stocks being rated by a particular analyst to the success of any one stock in terms of receiving a high evaluation. More specifically, they suggest that performing poorly relative to other highly rated stocks is associated with a lower likelihood of a high rating, particularly when a firm has a highly coherent market identity.

DISCUSSION

Classification is a fundamental process of organizing markets in order to foster exchange. While it is well established that easy-to-classify objects tend to have higher valuations, difficult-to-classify objects do receive high valuations, and easy-to-classify objects can receive low ones. In this paper, I suggested one reason that such differences occur. Rather than examining the entire universe of objects that could be classified, audiences often focus on a subset objects and compare within it (Markman and Gentner 1990, Payne 1976). These relative classifications mean that objects may fare better or worse because of the composition of that subset. Furthermore, once the relative comparisons have been taken into account, the role of ease of classification comes into sharper view. Easily classified firms are better understood by markets, but that also means that their performance is easier to judge, and poor performance harder to justify when compared to others under consideration.

In a sample of recommendations issued by equity analysts during the period from 1995 to 2007, poor expected performance relative to stocks the analyst had already rated highly was associated with a greater likelihood of receiving a high rating, while the reverse was also true. This effect was magnified to the extent that the focal stock had very high levels of coverage coherence. Stocks with low expected performance but high coherence are associated with a lower likelihood of a top rating than those that are low coherence and similar expected performance. This suggests that the effect of coherence is contingent on the portfolio of stocks covered by an individual analyst.

More broadly, this study speaks to the need to consider the process of rating as much as the qualities of the object being rated or the rater himself. Prior literature has well established that object qualities, including classification coherence, impact evaluation outcomes (Zuckerman 1999, 2004, Ruef and Patterson 2009, Hsu 2006, Curry, Fissel and Hanweck 2008). Prior literature has also established that social processes influence evaluation (e.g. Rao, Greve and Davis 2001) as do strategic concerns of the evaluator or critic in question (e.g. Fleischer 2009, Hayward and Boeker 1999). Yet little research on organizational categorization has focused on the interrelations of the entire set of objects covered by a critic, and by extension, the larger cognitive processes of evaluation. While this study examined how the distribution of the other stocks concurrently covered by the analyst influenced rating outcomes, much remains to be explored. Several fruitful areas for further investigation include examining how changes in portfolio coverage among analysts or temporal ordering influence evaluation outcomes, particularly given research in consumer behaviour that suggests such variables may matter (e.g. Lefkoff-Hagius and Mason 1993).

In addition, like many studies of categorical coherence, this study calculates categorical coherence such that high values represent high grade of membership within a given category no matter what the category is. Since such a measure does not segment the data into particular labelled groups, it essentially captures structurally equivalent levels of category membership across observations in the sample. That is, all firms with a high grade of membership score are assumed to be full members of *a* category, but *which* category is not specified. However, attention to multiple specific clusters of firms would add important insight to understanding category structure.

This study also contributes to literature examining financial markets in general, and financial rating systems in particular. Financial rating systems have been vilified in recent years due to questions of self-interested evaluations (e.g. Hayward and Boeker 1999, Womack 1996, Story 2010). Yet despite their obvious flaws and potential for misuse, rating systems affect how firms are seen and evaluated simply by the boundaries they place around similarly rated firms. Many fruitful avenues remain in understanding how these boundaries affect stocks and market outcomes. For example, how do changes in classification schemes affect analysts' stock ratings and the market at large?

This study has limitations. First, it focuses on a particular industry with strong norms for classification. Thus care must be interpreted when applying some of the findings to other settings. For example, while these rating systems allow for many positive evaluations, other rating systems may limit the number of positive or negative evaluations that can be made. Also, this study did not address the selection of the analyst's stock portfolio. Like most studies that examine evaluation outcomes, I controlled for qualities of the other stocks being covered in subsequent analyses but my overall models are conditioned on the portfolio an analyst has, which may be determined by many factors. A separate examination of the determinants of analyst portfolios would provide valuable insight.

Despite these limitations, my study points to the need to consider the other objects being evaluated by a given critic when determining a particular evaluation outcome, and, more generally, the need to explore the cognitive processes of evaluation of audiences more deeply. While market coherence is important for evaluation, its effect is contingent on other factors, at least in this setting. Taking this into account will open new doors for understanding how market classification works across competitors within markets as well as the audiences who transact with them.

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Table 1. Means, standard deviations, and correlations

