THE DETERMINANTS AND CONSEQUENCES OF THE EFFICIENCY OF INFORMATION DISSEMINATION IN SECURITY MARKETS

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ABSTRACT OF THE DISSERTATION

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This dissertation consists of three interrelated essays that examine the determinants and consequences of the efficiency of information dissemination in security markets.

In the first essay, a new measure of investors' divergence of opinion derived from analysts' conditional forecasts revisions is constructed and the relationship between divergence of opinion and M&A-related target characteristics is analyzed. The new measure of divergence of opinion is negatively associated with takeover likelihood, positively associated with takeover completion likelihood, and positively associated with target abnormal announcement returns. The evidence also suggests that this new measure has more informational content and is a more efficient predictor compared with three other traditional measures of divergence of opinion in predicting M&A characteristics. Finally, the evidence suggests that the cumulative target abnormal announcement return contains a value-creating component that dominates its takeover premium component.

The second essay explores characteristics of financial analysts who deliver more consistent forecast errors. First, by showing that analyst forecast consistency mitigates the "walk-down" pattern, we demonstrate that consistent analysts use earnings forecasts both to provide value-related information and to achieve alternative personal goals. Second, by showing that analyst forecast consistency increases the relationship between stock valuations and stock recommendations, we demonstrate that consistency increases the forecast-recommendation translational effectiveness. Third, by showing that analyst forecast consistency increases the relationship between forecasts and short-term market returns but decreases the relationship between recommendations and short-term market returns, we demonstrate that consistent analysts allocate more information to forecasts than to recommendations. Finally, we find that analyst forecast consistency increases in firms' information environment, analysts' ability, analysts' voluntary supplementary-information seeking behavior and decreases in analysts' voluntary redundant-information seeking behavior and risk-related-information seeking behavior. We conclude that consistent analysts rely more on forecasts than on recommendations to serve investors' needs for earnings information and analysts' own personal needs, such as increasing trade volume, generating investment banking business, and currying favor with managers. Once forecasts are made, the forecast-recommendation translational process is less contaminated by incentives other than providing value-related information.

The third essay examines the relationship between the informativeness of financial analysts' stock recommendations and earnings forecasts and firms' brand capital intensity. Because brand assets are generally not capitalized and are more difficult to evaluate, analysts' recommendations and forecasts for firms with higher brand capital

intensity are expected to convey more information about firms' value. As predicted, the results suggest that (1) analysts discuss more topics related to brand capital in their reports for firms with higher brand capital intensity, (2) the short-term market reactions to recommendations and forecasts are significantly higher for firms with higher brand capital intensity, (3) calendar-time portfolios based on analysts' recommendations earn significantly greater abnormal returns for firms with higher brand capital intensity and (4) short-term market reactions to recommendations and forecasts are significantly positively related to brand capital intensity. In addition, the relationship is stronger when market news sentiment is more extreme. The relationship is also stronger when market news sentiment conflicts with forecast revisions but is indifferent when it conflicts with recommendation revisions. Furthermore, revision frequency and forecast accuracy decrease in brand capital intensity. These findings indicate that analysts expend more effort in evaluating brand capital and their stock recommendations and earnings forecasts are more valuable for firms with higher brand capital intensity.

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Table of Contents

List of Tables

List of Figures

Chapter 1. Investors' Divergence of Opinion and M&A Characteristics: A New Approach

1.1 Introduction

Using a new measure of investors' divergence of opinion, we revisit the relationship between investors' divergence of opinion and merger & acquisition related characteristics. Specifically, we demonstrate that the new measure, which captures analysts' differential interpretation of public signals, better explains the relationship between investors' divergence of opinion about a specific firm and (i) the likelihood of the firm being selected as a takeover target, (ii) the successful rate of the takeover and (iii) the abnormal stock return of the target firm around the announcement date.

It has been well established that heterogeneous belief among investors generally leads to overvaluation of stocks since short sale constraints, including but not limited to the difficulty of borrowing shares, recall risk, and legal restrictions, prohibit pessimistic opinions from being reflected in stock prices (e.g. Miller 1977), and that a high level of divergence of investors' opinions decreases the likelihood of a takeover and increases the takeover premium (e.g. Chatterjee et al. 2012). However, there has also been heated discussion about the suitability of the most frequently used proxies for the investors' divergence of opinion and for the takeover premium. Many prior studies use analysts' forecast dispersion to proxy for divergence of opinion. However, this measure suffers from endogeneity concerns, since it also captures future uncertainty about the stock and the analysts' own irrationality. Many studies also use bid-ask spread to proxy for investors' divergence of opinion, but bid-ask spread only captures information asymmetry among investors, which is related but not identical to divergence of opinion

(Sheng and Thevenot 2015). Besides, bid-ask spread also captures the brokers' order processing and inventory costs, and the order processing costs dominate (e.g. Huang et al. 1997). A third frequently used proxy for divergence of opinion is idiosyncratic return volatility, although this measure is also more of a proxy for information risk and uncertainty. For the takeover premium, many prior studies use cumulative abnormal returns (CAR) around the announcement date (pre-announcement run-up plus post-announcement markup) as proxy. However, this proxy not only captures takeover premium, which is the price paid by the bidder in excess of intrinsic value, but also captures the increase in intrinsic value (e.g. Officer 2003), which includes but is not limited to synergy effect and merger completion risk. Simply using cumulative abnormal announcement return to proxy for the takeover premium would lead to mixed results.

In this paper, we implement a new measure of investors' divergence of opinion based on the Bayesian learning model (Kandel and Pearson 1995) and readopted by Sheng and Thevenot (2015). We quantify the analysts' differential interpretation of quarterly earnings announcements based on forecasts revisions to develop the new measure of divergence of opinion. We then compare the new measure with the three traditional measures by putting each one in the same regression models in which the independent variables are takeover likelihood, takeover completion likelihood, and target abnormal announcement returns. The results obtained from the regressions using the new measure are consistent with the results in prior studies and the hypotheses in this paper. Specifically, we find that divergence of opinion is negatively associated with takeover likelihood, positively associated with takeover completion likelihood, and positively associated with target abnormal announcement returns. The results generated from the three traditional measures are either not as good as the results from the new measure or inconsistent with well-adopted hypotheses. We also use several model specifications to create variants of the new measure of divergence of opinion and find similar results.

Our findings contribute to the existing literatures in several ways. We are the first to implement the quantified differential interpretation of earnings announcements from the Bayesian learning model in analyzing M&A-related characteristics. The validity of our results not only demonstrates the practicability of the new measure of divergence of opinion, but also enhances the existing theories underlying this field. In addition, we are the first to analyze the impact of divergence of opinion on takeover completion likelihood, which is a critical determinant of losses and gains for M&A arbitragers.

The rest of the paper is organized as follows. Section 1.2 provides a review of related literature in the field of divergence of opinion and M&A activities and shows the development of our hypotheses. Section 1.3 describes model specifications, variables, and data sources. Section 1.4 provides our main results. Section 1.5 concludes the paper.

1.2 Literature Review and Hypotheses Development

This section provides some arguments from previous literature about the interaction between divergence of opinion and M&A-related firm characteristics. We begin this section by briefly interpreting the dominant theoretical argument about overvaluation of a firm due to divergence of opinion and the short sale constraint, and its possible ramifications on M&A-related characteristics such as takeover likelihood, takeover status and abnormal target announcement returns. Then we develop our testable hypotheses. We also discuss the framework for the quantified measure of differential interpretation developed by Sheng and Thevenot (2015) and other frequently used measures of divergence of opinion in this section.

1.2.1 Measures of Divergence of Opinion

It has long been argued that when divergence of opinion among investors is significant, stock price tends to reflect only the opinion of the most optimistic investors due to the short sale constraint, which leads to overvaluation because it prevents rational, pessimistic investors from selling the firm's stock short (Miller 1977; Harrison and Kreps 1978; Morris 1996). However, several prevailing measures of divergence of opinion are generally thought to be endogenous, and the results generated from these measures are mixed. One of the most frequently used measures is the dispersion of analysts' earnings forecasts. However, Barron et al. (1998) show that the dispersion of analysts' earnings forecasts is an interaction between uncertainty and disagreement, which would introduce some noise to the model. In addition, Sheng and Thevenot (2012) show that the dispersion of analysts' earnings forecasts also captures idiosyncratic risk. Furthermore, analysts of a specific stock tend to underemphasize good news about earnings and overemphasize bad news about earnings when they make forecasts, a fact that may shift all analysts' opinion to one direction, weakening the relationship between dispersion and divergence of opinion.

Another measure of divergence of opinion is bid-ask spread. However, bid-ask spread contains three components: inventory cost, order processing cost, and information asymmetry cost, which have already been demonstrated by several theoretical models (George et al. 1991; Lin et al. 1995; Madhavan et al. 1997; Huang et al. 1997). The most dominant component in bid-ask spread is the processing cost, whereas the information asymmetry component is smaller and less correlated with the spread (George et al. 1991; Huang et al. 1997). Another problem with this measure is that, although the definitions of information asymmetry and divergence of opinion overlap, they cannot substitute one another (Bloomfield and Fischer 2011).

Idiosyncratic return volatility is another measure of divergence of opinion used in several studies, based on the rationale that idiosyncratic return volatility signals higher risk that could stem from a more volatile, less predictable earnings stream represented by the dispersion of analysts' earnings forecasts (Diether et al. 2002; Boehme et al. 2006). However, the ex-post idiosyncratic return volatility is just the ramification of divergence of opinion and the short sale constraint. Simply interpreting idiosyncratic return volatility as a measure of divergence of opinion ignores many other factors that relate to idiosyncratic return volatility itself.

Prior studies also interpret the revision of analysts' earnings forecasts using the Bayesian learning model to develop a new measure of divergence of opinion. These studies stem from Kandel and Pearson's (1995) framework in which they assume that different analysts have different likelihood functions for interpreting public signals. Specifically, under the normality assumption, the Bayesian learning model implies that:

$$Y_i = \rho_i X_i + (1 - \rho_i)(L - \mu_i),$$

where X_i is the earnings forecasts prior to the public signal and Y_i is the earnings forecasts after the public signal, L is the common signal, μ_i is analyst i's interpretation of the common signal, and ρ_i is the weight that analyst i puts on the prior belief. If analysts have different likelihood models, i.e. $\mu_i \neq \mu_j$, the divergence of interpretation can be observed. Specifically, the posterior means of forecasts from two different analysts need not be revised in the same direction. Thus, the sign of the difference between the prior forecasts and the revised forecasts need not to be identical:

$$sign(Y_i - X_i) \neq sign(Y_j - X_j)$$

Sheng and Thevenot (2015) extend the model in which they further assume that the prior mean of all analysts' forecasts and the differential interpretation are mutually independent. In that case, the differential interpretation, which is the variance of μ_i, can be expressed by the variance of the prior belief and the variance of the posterior belief:

$$AD_t = \rho_i{}^2 BD_t + (1 - \rho_i)^2 \, DI_t,$$

where AD_t is the variance of earnings forecasts after the public signal, BD_t is the variance of earnings forecasts before the public signal, and DI_t is the variance of μ_i, which is the quantified measure of divergence of opinion.

While the relationship between investor divergence of opinion and takeover likelihood is readily observable in regression models, two different assumptions could possibly lead to the same results. First, divergence of opinion among investors is usually accompanied by information asymmetry stemmed from the financial outlook and internal operating situation of a firm. Furthermore, firms with greater information asymmetry are less likely to be selected as a takeover target due to increased uncertainty in the post-acquisition value of the combined firm. Thus, an observed negative relationship between divergence of opinion and takeover likelihood could be fundamentally attributable to information asymmetry. Alternatively, divergence of opinion among investors creates both downward and upward price pressure. The downward price pressure is weaker if short sale constraint exists, making the perceived price positively diverged from the intrinsic value at equilibrium. Furthermore, such overvaluation will suppress the likelihood of a firm being selected as a takeover target because it makes the firm more "expensive". As a result, the observed negative relationship between divergence of opinion and takeover likelihood could also be fundamentally attributable to overvaluation resulting from the interaction between divergence of opinion and short sale constraint. Considering these two possible assumptions as a whole, we state our first hypothesis as follows:

$H_{1.1}$: The quantified measure of divergence of opinion DI_t is superior to dispersion of analysts' earnings forecasts, bid-ask spread and idiosyncratic return volatility in predicting takeover likelihood.

This hypothesis is based on the fact that DI_t relies on the more relaxed assumption that analysts interpret common signals differently, regardless of whether the differential interpretation stems from information asymmetry, idiosyncratic risk, or other unobservable factors. By using earnings announcement as the fundamental benchmark and using analysts' different interpretations of earnings announcement to represent the divergence of opinions from the market, the measure is built simply from observable factors that are less likely to be affected by other factors that could also drive merger & acquisition related firm characteristics. For example, factors such as information asymmetry that would commonly affect analysts' forecasts dispersion, are less of a concern in the new measure because all analysts would get the same level of information from the earnings announcement and there is no variance of the information dissemination process among different analysts. The only factor affecting their subsequent forecasts is their own differential interpretation of the earnings announcement. In addition, although the altering of dispersion captures information asymmetry (Barron et al. 2009) due to differential interpretation, divergence of opinion may also occur without increased information asymmetry (Bloomfield et al. 2011). However, DI_t captures any divergence of opinion including but not limited to the divergence of opinion related to information asymmetry.

1.2.2 Divergence of Opinion and Takeover Likelihood

Previous studies have analyzed the relationship between M&A events and the divergence of opinion. For example, Chatterjee et al. (2012) provide evidence on the relationship between several takeover characteristics such as takeover premium, pre-announcement price run-up, post-announcement price markup, takeover likelihood and synergy effect, and divergence of opinion on the targets. They argue that if a firm is subject to a high level of divergence of opinion, investors would expect the firm to receive a high takeover premium in an M&A event, which makes the firm more "expensive". These expensive firms will be less likely to be selected as a takeover target compared with accurately valued firms or undervalued firms. For example, Belkaoui (1978) and Trautwein (1990) suggests that, on average, undervalued firms will be more attractive takeover targets to the bidders if there are no assumptions about the characteristics of the respective bidders. Other studies have generally found a negative relationship between market valuation and takeover likelihood. For example, Cremers et al. (2009) and Bates et al. (2008) find a negative relationship between takeover likelihood and Tobin's Q. Edmans et al. (2012) create a measure of valuation discount using mutual fund redemption as an instrument variable and find that the likelihood of takeover is higher for firms with high valuation discount. Hence, if a high level of divergence of opinion results in overvaluation due to the short sale constraint, it would also make these firms less likely to be selected as targets because, *ceteris paribus*, the value-increasing potential of these firms would be smaller than for undervalued or accurately valued firms. Chatterjee et al. (2012) further demonstrate that, since firms with high levels of divergence of opinion are more "expensive", a rational bidder would only acquire the one that creates enough synergy effect to compensate for the high takeover premium.

However, such compensation can also be achieved through other circumstances that may boost the post-merger value of the target. For example, a potential acquirer can hold private information on how much higher the value is expected to be in the post-merger period (Trautwein 1990) and target the firm with a takeover premium that is smaller than the post-merger value markup. Dong et al. (2006) suggest that the acquirer can profit from offering stock to buy overvalued firms, knowing that its own shares are more overvalued than the target. Palepu (1986) suggests that an acquirer who holds more private information about a target firm may have a higher valuation for that firm even if the market thinks that the target is overvalued, creating a "cheap buy" opportunity for the acquirer. Thus, these synergy effects and information asymmetry effects are all conditional on the characteristics of the acquirer. In a more generalized situation, market overvaluation of a firm, as created by divergence of opinion, would decrease the likelihood of takeover. Hence, we state our second hypothesis as follows:

$H_{1.2}$: Ceteris paribus, the probability of a firm being selected as a takeover target decrease with the level of divergence of opinion about the firm.

1.2.3 Divergence of Opinion and Takeover Status

Literature addressing the relationship between divergence of opinion and the rate of successful mergers is relatively scarce. On average, the stock price of a target generally experiences a substantial markup during a short window around the announcement date of the acquisition. If the acquisition is successful, the stock price would reach the offer price on the consummation date, and the difference between the offer price and the price after the announcement date creates an opportunity for merger arbitragers. However, if the acquisition offer is withdrawn, the price would fall rapidly on the withdrawal date. Thus, the success or failure of the acquisition is important for merger arbitrage funds that buy the shares of the target at the announcement date in a merger they believe will be completed. In fact, although the average completion rate is as high as 89% (Branch et al. 2003), merger completion risk is still a major risk factor in determining the returns of a merger arbitrage (Baker et al. 2002), and the losses from merger arbitrages are positively related to the probability of merger failure (Mitchell et al. 2001).

Branch et al. (2003) find that mergers using stock offers are less likely to be completed than mergers using cash offers because the uncertainty about the intrinsic value of the acquirer's stock impedes the target's acceptance of the offer. In fact, the information asymmetry (Myers et al. 1984) that results in different choices of payment methods is a fundamental determinant of the probability of completion. In the framework of information asymmetry when the level of divergence of opinion is high, the optimistic information will be more reflected in the market price, biasing the valuation upward, whereas the pessimistic information is less reflected or not reflected at all in the market price. As Chatterjee et al. (2012) show, the demand curve of the target stock becomes steeper when divergence of opinion increases. Therefore, the acquirer must pay a higher takeover premium to acquire a significant amount of the target's stock to gain control. Thus, the difference between the bidding price and the average valuation among all investors is larger when the level of divergence of opinion is high.

Furthermore, if we assume that all bidders are homogeneous and that the takeover premium depends only on the target's characteristics, the managers of an overvalued firm are more likely to accept the bid. This framework is illustrated by Tunyi et al. (2014). They show that, in the absence of information asymmetry when the management of a potential target and a potential bidder have absolute equal access to all information related to the intrinsic value of the target, the bidder would provide a bidding price equal to the true intrinsic value V_0. However, different levels of information asymmetry often prevent the bidder from measuring V_0 accurately. Hence, the bidding price V_b may diverge from the true intrinsic value V_0. Also, $V_b - V_0 > 0$ because any bidding price smaller than the true intrinsic value would be rejected by the target.

Following the previous theory, we further assume that the post-merger value of the combined firm V_p consists of the combined intrinsic value of the target and the bidder V_c, the synergy effect V_s, and the merger premium V_m. If there is no information asymmetry between the target and the acquirer, the following equation should hold:

$$V_p = V_c + V_s - V_m$$

Thus, the post-merger value of the combined firm equals the combined value plus the synergy effect minus the takeover premium. However, if the bidder's valuation of the target deviates from V_0, the post-merger value of the combined firm would also have a value depletion component, V_b - V_0. In that case, the post-merger value of the combined firm V'_p becomes:

$$V'_p = V_c + V_s - (V_b - V_0) - V_m$$

i.e.

$$V'_p = V_p - (V_b - V_0)$$

In the framework of information asymmetry, a higher level of divergence of opinion will lead to a greater overvaluation. The managers of the more overvalued firm are aware of the larger difference between the intrinsic value and the bidding price. Thus, they are more willing to accept the bid than the managers of a less overvalued firm or an undervalued firm would be. The resulting larger profit will facilitate the merger to be completed. As a result, we state our third hypothesis as follows:

$H_{1.3}$: In the context of information asymmetry, the probability of a merger being completed increases with the level of divergence of opinion among all investors about the target.

In addition, an attractive valuation resulting from a low level of divergence of opinion among all investors may appeal to more investors and other bidders, making it more difficult for the target to be acquired by any one of the observed bidders. On the contrary, if too much divergence of opinion results in overvaluation and a bidder still wants to acquire that firm, the lack of competition would increase the success rate.

1.2.4 Divergence of Opinion and Abnormal Target Announcement Return

By definition, the takeover premium is the excess of bidding price over the real post-merger value of the target. This could include agency costs, negotiation costs, regulation costs, and the cost of overconfidence, hubris, or any other behavioral quirks of the acquirers (Roll 1986; Malmendier et al. 2005; Sudarsanam et al. 2004), as well as tactical reasons for persuading target shareholders to tender their shares (Sudarsanam et al. 2010). Previous studies generally use target CAR around the announcement date to proxy for the takeover premium. However, CAR is endogenous since it contains not only the takeover premium, but also the updating of the likelihood of the takeover being successful (Eckbo et al. 2009; Chatterjee et al. 2012; Officer 2003), the revealing of the true value of a previously undervalued target, and the potential synergy yield to investors (Sudarsanam et al. 2010). Chatterjee et al. (2012) use cumulative target abnormal return around the announcement date as a proxy for the takeover premium and document that the takeover premium is positively associated with investors' divergence of opinion. However, this result should be interpreted with caution. First, the proxies for investors' divergence of opinion used by Chatterjee et al. (2012) are dispersions of analysts' forecasts and idiosyncratic risk, which are subject to endogeneity problem as discussed in section 2.1. Second, the proxy used for the takeover premium is cumulative target abnormal return, which also measures the increase in the intrinsic value of the target, including completion risk and the synergy effect discussed above. We formulate the cumulative target abnormal return as follows:

$$CAR_i = V_{i,b} - V_{i,a} + V_{i,p} - V_{i,c} + \varepsilon_i$$

or:

$$CAR_i = (V_{i,b} - V_{i,a}) + (V_{i,p} - V_{i,c}) + \varepsilon_i$$

where CAR_i is the cumulative abnormal returns around the announcement date for target i, $V_{i,b}$ is the investors' expectation about the post-merger intrinsic value of target i, $V_{i,a}$ is the pre-merger value of target *i*, $V_{i,p}$ is the takeover premium paid to target *i* and $V_{i,c}$ is the value depletion due to completion risk.

Thus, the effect of investor divergence of opinion on cumulative target announcement return is ambiguous. On the one hand, if investors' divergence of opinion has a positive relationship with the takeover premium (Chatterjee et al. 2012) and a negative relationship with completion risk, CAR would increase with divergence of opinion. On the other hand, the overvaluation of the target resulting from divergence of opinion would reduce the upward potential of the intrinsic value of the target, leading to a smaller CAR. Therefore, the impact of investors' divergence of opinion on the cumulative target abnormal return is a combination of the overvaluation effect and the takeover premium effect.

Alternatively, we argue that the effect of investors' divergence of opinion could still have a positive effect on announcement abnormal returns even when short sale constraint is weak. The information asymmetry stemmed from investors' divergence of opinion implies a greater takeover premium based on the winner's curve theory. Thus, we state our fourth hypothesis as follows:

$H_{1.4}$: The overvaluation effect dominates if the impact of investors' divergence of opinion on announcement cumulative target abnormal return is significantly negative, and the takeover premium effect dominates if the impact of investor's divergence of opinion on announcement cumulative target abnormal return is significantly positive.

1.3 Research Design

In this section, we first introduce the construction of the quantified measure of differential interpretation, and then provide the framework for the main models, as well as the definition and descriptive statistics of the variables.

1.3.1 Construction of Differential Interpretation

We follow Sheng and Thevenot's (2015) framework for the Bayesian learning model to develop the quantified measure of differential interpretation. Unlike Sheng and Thevenot (2015), who focus only on three horizons and measure differential interpretation around the first three quarters' earnings reports using analyst forecasts for the current fiscal year's earnings, we use data for up to seven horizons (i.e., up to seven forecasts revisions before the fiscal year earnings report). Specifically, we estimate the following regression:

$$(AF_{it} - AF_t) = \alpha_t + \rho_i(BF_{it} - BF_t) + \sum_{t=1}^{7} \beta_t \, Quarter_t + \varepsilon_{it}$$

where AF_{it} (BF_{it}) is the forecast of fiscal year earnings made by analyst *i* after (before) the quarterly earnings report in quarter *t*, AF_t (BF_t) is the average earnings forecasts made by all analysts after (before) the quarterly earnings report in quarter t, and $Quarter_{it}$ is the quarter indicator. Similar to Sheng and Thevenot's (2015) method, if an analyst makes multiple forecasts in either of these windows, we only use the forecasts closest to the fiscal year earnings report. Since ρ_i is bounded by 0 and 1, we also truncate the estimation of ρ_i to let all the estimations fall between 0 and 1. Then, we use the following formula to compute the quantified differential interpretation:

$$AD_t = {\rho_i}^2 BD_t + (1 - \rho_i)^2 \, DI_t,$$

or:

$$DI_t = \frac{AD_t - {\rho_i}^2 BD_t}{(1 - \rho_i)^2}$$

Our measure differs from the measure developed by Sheng and Thevenot (2015) in that we use seven forecasts revisions instead of three, which yields a larger sample size for each firm. Since we also require that at least ten analysts follow a given firm at each revision point, the modification of the number of horizons not only increases the sample size for the estimation of each individual ρ_i, but also increases the total sample size of the main model. However, we also compare the change in estimation of each individual ρ_i and find that, although the estimation changes slightly as we increase horizons from four to six, there is no difference between the estimations under horizons of six and seven revisions, which suggests that no analysts make forecasts eight quarters before the fiscal year earnings report. Even if a few analysts do issue forecasts eight quarters before the report, which may not be captured by our sample, it is safe to assume that the size of these forecasts revisions is too small to affect our results. Hence, we only report results based on three through six horizons.

1.3.2 Data and Variable Description

After we obtained the quantified differential interpretation, we estimate the following regression models:

$$Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$$

where $Y_{i,t}$ represents each of the four M&A-related characteristics:

Takeover: The likelihood of firm i receiving an M&A bid in year t, which equals 1 if the firm receives an M&A bid and 0 otherwise.

Status: The outcome of M&A activity, which equals 1 if the merger is successful and 0 otherwise.

CAR: The cumulative abnormal returns of target firm i around the announcement date, measured using the Fama-French 5 factor model, starting from 63 days before the announcement date to 126 days after it.

BHAR: The cumulative buy-and-hold abnormal return of target firm i around the announcement date, starting from 63 days before the announcement date to 126 days after it.

and $X_{i,t-1}$ are the four independent variables:

DI: The quantified measure of differential interpretation based on the Bayesian learning model.

IDIOVAR: The volatility of abnormal return for firm i in year t-1, measured using the Fama-French 5 factor model. We eliminated firm-year observations if there are less than 60 days with data for abnormal returns.

Spread: The yearly average of bid-ask spread of the common stock for firm i in year t-1, scaled by stock price.

Disper: The standard deviation of analysts' forecasts of earnings per share throughout year t-1 for firm i. We calculated this measure with detailed history file from I/B/E/S database using methods from Diether, Malloy, and Scherbina (2002).

To control for the effect of short sale constraint, we also estimate the following model:

$$Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \beta_2 * Instown_{i,t-1} + \beta_3 * X_{i,t-1} * Instown_{i,t-1} \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$$

Where *Instown* is the percentage of stocks held by institutional investors.

We collect data about M&A deals from the Thomson Reuters SDC database from 1990 to 2016, focusing only on deals in which the acquirer attempts to acquire 100% of the target, but eliminating self-acquiring deals. We winsorize the data at the 1% and 99% levels. The final sample contains 11,268 firm-year observations for 1,102 M&A cases. The total sample size used in each regression may vary slightly due to missing data for some individual variables. Table 1.1 provides definitions of variables and summary statistics.

[Insert Table 1.1 here]

Table 1.2 provides the Pearson correlation among selected variables using data for all 1,102 takeover samples. The table shows that the correlations among all four measures of divergence of opinion and takeover status are positive, consistent with the hypothesis that completion rate increases with the level of divergence of opinion. Moreover, the quantified measure of differential interpretation and other three traditional measures are positively correlated with both measure of abnormal announcement returns, CAR, and BHAR, suggesting that the takeover premium effect dominates the overvaluation effect resulting from divergence of opinion. This provides preliminary support for our hypotheses. In the next section, we present the main results of our regression models.

[Insert Table 1.2 here]

1.4 Results

In this section, we provide the results from models using the quantified measure of differential interpretation and those using traditional measures of divergence of opinion.

1.4.1 Impact of Divergence of Opinion on Takeover Likelihood

In Table 1.3, we partition our sample into 10,166 non-takeover observations and 1,102 takeover observations. The means of all the four measures of divergence of opinion in the non-takeover group are greater than those in the takeover group. For example, the mean of DI in the non-takeover group is 1.3771, which is greater than 0.8450 in the takeover group. This suggests that, on average, firms with higher level of divergence of opinion are less likely to attract takeover offers. We further partition the 1,102 takeover observations into 443 withdrawn deals and 659 completed deals. We find that the means of all four measures of divergence of opinion in the withdrawn group are smaller than those in the completed group. This provides initial evidence to support our hypothesis that targets with higher levels of divergence of opinion are more likely to complete an M&A deal.

[Insert Table 1.3 here]

Panel A of Table 1.4 provides the results of the regression of *TAKEOVER* on *DI, VAR, Spread* and *Disper*. In this test, *DI* is constructed using six horizons (revisions) before the fiscal year earnings report. We use *DI* two months before the event date. In models without *Instown*, the table shows that DI_6 is significantly negatively related to the takeover indicator with a t-value of -8.06. Similarly, the coefficient estimates on *Spread* and *Disper* are all negatively significant with t-values of -9 and -11.94 respectively. The coefficient estimate on *IDIOVAR* is not significant. The result is consistent with our hypothesis and the results of Chatterjee et al. (2012). In general, we argue that the probability of receiving an acquisition offer decreases with the level of investor divergence of opinion.

[Insert Table 1.4 here]

1.4.2 Impact of Divergence of Opinion on Takeover Status

Panel A of Table 1.5 reports the results of the regression of *STATUS* on *DI, IDIOVAR, Spread* and *Disper*. As with the regression of *TAKEOVER* on *DI*, we use *DI* created by using three to six revisions two months before the event date to test for robustness. The coefficient estimate on *DI* is significantly positive with a t-value of 10.1. This finding is consistent with our hypothesis that the probability of M&A completion increases with the level of divergence of opinion. We also find the regression of *STATUS* on other two traditional measures of divergence of opinion are significantly positive with the t-values of the estimates of *IDIOVAR* and *Disper* 3.21 and 6.19 respectively. In general, all the four measures of investor divergence of opinion generate consistent results.

[Insert Table 1.5 here]

1.4.3 Impact of Divergence of Opinion on Target Announcement Abnormal returns

We use cumulative abnormal returns from the Fama-French 5 factor model and buy-and-hold cumulative abnormal returns to proxy for target announcement abnormal returns. We need to select a time window that captures sufficient price markup that reflects as much information about the takeover announcement as possible, but not so long that it introduces additional noise. Following Chatterjee et al. (2012), we choose a time window of [-63,126] to calculate *CAR* and *BHAR*.

Panel A of Table 1.6 presents the results of the regression of *CAR* on *DI, IDIOVAR, Spread* and *Disper*. The coefficient estimate on *DI* is significantly positive with a t-value of 9.92, suggesting that there is a positive relationship between investor divergence of opinion and target announcement abnormal returns. Also, *IDIOVAR* and *Disper* all generate significant results with t-values of 3.49 and 6.58, respectively. This finding favors the hypothesis that the takeover premium effect dominates the overvaluation effect, which means that stocks with high levels of divergence of opinion still have great potential for announcement markups because of the lower completion risk and the larger takeover premium paid by the bidders.

[Insert Table 1.6 here]

Panel A of Table 1.7 presents the results of the regression of *BHAR* on *DI*, *IDIOVAR*, *Spread* and *Disper*. The coefficient estimate on *DI* is significantly positive with a t-value of 8.88, suggesting that there is a positive relationship between investor divergence of opinion and target announcement abnormal returns. Also, *IDIOVAR* and *Disper* all generate significant results with t-values of 2.62 and 6.84, respectively. These findings are similar to those of regression models of *CAR*. All these findings are consistent with the hypothesis that takeover premium effect dominates value-creating effect.

[Insert Table 1.7 here]

We argue that these results should be interpreted with caution. First, although bid-ask spread contains an adverse selection component (George et al. 1991; Lin et al. 1995; Madhavan et al. 1997; Huang et al. 1997) that could result in heterogeneous investor interpretation, Huang et al. (1997) argue that a negative serial covariance in trade flows that creates quote reversals is required for market makers to recover inventory holding costs. Therefore, when inventory holding costs are trivial, order processing costs should be the largest component of the bid-ask spread. In fact, Huang et al. (1997) document that the average percentage of order processing cost in bid-ask spread is approximately

80%, whereas the adverse selection component is only about 10%. Furthermore, Nicolas et al. (2002) argue that, in a highly competitive market, order processing cost can be amortized over total trading volume across securities, and the bid-ask spread should only equal the expected marginal cost of supplying liquidity. Second, bid-ask spread also decrease with the number of market makers. The larger the number of market makers trading on the stock of the same company, the smaller the start-up costs of creating a competing exchange for market makers to recoup their fixed costs and earn an economic profit (Nicolas et al. 2002). However, the number of market makers trading on the same company is difficult to observe, and Nicolas et al. (2002) use the Herfindahl index to proxy for it. Moreover, even if the Herfindahl index is a good proxy for the number of market makers trading on the same company, its influence on target announcement abnormal return through its effect on bid-ask spread is still unknown. As a consequence, the effect of bid-ask spread on announcement target abnormal returns depends significantly on market efficiency and the part played by order processing cost, market competition, and maybe some other unobserved factors.

1.4.4 A Comparison of the M&A-Related Information Content between DI and Other Measures

In this section, we provide statistical evidences that DI contains more relevant information in predicting M&A-related firm characteristics compared to other three measures. As discussed above, the three traditional measures are subject either to irrelevant information (e.g., bid-ask spread also captures order processing costs and inventory costs) or to controversial effect (e.g., idiosyncratic return volatility also contains the increase in intrinsic value of the targets that could potentially counteract the effect of investors' divergence of opinion). To compare DI with the other three measures, we use Likelihood-Ratio Test and Wald Test to analyze the constraint efficiency of DI in both un-nested and nested model specifications. Since we use OLS to estimate all models' coefficients, we calculate test statistics using the form that incorporates the residual sum square (RSS) of each model, rather than the likelihood function. Specifically, we apply two model specifications. In specification A, test statistics are calculated from two un-nested models:

$$Y_{i,t} = \beta_i + \beta_1 * DI_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$$

And

$$Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e'_{i,t}$$

where $Y_{i,t}$ represents each of the four M&A-related characteristics and $X_{i,t-1}$ are the three traditional measures.

In specification B, test statistics are calculated from models using traditional measures and nested models with the addition of DI:

$$Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e'_{i,t}$$

And

$$Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \beta_2 * DI_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$$

The Likelihood-Ratio statistic and Wald statistic are calculated as follows:

$$LR = -n[Ln\left(\sum e_{i,t}{}^2\right) - Ln(\sum e'_{i,t}{}^2)]$$

$$Wald = \frac{-n(\sum e_{i,t}{}^2 - \sum e'_{i,t}{}^2)}{\sum e'_{i,t}{}^2}$$

Penal B of Table 1.4 presents the results of regression models on *TAKEOVER*. Almost all three test specifications show statistically significant results except for model specification A when adding *DI* to models using *Spread* and *Disper*, demonstrating that *DI* is an efficient constraint in predicting takeover likelihood. Penal B of Table 1.5 presents the results of regression models on *STATUS*. Similarly, almost all three test specifications show statistically significant results except for model specification A when adding *DI* to models using *Disper*. Penal B of Table 1.6 and Table 1.7 presents the results of regression models on *CAR* and *BHAR* respectively. All three test specifications show statistically significant results, suggesting that *DI* is an efficient constraint in predicting takeover abnormal announcement returns. These results together provide evidence that DI is more information-relevant in predicting the likelihood of a firm being selected as a takeover target, takeover completion likelihood and the abnormal announcement returns associated with these M&A bids.

1.5 Conclusions

This article analyzes the relationship between investor divergence of opinion and M&A characteristics. Using a new measure of analysts' differential interpretation from the Bayesian learning model, we document that divergence of opinion is negatively related to takeover likelihood, positively related to takeover completion likelihood, and positively related to cumulative target announcement abnormal return. We show that the new measure has more informational content and is a more efficient predictor of M&A characteristics compared with other three traditional measures of divergence of opinion. Our results also provide preliminary evidence that the cumulative target announcement abnormal returns are more significantly affected by the takeover-premium component, rather than by the value-creating component. The overvaluation caused by divergence of opinion prior to the takeover announcement would reduce the value increasing potential at the announcement, but not large enough to make the abnormal returns around the announcement date smaller. This paper demonstrates the eligibility of using conditional forecasts revisions to interpret divergence of opinion and also contributes to the understanding of acquiring firms' underlying target-selection mechanism, as well as the *ex post* takeover outcome and value-creating potential.

Table 1.1. Summary of Variables

Panel A: Variable Definitions

Dependent Variables:

BHAR	The buy-and-hold abnormal return around the announcement date with a window size of [-63,126] [Event Study by WRDS]
CAR	Cumulative target abnormal returns around the announcement date, measured using Fama-French factor model plus momentum with window size of [-63,126] [Event Study by WRDS]
STATUS	The final outcome of a M&A activity, which equals 1 if the merger is complete and 0 otherwise [Thomson Routers SDC Database]
TAKEOVER	An indicator variable equal to 1 if the firm received takeover bid and 0 otherwise [Thomson Routers SDC Database]

Independent Variables:

DI	The Sheng and Thevenot (2015) measure of investor divergence of opinion
Disper	The standard deviation of analysts' forecasts across 3 months before the announcement date of *EPS* [I/B/E/S]
Spread	The 3-month average of bid-ask spread scaled by stock price [CRSP]
IDIOVAR	The volatility of abnormal returns across 3 months before the announcement date, measured using Fama-French factor model plus momentum [Event Study by WRDS]

Control Variables:

ATO	Asset turnover [Sales (Compustat data item #12)/(Compustat data item #6)]
FCF	'Cash flow in excess of that required to fund all projects that have positive net present values (NPV) when discounted at the relevant cost of capital' (Jensen 1986). Calculated as the cash flow from operations minus cash dividends scaled by total assets [((Compustat data item #308) - (Compustat data item #127))/(Compustat data item #6)]
Growth	Average sales growth during past (up to) 3 years [Compustat data item #12]
HHIfirm	Herfindahl index of a firm's sales in different business segments, which measures the degree of market concentration and competition which may impede merger and acquisition (Edmans, Goldstein, and Jiang 2012)
Instown	Percentage of shares held by institutional owners [Thompson Financial]. (For example, Mikkelson and Partch (1989) and Shivdasani (1993) find that block ownership increases the probability of a takeover attempt)
Intangible	Intangible assets scaled by total assets ([Compustat data item #12]/[Compustat data item #6])
Leverage	Leverage ratio of total liabilities to total assets [(Compustat data item #6 – Compustat data item #60)/ Compustat data item #6]
Liquidity	Current assets divided by current liabilities [(Compustat data item #4)/(Compustat data item #5)]
Logsize	The natural log of the total value of asset of the company [Compustat data item #6]
Loss	An indicator variable equal to 1 if the company had net loss in the previous year and 0 otherwise [Compustat data item #172]
Mtb	Market to book value [share price times the number of shares outstanding [Compustat data item #25 Compustat data item #199] divided by Compustat data item # 60]
Mktshr	The proportion of sales to the total sales of that industry, measured using three-digit SIC code
Payout	(Dividends [Compustat data item #21] + Repurchases [Compustat data item #115])/Net Income [Compustat data item #18]; zero if numerator is zero or missing, and 1 if

	numerator > 0 and denominator = 0. (For example, Powell and Yawson (2007) and Espahbodi and Espahbodi (2003) find that targets, on average, have lower payout ratios and therefore lower yields.)
R&D	Research and Development expense [Compustat data item #46]/Sales [Compustat data item #12]; zero if missing
Repurchase	An indicator variable equal to 1 if the company has engaged in stock repurchase activities and 0 otherwise.
ROA	Return on assets calculated as net income divided by total assets at the beginning of the fiscal year [(Compustat data item #13)/(Compustat data item #6)]
Z	Z-Score, a measure of financial distress developed by Taffler (1983)

Panel B: Descriptive Statistics

				Percentiles		
Variables	N	Mean	S.D.	25%	50%	75%
BHAR	1,102	0.13	1.04	-0.19	0.16	0.52
CAR	1,102	0.21	0.67	-0.12	0.19	0.55
Status	1,102	0.6	0.49	0	1	1
Takeover	11,268	0.1	0.3	0	0	0
ATO	11,268	0.99	0.7	0.49	0.79	1.27
FCF	11,268	0.1	0.09	0.06	0.1	0.14
Growth	11,268	0.17	0.27	0.03	0.1	0.22
HHIfirm	11,268	0.47	0.26	0.27	0.39	0.56
Instown	11,268	0.77	0.21	0.66	0.81	0.92
Intangible	11,268	0.19	0.2	0.01	0.12	0.31
Leverage	11,268	0.53	0.22	0.37	0.53	0.67
Liquidity	11,268	2.35	1.7	1.26	1.85	2.84
Logsize	11,268	8.03	1.54	6.91	7.96	9.05
Loss	11,268	0.18	0.38	0	0	0
Mktshr	11,268	0.15	0.22	0.01	0.05	0.19
Mtb	11,268	3.93	5.22	1.73	2.79	4.47
Payout	11,268	0.64	1	0	0.29	0.9
R&D	11,268	0.04	0.06	0	0	0.06
Repurchase	11,268	0.6	0.49	0	1	1
ROA	11,268	0.04	0.11	0.02	0.06	0.1
Z	11,268	5.91	6.01	2.59	4.12	6.82
DI3	11,268	0.93	3.44	0.02	0.08	0.36
DI4	11,268	0.9	3.3	0.02	0.08	0.36
DI5	11,268	0.9	3.3	0.02	0.08	0.36
DI6	11,268	0.9	3.28	0.02	0.08	0.36
Disper	11,268	0.4	0.68	0.08	0.17	0.4
Spread	11,268	0.2	0.36	0.04	0.07	0.16
IDIOVAR	11,268	0.02	0.01	0.01	0.02	0.02

Table 1.2. Pearson Correlation of Selected Variables

Variables	*Status*	*CAR*	*BHAR*	*DI6*	*IDIOVAR*	*Spread*	*Disper*
Status	1.00	0.75	0.69	0.27	0.12	0.06	0.27
		<.0001	<.0001	<.0001	<.0001	0.04	<.0001
CAR		1.00	0.93	0.34	0.13	0.06	0.26
			<.0001	<.0001	<.0001	0.04	<.0001
BHAR			1.00	0.28	0.10	0.07	0.25
				<.0001	0.00	0.02	<.0001
DI6				1.00	0.15	0.00	0.23
					<.0001	0.90	<.0001
IDIOVAR					1.00	0.29	0.48
						<.0001	<.0001
Spread						1.00	0.25
							<.0001
Disper							1.00

This table presents the Pearson Correlation of selected variables. *STATUS* is the probability of a merger bid being successful. *CAR* is the cumulative abnormal returns around the announcement date with a window size of [-63,126]. *BHAR* is the buy-and-hold abnormal return around the announcement date with a window size of [-63,126]. DI_8 is the Sheng and Thevenot (2015) measure of investor divergence of opinion 1 month prior to the M&A event. *IDIOVAR* is the volatility of abnormal returns across 3 months before the announcement date, measured using Fama-French factor model plus momentum. *Spread* is the 3-month average of bid-ask spread scaled by stock price. *Disper* is the standard deviation of analysts' forecasts across 3 months before the announcement date of EPS.

Table 1.3. Means of Dependent Variables in Takeover and Non-Takeover Sample

	Takeover=0		*Takeover=1*	
Variables	N	Mean	N	Mean
DI_6	10,166	1.38	1,102	0.84
IDIOVAR	10,166	0.02	1,102	0.02
Spread	10,166	0.25	1,102	0.20
Disper	10,166	0.59	1,102	0.37

	Status=0		*Status=1*	
Variables	N	Mean	N	Mean
DI_6	443	0.03	659	2.28
IDIOVAR	443	0.02	659	0.03
Spread	443	0.22	659	0.27
Disper	443	0.28	659	0.80

This table presents the Means of dependent variables partitioned into takeover observations and a non-takeover control group. DI_6 is the Sheng and Thevenot (2015) measure of investor divergence of opinion 2 months before the M&A event. *IDIOVAR* is the volatility of abnormal returns across 3 months before the announcement date, measured using Fama-French factor model plus momentum. *Spread* is the 3-month average of bid-ask spread scaled by stock price. *Disper* is the standard deviation of analysts' forecasts across 3 months before the announcement date of EPS.