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Coherence	0.212	0.100	1.00																		
2	Rank of performance	3.392	3.932	-0.06	1.00																	
3	Size of analyst's portfolio	14.594	9.834	0.02	0.32	1.00																
4	Mean performance (in category)	0.034	1.271	0.00	0.03	0.00	1.00															
5	Variance of performance (in category)	3.687	69.486	0.00	0.03	0.01	-0.09	1.00														
6	Forecasted earnings growth (performance)	0.004	2.900	0.00	-0.08	0.00	0.00	0.00	1.00													
7	Average recommendation (all analysts)	2.251	0.518	0.20	-0.07	0.02	0.00	-0.01	-0.01	1.00												
8	Standard deviation of recommendation (all analys	0.769	0.292	0.17	-0.05	-0.03	0.00	0.00	0.00	0.09	1.00											
9	Number of analysts covering this stock	11.239	7.155	0.33	-0.05	-0.04	-0.01	0.00	0.01	0.00	0.21	1.00										
10	Assets (ln)	7.198	2.105	0.43	-0.08	0.08	0.00	0.00	0.00	0.14	0.18	0.58	1.00									
11	Adjusted turnover	0.007	0.007	0.08	-0.03	-0.10	-0.01	0.01	-0.01	0.01	0.08	0.19	-0.07	1.00								
12	Earnings per share	0.283	7.202	0.01	0.01	0.02	0.01	0.00	0.00	0.00	0.01	0.01	0.05	-0.03	1.00							
13	Net income	296.495	1713.502	0.09	-0.01	0.00	0.00	0.00	0.00	-0.03	0.03	0.18	0.29	-0.07	0.05	1.00						
14	Cumulative *Institutional Investor* All Star awards	1.226	2.644	0.18	0.06	0.16	0.02	0.00	0.00	0.04	0.04	0.06	0.21	-0.05	0.02	0.06	1.00					
15	Analyst experience (days)	905.242	788.736	0.21	0.03	0.10	0.01	0.00	0.00	0.12	0.06	0.15	0.26	-0.02	0.02	0.09	0.31	1.00				
16	Lead underwriting (brokerage)	0.134	0.498	-0.04	0.04	0.05	0.01	0.00	0.00	-0.04	-0.05	-0.12	-0.12	0.00	-0.01	-0.03	0.10	0.00	1.00			
17	Total categories in brokerage rating system	3.655	0.778	-0.01	-0.02	0.09	0.00	-0.01	0.00	-0.11	-0.03	0.02	0.02	-0.07	0.00	-0.01	0.07	-0.08	0.01	1.00		
18	Highest brokerage category	1.214	0.410	0.15	0.01	-0.02	0.00	0.02	0.00	0.18	0.04	0.05	0.12	0.08	0.01	0.04	0.10	0.12	0.03	-0.45	1.00	
19	Total recommendations (brokerage)	578.493	449.643	0.18	0.00	0.09	0.00	0.00	0.00	-0.02	0.02	0.10	0.17	0.02	0.00	0.03	0.39	0.05	0.16	0.37	0.03	1.00

118,133 Recommendations by 4141 analysts

Table 2. Conditional Logit Models on likelihood of top rating

	Model 1			Model 2			Model 3			Model 4			Model 5		
Variable	Coeff.	SE	P	Coeff.	SE	P	Coeff.	SE	P	Coeff.	SE	P	Coeff.	SE	P
Coherence				1.228	(0.112)	***				1.228	(0.112)	***	1.516	(0.134)	***
Rank of performance							-0.006	(0.002)	**	-0.007	(0.002)	***	0.008	(0.005)	
Coherence * Rank													-0.079	(0.020)	***
Size of analyst's portfolio	-0.008	(0.002)	***	-0.009	(0.002)	***	-0.008	(0.002)	***	-0.008	(0.002)	***	-0.008	(0.002)	***
Mean performance (in category)	0.005	(0.006)		0.005	(0.006)		0.006	(0.006)		0.006	(0.006)		0.006	(0.006)	
Variance of performance (in category)	0.000	(0.000)	*	0.000	(0.000)	*	0.000	(0.000)	*	0.000	(0.000)	**	0.000	(0.000)	*
Forecasted earnings growth (performance)	0.005	(0.003)		0.005	(0.003)		0.004	(0.003)		0.004	(0.003)		0.004	(0.003)	
Average recommendation (all analysts)	-2.607	(0.021)	***	-2.629	(0.022)	***	-2.607	(0.021)	***	-2.629	(0.022)	***	-2.630	(0.022)	***
Standard deviation of recommendation (all analysts)	0.735	(0.031)	***	0.752	(0.032)	***	0.735	(0.031)	***	0.752	(0.032)	***	0.754	(0.032)	***
Number of analysts covering this stock	0.000	(0.002)		-0.001	(0.002)		0.000	(0.002)		-0.001	(0.002)		-0.001	(0.002)	
Assets (ln)	0.084	(0.007)	***	0.075	(0.007)	***	0.083	(0.007)	***	0.075	(0.007)	***	0.075	(0.007)	***
Adjusted turnover	1.197	(1.262)		0.840	(1.273)		1.216	(1.262)		0.866	(1.272)		0.836	(1.273)	
Earnings per share	0.000	(0.002)		0.001	(0.002)		0.000	(0.002)		0.001	(0.002)		0.001	(0.002)	
Net income	0.000	(0.000)	***	0.000	(0.000)	***	0.000	(0.000)	***	0.000	(0.000)	***	0.000	(0.000)	***
Cumulative *Institutional Investor* All Star awards	-0.057	(0.009)	***	-0.058	(0.009)	***	-0.056	(0.009)	***	-0.058	(0.009)	***	-0.058	(0.009)	***
Analyst experience (days)	0.000	(0.000)	***	0.000	(0.000)	***	0.000	(0.000)	***	0.000	(0.000)	***	0.000	(0.000)	***
Lead underwriting (brokerage)	0.050	(0.016)	**	0.041	(0.016)	*	0.050	(0.016)	***	0.041	(0.016)	**	0.041	(0.016)	*
Total categories in brokerage rating system	-0.350	(0.017)	***	-0.351	(0.017)	***	-0.352	(0.017)	***	-0.353	(0.017)	***	-0.353	(0.017)	***
Highest brokerage category	0.999	(0.033)	***	0.983	(0.033)	***	1.005	(0.033)	***	0.990	(0.033)	***	0.991	(0.033)	***
Total recommendations (brokerage)	0.000	(0.000)		0.000	(0.000)		0.000	(0.000)		0.000	(0.000)		0.000	(0.000)	
Log Likelihood	-50217.742			-50543.505			-50539.714			-50212.598			-50204.744		
Pr<χ2	0.000			0.000			0.000			0.000			0.000		

***p<.001, **p<.01, *P<.05; 118133 recommendations by 4141 analysts; year and analyst fixed effects omitted.

Figure 1. Graph of the interaction between categorical coherence and rank of performance