Table 1.4. Effect of Quantified Differential Interpretation on Takeover Likelihood

Panel A. Coefficient Estimates

Variables	TAKEOVER							
	DI		IDIOVAR		DISPER		SPREAD	
INSTOWN		-0.0774***		-0.0965***		-0.0841***		-0.0654***
		(-5.89)		(-3.9)		(-5.21)		(-4.62)
X	-0.4566***	-0.8791***	-0.0258	-0.115*	-0.0348***	-0.0401***	0.077***	-0.007
	(-8.06)	(-6.57)	(-1.01)	(-1.72)	(-11.94)	(-5.27)	(9)	(-0.31)
X*INSTOWN		0.5736***		0.0917		0.0043		0.1256***
		(3.47)		(1.12)		(0.42)		(3.44)
Control	Yes		Yes		Yes		Yes	
Observation	11268	11268	11268	11268	11268	11268	11268	11268
Adjusted R^2	0.1115	0.1141	0.1091	0.1118	0.1136	0.1167	0.1167	0.1183
Panel B. LR and Wald Tests								
LR test (un-nested)			64.3***	64.39***	-64.39	-64.48	-128.87	-96.76
Wald test (un-nested)			32.1***	32.15***	-32.24	-32.29	-64.62	-48.48
LR (nested)			64.3***	64.39***	16.11	32.27**	64.57***	64.62***
Wald (nested)			32.1**	32.15**	8.05	16.13	32.24**	32.26**

This table presents results of the relationship between takeover likelihood and several measures of investor divergence of opinion. Panel A presents coefficient estimates and p-values. The dependent variable in this equation is TAKEOVER, which is the probability of a firm receiving a merger bid. X represent four different measures of investor divergence of opinion including DI, the Sheng and Thevenot (2015) measure of investor divergence of opinion measured over 6 quarters; IDIOVAR, the volatility of abnormal returns across 3 months before the announcement date, measured using Fama-French factor model plus momentum; DISPER, the standard deviation of analysts' forecasts across 3 months before the announcement date of EPS and SPREAD, the 3-month average of bid-ask spread scaled by stock price. All models are estimated using OLS method. INSTOWN a measure of short sale constraint which is the percentage of shares held by institutional owners. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel B presents the Likelihood-Ratio test and Wald test between models using DI and other measures of investors' divergence of opinion. We applied two model specifications. In specification A, we calculate the test statistics using RSS from model of DI and each of the model of other measures. In specification B, we calculate the test statistics using RSS from the unconstrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$) and the constrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \beta_2 * DI_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$). *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.5. Effect of Quantified Differential Interpretation on Takeover Status

Panel A. Coefficient Estimates

Variables	STATUS							
	DI		IDIOVAR		DISPER		SPREAD	
INSTOWN		-0.0485		-0.0761		-0.0198		-0.0342
		(-0.68)		(-0.58)		(-0.24)		(-0.43)

X	2.5173***	1.5764**	0.3919***	0.1303	0.1042***	0.0654**	0.0101	-0.0833
	(10.1)	(2.51)	(3.21)	(0.42)	(6.19)	(1.99)	(0.27)	(-0.85)
X*INSTOWN		-1.2487***		-0.3605		-0.0583		-0.1548
		(-3.44)		(-0.95)		(-1.41)		(-1.1)
Control	Yes		Yes		Yes		Yes	
Observation	1102	1102	1102	1102	1102	1102	1102	1102
Adjusted R^2	0.1636	0.1645	0.1286	0.1293	0.1478	0.1489	0.1214	0.1222
Panel B. LR and Wald Tests								
LR test (un-nested)			62.11***	113.83***	128.06***	138.33***	227.01***	206.23***
Wald test (un-nested)			31.1***	57.06***	65.56***	71.4***	112.94***	102.65***
LR (nested)			197.25***	218.12***	85.22***	85.34***	268.41***	268.29***
Wald (nested)			98.2***	108.53***	42.53***	42.59***	133.41***	133.35***

This table presents results of the relationship between takeover likelihood and several measures of investor divergence of opinion. Panel A presents coefficient estimates and p-values. The dependent variable in this equation is *STATUS*, which is the probability of a merger bid being successful. X represent four different measures of investor divergence of opinion including DI, the Sheng and Thevenot (2015) measure of investor divergence of opinion measured over 6 quarters; IDIOVAR, the volatility of abnormal returns across 3 months before the announcement date, measured using Fama-French factor model plus momentum; DISPER, the standard deviation of analysts' forecasts across 3 months before the announcement date of EPS and SPREAD, the 3-month average of bid-ask spread scaled by stock price. All models are estimated using OLS method. INSTOWN a measure of short sale constraint which is the percentage of shares held by institutional owners. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel B presents the Likelihood-Ratio test and Wald test between models using DI and other measures of investors' divergence of opinion. We applied two model specifications. In specification A, we calculate the test statistics using RSS from model of DI and each of the model of other measures. In specification B, we calculate the test statistics using RSS from the unconstrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$) and the constrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \beta_2 * DI_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$). *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.6. Effect of Quantified Differential Interpretation on CAR

Panel A. Coefficient Estimates

Variables	CAR							
	DI		IDIOVAR		DISPER		SPREAD	
INSTOWN		0.0369		0.0259		0.0874		0.1019
		(0.35)		(0.13)		(0.69)		(0.84)
X	5.198***	3.7722***	0.7008***	0.3622***	0.1746***	0.1091**	0.0419	-0.06
	(9.92)	(2.58)	(3.49)	(2.46)	(6.58)	(2.08)	(0.75)	(-0.44)

X*INSTOWN		-1.8495		-0.5045		-0.1021		-0.2092
		(-1.06)		(-0.85)		(-1.59)		(-1)
Control	Yes		Yes		Yes		Yes	
Observation	1102	1102	1102	1102	1102	1102	1102	1102
Adjusted R^2	0.1916	0.1928	0.1235	0.1262	0.1456	0.1494	0.1138	0.1163
Panel B. LR and Wald Tests								
LR test (un-nested)			37.22 ***	39.22 ***	28.67 ***	30.87 ***	125.05 ***	145.83 ***
Wald test (un-nested)			18.64 **	20.88 **	15.87 **	16.78 **	62.35 ***	72.68 ***
LR (nested)			112.36 ***	140.56 ***	7.41 *	74.43 ***	180.73 ***	201.51 ***
Wald (nested)			56.04 ***	70.06 ***	3.71 *	37.15 ***	90.01 ***	100.31 ***

This table presents results of the relationship between takeover likelihood and several measures of investor divergence of opinion. Panel A presents coefficient estimates and p-values. The dependent variable in this equation are *CAR*, which is the cumulative abnormal returns around the announcement date with a window size of [-63,126]. X represent four different measures of investor divergence of opinion including DI, the Sheng and Thevenot (2015) measure of investor divergence of opinion measured over 6 quarters; IDIOVAR, the volatility of abnormal returns across 3 months before the announcement date, measured using Fama-French factor model plus momentum; DISPER, the standard deviation of analysts' forecasts across 3 months before the announcement date of EPS and SPREAD, the 3-month average of bid-ask spread scaled by stock price. All models are estimated using OLS method. INSTOWN a measure of short sale constraint which is the percentage of shares held by institutional owners. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel B presents the Likelihood-Ratio test and Wald test between models using DI and other measures of investors' divergence of opinion. We applied two model specifications. In specification A, we calculate the test statistics using RSS from model of DI and each of the model of other measures. In specification B, we calculate the test statistics using RSS from the unconstrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$) and the constrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \beta_2 * DI_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$). *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.7. Effect of Quantified Differential Interpretation on BHAR

Panel A. Coefficient Estimates

Variables	BHAR							
	DI		IDIOVAR		DISPER		SPREAD	
INSTOWN		0.0635		0.0152		0.1163		0.1538
		(0.45)		(0.06)		(0.69)		(0.98)
X	5.5693 ***	3.6461 **	0.647 ***	0.1777 **	0.2141 ***	0.13 **	0.0914	-0.0444
	(8.88)	(2.26)	(2.62)	(0.29)	(6.84)	(2.08)	(1.34)	(-0.27)
X*INSTOWN		-2.4895		-0.6929		-0.1314 *		-0.2839
		(-1.27)		(-0.95)		(-1.69)		(-1.15)
Control	Yes		Yes		Yes		Yes	
Observation	1102	1102	1102	1102	1102	1102	1102	1102

Adjusted R^2	0.1435	0.1448	0.09769	0.1001	0.1202	0.1238	0.09396	0.09682
Panel B. LR and Wald Tests								
LR test (un-nested)			13.97 **	14.24 **	14.03 **	15.65 **	146.66 ***	192.2 ***
Wald test (un-nested)			6.7 *	7.86 *	7.25 *	7.8 *	73.09 ***	95.69 ***
LR (nested)			15.78 **	20.99 **	4.12 *	13.32 *	217.63 ***	268.3 ***
Wald (nested)			7.62 *	10.01 *	23.53 **	65.47 ***	108.29 ***	133.36 ***

This table presents results of the relationship between takeover likelihood and several measures of investor divergence of opinion. Panel A presents coefficient estimates and p-values. The dependent variable in this equation are *BHAR*, which is the buy-and-hold abnormal returns around the announcement date with a window size of [-63,126]. X represent four different measures of investor divergence of opinion including DI, the Sheng and Thevenot (2015) measure of investor divergence of opinion measured over 6 quarters; IDIOVAR, the volatility of abnormal returns across 3 months before the announcement date, measured using Fama-French factor model plus momentum; DISPER, the standard deviation of analysts' forecasts across 3 months before the announcement date of EPS and SPREAD, the 3-month average of bid-ask spread scaled by stock price. All models are estimated using OLS method. INSTOWN a measure of short sale constraint which is the percentage of shares held by institutional owners. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel B presents the Likelihood-Ratio test and Wald test between models using DI and other measures of investors' divergence of opinion. We applied two model specifications. In specification A, we calculate the test statistics using RSS from model of DI and each of the model of other measures. In specification B, we calculate the test statistics using RSS from the unconstrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$) and the constrained model ($Y_{i,t} = \beta_i + \beta_1 * X_{i,t-1} + \beta_2 * DI_{i,t-1} + \sum \beta_j * Control_{i,t-1} + \sum y * year_{t-1} + e_{i,t}$). *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Chapter 2. On the Information Role of Analyst Forecast Consistency

2.1 Introduction

We building on previous research and analyze the ramifications and determinants of analyst forecast consistency, a firm-analyst specific characteristic in which analysts deliver earnings forecasts with comparatively smaller variation in forecast errors. Specifically, in addition to previous research that shows analyst forecast consistency is a more favorable characteristic than forecast accuracy in several aspects, we further demonstrate that analysts who make more consistent forecasts (i) establish less significant "walk-down" pattern in forecast errors in each forecasting period, (ii) establish greater translational effectiveness from earnings forecasts to stock recommendations and (iii) allocate more information to earnings forecasts than to stock recommendations. In addition, analysts forecast consistency decreases in the level of information asymmetry between firms and analysts and increases in analysts' ability. Furthermore, by textually modeling the topics discussed in the Q&A sessions of conference calls, we find that analysts who discuss relatively less topics about firms' financial outlook and potential risks but more topics about firms' business outlook, future perspective and emerging technologies establish greater forecast consistency.

Hilary and Hsu (2013) find that, although consistent forecasts might be less accurate than other forecasts, they have a stronger ability to move prices because the forecasting errors are more systematic and easier for the market to correct. Analysts who issue consistent forecasts are also less likely to be demoted to less prestigious positions and are more likely to be named All Star analysts. These findings imply that consistent earnings forecasts mitigate analysts' incentives to some extent, allowing the analysts to serve their personal goals of increasing trading volumes, generating investment banking business and commissions, and getting access to managerial information without jeopardizing investors' needs.

We build on these findings and provide additional analyses of the ramifications of analysts forecast consistency. First, we demonstrate that earnings forecasts generally follow the "walk-down" pattern of being more optimistic at the beginning and more pessimistic at the end of the entire forecasting periods (generally two years). The walk-down pattern signals the level of incentive misalignment of analysts. We hypothesize that analyst consistency reduces the walk-down pattern by being less optimistic at the beginning of the forecast period and more optimistic at the end compared to normal forecasts. We find that the first forecast made by a consistent analyst is less optimistic and the last forecast is more optimistic compared to other analysts. The differences between the last forecasts and the first forecasts also increase in consistency. Furthermore, by running quarterly regressions of forecasting optimism on analyst consistency, we find that forecast optimism decreases in consistency in the first few quarters and increase in consistency in the last few quarters. The quarterly pattern is shown below, where "+" and "-" mean positive and negative relationships between consistency and optimism:

Quarter:	Q_9	Q_8	Q_7	Q_6	Q_5	Q_4	Q_3	Q_2	Q_1
Relationship:	-	-	-	-	-	+	+	+	+

We also regress forecast optimism on forecast horizon with analyst consistency as an interacting variable and find that consistency decreases the relationship between optimism and horizon, suggesting that consistency mitigates the walk-down pattern by smoothing the forecast pattern. These findings further strengthen Hilary and Hsu's (2013) idea that consistent analysts deliver predictable forecast errors that are easier to disentangle, and indicates that consistent forecasts serve investors' needs better by providing more comprehensible information. This finding, together with Hilary and Hsu (2013)'s findings about analysts' welfare and All-Star status, suggests that consistent analysts are able to serve both investors' needs for information and personal goals. We attribute the alignment of personal goals and investors' needs to the systematic error contained in consistent forecasts.

Second, to support this idea, we analyze the process through which analysts use earnings forecasts to generate stock recommendations. If consistent analysts are better able to use earnings forecasts to align investors' needs for earnings information with their personal goals, then once an earnings forecast is made, the recommendation is more of a pure transformation of the earnings forecast. With this in mind, we follow Bradshaw's (2004) method to analyze the translational effectiveness between forecasts-related stock valuations and recommendations with consistency as an interacting variable. We find that the relationships between price-to-earnings-growth valuation, long term growth, and recommendations all increase in consistency, whereas the relationship between residual income-based valuation and recommendations is not significant, consistent with Bradshaw (2004). These findings suggest that the translational effectiveness increases in analyst consistency, which indicates that the translation process is less contaminated by analysts' personal incentives. This also suggests that personal incentives are more likely to be incorporated into earnings forecasts, rather than recommendations.

Third, we analyze the information allocation between earnings forecasts and stock recommendations. We hypothesize that if an analyst's total information content stays unchanged during the process in which he or she issues a forecast and use that forecast to generate a recommendation, a forecast from a consistent analyst would contain more information since it contains both useful information about earnings and other personal incentives. Therefore, less information would be allocated to recommendations. By regressing short-term buy-and-hold abnormal returns on forecasts and recommendations respectively, we demonstrate that the market reacts more strongly to earnings forecasts made by consistent analysts and less strongly to the subsequent recommendations. This finding supports the idea that that consistent analysts allocate more information to forecasts than to recommendations.

In addition, we analyze the determinants of analysts forecast consistency from the aspects of both firms and analysts. Using several commonly accepted proxies of information asymmetry and analysts' ability, we demonstrate that analysts forecast consistency increases in firms' voluntary disclosure frequency, analysts' firm-specific experience and industry-specific expertise and decreases in firms' idiosyncratic stock return volatility, information complexity and tone pessimism in conference calls. Furthermore, using Latent Dirichlet Allocation Topic Modeling approach, a textual analyses technique capable of reducing a collection of textual documents down to several specific topics, we extract topics discussed by analysts and managers in Q&A sessions of conference calls and find that analyst forecast consistency increases in the proportion of topics about business outlook, future perspective and emerging technologies and decreases in the proportion of topics about financial outlook and potential risks in both analysts' questions and managers' answers.

This paper contributes to the existing literature in several ways. First, it provides supplementary evidence that analyst forecast consistency is favorable to both analysts and investors in that it is associated with less significant “walk-down” pattern. In other words, consistent analysts achieve both investors’ needs and their own personal goals through a smoother forecast pattern and more consistent forecast errors. Second, it provides evidence that consistent forecasts increase forecast-recommendation translational effectiveness, indicating that consistent analysts have already incorporated their personal incentives in earnings forecast, leaving the translational profess more efficient. Third, it demonstrates that consistent analysts allocate more information to forecasts, rather than to recommendations. Finally, it is the first paper applying textual analyses in studying the determinants of analyst forecast consistency and it provides original evidence that the topics discussed in Q&A sessions of conference calls explain analyst forecast consistency to some extent.

The rest of the paper is organized as follows. Section 2.2 provides a brief review of previous related studies and critical arguments about the research framework in this paper, as well as the main testable hypotheses. Section 2.3 provides a review of the data sources and construction of the research models. Section 2.4 shows the results, and Section 2.5 offers conclusions.

2.2 Literature Review and Hypotheses Development

2.2.1 Analyst Forecast Consistency

Hilary and Hsu (2013) are the first to investigate analyst forecast consistency. They argue that the usefulness of analysts’ forecasts should not be based on forecast accuracy, but on the extent to which an analyst delivers consistent forecast errors. Consistent forecasts represent more predictable transformations of realized earnings. Hence, they are more informative than volatile forecasts. Based on this idea, they documented that consistent forecasts have greater ability to move prices. Consistent analysts are also more likely to be named All Star analysts and less likely to be demoted to less prestigious brokerage houses. Furthermore, consistent analysts are more likely to lowball their forecasts to help managers beat earnings targets.

Besides these findings, there are many other characteristics of consistent analysts that have not been fully revealed. For example, how would consistent analysts behave when they face alternative incentives, such as pressure from investment banks or to generate trades? How would consistent analysts make stock recommendations using their earnings forecasts? In this paper, we build on prior literature about analysts' behavior to address these research questions.

2.2.2 Analyst Consistency and Incentive Alignment

It has long been argued that "analysts' stock recommendations do not reflect analysts' actual opinions about the investment potential of subject companies but are instead influenced by incentives to generate investment banking business and commission revenues" (Chen and Chen 2009). In an effort to mitigate such incentive misalignment, rules such as Regulation Fair Disclosure (Reg FD), NASD Rule 2711, and NYSE Rule 472 were implemented in 2002 (Barniv, Hope, Myring, and Thomas 2009; Chen and Chen 2009). However, later studies still found evidence that incentive misalignments have not been fully eliminated. For example, Barniv, Hope, Myring, and Thomas (2009) find that regulatory reforms seem to be adjusting analysts' earnings forecasts and recommendations in the expected direction, but the adjustment may be incomplete. The remaining incentive misalignments include but are not limited to analysts strategically issuing positive recommendations for stocks they hold (Boni and Womack 2002) in order to increase blockage trading volumes (Lin and McNichols 1998; Irvine 2004; Ertimur, Sunder, and Sunder 2007), to be more optimistic in forecasts when the analysts are employed by brokerages that are a firm's IPO or SEO underwriters (Dugar and Nathan 1995; Lin and McNichols 1998; Kadan et al. 2009),[1] and to please company management and/or induce investors to purchase the stock (Michaely and Womack 1999; Francis and Philbrick 1993; McNichols and O'Brien 1997; Francis, Hanna, and Philbrick 1997; Chen and Matsumoto 2006; Malmendier and Shanthikumar 2014). Analysts also issue less optimistic or even pessimistic earnings forecasts to allow the firm to beat the consensus of other analysts and avoid negative earnings surprises (Richardson, Teoh, and Wysocki 2004; Chan, Karceski, and Lakonishok 2007; Baik and Yi 2007),[2] as an approach to curry favor with managers and to gain better access to managerial information (Lim 2001; Libby et al. 2008; Hilary and Hsu 2013). Following these lines of research, Malmendier and Shanthikumar (2014) develop a "two-tongue metric" to measure strategic distortion and find that such incentive misalignments are widespread.

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[1] Lin and McNichols (1998) find that underwriting relationships generally lead to overoptimistic recommendations, but not overoptimistic earnings forecasts. Hansen and Sarin (1996) attribute the lack of difference of forecast optimism between affiliated analysts and unaffiliated analysts to reputational forces. Nevertheless, Ali (1996) and Dechow et al. (1997) find significant difference in the long-term earnings forecasts between affiliated analysts and unaffiliated analysts. Underwriting relationships are also related to analysts' compensation because annual bonuses are typically a portion of investment bankers' total compensation, which depends on their contributions to deals done over the year (Eccles and Crane 1988).

[2] Several studies have demonstrated that the penalties for missing earnings targets are high, so managers consequently try to avoid missing benchmarks, including analyst forecasts (e.g., Matsumoto 2002; Bartov, Givoly, and Hayn 2002).

In this article, we argue that the characteristics of consistent analysts mitigate incentive misalignments. Personal incentives, such as generating trading volumes and currying favor with management, generally lead to a walk-down pattern of earnings forecasts. In other words, analysts generally walk down their forecasts over time, so the forecasts made right before the earnings announcement dates are less optimistic than those made near the beginning of the period (Barniv, Hope, Myring, and Thomas 2009; Richardson, Teoh, and Wysocki 2004; Ke and Yu 2006; Schipper 1991). This pattern indicates that analysts have alternative incentives other than providing investors with the most accurate information about earnings. Consistent analysts, however, reduce the walk-down pattern by issuing smoother forecasts. Because they are trying to deliver a more identifiable systematic forecast error, they would be less optimistic at the beginning of the forecast period and more optimistic at the end compared to other analysts. This leads to the first hypotheses:

$H_{2.1a}$: Forecast optimism at the beginning of the forecast period decreases in analyst consistency and forecast optimism at the end of the forecast period increases in analyst consistency.

$H_{2.1b}$: The significance of the walk-down pattern throughout a forecast period decreases in analyst consistency.

Hilary and Hsu (2013) document that the frequency of “lowballing” (issuing downwardly-biased forecasts) increases in analyst consistency. This finding implies that consistent analysts have stronger incentive to use downwardly-biased earnings forecasts to please management in order to avoid negative earnings surprises and to get more access to managerial information. In addition, the trade-generation incentive, which often leads to upwardly-biased forecasts, is less of a concern for consistent analysts. Mikhail, Walther, and Willis (1999), Hong and Kubik (2003), and Jackson (2005) shows that analysts face conflicting incentives: generating short-term increases in trading commissions by issuing optimistic earnings forecasts versus generating higher reputations by issuing accurate earnings forecasts. However, the systematic bias contained in a consistent forecast allows it to be extrapolate to a more accurate forecast, which could also generate short-term trading volumes. Thus, consistent analysts are less constrained by the trade-generation incentive. Furthermore, systematic biases can also prevent the biased forecasts from jeopardizing analysts' reputation. As a result, we argue that consistent forecasts mitigate incentive misalignment by securing analysts' personal goals while providing investors with useful information about earnings. This leads to a discussion of the role that analyst consistency plays in the process of generating recommendations.

2.2.3 Forecast-Recommendation Translational Effectiveness

Bradshaw (2004) builds a comprehensive framework that links earnings forecasts to stock recommendations. In this framework, he says that "analysts use their earnings forecasts along with other information to estimate a stock's value, which is then compared to the actual trading price of the stock and forms the basis for the recommendation." Bradshaw (2004) considers two sets of valuation models: residual income valuation models and the price-earnings-to-growth (PEG) model. Although residual income valuation models, which incorporate analysts' forecasts of earnings, are superior for identifying mispricing (Ohlson 1995; Frankel and Lee 1998), little evidence is found that analysts rely on residual income-based approaches as justification for stock recommendations (Block 1999; Bradshaw 2002). Conversely, the PEG model is more related to recommendations (Bradshaw 2004). This result is supported by the argument that analysts favor growth as a primary determinant of favorable recommendations (Block 1999; Bradshaw 2002) and that analysts give the highest recommendations to stocks whose valuation, as determined by the PEG model, exceeds current trading prices (Ohlson and Juettner-Nauroth 2005; Easton 2004).

These arguments lead to a discussion of the choice between different valuation models in terms of analyst consistency. On average, the target prices generated from residual income valuation models are lower than those generated from the PEG model. Bradshaw (2004) shows that the target price generated from residual income valuation models are, on average, below current trading prices, but those generated from the PEG model are above current trading prices. The PEG model, consequently, is in line with the mean buy recommendations. Intuitively, if consistent analysts want to be as optimistic in stock recommendations as other analysts, they would be more willing to choose a valuation model that results in a higher target price because their earnings forecasts are more downwardly biased. In other words, if they choose the same valuation model as other analysts do, their downwardly-biased earnings forecasts would result in lower target prices and, hence, less optimistic or even pessimistic stock recommendations. Thus, consistent analysts would rely more on the PEG model to generate higher target prices.

Consistent analysts are also generally more reputable and more likely to be named All Star analysts (Hilary and Hsu 2013), which means that they are presumably the most sophisticated analysts (Barniv, Hope, Myring, and Thomas 2009). These analysts are less likely to use discounted cash flows in formulating target prices (Asquith, Mikhail, and Au 2005). Thus, our framework of forecast-recommendation translational effectiveness relies primarily on the PEG model, rather than residual income-based models.

To analyze the effect of forecast consistency on forecast-recommendation translational effectiveness, we follow the approach used by Ke and Yu (2009) to analyze the association between earnings forecasts and recommendations as a function of analyst consistency. Specifically, we postulate that analysts form recommendations from valuation models that incorporate earnings forecasts, and add analyst consistency as an interaction variable. Intuitively speaking, although analysts are generally more likely to distort recommendations strategically than forecasts,[3] assuming Hypothesis 1 is true (i.e., alternative incentives that would result in biased analyst behavior are more likely to be incorporated into consistent analysts' earnings forecasts), their recommendations would establish a stronger relationship with the valuations. Otherwise, these incentives would be reflected in the transformation from valuations to recommendations, decreasing the translational effectiveness. This concept is in line with Ertimur, Sunder, and Sunder (2007), who posit that any friction in the translation process reduces the usefulness of stock recommendations to investors.

Regarding incentives, consistent analysts experience less pressure from investment banks in forming recommendations, compared to other analysts. Investment banking pressure can result in misleading behavior in which analysts issue positive public information that conflicts with their negative views about the stock (De Franco, Lu, and Vasvari 2007). This incentive would result in overoptimistic recommendations.

[3] Lin and McNichols (1998) argue that manipulation of recommendations is more difficult for investors to detect than manipulation of earnings forecasts because the outcomes of earnings forecasts will be realized eventually, whereas the outcomes of recommendations depend on the investment horizon and the expected rate of return, which are not clearly specified.

However, consistent analysts are more likely to incorporate the incentive of investment banking pressure into their earnings forecasts, but not their recommendations. Specifically, by incorporating a systematic bias into their forecasts, they can still deliver their positive opinion about the stock without issuing overoptimistic recommendations. In other words, consistent analysts' "real" forecasts are more optimistic under investment banking pressure, but their recommendations are not.

Trading commission concerns can be another alternative incentive that distorts analysts' behavior. The literature shows that analysts may misbehave to increase trading volumes and to maximize their own compensation (Lin and McNichols 1998; Michaely and Womack 1999, 2005). Furthermore, Ke and Yu (2009) demonstrate that analysts' translational effectiveness is lower when their brokerage houses rely more on trading volumes. However, consistent forecasts have greater ability to move prices at the time of announcement, in a way freeing the consistent analysts from incorporating trading commission concerns in their recommendations. Overall, consistent analysts are more likely to use earnings forecasts instead of recommendations to serve personal needs. Although all analysts are more likely to be held responsible for issuing biased earnings forecasts than for issuing biased recommendations (Ke and Yu 2006; Ljungqvist, Malloy, and Marston 2009), consistent analysts would suffer less cost when they issue biased forecasts because the systematic biases are easier for investors to disentangle.

Analyst consistency could also increase forecast-recommendation translational effectiveness by decreasing insider trading, a factor that would reduce the relationship between forecasts and recommendations (Ke and Yu 2009). Analysts are generally likely to lowball their earnings forecasts (Hilary and Hsu 2013) and follow the walk-down pattern, which gives them better access to firm management (Ke and Yu 2006). The walk-down pattern is most pronounced when managers have an incentive to trade on stocks after earnings announcement on the firm's behalf or from their personal accounts (Richardson, Teon, and Wysocki 2004). Consistent forecasts could reduce such insider trading because investors are able to unravel the systematic bias, resulting in less earnings announcement drift and, hence, reducing the potential for insider trading. Consistent analysts also have greater ability to move prices (Hilary and Hsu 2013), which implies that the information contained in their earnings forecasts are more reflected at the time of forecast announcement. The nominal earnings surprises at the earnings announcement could be high, but the potential for post-earnings announcement drift is limited because the systematic component in the earnings surprise is already reflected in price, leading to limited potential for insider trading. Since insider trading is a key factor that decreases forecast-recommendation translational effectiveness, more consistent earnings forecasts could increase translational effectiveness to some extent by decreasing insider trading.

Based on these issues, we form hypotheses regarding valuation models and forecast-recommendation translational effectiveness as follows:

$H_{2.2}$: The forecast-recommendation translational effectiveness increases in earnings analyst consistency.

2.2.4 Market Reactions and Information Allocation

We use market reactions to strengthen the idea that consistent analysts incorporate more incentives into earnings forecasts, resulting in a less contaminated transformation from forecasts to recommendations. In other words, more information is allocated to their earnings forecasts than to their stock recommendations. We discuss market reactions to earnings forecasts and recommendations separately in this section. Specifically, we focus on short-term announcement abnormal returns around earnings forecasts and recommendations.

Our argument concerning market reactions relies essentially on the assumption that consistent analysts incorporate alternative incentives into their earnings forecasts. Thus, these forecasts become more informative. Regarding short-term announcement abnormal returns, in line with Hilary and Hsu (2013), we predict that consistent earnings forecasts have greater ability to move prices than other earnings forecasts do. We further predict that consistent analysts are able to generate more short-term price movement through their earnings announcements, but not through their recommendations announcements.

Besides the aligned incentives in earnings forecasts, other characteristics of consistent forecasts could also increase their informativeness. Consistent earnings forecasts contain a systematic error component that is easier for investors to transform into more unbiased earnings forecasts. This attribute leads to less divergence of opinions among investors. Therefore, the price movement would be more significant. On the other hand, inconsistent earnings are more volatile, so they are more difficult for investors to interpret. Investors' opinions around the forecast announcement dates would be more divergent, leading to less significant price movements. In addition, consistent analysts are generally more reputable and more influential in the market. They are more likely to be employed by prestigious brokerage houses and more likely to be named All Star analysts (Hilary and Hsu 2013), which means that they are presumably the most sophisticated analysts (Barniv, Hope, Myring, and Thomas 2009). These analysts are better able to separate the value-relevant and value-irrelevant components of earnings (Ertimur, Sunder, and Sunder 2007), which makes their forecasts more value-relevant (e.g., Liu, Nissim, and Thomas 2002; Gu and Chen 2004).[4]

In terms of information allocation, assuming the overall information content stays unchanged, stock recommendations would be less informative if earnings forecasts are more informative. Although there has been heated discussion over whether analyst recommendations provide useful information to investors, many studies reveal factors that drive analysts to issue informative recommendations (e.g., Stickel 1995; Womack 1996; Barber, Lehavy, and Trueman 2010; Kecskes, Michaely, and Womack 2010; Yezegel 2015).[5] For example, Yezegel (2015) finds that investors' demand for information, the supply of information, and mispricing all stimulate analysts to provide useful recommendations. However, demand for information is lower shortly after earnings forecasts and even lower if the forecasts are issued by consistent analysts. The supply of information could be higher since the forecasts made by consistent analysts are more informative, but the information is provided by analysts themselves and does not need further interpretation. Mispricing is also smaller after consistent analysts issue forecasts because these forecasts have greater ability to create price movements. Thus,

[4] For example, Liu, Nissim, and Thomas (2002) find that valuations based on I/B/E/S earnings multiples perform better than those based on Compustat earnings. Gu and Chen (2004) show that analysts are able to isolate the transitory component of reported earnings that are either value-irrelevant or have a limited valuation impact in their forecasts of earnings.

[5] Kecskes, Michaely, and Womack (2010) find that earnings-based recommendation changes are more informative than discount rate-based recommendation changes. Barber, Lehavy, and Trueman (2010) find that recommendation levels and changes in those levels are associated with future returns.

the stock recommendations made by consistent analysts are less likely to generate short-term price movement. This leads to the third hypotheses:

$H_{2.3a}$: The relationship between short-term abnormal returns and earnings forecasts announcements increases in analyst consistency.

$H_{2.3b}$: The relationship between short-term abnormal returns and recommendations announcements decreases in analyst consistency.

Note that the market reactions to forecasts and recommendations include both short-term price reactions and post-event drifts (Womack 1996; Barber, Lehavy, McNichols, and Trueman 2001; Boni and Womack 2006; Barber, Lehavy, and Trueman 2010; Loh 2010).[6] However, the magnitude of post-event drifts is generally small compared to the short-term announcement reactions. In addition, the fact that forecasts and recommendations are issued frequently over time increases the difficulty of isolating the long-term post-event drift for a specific forecast or recommendation. In this paper, we only focus on the short-term reactions and do not address the relationship between analyst consistency and long-term post-event drifts.

2.2.5 Determinants of Analyst Forecast Consistency

Hillary and Hsu (2013) also attempted to reveal the determinants of the systematic forecast errors by regressing forecast errors on several analyst-firm variables. These variables, although are significantly related to forecast errors, result in an R^2 of zero

[6] For example, Diether, Malloy, and Scherbina (2002) and Nagel (2005) attribute this market inefficiency to short-sale constraints. Hirshleifer, Lim, and Teoh (2010), Peng and Xiong (2006), DellaVigna and Pollet (2005), and Loh (2010) explain the inefficiency as investors' inattention around the event dates. Cohen and Frazzini (2008) and Hou, Peng, and Xiong (2010) find positive abnormal returns associated with trading strategies constructed based on momentum.

after the lagged forecast error has been removed from the regression. However, they found that simply regressing forecast errors on a vector of firm-analyst fixed effects and the lagged forecast errors provides a more reasonable approximation with an R^2 of 20.23%. In this paper, we investigate more details on the determinants of analyst forecast consistency by regressing the observed analyst forecast consistency on three sets of variables, namely, variables about information asymmetry between firms and analysts, variables about analysts' ability and variables about analysts' information discovery behavior.

First, we use the number of management guidance, R&D expense and idiosyncratic volatility as the measures of information asymmetry between firms and analysts. Management guidance can reduce information asymmetry because they contain private information that is otherwise not available (e.g., Diamond and Verrecchia 1991, Kim and Verrecchia 1994) and thus we expect to find a positive relationship between the number of management guidance and analyst forecast consistency. R&D expenses introduce greater information asymmetry (e.g., Aboody and Lev 2000) as such expenses require more effort and expertise to evaluate. Thus, we expect to find a negative relationship between the proportion of R&D expenses in total sales and analyst forecast consistency. In addition, more volatile stock returns represent higher information asymmetry (e.g., Officer et al. 2009) which may lead to greater valuation error in analysts' earnings forecasts. Furthermore, we also measure information complexity of firms' disclosure by constructing three textual measures from the presentation session of firms' conference call transcripts, namely, fog index, sentiment and sentiment volatility. First, the readability of the presentation sessions of conference calls, as represented by fog index, is positively associated with the difficulty for analysts to assess firms' performance (e.g. Li 2008). Second, negative news is more likely to be overemphasized than good news by analysts, resulting in greater forecast error. Lastly, greater volatility of sentiment implies higher information asymmetry (e.g., Loughran and Mcdonald 2016), which may result in greater valuation error. By measuring information asymmetry from both observable quantitative factors and qualitative information from conference calls, the set of variables is likely to have greater explanatory power on analyst forecast consistency than financial statement data do.

Second, we apply three measures of analysts' ability, namely, Allstar, firm-specific experience and industry-specific expertise. Allstar analysts are likely to know more firm-specific information which leads to more accurate earnings forecasts (e.g., Xu, Chan and Yi 2013). Furthermore, analysts' forecast accuracy increases in their firm-specific experience as measured by the number of years the analyst has been following the firm (e.g., Sunder and Sunder 2007, Clement 1999). In addition, analysts' forecast accuracy also increases in their industry-specific expertise (e.g., Palmon & Yezegel 2012) that may fail to be captured by analysts' firm-specific experience.

We also directly measure analysts' self-information-discovery behavior by analyzing the topics discussed in the Q&A session of conference calls. The Q&A session of conference calls is one of the major channels for analysts to voluntarily gather information and may convey more information than the presentation sessions due to more analysts' involvement (Matsumoto et al. 2011). It may also reflect analysts' personal concerns about the firm which could be considered to a greater extent when analysts are evaluating the firm. For example, previous research found that the tone signal in Q&A sessions is significant predictor of abnormal returns over and above earnings news (Price et al. 2012).

To analyze the topics discussed in the Q&A sessions of conference calls, we apply Latent Dirichlet Allocation (LDA) topic modeling approach to extract the mostly discussed topics from the Q&A sessions of conference call transcripts. LDA model is a generative probabilistic model for collections of discrete data such as text corpora in which each item is modeled as a finite mixture over an underlying set of topics (Blei et al. 2003). The advantage of LDA model is that it is an unsupervised statistical learnings method that does not require any pre-specified set of topics (e.g., Grimmer 2010). In addition, LDA model is well suited for a large group of lengthy documents over time in an objective and replicable matter and relies on limited set of assumptions. (Dyer, Lang and Stice-Lawrance 2017). As a result, it has been extensively used in social science research to deconstruct corpus of textual documents into latent topics, especially for documents with multiple interspersed topics (Dyer et al. 2017). Following previous research, we extract 30 topics from analysts' questions and 30 topics from managers' answers and manually label them into 5 categories, namely, business outlook, emerging technologies, forecasts and predictions, financial outlook and potential risks. Then we compute the percentage of each topic categories in the total number of topics as the frequency of such topic category in each analyst-firm pair.

2.3 Data and Research Design

We collect data from 1995 through 2017 from multiple databases. We collect analysts' forecasts and recommendations data from the I/B/E/S database, market return data from

Event Study by WRDS, stock price data from CRSP, and firm-specific data from COMPUSTAT.

We conduct three sets of regression models to provide statistical evidence that consistency aligns analysts' incentives. In Model Set 1, we regress the optimism of the first and the last forecasts of annual earnings within a 2-year forecast period on analyst consistency of each analyst-firm pair respectively, where optimism is an earnings forecast of a company made by an analyst minus the forecast consensus, scaled by the stock price on the earnings announcement date, and consensus is the average of the three preceding earnings forecasts for the same company. Analyst consistency is an analyst-firm level measure that is defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company in the past 5 years scaled by price. We multiply the measure of consistency by -10 so that the greater the value is, the more consistent the analyst is. We also regress EPS gap, which is the scaled difference between the last forecast and the first forecast, on consistency. After merging all forecast observations with other control variables and eliminating observations with missing values, we obtain 428,212 unique forecast observations. All variables are winsorized at the 1% and 99% levels. We then select the first and last forecasts of each analyst-firm-earnings-date observation, which yields 109,243 unique observations.

In Model Set 2, we analyze the quarterly pattern of earnings forecasts using the following regression model:

$$FORE\_OPT_{ijq} = \alpha + \beta_1 CONSIS_{ij} + \sum_{k=1} \gamma_k Control_{ijq} + \varepsilon_{ijq}$$

where $FORE\_OPT_{ijq}$ is a measure of forecast optimism, defined as an earnings forecast for company j made by analyst i in quarter q minus the forecast consensus, scaled by the stock price on the earnings announcement date, where consensus is the average of the three preceding earnings forecasts for the same company. $CONSIS_{ij}$ is an analyst-firm level measure of analyst consistency calculated as the standard deviation of the forecast error of the last forecasts of each quarter made by analyst *i* for company *j* in the past five years, scaled by stock price. We multiply $CONSIS_{ij}$ by -10 so that the greater the value is, the more consistent the analyst is. $Control_{jq}$ is a vector of analyst-specific variables and firm-specific variables. More detailed definitions of control variables can be found in Appendix A. We split all 428,212 observations into nine quarter groups based on forecast horizons, where *q=1* indicates that the forecast is made within the first quarter preceding the earnings date, *q=2* indicates that the forecast is made within the second quarter preceding the earnings date, while *q=9* indicates the forecast is made more than two years before the earnings date. The nine groups contain observations ranging from 27,507 (*q=2* group) to 78,852 (*q=5* group). The average sample size of the eight groups is 53,063 observations.

In Model Set 3, we regress forecast optimism on forecast horizon with consistency as an interacting variable:

$$FORE\_OPT_{ij} = \alpha + \beta_1 CONSIS + \beta_2 HORIZON + \beta_3 CONSIS \times HORIZON + \sum_{k=1} \gamma_k Control + \varepsilon$$

where $HORIZON$ is the number of days between the forecast announcement date and the earnings announcement date, scaled by 365. We use all 428,212 observations to run the regressions.

In analyzing the relationship between consistency and forecast-recommendation translational effectiveness, we first follow Bradshaw (2004) to construct stock valuations based on residual income valuation model and the PEG heuristic valuation model. Specifically, the residual income valuation model is constructed as follows:

$$V_{RI,t} = BVPS_t + \sum_{\tau=1}^{5} \frac{E_t[RI_{t+\tau}]}{(1+r)^{\tau}} + \frac{E_t[RI_{t+5}]}{r(1+r)^5}$$

where $V_{RI,t}$ is the intrinsic value of the stock at time *t*, $BVPS$ is the book value per share, RI is the residual income at time $t+\tau$, computed as $EPS_{t+\tau} - r \times BVPS_{t+\tau-1}$ and *r* is the industry cost of capital based on the Fama-French (2015) five factor model. Like Bradshaw (2004), we use the present value of the expected residual income for the next five years plus the terminal value to estimate the intrinsic value. We require each analyst-firm pair to have at least 4-years ahead earnings forecasts. If the 5-year ahead earnings forecasts are missing, we use the actual earnings for that year instead. The final sample of V_{RI} contains 10,957 observations.

The PEG heuristic valuation model is constructed as follows:

$$V_{PEG} = E_t[EPS] \times LTG \times 100$$

where EPS is the two-year ahead earnings forecast and LTG is the analyst's projection of long-term annual earnings growth. Like Bradshaw (2004), we use the projection of the long-term earnings growth rate directly as a third predicting factor for recommendations because the favorable growth projection is a primary determinant of favorable recommendations (Block 1999; Bradshaw 2002). The final sample for V_{PEG} and LTG contains 24,579 observations.

Once stock valuations are constructed, we use the following regression model:

$$REC = \alpha + \beta_1 CONSIS + \beta_2 V/P + \beta_3 CONSIS \times V/P + \sum_{k=1} \gamma_k Control + \varepsilon$$

where REC is the average recommendations made by an analyst for a stock each year and V/P represents the three valuations, V_{RI}, V_{PEG} and LTG, scaled by the current price.

In analyzing the information allocation between earnings forecasts and stock recommendations, we use short-term buy-and-hold abnormal returns to capture information content, and we regress $BHAR$ on $FORE\_OPT$ and REC_OPT respectively with $CONSIS$ as an interacting variable:

$$BHAR = \alpha + \beta_1 CONSIS + \beta_2 FORE\_OPT + \beta_3 CONSIS \times FORE\_OPT + \sum_{k=1} \gamma_k Control + \varepsilon$$

$$BHAR = \alpha + \beta_1 CONSIS + \beta_2 REC\_OPT + \beta_3 CONSIS \times REC\_OPT + \sum_{k=1} \gamma_k Control + \varepsilon$$

where $BHAR$ is the buy-and-hold abnormal return with a window size of (-2,2), and REC_OPT is recommendation optimism calculated as a recommendation minus the recommendation consensus, which is the average of all recommendations for a stock in the past three months. We reverse the direction of recommendation indicators so that 1 means strong sell, 2 means sell, 3 means hold, 4 means buy, and 5 means strong buy. The final sample contains 62,744 observations.

In analyzing the determinants of analysts forecast consistency, we apply the following regression models:

$$CONSIS = \alpha + \beta_1 FIRM + \beta_2 ANALYST + \beta_3 Q\&A + \varepsilon$$

where *FIRM* represents a vector of variables about the information asymmetry between firms and analysts, *ANALYST* represents a vector of variables about analysts' ability and *Q&A* represents a vector of variables about topic frequency in the Q&A sessions of conference calls.

2.4. Results

2.4.1 Descriptive Statistics

Table 2.1 shows the descriptive statistics including number of observations, mean, standard deviation, and quartile values for all variables. In terms of independent variables, the variable of primary interest, *CONSIS*, has a mean of -0.04 and a median of -0.02. The average forecast horizon is 1.04 years. The long-term-growth projection ranges from 11% to 20% with a mean value of 17%. The mean value of *REC_OPT* is -

0.02. The mean values of V_{PEG}/P and V_{RI}/P are 0.75 and 0.87 respectively. In terms of dependent variables, the mean values of *FORE_OPT_FIRST* and *FORE_OPT_LAST* are 0.42 and -0.41 respectively, suggesting that the walk-down pattern exists on average in the whole sample. Furthermore, the mean values of *ERROR* and *FORE_OPT* are all insignificantly different from 0, reflecting no sign of forecast bias. This might be attributable to the fact that the beginning upward bias and the later downward bias throughout the 2-year period cancel each other out, leaving no identifiable bias on average.

[Insert Table 2.1 here]

2.4.2 Analyst Consistency and Incentive Alignment

2.4.2.1 Analyst Consistency and the Change in Forecast Optimism

In Model Set 1, which focuses on the change in optimism from the first to the last forecast and the EPS gap, we partition all forecast observations into 10 decile groups based on analyst consistency, and then compare the average values of *FORE_OPT_FIRST*, *FORE_OPT_LAST* and *EPS_LAST_FIRST*. Table 2.2 shows the results of the regressions for Model Set 1. As predicted, *FORE_OPT_FIRST* is significantly negatively related to *CONSIS* with a coefficient estimate of -2.7669 and a significant t-value of -6.1 at the 1% level. The constant is 0.108, which is greater than 0, but not statistically significant. On the other hand, *FORE_OPT_LAST* is significantly positively related to *CONSIS* with a coefficient estimate of 1.3045 and a significant t-value of 3.63 at the 1% level. *EPS_LAST_FIRST* is statistically negatively associated with *CONSIS* with a t-value of -9.7. This implies that analyst consistency decreases the EPS gap. Panel A of Table 2.3 shows, the paired t-tests between high consistency groups (upper 10% of all observations) and low consistency groups (lower 10% of all observations). The table shows that the mean of *FORE_OPT_FIRST* is 0.06 for the high consistency group, which is significantly smaller than the mean of 1.03 for the low consistency group, indicating less optimism among highly consistent analysts at the beginning of the period. However, the mean of *FORE_OPT_LAST* is -0.06 for the high consistency group, which is significantly greater than the mean of -1.05 for the low consistency group, indicating less pessimism among highly consistent analysts at the end of the period. The mean of *EPS_LAST_FIRST* is 0.00 for the high consistency group, implying no walk-down pattern. By contrast, the mean of *EPS_LAST_FIRST* is -0.04 for the low consistency group, which is significantly smaller than that for the high consistency group, suggesting that the degree to which the last forecast downwardly diverge from the first forecast is greater for the low consistency group than for the high consistency group. These results suggest that analyst consistency mitigates the walk-down pattern by being less optimistic at the beginning of the forecast period and less pessimistic at the end.

[Insert Table 2.2 here]

2.4.2.2 Analyst Consistency and the Quarterly Patterns of Forecast Optimism

In Model Set 2, which focuses on quarterly patterns of forecast optimism, we also partition all quarterly forecast optimism observations into 10 decile groups based on the level of consistency and then calculate the mean of forecast optimism of each group. Figure 2.1 shows the quarterly pattern of optimism for the high consistency group (blue curve), low consistency group (orange curve), and all observations (gray curve). As predicted, the quarterly trend of optimism for the high consistency group shows almost no sign of a walk-down pattern, whereas the quarterly trend of optimism for the low consistency group show a strong walk-down pattern. The walk-down pattern of the entire sample is less strong compared to the low consistency group, but stronger than the high consistency group.

Panel B of Table 2.3 shows the paired t-tests of the quarterly mean optimism between the high consistency group and the low consistency group. The mean optimism for the high consistency group is significantly greater than the mean for the low consistency group during $Q_1 - Q_4$, insignificantly greater than the mean for the low consistency group during Q_5 and significantly smaller than the mean for the low consistency group during $Q_6 - Q_9$. This indicates that the sign of the difference in optimism between the low consistency group and the high consistency group reverses as the earnings date approaches; consistent analysts are less optimistic at the beginning of the forecast period and more optimistic right before the earnings date.

[Insert Table 2.3 here]

Panel A of Table 2.4 shows the quarterly regressions of forecast optimism on analyst consistency. The coefficients of *CONSIS* are all significantly negative during $Q_4 - Q_9$, insignificantly negative during $Q_2 - Q_3$ and insignificantly positive in Q_1. which is generally consistent with the paired t-tests that reflect the reversion of optimism. In addition, the absolute values of the coefficients are generally decreasing from Q_9 (-2,0931) to Q_4 (-0.2056). This indicates that the relationship between consistency and optimism is the strongest at the beginning of the forecast period, and becomes less as strong toward the end of the period around the 3rd or 4th quarter before the earnings dates. Furthermore, the adjusted R^2 shows a similar pattern, decreasing from Q_9 (0.3714) to Q_5 (0.0659) and increasing from Q_2 (0.2721) to Q_1 (0.2766). This suggests the fitness of the quarterly regression model is the best at the beginning of the forecast period and at the end, whereas the fitness is not as good at around the 5th quarter before the earnings dates. These findings further indicate that forecast optimism does not fluctuate much in terms of consistency during the middle of the whole forecast period, but differs significantly in terms of consistency in the beginning and again as the earnings date approaches. Panel B of Table 4 shows the quarterly regressions of forecast optimism on ranked analyst consistency, where the rank is based on decile groups ranging from -0.5 to 0.5. The results are similar to those in Panel A but provide stronger evidence consistent with our hypothesis. The absolute values of coefficients and the value of adjusted R^2 are the greatest at the beginning, decrease through the first few quarters, increase through the last few quarters, and become large again in the last quarter. Overall, these results are consistent with our hypothesis that the walk-down pattern throughout a forecast period decreases in consistency.

[Insert Table 2.4 here]

2.4.2.3 Analyst Consistency, Forecast Horizon and Forecast Optimism

Table 2.5 shows the regression of forecast optimism on forecast horizon with consistency as an interacting variable. In the first column, the relationship between *CONSIS* and *FORE_OPT* is significantly negative with a coefficient of -1.4874 and a t-value of -8.26. This is consistent with previous literature that consistent analysts tend to be less optimistic on average to avoid negative earnings surprises. In the second column, *HORIZON* is positively related to *FORE_OPT* with a coefficient of 0.537 and a significant t-value of 116.92 at 1% level. This is consistent with the walk-down pattern in which the longer the forecast horizon is, the more optimistic the forecast is. In the third column, the coefficient on *CONSIS* × *HORIZON* is -2.1885 and is significant at 1% level, suggesting that analyst consistency decreases the relationship between horizon and forecast optimism on average. Overall, the results indicate that analyst consistency mitigates the walk-down pattern, making the forecast trend smoother.

[Insert Table 2.5 here]

Overall, we use the walk-down pattern as a proxy for incentive misalignment and demonstrate that analyst consistency decreases the walk-down pattern and makes the forecast trend smoother. Furthermore, consistent analysts are also better at achieving personal goals, such as better access to managerial information through lowballing and issuing downwardly-biased earnings forecasts. These findings lead to the conclusion that consistent earnings forecasts are more informative and that consistent analysts are more likely to use earnings forecasts to achieve both investors' needs for information about earnings and personal goals, such as curving favor with managers.

2.4.3 Translational Effectiveness and Analyst Consistency

Table 2.6 shows the results of regression models of stock recommendations on stock valuations with *CONSIS* as an interacting variable. Columns 1 and 2 contain results of the residual income valuation model, Columns 3 and 4 contain results of the *PEG* valuation model, and Columns 5 and 6 contain results of the *LTG* projection. All control variables, year fixed effects, and industry fixed effects are included. The estimates of the constants in all six columns range from 2.78 to 3.48 and are statistically significant, suggesting that the average recommendation is between hold and buy and that the recommendations are optimistic on average. In Column 1, the relationship between *Rec* and V_{RI}/P is insignificant, which is consistent with previous literature that analyst do not use residual income valuations to determine their recommendations. In Column 1, there is no evidence that *CONSIS* increases the relationship between *REC* and V_{RI}/P. However, since the residual income valuation model is not used by analysts to justify their recommendations *per se*, the significance of the incremental effect of *CONSIS* on the relationship between *REC* and V_{RI}/P has limited explanatory power for our hypothesis that analyst consistency increases translational effectiveness.

Column 3 shows a significantly positive relationship between *REC* and V_{PEG}/P, which is consistent with previous literature that analysts are more likely to use price-to-earnings-growth model to generate recommendations. In Column 4, the coefficient on $CONSIS \times V_{PEG}/P$ is significantly positive with a t-value of 3.99, which indicates that analyst consistency increases the relationship between *REC* and V_{PEG}/P and is consistent with our hypothesis. Column 5 shows a significantly positive relationship between *REC* and *LTG*. In addition, the coefficient on *LTG* is 1.7062, which is greater than the coefficient of 0.2005 on V_{PEG}/P; the t-value on *LTG* is 32.07 is also greater than the t-value of 23.33 on V_{PEG}/P. The adjusted R^2 (0.1674) in Column 5 is also greater than the adjusted R^2 (0.1497) in Column 3. All of these findings are consistent with previous literature that analysts' long-term earnings growth projections have the greatest explanatory power for stock recommendations and that analysts favor growth as a primary determinant of favorable recommendations. In Column 6, the coefficient on $CONSIS \times LTG$ is significantly positive with a t-value of 6.08, which indicates that analyst consistency increases the relationship between *REC* and *LTG* and is consistent with our hypothesis. Interestingly, the coefficient on *CONSIS* in 6 is insignificantly smaller than zero, indicating a mild negative relationship between *CONSIS* and *REC*. One possible explanation for the negative relationship is that consistent analysts use forecasts to increases trading volume and to generate investment banking business, so they are less likely to use optimistic recommendations to achieve the same goals. Thus, these recommendations are more precise representations of the consistent analysts' true opinion about the stocks. An alternative explanation is that consistent analysts are more sophisticated and more reputable, characteristics that can help them to achieve trading volume and commissions, goals that a normal analyst would have to use overoptimistic stock recommendations to achieve.

[Insert Table 2.6 here]

Overall, the evidence from the residual income valuation model, the price-to-earnings-growth model, and long-term-growth projection indicates that analyst consistency increases forecast-recommendation translational effectiveness. The evidences further indicate that consistent analysts' translation process is less contaminated by analysts' alternative incentives, such as investment banking pressure and concerns about trading commissions. As demonstrated in Section 2.4.2, these incentives are more likely to be incorporated into consistent analysts' earnings forecasts than into their recommendations.

2.4.4 Market Reactions and Information Allocation

Table 2.7 shows the results of the short-term abnormal market reactions to both earnings forecasts and stock recommendations with consistency as an interacting variable. Rather than using the standalone value of forecast and recommendation, we use forecast optimism and recommendation optimism to run the regressions because they are the differences between the standalone values and their corresponding consensus, which are better at capturing the incremental information content. In addition, abnormal return is a relative measure of market reaction that only captures the difference between the raw return and the normal market return, a situation that requires the dependent variables also to be relative measures, such as forecast optimism and recommendation optimism, but not the standalone values of forecasts and recommendations.

[Insert Table 2.7 here]

Columns 1 and 2 show the results of *BHAR* on *FORE_OPT* and *CONSIS*, and Columns 3 and 4 show the results of *BHAR* on *REC_OPT* and *CONSIS*. Note that the estimates of constants across all four columns are greater than zero, but insignificant, which means that the market does not react abnormally to any announcements of forecasts and recommendations on average. In Columns 1 and 3, the coefficients on *FORE_OPT* and *REC_OPT* are all significantly positive at the 1% level, which is consistent with commonsense that the market reacts correspondingly to newly issued forecasts and recommendations around the announcement dates. Column 2 shows that the coefficient on *CONSIS* × *FORE_OPT* is significantly positive with a t-value of 6.3, which is significant at the 1% level. This indicates that analyst consistency increases the relationship between *BHAR* and *FORE_OPT* and is consistent with our hypothesis that consistent analysts' forecasts are more informative. By contrast, Column 4 shows that the coefficient on *CONSIS* × *REC_OPT* is significantly negative with a t-value of -8,72, which is significant at the 1% level. This indicates that analyst consistency decreases the relationship between *BHAR* and *REC_OPT* and is consistent with our hypothesis that consistent analysts' recommendations are less informative than their forecasts. Together, these findings demonstrate that consistent analysts allocate more information to their earnings forecasts than to recommendations. In un-tabulated results we also use *BHAR (-2,8)* and *BHAR (-10,30)* as dependent variables to rerun the regressions, and the results are similar although not as significant as *BHAR (-2,2)*. This might be because more information comes into the market during the wider window and obscures the results.

2.4.5 Determinants of Analyst Forecast Consistency

Table 2.8 shows the 20 mostly appeared key words in each latent topic that is clustered into 5 broad categories, namely, Business Outlook, Emerging Technologies, Forecasts and Predictions, Financial Outlook and Potential Risks. Panel A shows the key words in analysts' questions in the Q&A sessions of conference calls throughout the whole sample period for each analyst-firm pair. Panel B of Table 8 shows the categorization of the 20 mostly appeared key words in each latent topic in managers' answers in the Q&A sessions of conference calls throughout the whole sample period for each analyst-firm pair.

[Insert Table 2.8 here]

Table 2.9 presents the average percentage of each topic category in both the analyst-firm observations with the lowest 20% of analyst forecast consistency and analyst-firm observations with the highest 20% of analyst forecast consistency. Business outlook, Financial outlook, Forecast & predictions, Potential risks and Emerging technologies constitutes 19.39%, 19.47%, 10.46%, 19.80% and 17.50% of total number of topics in analysts' questions in the low consistency group and 19.81%, 18.83%, 11.40%, 19.55% and 17.69% of total number of topics in analysts' questions in the high consistency group. The average percentage of "Business outlook", "Forecast & predictions" and "Emerging technologies" is significantly larger for high consistency groups than for low consistency groups. Similar results are found from the univariate analysis of topic composition of managers' answers. Business outlook, Financial outlook, Forecast & predictions, Potential risks and Emerging technologies constitutes 19.57%, 19.90%, 16.31%, 13.16% and 6.97% of total number of topics in managers' answers in the low consistency group and 19.89%, 19.85%, 18.49%, 11.11% and 7.38% of total number of topics in managers' answers in the high consistency group. The average percentage of "Business outlook", "Forecast & predictions" and "Emerging technologies" is significantly larger for high consistency groups than for low consistency groups. These findings suggest that discussions involving supplementary information that normally cannot be found in financial statements or the presentation sessions of conference calls are more likely to result in greater analyst forecast consistency. On the contrary, discussions involving redundant information about financial outlook that is already publicly available may not help increase analyst forecast consistency.

[Insert Table 2.9 here]

Table 2.10 shows the results of regression models of analyst forecast consistency on three sets of determinants, namely, firm-specific variables, analyst-specific variables and variables of analysts' voluntary information discovery behavior. The last column presents the results of the regression model that contains all intended variables and has the highest explanatory power of analyst forecast consistency with an adjusted R^2 of 26.87%. The coefficient estimate of MANFOR_FREQ is 0.1575 which is significantly positive, consistent with our hypothesis that analyst forecast consistency increases in the volume of information from firms' voluntary disclosure. The coefficient estimates of IDIO_VOL, FOG_INDEX, TONE and DIV_TONE are -0.36, -0.65, -0.89 and -0.62 respectively and are all significantly negative, suggesting that analyst forecast consistency decreases in firms' idiosyncratic volatility, information complexity of conference call and conference call pessimism. In terms of analyst-specific variables, the coefficient estimates of EXPERT and EXP are 0.08 and 0.21 which are significantly positive, suggesting analyst forecast consistency also increase in analysts' industry-specific expertise and firm-specific experience. Furthermore, in column 2, the model with only firm-specific variables and analyst-specific variables has an adjusted R2 of 23.87% which is similar to the R^2 documented in Hillary & Hsu (2013). Overall, the firm-specific variables and analyst-specific variables indicate that information asymmetry, information complexity and analysts' ability play an important role in determining analyst forecast consistency.

[Insert Table 2.10 here]

Similar to the findings documented in Table 2.9, the coefficient estimates of BUSINESS_Q, FORECAST_Q and TECH_Q are 0.3, 0.28 and 0.20 respectively and are all significant positive, consistent with our hypothesis that analysts forecast consistency increases in the proportion of analysts' questions about business outlook, forecasts & predictions and emerging technologies. The evidence on managers' answers is weaker but the coefficient estimate of BUSINESS_A is still significantly positive. In addition, the coefficient estimates of FINANCIAL_Q, RISK_Q, FINANCIAL_A and RISK_A are -0.40, -0.27, -0.29 and -0.30 respectively and are all significantly negative, consistent with our hypothesis that analyst forecast consistency decreases in analysts' questions and managers' answers about financial outlook and potential risks. Overall, our findings suggest that discussions in the Q&A sessions that involve information that may be absent in publicly available channels improve the consistency in analysts' earnings forecasts, while discussions involving information that may already be publicly available decrease analyst forecast consistency. Furthermore, discussions involving potential risks also lead to lower analyst forecast consistency. This result could be due to the increased valuation uncertainty from analysts' deeper understanding of firms' risk exposure after the discussion. It could also be attributable to the fact that analysts tend to overemphasize bad news than good news which leads to greater downwardly biased earnings forecasts that decrease analyst forecast consistency.

2.5 Conclusions

Hilary and Hsu (2013) consider analyst forecast consistency to be a favorable characteristic because forecasts made by these analysts contain a systematic bias that is easier for investors to disentangle. These forecasts have stronger ability to move prices, and the analysts who issue these forecasts are more reputable and less likely to be demoted. Consistent analysts are also more likely to lowball to avoid negative earnings surprises. We build on Hilary and Hsu's (2013) paper in order to reveal more attributes of analyst forecast consistency. First, we analyze the relationship between the forecast pattern and analyst consistency. The results show that, unlike normal analysts who follow the walk-down pattern, consistent analysts' forecasts are smoother and do not show identifiable difference between forecast optimism at the beginning of the 2-year forecast period and forecast optimism in the end of the period. We also find results similar to Hilary and Hsu (2013) that consistent analysts are more likely to lowball, and their forecasts are more downwardly biased. These findings further indicate that consistent analysts can achieve investors' needs for accurate information about earnings without sacrificing their personal goals, such as increasing investment banking business, generating trading volumes, and currying favor with managers. The investors can still extrapolate the accurate information about earnings by disentangling the systematic error even if the "nominal" forecasts are more biased.

Second, we analyze whether analyst consistency has an incremental effect on the forecast-recommendation translational effectiveness. We follow the framework of Bradshaw (2004) and use analyst earnings forecast as input to value stock prices using residual income models, PEG models, and LTG projection, respectively. Then, we analyze the relationship between the relative stock valuations and recommendations with analyst consistency as an interacting variable. We find that analyst consistency has incremental effect on the relationship between recommendations and the valuations from the PEG models and LTG projection, whereas the relationship between recommendations and the valuation from residual income model is not significant. These findings are in accordance with our hypothesis that analyst consistency increases the translational effectiveness between forecasts and recommendations because consistent analysts use forecasts instead of recommendations to achieve both investors' needs for information and their own personal goals. Once the forecasts are made, the translational process from forecasts to recommendations is less contaminated by incentives other than providing investors with value-related information.

Third, we strengthen our framework buy showing the effect of analyst consistency on information allocation. Assuming that analysts' information content stays unchanged in the short run, we show that analyst consistency increases the relationship between forecasts and short-term abnormal returns, but decreases the relationship between recommendations and short-term abnormal returns. These findings strengthen the argument that consistent analysts allocate more information including value-related information and personal-goal-related information into their forecasts, and the market reacts more strongly to forecasts issued by consistent analysts. Thus, the recommendations issues by consistent analysts are less informative and have weaker ability to move prices. Overall, consistent analysts rely more on earnings forecasts and the systematic error incorporated into their forecasts, rather than their stock recommendations, to do their duty as providers of financial information.

This paper contributes to the existing literature by revealing additional characteristics about analyst forecast consistency. We show that consistent analysts rely on a smoother forecast pattern and a systematic forecast error to disseminate both value-based information and personal-goal-related information. After issuing forecasts, the translation from forecasts to recommendations is less contaminated by consistent analysts' personal goals, and more focused on value-related goals. Thus, the market reacts more strongly to consistent analysts' forecasts, less strongly to their recommendations.

Appendix A. Variable Definition

Variables	Definition
Dependent Variables	
BHAR	The buy-and-hold abnormal return with a window size of (-2,2). (Event Study by WRDS)
EPS	The analyst forecast of the annual earnings per share, scaled by the stock price of the earnings announcement date. (I/B/E/S)
EPS_LAST_FIRST	The difference between the last earnings forecast and the first earnings forecast made by a specific analyst within a 2-year forecast period, scaled by the stock price of the earnings announcement date. (I/B/E/S)
ERROR	Forecast error measured as the forecasted value minus the realized value of earnings per share, scaled by the stock price of the earnings announcement date. (I/B/E/S)
ERROR_DUMMY	An indicator variable equal to 1 if the forecast error is greater than 0, and 0 otherwise. (I/B/E/S)
FORE_OPT	Forecast optimism, defined as an earnings forecast minus forecast consensus, scaled by the stock price of the earnings announcement date, where consensus is the average of the three preceding earnings forecasts of the same company. (I/B/E/S)
FORE_OPT_FIRST	The forecast optimism of the first forecast made by a specific analyst within a 2-year forecast period. (I/B/E/S)
FORE_OPT_LAST	The forecast optimism of the last forecast made by a specific analyst within a 2-year forecast period. (I/B/E/S)
Independent Variables	
CONSIS	An analyst-firm level measure of analyst consistency, defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company in the past 5 years, scaled by price and multiplied by -10. (I/B/E/S)
HORIZON	Number of days between the announcement date of a forecast and the earnings announcement date, scaled by 365. (I/B/E/S)
LTG	The forecast of long-term-earnings-growth ratio. (I/B/E/S)
REC_OPT	Recommendation optimism calculated as a recommendation minus the recommendation consensus, which is the average of all recommendations of a stock in the past three months.
V_{PEG}/P	The price-to-earnings-growth valuation, scaled by price. (I/B/E/S and CRSP)
V_{RI}/P	The residual income valuation, scaled by price. (I/B/E/S, COMPUSTAT and CRSP)
Control Variables	
ACC	Analyst forecast accuracy, defined as the average of the absolute values of forecast errors in the past five years, scaled by price. (I/B/E/S)
ATO	Asset turnover ratio. (Sales (Compustat data item #12)/Total Assets (Compustat data item #6))
BREADTH	Number of firms an analyst is following in the same fiscal year. (I/B/E/S)
EXP	Number of years an analyst has been following a specific firm. (I/B/E/S)
FCF	"Cash flow in excess of that required to fund all projects that have positive net present values (NPV) when discounted at the relevant cost of capital" (Jensen 1986). Calculated as the cash flow from operations minus cash dividends, scaled by total assets. [(Compustat data item #308) - (Compustat data item #127)]/ (Compustat data item #6)
GROWTH	Average sales growth during past (up to) three years. (Compustat data item #12)

INSTOWN	Percentage of shares held by institutional owners. (Thomson Routers Financial)
LEV	Leverage ratio of total liabilities to total assets. ((Compustat data item #6 – Compustat data item #60)/ Compustat data item #6)
LIQ	Current assets divided by current liabilities. (Compustat data item #4)/(Compustat data item #5)
LOGSIZE	The natural log of the total value of asset of the company. (Compustat data item #6)
LOSS	An indicator variable equal to 1 if the company had net loss in the previous year, and 0 otherwise. (Compustat data item #172)
MKTSHR	The proportion of sales to the total sales of that industry, measured using three-digit SIC code.
MTB	Market value to book value, calculated as share price times the number of shares outstanding (Compustat data item #25) (Compustat data item #199) divided by total value of equity Compustat data item # 60)
PAYOUT	(Dividends (Compustat data item #21) + Repurchases (Compustat data item #115))/Net Income (Compustat data item #18); zero if numerator is zero or missing, and 1 if numerator > 0 and denominator = 0.
R&D	Research and development expense. (Compustat data item #46)/Sales (Compustat data item #12); zero if missing.
ROA	Return on assets calculated as net income divided by total assets at the beginning of the fiscal year. (Compustat data item #13)/ (Compustat data item #6)
Z	Z-Score, a measure of financial distress developed by Taffler (1983).

Table 2.1. Descriptive Statistics

Variables	N	Mean	S.D.	25%	Median	75%
BHAR	62,744	-0.01	0.07	-0.04	0.00	0.03
EPS	428,212	0.06	0.04	0.04	0.05	0.07
EPS_LAST_FIRST	109,243	-0.02	0.05	-0.02	0.00	0.00
ERROR	428,212	0.01	0.03	0.00	0.00	0.01
ERROR_DUMMY	428,212	0.56	0.50	0.00	1.00	1.00
FORE_OPT	428,212	-0.01	1.73	-0.28	0.00	0.27
FORE_OPT_FIRST	109,243	0.42	2.18	-0.27	0.03	0.55
FORE_OPT_LAST	109,243	-0.41	1.86	-0.37	-0.01	0.14
CONSIS	428,212	-0.04	0.06	-0.04	-0.02	-0.01
HORIZON	428,212	1.04	0.56	0.55	1.00	1.53
LTG	24,579	0.17	0.11	0.11	0.15	0.20
REC_OPT	62,744	-0.02	0.77	-0.50	0.00	0.43
V_{PEG}/P	10,957	0.75	1.09	0.07	0.24	1.44
V_{RI}/P	24,579	0.87	0.72	0.45	0.74	1.07
ACC	428,212	-2.83	4.00	-3.10	-1.67	-0.88
ATO	428,212	0.94	0.70	0.45	0.72	1.23
BREADTH	428,212	0.12	0.05	0.09	0.12	0.14
EXP	428,212	0.23	0.15	0.11	0.19	0.30
FCF	428,212	0.10	0.07	0.06	0.09	0.13
GROWTH	428,212	0.09	0.14	0.01	0.07	0.15
INSTOWN	428,212	0.82	0.18	0.73	0.86	0.94
LEV	428,212	0.56	0.21	0.42	0.56	0.69
LIQ	428,212	2.18	1.47	1.24	1.76	2.61

LOGSIZE	428,212	8.63	1.64	7.47	8.61	9.77
LOSS	428,212	0.16	0.37	0.00	0.00	0.00
MKTSHR	428,212	0.17	0.24	0.02	0.07	0.22
MTB	428,212	3.89	5.65	1.68	2.72	4.61
PAYOUT	428,212	0.83	1.05	0.01	0.60	1.15
R&D	428,212	0.03	0.06	0.00	0.00	0.04
ROA	428,212	0.05	0.10	0.02	0.06	0.09
Z	428,212	5.22	4.88	2.47	3.93	6.06

See Appendix A for variable definition

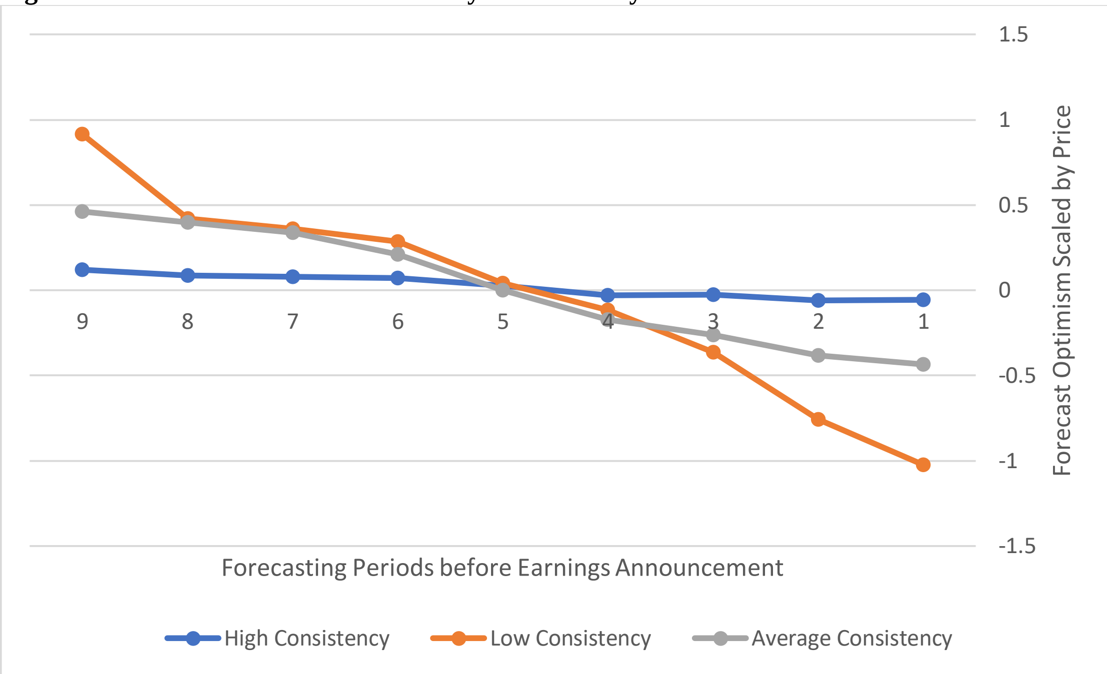
Table 2.2. Forecast Optimism of the First and Last Forecast and EPS Gap

Variables	*FORE_OPT_FIRST*	*FORE_OPT_LAST*	*EPS_LAST_FIRST*
Constant	0.108 (0.07)	0.562 (0.47)	-0.0188 (-0.76)
CONSIS	-2.7669*** (-6.1)	1.3045*** (3.63)	-0.0721*** (-9.7)
BREADTH	-0.6887*** (-4.13)	-0.2193 (-1.64)	0.0015 (0.54)
EXP	-0.0053 (-0.09)	-0.1217*** (-2.6)	0.0007 (0.74)
ACC	0.0859*** (10.54)	-0.0495*** (-7.43)	-0.0022*** (-15.63)
LOGSIZE	0.5386*** (23.37)	0.0026 (0.13)	0.0008* (1.86)
LEV	-0.4012*** (-4.89)	-0.0385 (-0.58)	-0.0005 (-0.39)
ATO	0.2768*** (6.87)	0.0001 (0.01)	0.0024*** (3.44)
MKTSHR	-0.5784*** (-4.99)	-0.2698*** (-2.83)	-0.0051*** (-2.6)
PAYOUT	0.0557*** (7.32)	-0.0363*** (-6.09)	-0.0014*** (-11.1)
MTB	-0.0116*** (-5.55)	0.0032** (2.15)	0.0001*** (4.65)
FCF	-1.5145*** (-10.46)	1.4233*** (11.66)	0.0447*** (17.67)

ROA	-1.7391***	3.6265***	0.143***
	(-11.3)	(28.82)	(54.87)
LOSS	0.3163***	-0.5714***	-0.0231***
	(9.86)	(-22.28)	(-43.46)
R&D	1.357***	0.2599	0.0269***
	(3.4)	(0.79)	(3.93)
LIQ	0.0525***	-0.0033	-0.0007***
	(5.83)	(-0.43)	(-4.35)
Z	-0.0064**	-0.0009	0.0001
	(-2.49)	(-0.39)	(0.97)
INSTOWN	0.082	0.5119***	0.0166***
	(1.08)	(7.61)	(11.9)
GROWTH	0.3065***	1.2156***	0.0475***
	(5.15)	(22.32)	(42.1)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
# Observations	109,243	109,243	109,243
Adjusted R^2	0.1391	0.2119	0.423

FORE_OPT_FIRST is the forecast optimism of the first forecast made by a specific analyst within a 2-year forecast period. *FORE_OPT_LAST* is the forecast optimism of the last forecast made by a specific analyst within a 2-year forecast period. *EPS_LAST_FIRST* is the difference between the last earnings forecast and the first earnings forecast made by a specific analyst within a 2-year forecast period scaled by the stock price of the earnings announcement date. *CONSIS* is an analyst-firm level measure of analyst consistency, defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company in the past 5 years, scaled by price and multiplied by -10. *BREADTH* is the number of firms an analyst is following in the same fiscal year. *EXP* is the number of years an analyst has been following a specific firm. *ACC* is the analyst forecast accuracy, defined as the average of the absolute values of forecast errors in the past five years, scaled by price. *LOGSIZE* is the natural log of the total value of asset of the company. *LEV* is the leverage ratio of total liabilities to total assets. *ATO* is the asset turnover ratio. *MKTSHR* is the proportion of sales to the total sales of that industry. *PAYOUT* is the company's payout rate including dividends and stock repurchases. *MTB* is the market-to-book ratio. *FCF* is the cash flow in excess of that required to fund all projects that have positive net present values (NPV) when discounted at the relevant cost of capital. *ROA* is the return on assets ratio. *LOSS* is an indicator variable equal to 1 if the company had net loss and 0 otherwise. *R&D* is the research and development expense. *LIQ* is the liquidity ratio. *Z* is the Z-score, a measure of financial distress. *INSTOWN* is the percentage of shares held by institutional owners. *GROWTH* is the average sales growth during past (up to) 3 years. Year fixed effects and firm fixed effects are included. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 2.1. Walk-down Pattern and Analyst Consistency



This figure shows the walk-down pattern of analyst earnings forecasts. The blue curve, orange curve and gray curve represent the movement of forecast optimism of highly consistent analysts, lowly consistent analysts and all analysts, respectively. High Consistency group and Low Consistency group represents analyst-firm observations of the upper and lower decile groups, respectively. Whereas average consistency group contains all analyst-firm observations. Q_1 – Q_8 represents the quarterly average forecast optimism of each analyst-firm pair (e.g., Q_8 represents the average forecast optimism eight quarters before the earnings announcement date) and Q_9 represents the average forecast optimism of each analyst-firm pair 2 years before the earnings announcement date.

Table 2.3. Univariate Analysts

Variables	N	High Consistency	Low Consistency	Difference in Mean	t-value
Panel A. Paired t-tests on Forecast Optimism and Forecast Gap between the First and Last Forecast					
FORE_OPT_FIRST	10,924	0.06	1.03	-0.97	-25.09***
FORE_OPT_LAST	10,924	-0.06	-1.05	0.99	29.19***
EPS_LAST_FIRST	10,924	0.00	-0.04	0.04	45.44***
Panel B. Paired t-tests on Mean Forecast Optimism of Each Forecast Quarter					
Q_9	834	0.12	0.92	-0.80	-6.91***
Q_8	5,438	0.09	0.42	-0.33	-7.3***
Q_7	4,450	0.08	0.36	-0.28	-5.8***
Q_6	4,712	0.07	0.29	-0.22	-4.76***
Q_5	4,092	0.02	0.04	-0.02	-0.33
Q_4	7,516	-0.03	-0.12	0.09	2.73***
Q_3	5,316	-0.03	-0.36	0.34	8.74***
Q_2	5,253	-0.06	-0.76	0.70	17.13***
Q_1	2,341	-0.05	-1.03	0.97	13.21***

High Consistency and Low Consistency represents analyst-firm observations of the upper and lower decile groups, respectively. *FORE_OPT_FIRST* is the forecast optimism of the first forecast made by a specific analyst within a 2-year forecast period. *FORE_OPT_LAST* is the forecast optimism of the last forecast made by a specific analyst within a 2-year forecast period. *EPS_LAST_FIRST* is the difference between the last earnings forecast and the first earnings forecast made by a specific analyst within a 2-year forecast period scaled by the stock price of the earnings announcement date. Q_1 – Q_8 represents the quarterly average forecast optimism of each analyst-firm pair (e.g., Q_8 represents the average forecast optimism eight quarters before the earnings announcement date) and Q_9 represents the average forecast optimism of each analyst-firm pair 2 years before the earnings announcement date. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2.4. Quarterly Regressions of Forecast Optimism on Analyst Consistency

Variables					*FORE_OPT*				
Panel A. Quarterly regression of forecast optimism on consistency									
	Q_9	Q_8	Q_7	Q_6	Q_5	Q_4	Q_3	Q_2	Q_1
Constant	-3.7737**	-5.1263***	-6.0182***	-6.4514***	-3.0813***	-4.6223***	-4.9023***	-6.1070***	-5.9782***
	(-2.06)	(-8.40)	(-9.62)	(-10.65)	(-4.52)	(-10.24)	(-10.04)	(-12.20)	(-7.20)
CONSIS	**-2.0931***	**-1.4011***	**-1.3873***	**-1.4382***	**-0.3345***	**-0.2056***	-0.0895	-0.0482	0.1082
	(-10.94)	**(-18.41)**	**(-18.09)**	**(-19.43)**	**(-4.13)**	**(-3.85)**	(-1.50)	(-0.82)	(-1.17)
Control					Yes				
Year FE					Yes				
Firm FE					Yes				
Adjusted R^2	0.3714	0.1914	0.1583	0.117	0.0659	0.1477	0.209	0.2721	0.2766
Panel B. Quarterly regression of forecast optimism on ranked consistency									
Constant	-3.6542**	-4.2181***	-5.0730***	-5.6276***	-2.7957***	-4.7403***	-5.1048***	-6.2694***	-6.1202***
	(-1.99)	(-6.91)	(-8.11)	(-9.28)	(-4.10)	(-10.48)	(-10.44)	(-12.51)	(-7.36)
CONSIS_RANK	**-1.3679***	**-1.5702***	**-1.6200***	**-1.4219***	**-0.4691***	**0.1826***	**0.2944***	**0.2590***	**0.2673***
	(-8.84)	**(-26.62)**	**(-26.27)**	**(-24.15)**	**(-6.92)**	**(4.26)**	**(6.10)**	**(5.34)**	**(3.29)**
Control					Yes				
Year FE					Yes				
Firm FE					Yes				
Adjusted R^2	0.3719	0.1911	0.1582	0.1163	0.066	0.1479	0.2086	0.2716	0.2767
# Observation	59,839	48,169	51,214	41,355	78,852	56,367	54,424	27,507	59,839

FORE_OPT is forecast optimism, defined as an earnings forecast minus forecast consensus scaled by the stock price of the earnings announcement date, where consensus is the average of the three preceding earnings forecasts of the same company. *CONSIS* is an analyst-firm level measure of analyst consistency, defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company in the past 5 years, scaled by price and multiplied by -10. *CONSIS_RANK* is the decile rank of consistency ranging from -0.5 to 0.5. Q_1 – Q_8 represents the quarterly average forecast optimism of each analyst-firm pair (e.g., Q_8 represents the average forecast optimism eight quarters before the earnings announcement date) and Q_9 represents the average forecast optimism of each analyst-firm pair 2 years before the earnings announcement date. All analyst-specific and firm-specific control variables are included. Year fixed effects and firm fixed effects are included. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2.5. Walk-Down Pattern and Analyst Consistency

Variables		*FORE_OPT*	
Constant	-5.784*** (-22.52)	-6.5751*** (-26)	-6.443*** (-25.5)
CONSIS	-1.4874*** (-8.26)		0.9358*** (4.83)
HORIZON	-2.1885*** (-29.57)	0.537*** (116.92)	0.4588*** (86.67)
CONSIS◊HORIZON			-2.1885*** (-29.57)
BREADTH	-0.0437 (-0.7)	-0.1106* (-1.8)	-0.1181* (-1.93)
EXP	-0.0724*** (-3.53)	-0.0663*** (-3.29)	-0.0785*** (-3.89)
ACC	0.0389*** (11.74)	0.0133*** (8.83)	0.0348*** (10.67)
LOGSIZE	0.5214*** (23.26)	0.5457*** (24.73)	0.5407*** (24.52)
LEV	-0.1115** (-1.97)	-0.132** (-2.37)	-0.1299** (-2.33)
ATO	0.0844*** (3.15)	0.1*** (3.79)	0.0969*** (3.68)
MKTSHR	0.0557 (0.49)	0.0097 (0.09)	0.0205 (0.18)
PAYOUT	0.0242*** (6.42)	0.0229*** (6.18)	0.0228*** (6.17)
MTB	0.0009 (1.05)	0.0006 (0.79)	0.0007 (0.87)
FCF	0.8402*** (10.42)	0.8268*** (10.42)	0.8327*** (10.5)
ROA	1.5065*** (22.01)	1.5098*** (22.41)	1.508*** (22.4)
LOSS	-0.1389*** (-9.14)	-0.1503*** (-10.05)	-0.1521*** (-10.18)
R&D	3.669*** (10.72)	3.5578*** (10.56)	3.5466*** (10.54)
LIQ	0.0002 (0.03)	-0.0013 (-0.23)	-0.0012 (-0.22)

Z	0.0081***	0.0072***	0.0068***
	(4.3)	(3.85)	(3.69)
INSTOWN	0.3552***	0.3842***	0.3905***
	(6.25)	(6.87)	(6.99)
GROWTH	0.3127***	0.2813***	0.3***
	(7.27)	(6.65)	(7.09)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
# Observations	428,212	428,212	428,212
Adjusted R^2	0.0343	0.0641	0.0662

FORE_OPT is forecast optimism, defined as an earnings forecast minus forecast consensus scaled by the stock price of the earnings announcement date, where consensus is the average of the three preceding earnings forecasts of the same company. HORIZON is the number of days between the announcement date of a forecast and the earnings announcement date, scaled by 365. *CONSIS* is an analyst-firm level measure of analyst consistency, defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company in the past 5 years, scaled by price and multiplied by -10. *BREADTH* is the number of firms an analyst is following in the same fiscal year. *EXP* is the number of years an analyst has been following a specific firm. *ACC* is the analyst forecast accuracy, defined as the average of the absolute values of forecast errors in the past five years, scaled by price. *LOGSIZE* is the natural log of the total value of asset of the company. *LEV* is the leverage ratio of total liabilities to total assets. *ATO* is the asset turnover ratio. *MKTSHR* is the proportion of sales to the total sales of that industry. *PAYOUT* is the company's payout rate including dividends and stock repurchases. *MTB* is the market-to-book ratio. *FCF* is the cash flow in excess of that required to fund all projects that have positive net present values (NPV) when discounted at the relevant cost of capital. *ROA* is the return on assets ratio. *LOSS* is an indicator variable equal to 1 if the company had net loss and 0 otherwise. *R&D* is the research and development expense. *LIQ* is the liquidity ratio. *Z* is the Z-score, a measure of financial distress. *INSTOWN* is the percentage of shares held by institutional owners. *GROWTH* is the average sales growth during past (up to) 3 years. Year fixed effects and firm fixed effects are included. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2.6. Translational Effectiveness and Analyst Consistency

Variables			*REC*			
Constant	3.4822***	3.4234***	2.7779***	2.8667***	2.9137***	2.9809***
	(7.63)	(7.48)	(3.86)	(3.99)	(4.09)	(4.19)
V_{RI}/P	-0.0168*	-0.0215*				
	(-1.69)	(-1.94)				
CONSIS		-0.0238				
		(-1.37)				
$CONSIS◊V_{RI}/P$		-0.0137				
		(-1.01)				
V_{PEG}/P			0.2005***	0.2214***		
			(23.33)	(22.27)		
CONSIS				0.0167		
				(1.55)		
$CONSIS◊V_{PEG}/P$				0.0197***		
				(3.99)		
LTG					1.7062***	1.8635***
					(32.07)	(31.49)
CONSIS						-0.0017
						(-0.16)
CONSIS◊LTG						0.2549***
						(6.08)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	10,957	10,957	24,579	24,579	24,579	24,579
Adjusted R^2	0.1627	0.1629	0.1497	0.1512	0.1674	0.1694

Recommendation is an indicator variable ranging from 1 to 5, indicating strong sell, sell, hold, buy and strong buy, respectively. V_{RI}/P is the residual income valuation scaled by price. V_{PEG}/P is the PEG valuation scaled by price. *LTG* is the long-term-growth projection. *CONSIS* is an analyst-firm level measure of analyst consistency, defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company in the past 5 years, scaled by price and multiplied by -10. All analyst-specific and firm-specific control variables are included. Year fixed effects and firm fixed effects are included. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2.7. Market Reaction to Forecasts and Recommendations

Variables	*BHAR (-2,2)*			
Constant	-0.0358 (-1.47)	-0.0321 (-1.32)	-0.0222 (-0.92)	-0.0141 (-0.58)
FORE_OPT	0.019*** (24.94)	0.023*** (23.05)		
CONSIS		0.0487*** (4.7)		
CONSIS◊FORE_OPT		0.0383*** (6.3)		
REC_OPT			0.0145*** (41.52)	0.0127*** (31.28)
CONSIS				0.035*** (3.44)
CONSIS◊REC_OPT				-0.0596*** (-8.72)
Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
# Observations	62,744	62,744	62,744	62,744
Adjusted R2	0.2176	0.2182	0.2313	0.2324

BHAR (-2,2) is the buy-and-hold abnormal return with a window size of (-2,2). *FORE_OPT* is forecast optimism, defined as an earnings forecast minus forecast consensus scaled by the stock price of the earnings announcement date, where consensus is the average of the three preceding earnings forecasts of the same company. *REC_OPT* is recommendation optimism calculated as a recommendation minus the recommendation consensus, which is the average of all recommendations of a stock in the past three months. *CONSIS* is an analyst-firm level measure of analyst consistency, defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company in the past 5 years, scaled by price and multiplied by -10. All analyst-specific and firm-specific control variables are included. Year fixed effects and firm fixed effects are included. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2.8. Key Words in Topics of Q&A Sessions of Conference Calls

Panel A. Top 2 topics in each of the 5 categories in analysts' questions

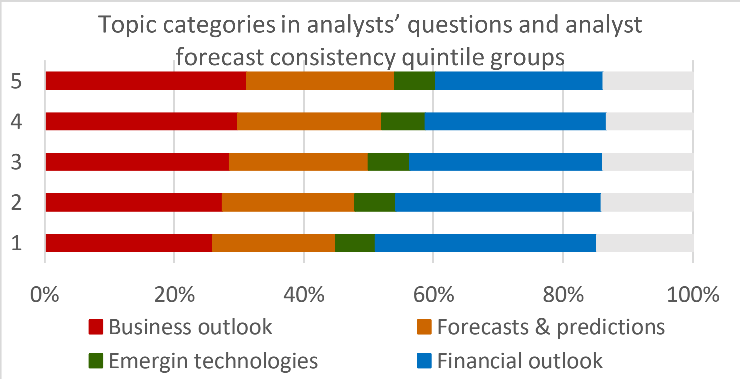
Category	Topic	Key Words
Business Outlook	Business integration	"business" "acquisition" "opportunity" "segment" "profit" "term" "companies" "grow" "core" "integrate" "area" "couple" "little" "change" "small" "size" "acquire" "focus" "help" "know"
	International business	"europe" "north" "america" "international" "region" "asia" "european" "american" "brazil" "china" "global" "mexico" "countries" "latin" "gari" "profit" "margin" "business" "south" "operate"
Emerging Technologie s	Information technologies	"product" "launch" "unit" "technology" "device" "market" "brian" "term" "eric" "wonder" "peter" "develop" "follow" "apple" "royalties" "rollout" "image" "window" "phone" "iphone"
	Online advertising	"mobile" "advertise" "revenue" "game" "network" "wonder" "content" "user" "spend" "online" "arpu" "take" "second" "follow" "term" "subscribe" "market" "monetary" "platform" "media"
Forecasts and Predictions	Business environment prediction	"little" "see" "maybe" "expect" "trend" "give" "color" "growth" "wonder" "help" "comment" "guidance" "market" "follow" "term" "outlook" "business" "environment" "improve" "strong"
	Management guidance	"margin" "gross" "expect" "improve" "basic" "operate" "point" "help" "guidance" "little" "sequential" "level" "higher" "understand" "follow" "impact" "forward" "lower" "revenue" "want"
Financial Outlook	Investment return	"billion" "invest" "fund" "term" "equities" "asset" "manage" "income" "risk" "mark" "change" "give" "hedge" "earning" "rate" "fix" "ratio" "follow" "strategies" "maybe"
	Return on equity	"share" "debt" "balance" "stock" "sheet" "million" "buyback" "dividend" "companies" "repurchase" "value" "acquisition" "cash" "plan" "sharehold" "buy" "term" "current" "right" "consider"
Potential Risks	Market competition	"market" "share" "supplies" "demand" "see" "paul" "region" "competitor" "competition" "term" "gain" "follow" "wonder" "want" "comment" "view" "give" "chain" "come" "generation"
	Industry specific risk	"price" "volume" "increase" "see" "cost" "impact" "material" "pressure" "term" "lower" "higher" "inflation" "versus" "industries" "point" "change" "commodity" "little" "come" "competition"

Panel A. Top 2 topics in each of the 5 categories in managers' answers

Business Outlook	Management directorship	"officer" "chief" "executive" "president" "director" "financial" "vice" "chairman" "yeah" "senior" "michael" "open" "mark" "treasury" "morning" "ahead" "relate" "robert" "richard" "investor"
	Customer solutions	"solution" "customer" "enterprise" "software" "data" "deal" "revenue" "application" "cloud" "technology" "sell" "sale" "platform" "secure" "channel" "partner" "large" "model" "base" "provide"

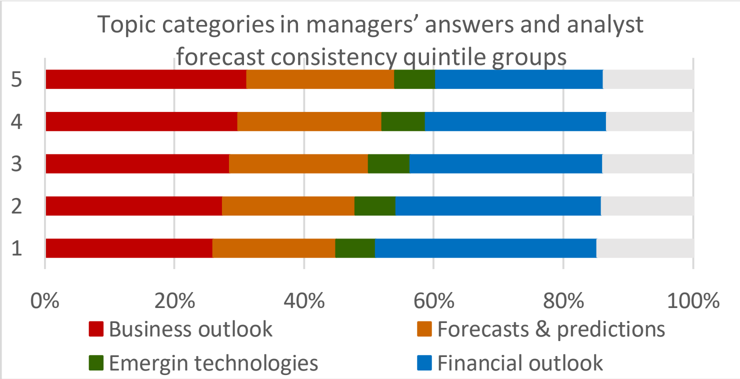
Emerging Technologies	Wireless technology	"customer" "technology" "design" "wireless" "device" "revenue" "high" "application" "ramp" "nanometer" "share" "power" "phone" "believe" "area" "base" "grow" "cell" "smartphone" "mobile"
	Online advertising	"mobile" "advertise" "revenue" "content" "game" "user" "consumer" "platform" "spend" "launch" "online" "media" "network" "brand" "traffic" "digital" "grow" "experience" "monetary" "differ"
Forecasts and Predictions	Management guidance	"margin" "revenue" "guidance" "half" "second" "gross" "impact" "range" "basic" "fourth" "improve" "give" "rate" "obvious" "overal" "level" "higher" "grow" "sale" "strong"
	Investment opportunities	"opportunity" "focus" "invest" "drive" "area" "team" "grow" "position" "strong" "perform" "improve" "organ" "technology" "strategies" "great" "portfolio" "certainlies" "build" "capable" "overall"
Financial Outlook	Profit margin	"price" "cost" "volume" "increase" "improve" "impact" "second" "margin" "half" "fourth" "sale" "lower" "higher" "material" "share" "change" "level" "decline" "position" "month"
	Capital structure	"client" "fund" "manage" "asset" "equities" "invest" "firm" "people" "large" "advisor" "sort" "marco" "institution" "activity" "perform" "revenue" "financial" "billion" "income" "fix"
Potential Risks	Project uncertainty	"course" "change" "plan" "issue" "need" "billion" "discuss" "position" "important" "comment" "decision" "clearly" "process" "view" "respect" "obvious" "give" "answer" "clear" "level"
	Operational risk	"agent" "loss" "rate" "insurance" "capital" "premium" "ratio" "reserve" "book" "ratio" "claim" "increase" "price" "change" "risk" "write" "trend" "reinsure" "result" "level"

Table 2.9. Univariate Analysis of Analyst forecast Consistency and Topic Categories in Q&A Sessions of Conference Calls



Univariate analysis on topic categories in analysts' questions

Topic categories	1 (low consistency)	5 (high consistency)	5 - 1
Business outlook	19.387	19.811	0.424***
Financial outlook	19.465	18.83	-0.635***
Forecasts & predictions	10.459	11.396	0.937***
Potential risks	19.799	19.552	-0.247***
Emerging technologies	17.497	17.687	0.191*



Univariate analysis on topic categories in managers' answers

Topic categories	1 (low consistency)	5 (high consistency)	5 - 1
Business outlook	19.57	19.889	0.319***
Financial outlook	19.904	19.847	-0.057***
Forecasts & predictions	16.313	18.491	2.178***
Potential risks	13.164	11.112	-2.052***
Emerging technologies	6.971	7.384	0.413**

Table 2.10. Analyst Forecast Consistency and Information Asymmetry, Analysts' Ability and Analysts' Voluntary Information Discovery Behavior

		CONSIS						
Firm-specific variables	*CONSTANT*	0.0475***	0.1626***	0.0762***	0.1778***	0.1636***	0.1659***	0.1552***
	MANFOR_FREQ	**0.369*****	**0.2384*****	**0.38*****	**0.2582*****	**0.1502****	**0.2253*****	**0.1575****
	RD	0.016	0.0997	0.3127	0.369*	0.2175	0.2496	0.1962
	IDIO_VOL	**-0.3826*****	**-0.358*****	**-0.3795*****	**-0.3548*****	**-0.3578*****	**-0.36*****	**-0.3594*****
	FOG_INDEX		**-0.6733*****		**-0.7662*****	**-0.6784*****	**-0.7178*****	**-0.647*****
	TONE		**-1.5823*****		**-1.5061*****	**-0.9805*****	**-1.1066*****	**-0.8884*****
	DIV_TONE		**-0.7496*****		**-0.7285*****	**-0.6616*****	**-0.6435*****	**-0.6195*****
Analyst-specific variables	*EXPERT*	**0.2108*****	**0.1827*****	**0.1984*****	**0.1789*****	**0.0993*****	**0.1381*****	**0.0832*****
	EXP	**0.2827*****	**0.2428*****	**0.2446*****	**0.2167*****	**0.228*****	**0.1994*****	**0.2148*****
	ALLSTAR	-0.287	-0.182	-0.147	-0.108	0.0228	0.0031	0.054
Information asymmetry in Q&A sessions	*TONE_Q*			-0.1527**	-0.0927	-0.0711	-0.0443	-0.0435
	TONE_A			**-0.7836*****	**-0.4514*****	**-0.3505*****	**-0.3062*****	**-0.28*****
	FOG_INDEX_Q			**-0.1481*****	**-0.1276*****	**-0.1262*****	**-0.119*****	**-0.1242*****
	FOG_INDEX_A			-0.054	0.1076**	0.0852*	0.0879*	0.0836*
Topic categories composition in analysts' questions	*BUEINESS_Q*					**0.353*****		**0.3*****
	FORECAST_Q					**0.301*****		**0.284*****
	TECH_Q					**0.284*****		0.199*
	FINANCIAL_Q					**-0.52*****		**-0.401*****
	RISK_Q					**-0.356*****		**-0.268*****
Topic categories composition in managers' answers	*BUSINESS_A*						**0.418*****	**0.323*****
	FORECAST_A						**0.346*****	0.108
	TECH_A						0.134	-0.0936
	FINANCIAL_A						**-0.399*****	**-0.289*****
	RISK_A						**-0.482*****	**-0.309****
	obs	8539	8539	7746	7746	7744	7744	7744
	Adj. R2	0.2044	0.2387	0.2105	0.2421	0.258	0.262	0.2687

CONSIS is an analyst-firm level measure of analyst consistency, defined as the standard deviation of the forecast error of the last forecasts of each quarter made by an analyst of a company, scaled by price and multiplied by -10. *MANFOR_FREQ* is the number of management forecasts issued during the sample period. *RD* is the R&D expenses scaled by total sales. *IDIO_VOL* is the idiosyncratic volatility measure as the standard deviation of the daily abnormal return from Fama-French 5 factor model. *FOG_INDEX* is the measure of readability calculated as the scaled complex words divided by total number of words. *TONE* is the number of positive words divided by the number of negative words. *DIV_TONE* is the standard deviation of *TONE* in all observations in each analyst-firm pair. *EXPERT* is the number of firms in a specific industry followed by an analyst scaled by total number of firms followed by that analyst. *EXP* is the number of years an analyst has been following the firm. *ALLSTAR* is an indicator variable equal to 1 if the analyst is named All-American Research Team by the Institutional Investor Magazine. *BUSINESS, FORECAST, TECH, FINANCIAL* and *RISK* are the number of topics discussed in the Q&A sessions of conference calls scaled by total number of topics in Q&A sessions of all conference calls of each analyst-firm pair. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Chapter 3. Financial Analysts' Information Role and Brand Capital Intensity

3.1 Introduction

We analyze the relationship between the informativeness of financial analysts' signal and firms' brand capital intensity. Specifically, the intangible nature of brand capital introduces greater information asymmetry between firms and investors. Thus, investors would rely more on publicly available information from financial specialists. As a consequence, we investigate whether analysts' earnings forecasts and stock recommendations are accompanied by greater short-term and long-term price movements for firms with greater brand capital intensity.

Brand capital has been increasingly important in explaining the abnormal returns in capital markets in recent decades. However, although the relationship between brand capital and stock return has been well documented in prior literature, studies focusing on the mechanism in which investors evaluate brand capital are comparatively rare. Even though brand capital is intangible in nature, a large portion of brand building investments such as advertising costs is expensed while incurred but not capitalized as intangible assets on financial statements, making it more difficult for investors, especially unsophisticated investors, to perceive the value of brand capital. The information asymmetry introduced by the absence of capitalization of brand building investments also results in biased estimate of firm values as well as future stock returns.

Financial analysts are knowledgeable experts who aim to reduce information asymmetry between firms and investors by constantly analyzing all aspects of firms including marketing activities such as brand building investments. Prior studies have found evidence of financial analysts engaging in brand-capital-related research including that analysts spend more effort on firms with comparatively more brand capital and that analysts partially mediate the relationship between brand capital and firms' risk factors. Nonetheless, it is still unknown whether financial analysts truly deliver value-related information regarding firms' brand building activities to investors.

This study builds on prior literature and focuses on the relationship between brand capital intensity, the proportion of brand capital to firms' total assets, and the informativeness of analysts' stock recommendations and earnings forecasts. Following prior literature, we construct the measure of brand capital as the capitalized advertising expenses and use stock market reactions to analysts' recommendations and forecasts as the measures of the informativeness of analysts' signals. Four different research methods, namely, textual analysis, univariate analysis, calendar-time portfolio analysis and linear regression analysis are conducted in this study. Firstly, in the textual analysis, *Latent Dirichlet Allocation* topic modeling is applied to extract the mostly discussed latent topics in analysts' reports and brand-capital-related topics are labeled. Firms are then put into five groups based on brand capital intensity and the proportion of brand-capital-related topics in each group is documented. Secondly, in the univariate analysis, firms are put into five groups based on brand capital intensity and the short-term buy-and-hold abnormal returns corresponding to analysts' recommendations and forecasts are documented for each group. Thirdly, in the calendar-time portfolio analysis, stocks with analysts' recommendation downgrades or forecast downgrades are put into a short portfolio, stocks with analysts' recommendation upgrades or forecast upgrades are put into a long portfolio and a hedge portfolio is created as an aggregation of the long portfolio and the short portfolio. Each portfolio is then put into five groups based on firms' brand capital intensity and the annualized raw returns, value-weighted-market-adjusted returns and excess returns from Fama-French four factor model are documented for each portfolio. Finally, in the regression analysis, short-term abnormal returns, revision frequency and forecast accuracy are regressed on brand capital intensity, news sentiment and other control variables.

The results are summarized as follows. Firstly, in the textual analysis, there are significantly more brand-capital-related topics in analysts' reports for the highest brand-capital-intensity group than for the lowest brand-capital-intensity group, suggesting analysts actively engage in discussing firms' brand building activities. This finding provides preliminary evidence that analysts' recommendations and forecasts could have incorporated brand-capital-related information. Secondly, in the univariate analysis, there are significantly stronger short-term abnormal returns corresponding to analysts' revisions for the highest brand-capital-intensity group than for the lowest brand-capital-intensity group and the stronger market reactions are more pervasive in forecast revisions sample than in recommendation revisions sample. By further clustering analysts' revisions based on revision magnitudes, we found that, in the recommendation revisions sample, the effect of brand capital intensity on market reactions to analysts' revisions is almost only pervasive in small revisions but is not significant in large revisions. This finding suggests that the long-term nature of brand building activities dictates that small and gradual revisions of stock recommendations are more likely to contain information about brand building, while rapid shift of stock recommendations are more likely due to other factors that may impact stock prices to a greater extent in the short run. On the contrary, in the forecast revisions sample, the effect of brand capital intensity on market reactions to analysts' revisions is pervasive across all revision magnitudes. These findings together suggest that the effect of brand capital intensity on market reactions to analysts' signals is more prompt and more complete in the short run for forecast revisions than for recommendation revisions.

Thirdly, in the calendar-time portfolio analysis, the long portfolios, short portfolios and long-short portfolios for each brand-capital-intensity group have significantly positive raw returns, value-weighted-market-adjusted returns and annualized alphas from Fama-French four factor model. Furthermore, the raw returns, value-weighted-market-adjusted returns and annualized alphas are significantly greater for the highest brand-capital-intensity group than for the lowest brand-capital-intensity group in all three portfolio settings, except for the annualized alpha for the short portfolios. These findings show that the effect of brand capital intensity on market reactions to analysts' recommendations is due to short-term overreaction and further enhance the argument that the informativeness of analysts' recommendations increases in firms' brand capital intensity. Lastly, in the regression analysis, the results show that short-term abnormal returns are significantly positively related to brand capital intensity after controlling for other pricing factors. Also, when analysts' signals conflict with news sentiment, short-term abnormal returns are not affected by brand capital intensity in recommendation revisions sample but are still positively related to brand capital intensity in the forecast revisions sample. This finding implies that forecasts revisions dominate news sentiment in terms of market reactions when they are on the opposite direction of news sentiments, while recommendation revisions and news sentiment are likely to be equally valued by investors when they conflict each other, rendering the market reactions insignificant. These findings also hold for short-term abnormal returns with different window sizes. In additional regression tests, brand capital intensity is positively related to revision frequency and negatively related to forecast accuracy, suggesting analysts spend more time in forming recommendations and forecasts for firms with comparatively more brand capital, which also increases the difficulty for analysts to make unbiased earnings forecasts.

This study contributes to existing literature in several ways. First, it adds to the marketing literature by showing firms' marketing activities such as brand capital investments are not fully understood by investors and financial analysts' engagement could help reduce the valuation biases stemmed from the information asymmetry between investors and firms' marketing activities. It is also the first paper directly analyzing the relationship between brand capital intensity and market reactions to analysts' investment advice. Secondly, it adds to the existing information asymmetry literature by creating a setting where information asymmetry between firms and investors are introduced by the marketing costs that are expensed while incurred. Capitalization of advertising expenses allows us to relate information asymmetry to brand capital quantitatively and thus reveal more statistical evidence. Although prior literature has documented that analysts are able to reduce information asymmetry introduced by intangible assets, brand capital differ from intangible assets in that brand capital is not capitalized on balance sheets and may be accompanied by greater investors' inattention compared with capitalized intangible assets.

Consequently, information asymmetry introduced by brand capital and intangible assets are, although not mutually exclusive, different aspects of firms and may be accompanied by distinguishing analysts' treatments and investors' valuations. Finally, this paper documents qualitative evidence that financial analysts actively engage in brand-capital-related studies by analyzing latent topics from analysts' reports using LDA topic modeling. This textual analysis approach establishes a critical link between firms' brand capital intensity and analysts' information intermediary role, which is absent in prior studies. By showing brand capital is also one of many factors that financial analysts consider when forming investment advice, the textual analysis enhances the main argument in this paper that financial analysts reduce the information asymmetry introduced by firms' brand building activities.

The rest of this paper is organized as follows. Section 3.2 provides a brief review of prior literature about brand capital and financial analysts as information intermediaries as well as the development of hypotheses; section 3.3 shows the details of the research design as well as descriptive statistics; section 3.4 provides interpretations of the research results and section 3.5 concludes the paper.

3.2 Literature review and hypotheses development

3.2.1 Brand Capital and Advertising activities

Intangible capital has become more important in firm valuation in recent decades. The explanatory power of the observed investment on the increase of capital, as recorded from the security market, has been decreasing, indicating that firms have produced and accumulated additional non-observable capital (Hall 2001).

Some studies focus on the relationship between brand capital and firm value. For example, a recent study of Belo et al. (2014) found that higher brand capital intensive firms are associated with higher average returns compared with less brand capital intensive firms, a finding that indicates brand capital has similar characteristics as physical capital investment does. Another study of Vitorino (2014) implemented an investment-based structure model with brand capital as input and found that the value of brand capital accounts for a substantial fraction of firm market value. Simon et al. (1993) applied an approach to extract the value of brand equity from the value of other assets of a company and successfully applied it to several renowned companies, demonstrating brand equity has incremental effect on companies' value. Mizik et al. (2007) further found that changes in firms' brand assets are associated with changes in firms' market valuation. Frieder et al. (2005) found that individual investors prefer to hold stocks of firms with high brand recognition. Furthermore, Madden et al. (2006) applied a portfolio-based approach and found that firms with stronger brand names not only create greater returns to investors but also do so with less risk. Lane et al. (1995) applied an event study approach and found that stock market reactions to brand extension announcements are interactively and nonmonotonically affected by brand attitude and familiarity. Rao et al. (2004) analyzed several branding strategies and found that companies that use consistent brand names for their products have higher Tobin's Q. In Addition, brand attitude, a key component of brand equity, helps predict future earnings and thus firm value (Aaker et al. 2001).

There were several different theories on the mechanism with which brand capital creates value. For example, Belo et al. (2014) argued that brand capital can increase firms' operating profit by increasing customer loyalty or visibility. Simon et al. (1993) argued that brand capital investment can increase the ability of the companies' other assets to generate future cash flow and thus increase the present value of the company. Some studies also found that brand capital creates firm value by increasing customer satisfaction. For example, several studies applied the American Customer Satisfaction Index (ACSI) and found a positive relationship between customer satisfaction and some value-related factors such as cumulated abnormal returns, future cash flows and cash flow volatilities (e.g. Anderson et al. 2004, Ittner et al. 1998, Gruca et al. 2005, Fornell et al. 2006 and Mittal et al. 2005). In addition, some studies also found that brand capital creates firm value by increasing the perceived product quality (e.g. Mizik et al. 2003, Aaker et al. 1994, Srinivasan et al. 2009 and Tellis et al. 2007).

Firms can create strong brand associations with customers through appropriate advertising strategies[7]. (Aaker 1991). Barth et al. (1998) applied the data from a survey-based estimate of brand value and found that the estimate of brand value is significantly positively associated with advertising expenses. Advertising expenditure creates brand capital, which is a productive asset that symbolizes customers' willingness to pay for the company's products (Belo et al. 2014). Such brand loyalty created by advertising activities may be

[7] The aggregated advertising expenditure represents about 5% of annual GDP in the U.S. economy (Arkolakis, 2010).

subject to increasing returns to scale (Bagwell 2007) and may facilitate customer value communication, leading to favorable stock returns to investors (Srinivasan et al. 2009). In addition, advertising activities could also have direct effect on firm valuation through spillover and signaling of financial well-being or competitive viability of the firm (Joshi et al. 2008). For example, Mathur et al. (2000) showed that advertising expenditures mitigate negative stock market reactions by signaling strong financial well-being. Mathur et al. (1997) further demonstrated that public celebrity's endorsement increases firms' competitive viability.

Consistent with the value creation mechanism of advertising activities, several studies found a positive relationship between advertising investment and firm value. For example, Joshi et al. (2009) found statistical evidences that advertising investment increases firm value in both the short-run and the long-run. More insight on the value creation mechanism of advertising activities can be found in McAlister et al. (2007) which demonstrated that advertising expenditures create intangible capital that isolates it from stock market changes, lowering the systematic risk of the firm. Furthermore, Srinivasan et al. (2009) found that communications between the firm and customers about innovative products has positive effects on firm valuation.

Although the evidence of a positive relationship between brand capital and firm value is abundant, the market reaction to brand capital investment may be incomplete, especially in the short-run, due to the difficulty in assessing the value of brand capital. One of the reasons causing such a difficulty is that the progress in brand capital investment is not completely visible in firms' quarterly earnings in that the outcome is either difficult to measure financially or could be substantially delayed (Srinivasan et al. 2009). Other determinants of the stock market reaction of brand-capital-related investments include several aspects of such investments such as their magnitude, speed and volatility (Srivastava et al. 1998). The results of incomplete market reaction to brand-capital-related investments could potentially lead to mispricing of firms' market value. On the one hand, incomplete market reaction to brand building may lead to undervaluation of stock prices. For example, Lev (2004) reported that "intangible-intensive" firms are systematically undervalued which, in turn, adversely affects reinvestments in intangibles such as brand building, leading to limited future earnings growth. On the other hand, unsophisticated investors may be influenced by persuasive and exaggerated communication through advertising activities (Gallaher et al. 2006, Sirri et al. 1998), leading to overvaluation of stock prices. Thus, mispricing caused by information asymmetry increases in brand capital intensity.

3.2.2 Financial analysts as information intermediary

Financial analysts are visible and knowledgeable experts who constantly collect, analyze, and disseminate information about the future prospects of publicly listed firms (Brauer et al. 2018). Financial analysts can reduce information asymmetry between firms and investors by providing informative investment advice to the market (Stickel 1992, Womack 1996) due to their perceived expertise (Zuckerman 1999), independence (Fogarty et al. 2005) and the wide dissemination of their opinions (Groysberg et al. 2008, Michaely et al. 1999, Pollock et al. 2003, Stickel 1995, Brauer et al. 2018). Among the information provided by financial analysts, earnings forecasts and stock recommendations are two of the mostly studied information outputs by previous literature. Analyst earnings forecasts are thought to be more accurate than prediction from past time-series of earnings (Das et al. 1998) because analysts use more information to form earnings forecasts than that contained in historical earnings data (Brown et al. 1987). For example, Ettredge et al. (1995) found that analysts' forecast revisions around earnings announcements contain undisclosed overstatements adjust for part of the overstatement amounts, implying that analysts use alternative information to “see through” earnings manipulations. Analysts’ stock recommendations also provide information beyond publicly available information. For example, Clement (1999) and Brown et al. (2015) found that analysts at large brokerage houses are more likely to use private communication with management as a useful input to their stock recommendations, giving them a potential information advantage.

Financial analysts’ reports are generally thought to be informative. Frankel et al. (1998) demonstrated that analysts' forecasts of the current year EPS, next year's EPS and the following three years' EPS growth rates contribute significantly to models explaining the cross-section of current year price-to-book ratios. They concluded that valuation estimates based on consensus forecasts are good predictors of future stock returns, especially over longer horizons. Liu et al. (2001) further showed that returns-earnings regression R^2 can be improved dramatically by including revisions in analysts' forecasts of next year or two-year-ahead earnings. In addition, Francis et al. (1997) found that Stock recommendation revisions contain information incremental to the information in earnings forecast revisions. Asquith et al. (2005) demonstrated that earnings forecast revisions, stock recommendations, target price revisions and a coding of the strength of the analysts' (positive or negative) arguments in support of the stock recommendations combine to explain 25% of the variation in returns around the release of analysts' research reports. Barber et al. (2001) constructed a trading strategy based on buying (selling short) stocks with the most (least) favorable stock recommendations which yields significant annual abnormal returns. Another study incorporating trading strategy is Barth et al. (2004) in which the trading strategy that simultaneously exploits the accrual anomaly and the forecast revision anomaly yields annual returns of over 28%.

3.2.3 Financial analysts and brand capital

Evidences of financial analysts engaging in brand-capital-related research can be found in several studies. An earlier research of Barth et al. (2001) found that companies with high brand capital intensity are covered by more analysts and that analysts expend greater effort on companies with more brand capital. Whitwell et al. (2007) implemented an interview-based approach to analyze the determinants of the accuracy of financial analysts' assessment of firms' intangible assets. Luo et al. (2010) found that analyst recommendations partially mediate the effects of the changes in customer satisfaction on firms' abnormal returns, systematic risks and idiosyncratic risks. Kui et al. (2019) applied data of Chinese companies and found that analyst recommendations mediate the relationship between brand equity and a firm's sustainable performance in terms of abnormal return, systematic and idiosyncratic risk.

The evidences of financial analysts' discussion about firms' brand capital recognition can also be directly found in their reports. For example, in an investment thesis in 2018 of Bayer, one of the largest pharmaceutical company in the world, the financial analyst wrote:

"Bayer's healthcare segment also includes a consumer health business with leading brands Aspirin and Aleve. Brand recognition is key in this segment, as evidenced by the company's iconic Aspirin, which continues to produce strong sales even after decades of generic competition. The 2014 acquisition of Merck's consumer products increased the scale of Bayer's consumer group." (Conover 2018)

This paragraph identifies the brand recognition as the essential factor that generates continuous revenue for the company, an argument that may help investors relate the earnings potential of the company to its brand recognition to a greater extent. Another evidence can be found from an analyst report in 2013 of Abbott, an American healthcare company, the analyst wrote:

"These building blocks and experience with nutritionals should also play out well when applied to Abbott's established pharmaceutical product segment, which is mainly sold outside the United States. This business, frequently called branded generics, operates more like a consumer business than traditional branded drugs. For example, Abbott's branded generics will mainly be sold in less developed markets that often lack a well-developed infrastructure for distribution. Instead, Abbott must sell its products directly to pharmacy chains and physicians. As a result, brand recognition and reputation are key factors that Abbott can leverage. Selling to a fragmented market also translates into less pricing pressure for Abbott. This could change over the longer term once more emerging markets turn to the tender system that characterizes developed nations. However, that change remains far off." (Wang 2013)

This paragraph indicates that brand recognition and reputation are key factors that the company can leverage when expanding its business to less developed markets. As a consequence, those investors who hold pessimistic opinion about the company's expansion to emerging markets may now feel more confident and hence rethink about their investment strategies. On the other hand, analysts' discussion about companies' brand recognition may also have negative effects on companies' value. Such effects could be more overwhelming if the analyst either indicates that the company's brand capital is overvalued or argues that the company's lack of brand capital would adversely affect the company's business. For example, in an analyst investment report published in 2018 about Alibaba Group, one of the Chinese largest e-commerce companies, the analyst wrote:

> *"Other downside risks include expansion into peripheral businesses, which might distract management and may not materially improve Alibaba's ecosystem. While we're optimistic about Alibaba's ability to become a preferred partner for international retailers and consumer brands looking to sell in China, the firm does not enjoy the same network effect and brand recognition in other countries, and it may face challenges directly expanding in these markets." (Hottovy 2018)*

This analysis clearly points out that Alibaba's lack of brand recognition outside China would negatively affect its expansion internationally, an argument that may potentially correct the component of brand-capital-related overvaluation to some extent. In other words, some investors who are overconfident about the company's brand value would realize the brand value of the company in the international market is not as high as that in China after reading the analyst report. Furthermore, financial analysts would discuss about brand capital in their reports more intensively if the firm has more brand capital compared to firm assets because financial analysts tend to allocate their effort proportionally to each aspect of a firm. Hence, the first hypothesis is as covers:

$H_{3.1}$: the portion of brand-capital-related discussion and analyses in financial analysts' reports increases proportionally in the ratio of firms' brand capital to their total assets.

Financial analysts act as information intermediary between firms' brand capital and customers in several ways. First, financial analysts, with their expertise on assessing the quality of firms' products, provide additional information on firms' brand credibility, which is the ability and willingness for the firm to continuously deliver products that meet the description the firm previously stated (Erden et al. 2006). Such assessment helps investors better understand the actual value of products than that perceived from firms' own advertisements which may be subject to exaggeration. It also helps investors get more insight of firms whose brand value is underappreciated due to lack of advertising activities. The market thus corrects for any brand-capital-related mispricing to some extent due to the decrease in information asymmetry. Second, financial analysts' reports accelerate the progress for brand capital investments to be reflected in stock prices. Value-creating mechanism of brand capital investments requires certain estimates of future cash flows generated from either the direct effect from intangible building or the indirect effect of increases in sales, earnings and customer satisfaction. Such outcomes are not readily visible in the short run and may take several years to be realized. Financial analysts provide professional and less-biased assessment of future cash flow generated from brand building that may be superior to that predicted by less sophisticated investors, thus make the information of brand building to be reflected in stock prices on a timelier basis. Third, financial analysts could potentially make brand capital investments to be more completely valued. Brand capital is difficult to value due to its intangible nature. Financial analysts have more expertise in collecting, interpreting and summarizing any publicly available information and private information they gathered from back channels such as their affiliation with the firms. Such informational advantage would result in more complete estimation of the value of brand capital investments than public investors. Thus, information outputs from financial analysts could help stock prices converge to their intrinsic values more completely. Furthermore, analysts' reports would be more informative for firms with more brand capital scaled by firm size as the valuation difficulty increases proportionally with the portion of brand capital. Hence, the second hypothesis is stated as follows:

$H_{3.2}$: Market reactions to financial analysts' earnings forecasts and stock recommendations increase in the proportion of firms' brand capital to their total assets.

3.2.4 Other testable hypotheses

3.2.4.1 Brand capital intensity and news sentiment

Studies have found that the daily news sentiment in the market affect stock traders' behavior. For example, Delong et al. (1990) found that low sentiment would generate downward price pressure and extremely high or low values of news sentiment would lead to greater trading volume. Tetlock (2007) predicted that pessimistic investor sentiment leads to negative market reaction in the short-run and such negative market reaction would probably reverse in the long-run based on the sentiment theory. Other empirical studies using a variety of measures of news sentiment generally found that a positive average stock price movement when news sentiment is optimistic and a negative average stock price movement when news sentiment is pessimistic, regarding both overall news sentiment and firm-specific news sentiment.

If the news sentiment is optimistic and an analyst upgrades the stock recommendation or earnings forecast at the same day, there could be two implications. First, if the upgrade contains information that is also in the overall news sentiment, there would be no incremental effect of the revision on stock price movement. Second, if the information content of the upgrade serves as a complement to the information contained in the news sentiment, there would be a stronger upward stock price movement around the analyst's signal. Similarly, there could be either no incremental effect of a recommendation or forecast downgrade on stock movement or a stronger downward stock price movement depending on whether the analyst's signal is complementary to the news sentiment. Giving that some of the analysts' signals could contain additional information that news sentiment fails to capture, there should be, on average, an observable incremental effect of recommendation or forecast revisions that are in the same direction of the news sentiment. Furthermore, the incremental effect could be even stronger when firms have more brand capital because such firms possess higher asymmetry of information which could be reduced by a greater extent by analysts' signals. As a result, the hypothesis is stated as follows:

$H_{3.3a}$: There is a positive incremental effect of news sentiment on the relationship between the magnitude of market reactions to analysts' recommendation and forecast revisions and the proportion of firms' brand capital to their total assets.

In addition, the situation of a forecast or recommendation revision in the opposite direction of news sentiment also exist and there could be two implications regarding that situation. First, the analyst's signal might be truly informative in that it may capture additional private information in the opposite direction of the news sentiment, in which case the stock price would move in the direction of news sentiment if the effect of news sentiment is stronger, or move in the direction of analyst signal if the effect of analyst's private information is stronger. Second, the analyst's signal could be a trick to impress the market and contains no private information, in which case the stock price would move in the direction of news sentiment should the market be efficient, or in the direction of the analyst's signal but with a weaker magnitude should the market be less efficient. As a consequence, the presence of a news sentiment in the opposite direction of analyst's signal would result in a stronger market reaction in the direction of the analyst's signal should the signal be informative, or a weaker market reaction in the direction of the signal or even an opposite market reaction should the signal be uninformative. Furthermore, we expect a stronger relationship between conflicting forecast or recommendation revisions and the magnitude of market reactions if the firm has more brand capital because any public signal including analysts' signals and news outlets would reduce information asymmetry of such firm by a greater extent. Since the informativeness of the analysts' signals is unknown, the conflicting signal could either strengthen or weaken the relationship between brand capital intensity and the magnitude of market reaction to the signal. As a result, we state the following nondirectional null hypothesis:

$H_{3.3b}$: There is no incremental effect of the conflicting analyst's forecasts or *recommendations on the relationship between the proportion of firms' brand capital to their total assets and the market reactions to analysts' recommendation and forecast revisions.*

3.2.4.2 Brand capital intensity and revision frequency

Many studies have demonstrated that the period which analysts take to process information and make stock recommendations or earnings forecasts increases in the complexity of the information. Studies such as Barth et al. (2001) have shown that analysts expend greater effort on companies with more brand capital. Giving the intangible nature of brand capital and the greater information asymmetry raised from brand building activities, analysts would thus spend more time in disentangling the brand-capital-related information in order to make informative investment guidance. In addition, the indirect effect in which brand capital affects earnings and stock prices through the incremental effect on factors such as customer satisfaction, customer loyalty and financial well-being are more difficult to evaluate compared with mandatorily capitalized assets. Analysts would thus spend more time in evaluating these factors which would potentially delay their process in delivering informative signals. As a result, the fourth hypothesis is stated as follows:

$H_{3.4}$: The number of days between analysts' current earnings forecasts or stock recommendations and their last earnings forecasts or stock recommendations increases in the proportion of firms' brand capital to their total assets.

3.2.4.3 Brand capital intensity and forecast accuracy

Several studies found that forecast complexity affects forecast accuracy (e.g. Haw et al. 1994, Duru et al. 2002). Forecast complexity of earnings depends on the difficulty in evaluating the ability to generate future cash flows from different kinds of investments, regardless of whether the investment is capitalized or not. Since brand capital investment is highly intangible and the future cash flow generated from brand capital investments is more difficult to estimate compare with tangible investments, the earnings forecasts based on future cash flow for firms with larger proportion of brand capital investments are subject to higher variation, leading to less accurate forecasts. In addition, factors such as financial well-being and competitiveness, as could be signaled by advertising investments, also increase firms' profitability in the long-run and affect analysts' prediction about the firms' future perspective to some extent and may lead to greater analysts' divergence of opinion. Other things equal, earnings forecast accuracy would decrease with more uncertain information for analysts to process. As a result, the fifth hypothesis is stated as follows:

$H_{3.5}$: Analyst earnings forecast accuracy decreases in the proportion of firms' brand capital to their total assets.

3.3 Research design and sample description

3.3.1 Measure of brand capital

The measurement of brand capital has been thoroughly discussed in previous literature. In this paper, we do not intend to compare the advantages and disadvantages of several archive-based and survey-based measures of brand capital. Instead, we apply a measure developed based on the perpetual inventory method by Belo et al. (2014) which not only follows general theory that advertising expenditure creates brand capital, but also considers the time value and amortization of advertising spending in different accounting periods. The detailed construction is as follows:

$$B_{it} = (1 - a) \times B_{i,t-1} + A_{it}$$

and

$$B_{i0} = A_{i0} / (g + a)$$

where B_t is the value of brand capital of firm *i* in year *t*. B_{i0} is the value of brand capital of firm *i* in the first year the data of the firm is available in *COMPUSTAT*. A_{it} is the advertising expense of firm *i* in year *t*. A_{i0} is the advertising expense of firm *i* in the first year the data of the firm is available in *COMPUSTAT*. a is the amortization rate of brand capital and g is the growth rate of advertising expenses. Same as Belo et al. (2014), the amortization rate a is assigned the value of 50% and the growth rate of advertising expenses g is assigned the value of 10% which correspond with the average values in previous literature. This perpetual inventory method to measure brand capital is also widely used in measuring other similar intangible capitals such as organization capital (Eisfeldt et al. 2012) and R&D capital (Sliker 2007) and is superior to simply using advertising expenses as the measure of brand capital in that the method also captures the cumulative effect of past advertising activities, consistent with the idea that brand building is a prolonged process that may take several accounting periods.

3.3.2 Textual analysis

To test the first hypothesis that analysts discuss more about brand capital in their reports for firms with more brand capital, 35,992 analyst reports were collected from Morningstar.com which is a financial service company that provides a variety of investment-related datasets. The original set of analyst reports contains 1,758 companies that cover 175 4-digits Standard Industry Classification Code from 2000 to 2018. Latent Dirichlet Allocation (LDA) approach is applied to model the topics of these reports[8]. Specifically, two sets of mostly discussed topics in these reports were generated using equal-weighting approach and tf-idf weighting approach[9] respectively, with each set containing 100 topics. Topics with the word "brand" and "advertise" were identified as brand-capital-related topics. Total number of topics and the numbers of brand-capital-related topics were counted in each analyst report.

In order to analyze the relationship between the proportion of firms' brand capital and the proportion of brand-capital-related topics in analyst reports, we sort firms into five groups based on the ratio of firms' brand capital to total assets, with group 1 being the low-brand-

[8] LDA model is a generative probabilistic model for collections of discrete data such as text corpora in which each item is modeled as a finite mixture over an underlying set of topics (Blei et al. 2003). It has been extensively used in social science research to deconstruct corpus of textual documents into latent topics, especially for documents with multiple interspersed topics (Dyer et al. 2017).

[9] Tf-idf is short for "term frequency – inverse document frequency", which is a generally applied method in topic modeling to reduce the relative importance of words or terms that appear more often in general, such as the word "the" and "a".

capital group and group 5 being the high-brand-capital group. The variation of brand-capital-related topics among these groups were then analyzed. Specifically, the average number of brand-capital-related topics and the average number of brand-capital-related topics scaled by total number of topics were computed based on equal-weighting method and tf-idf weighting method, respectively. The difference between the low-brand-capital group and the high-brand-capital group were also tabulated with t-statistics with one-way standard errors.

3.3.3 Univariate analysis

Similar to Palmon et al. (2012), we sort our sample into 5 groups based on the ratio of brand capital to total assets and compare the variation of buy-and-hold abnormal returns to earnings forecast announcements and to stock recommendations among these groups. Buy-and-hold abnormal returns is the raw returns minus the value-weighted market returns. In first test of market reactions to stock recommendations, the whole sample is split into two a subsample of recommendation upgrades and a subsample of recommendation downgrades based on the comparison between the new recommendation and the previous recommendation made by the same analyst. Within each subsample, the average buy-and-hold abnormal returns for each brand capital intensity group is presented and the difference in the average buy-and-hold abnormal returns between the low-brand-capital group and the high-brand-capital group is also presented with t-statistics. In the second test of market reactions to stock recommendations, the average buy-and-hold abnormal returns to different revision paths in each brand capital intensity group are also tabulated because different revision paths may convey different information (Palmon et al. 2012).

In the first test of market reactions to earnings forecasts, similar to stock recommendations, the whole sample is split into two a forecast upgrades subsample and a forecast downgrades subsample based on the comparison between the new forecast and the previous forecast made by the same analyst. The variations of buy-and-hold abnormal returns to forecast revisions among different brand capital intensity groups are then analyzed. In the second test of market reactions to earnings forecasts, earnings forecast revisions are sorted into three size groups: small, medium and large, based on the ranking of the absolute value of the change of forecast as a percentage of the previous forecast made by the same analyst. The variation of the average buy-and-hold abnormal returns among different brand capital intensity groups within each revision size group are then analyzed.

3.3.4 Long-term portfolio analysis

To rule out the possibility of market overaction to analysts' signals and post-event return reversal due to uninformative signals, long-term portfolios are constructed based on a trading strategy on analysts signals and firms' brand capital intensity. The main reason for using portfolio analysis instead of univariate tests or regression models is that any dependent variables that capture long-term market reactions may also reflect information unrelated to analysts' signals, thus lowering the explanatory power of the results. The calendar-time portfolio approach has been extensively used in accounting and finance literatures to assess long-term security performance (Jaffee 1974, Sloan 1996, Fama 1998, Palmon et al. 2012).

The portfolios were constructed as follows. Stock that was upgraded by an analyst was put into a long portfolio one day before the recommendation revision. The stock was then held in the long portfolio for one year unless it was downgraded by the same analyst. If another analyst also upgraded the same stock during the year, the shares of the stock were then doubled in the long portfolio. Similarly, stock that was downgraded by an analyst was put into a short portfolio one day before the recommendation revision and held in the short portfolio unless it was upgraded by the same analyst. If another analyst also downgraded the same stock during the year, the shares of the stock were then doubled in the short portfolio. The daily raw returns of both portfolios were then computed as follows:

$$R_t = \frac{\sum_{i=1}^{n} Vol_{it}\,(1 + r_{it})}{\sum_{i=1}^{n} Vol_{it}} - 1$$

where R_t is the raw return at day *t* for the portfolio, Vol_{it} is the number of shares of stock *i* at day *t* in that portfolio, r_{it} is the raw return of stock *i* at day *t* and *n* is the number of stocks at day *t* in that portfolio. The daily raw return of that portfolio was thus the weighted average of the raw returns of each stock in that portfolio, which controls for the fact that stocks with more analysts' upgrades or downgrades may be accompanied with more information and need to take heavier weights in the portfolio. For robustness check, we also construct a long-short portfolio that takes a long position of those upgraded stocks and a short position of those downgraded stocks.

Within each brand capital intensity group, the average daily raw return in the long, short and long-short portfolios were calculated and the average daily market adjusted returns were also calculated as the raw returns minus the value-weighted daily market returns. To control for systematic risk factors, we also tabulate the annualized Jensen's alpha as another proxy for abnormal return by regressing daily excess return on market premium ($R_{mt} - R_{ft}$), size effect (*SMB*), book-to-market factor (*HML*) and the premium on winners minus losers (*UMD*). Finally, to compare the information content between the high brand capital intensity group and the low brand capital intensity group, we construct a new portfolio by taking a long position of the high brand capital intensity portfolio and a short position of the low brand capital intensity portfolio. The implications as to whether analysts' recommendations convey more long-lasting information for high brand capital intensity firms than for low brand capital intensity firms rely mainly on the statistical characteristics of the raw returns and abnormal returns of the new portfolio.

3.3.5 Regression analysis

The following regression model is applied to test the main hypothesis that analysts convey more information for firms with higher brand capital intensity.

$$
\begin{aligned}
BHAR_{itj} = \alpha &+ \beta_1 SIZE_{itj} + \beta_2 B/M_{itj} + \beta_3 COVER_{itj} + \beta_4 AMIHUD_{itj} + \beta_5 FOR_{itj} \\
&+ \beta_6 REC_{itj} + \beta_7 REV\_MAG_{itj} + \beta_8 BOLDNESS_{itj} + \beta_9 BRANDCAP_{itj} \\
&+ \beta_{10} CSS_{itj} + \beta_{11} CSS_{itj} \times BRANDCAP_{itj} \\
&+ \beta_{12} CONFLICT_{itj} + \beta_{13} CONFLICT_{itj} \times BRANDCAP_{itj} \\
&+ \beta_{14} CONFLICT_{itj} \times CSS_{itj} + \varepsilon_{itj}
\end{aligned}
$$

where

$BHAR$	=	Three-day buy-and-hold abnormal return around forecast or recommendation revisions.
$SIZE$	=	Nature logarithm of firm size at fiscal yearend.
B/M	=	Book-to-market ratio at fiscal yearend.
$COVER$	=	Number of analysts following the firm during that fiscal year.
$AMIHUD$	=	Amihud (2002) illiquidity ratio.
FOR	=	An indicator variable equal to one if the recommendation revision is accompanied by earnings forecast revisions made by the same analyst within the three-day period around the recommendation revision date, and zero otherwise.
REC	=	An indicator variable equal to one if the forecast revision is accompanied by recommendation revisions made by the same analyst within the three-day period around the forecast revision date, and zero otherwise.
REV_MAG	=	A measure of revision magnitude. For earnings forecast it is calculated as the absolute value of the difference between the new forecast and the previous forecast made by the same analyst divided by the previous forecast. For recommendations it is calculated as the absolute value of the new recommendation minus the previous recommendation made by the same analyst and takes the value of 1, 2, 3 and 4.

$BOLDNESS$	=	A measure of analyst boldness. For earnings forecast it is calculated as the absolute value of the difference between the new forecast and the previous forecast consensus divided by the previous forecast consensus. For recommendations it is calculated as the absolute value of the difference between the new recommendation minus the previous recommendation consensus.
$BRANDCAP$	=	A measure of brand capital calculated as the capitalized and amortized advertisement expenses scaled by total assets.
CSS	=	Composite sentiment score, a measure of daily news sentiment from RavenPack Database
$CONFLICT$	=	An indicator variable equal to one if the forecast or recommendation revision is on the opposite direction of daily news sentiment, and zero

In order to uniformly analyze the magnitude of market reactions to both upgrades and downgrades, we multiply *BHAR* of forecast and recommendation downgrades by -1. We also adjust *CSS* to eliminate the direction effect by using 50 minus *CSS* for all *CSS* below 50 and using *CSS* minus 50 for all *CSS* above or equal to 50 so that a larger value indicates more divergence of market sentiment from the neutral sentiment[10]. Therefore, the regression model is aimed to analyze the effect of magnitude but not the direction among the variables.

[10] The Composite sentiment score (CSS) takes the value between 0 to 100 where a value below 50 is considered as a negative news sentiment, a value above 50 is considered as a positive news sentiment and a value equal to 50 is considered as a neutral news sentiment. A stronger divergence from 50 imply a stronger extremity of the sentiment.

Firm size is of significant impact on stock returns in that, other things equal, the magnitude of return decreases in firm size. Market valuation is also another determinant of stock returns. The size effect (*SIZE*) and market valuation effect (*B/M*) are thus controlled in the model. Analyst coverage (*COVER*) also affects stock returns because firms followed by more analysts would have less information asymmetry, leading to smaller market reactions to analysts' signal. As greater liquidity of stocks would result in higher trading volume and possibly stronger market reaction, the Amihud 2002 illiquidity ratio (*AMIHUD*) is included in the regression model. Similar to Palmon et al. (2012), to control for the possibility that the information content in earnings forecasts and recommendations is not mutually exclusive, we controlled for the situation in which the forecast revision is accompanied by recommendation revisions made by the same analyst within the three-day period around the forecast revision date (*REC*) and the situation in which the recommendation revision is accompanied by forecast revisions made by the same analyst within the three-day recommendation date (*FOR*). The revision magnitudes (*REV_MAG*) of earnings forecasts and recommendations are also added to the model as larger revision strength often leads to stronger market reaction. Forecast and recommendation boldness (*BOLDNESS*) is also included in the control variables because bold forecasts and recommendations could be either informative or tricks to impress the market (Palmon et al. 2019).

To test the hypotheses about the relationship between brand capital intensity, revision frequency and forecast accuracy, we change the dependent variable in the main regression model to *REC_FREQ* and *FOR_FREQ*, which are the number of days between the current revision and the last revision scaled by 365, and *FOR_ACCU* which is the absolute value of the difference between earnings forecasts and actual earnings, scaled by the absolute value of the actual earnings.

3.3.6 Descriptive statistics

Panel A of Table 3.1 summarizes the 10 most frequent key words in each brand-capital-related topics in our textual analysis. Panel B of Table 3.1 summarizes the means of selected variables in each brand capital quintile group in our textual analysis. BRANDCAP and Advertising expense is highly correlated, suggesting that firms' advertising strategies do not often change and that a firm is very likely to stay in the same brand capital quintile group for several years. This finding enhances the explanatory power of the rest of our tests. There is not much fluctuation in the average number of topics across all quintile groups. However, there is also not much fluctuation in the average intangible assets across firms with non-zero BRANDCAP and non-zero Advertising expense, suggesting that brand capital, although is intangible per se, is rarely reflected on financial statements. In addition, the average number of analysts following the firm increases with BRANDCAP and Advertising expense for quintile groups with non-zero BRANDCAP and non-zero Advertising expense, consistent with the finding in Barth et al. (2001) that companies with high brand capital intensity are covered by more analysts.

[Insert Table 3.1 here]

Table 3.2 shows the means of selected variables for each brand capital quintile group in our univariate analysis. Figure 3.1 shows the 20-day cumulative abnormal return curves for both recommendation revisions and forecast revisions for each brand capital quintile group in our univariate analysis. Visual inspection implies market reactions to forecast revisions provide more support to $H_{3.2}$ than market reactions to recommendation revisions do that analysts' signals are more informative for firms with greater brand capital. There is visible monochronic decrease in average cumulative abnormal returns from low brand-capital-intensity groups to high brand-capital intensity groups for analysts' forecast downgrades. Similar pattern can be found in the figure for analysts' forecast upgrades. In addition, in the figure for analysts' forecast upgrades, the price upward trend seems to persist only for the highest brand-capital-intensity group but the price upward trends seem to reverse for other groups, suggesting that analysts' signals are the most informative for firms with the largest brand capital and that such signals may take longer to be fully reflect in stock prices. For stock recommendation revisions, however, although there are visible differences between cumulative abnormal returns for the lowest and the highest brand-capital-intensity groups, the cumulative abnormal returns for other quintile groups do not strictly establish a pattern. The fact that the relationship between market reactions to recommendation revisions and brand capital intensity is not as evident as that between market reactions to forecast revisions and brand capital intensity is probably because brand capital is directly built out of advertising expenses which directly affect earnings in each accounting cycle. Therefore, earnings forecast revisions might be more interpretable by investors in terms of brand building than recommendation revisions are. Furthermore, different recommendation revision paths might have different magnitude of market reactions. For example, an upgrade from "sell" to "buy" is highly likely to be accompanied by stronger price markup than an upgrade from "strong sell" to "sell". Simply clustering recommendation revisions into upgrades and downgrades overlooks the effect of revision paths and will likely result in mixed results.

[Insert Table 3.2 here]

[Insert Figure 3.1 here]

Table 3.3 documents the minimum, average and maximum number of stocks in both long portfolios and short portfolios in each brand-capital quintile group between 2005 and 2018 in our calendar-time portfolio analysis. Figure 3.2 shows the long-term cumulative market-adjusted returns in long, short and long-short portfolios in each brand capital quintile group and the cumulative value-weighted market return between 2005 and 2018. In the of long portfolios, visual inspection suggests there is a monochronic increase of long-term cumulative market-adjusted returns during most time of 2005 – 2018 from the lowest brand-capital-intensity group to the highest brand-capital-intensity group and that all the 5 portfolios earn greater cumulative abnormal returns than the market portfolio does. Furthermore, the differences between the returns of all the 5 portfolios and that of the market portfolio increase in the duration of holding period and there is no visible sign that the return trend would reverse. This finding indicates that the higher cumulative abnormal returns for the 5 portfolios are unlikely due to temporary market overreactions to recommendation revisions. In addition, the cumulative market-adjusted return of the long portfolio for the highest brand-capital-intensity group almost twelvefold the return of the market portfolio at the end of 2018. Surprisingly, the cumulative abnormal returns in the short portfolios and the long-short portfolios do not show a strictly monochronic pattern. Although the cumulative abnormal returns for the highest brand-capital-intensity groups are greater than those for the lowest brand-capital-intensity groups in both figures for short portfolios and long-short portfolios and the cumulative abnormal returns for all the 5 groups are all greater than the return for the market portfolio, the second brand-capital-intensity groups earn greater return than the highest ones in both figures. An explanation is that more than 40% firms in the sample have zero brand capital, a situation that may result in the sorting of the first and second groups to be based on other variables that may be correlated to abnormal returns. Also, the effect of different revision paths is not controlled in the calendar-time portfolio analysis, which could lead to mixed results.

[Insert Table 3.3 here]

[Insert Figure 3.2 here]

Table 3.4 provides summary statistics of variables in the regression analysis. The mean *BHAR* of the recommendation revision sample is 2.33% which is greater than the mean *BHAR* of 0.58% of the forecast revision sample, consistent with theory that stock recommendations are more capable of moving prices than earnings forecasts. The mean *REC_FREQ* of the recommendation sample is 0.94 which is greater than the mean *REC_FREQ* of 0.16 of the forecast revision sample, suggesting that analysts make approximately 6 times more forecasts than recommendations. This finding further implies that the information allocated to each forecast may be less than the information allocated to each recommendation, which further explains the higher average *BHAR* for recommendation revision than for forecast revisions.

[Insert Table 3.4 here]

3.4 Empirical results.

3.4.1 Textual analysis

Table 3.5 documents the results for the variation of the proportion of brand-capital-related topics in analysts' reports among each brand-capital-intensity group. The average number of brand-capital-related topics ranges from 0.51 to 1.77 in the equally weighed sample and from 1.08 to 1.38 in the tf-idf sample. The average number of brand-capital-related topics scaled by total number of topics ranges from 0.04 to 0.16 in the equally weighted sample and from 0.23 to 0.30 in the tf-idf sample. The differences of TOPIC_TOTAL and TOPIC_SCALED between the lowest brand-capital-intensity groups and the highest brand-capital-intensity groups are 1.19, 0.003, 0.30 and 0.07, which are all statistically significant, in the four model specifications, suggesting that the proportion of brand-capital-related topics in analysts' reports increases in the scaled capitalized brand capital of firms, consistent with the first hypothesis. This finding provides evidence that financial analysts intentionally take efforts in evaluating the advertising expense as well as the brand capital not realized as intangible assets on the balance sheets and may have incorporated the value-related information in their earnings forecasts and stock recommendations.

[Insert Table 3.5 here]

3.4.2 Univariate analysis

The results of univariate analysis are shown in Table 3.6. The one-day post-revision *BHAR* for recommendation downgrades ranges from -1.81% to -2.24% and the difference of one-day post-revision *BHAR* between the highest and the lowest brand-capital-intensity groups is -0.32% which is statistically significant with a t-value of -3.65. This finding suggests stock recommendation downgrades are more capable of moving prices for firms with relatively more brand capital, which is consistent with hypothesis 3.2 that the incremental information contained in stock recommendations is greater for brand-capital-intensive firms. Similar findings can be found in five-day, ten-day and twenty-day post revision *BHAR*s for both recommendation downgrades and upgrades. Interestingly, the post-revision *BHAR*s do not show any strictly monochronic pattern in the recommendation downgrade sample. For example, the fourth brand-capital-intensity group has the smallest *BHAR* (0,1) of -1.81% in the recommendation downgrade sample and the third brand-capital-intensity group has the smallest *BHAR* (0,5) of -2.22% in the recommendation downgrade sample. On the contrary, almost all post-revision *BHAR*s are strictly increasing from the lowest group to the highest group in the recommendation upgrade sample. This finding suggests brand building activities might be more informationally relevant when analysts issue favorable stock recommendations than when analysts issue adverse stock recommendations. In other words, analysts' favorable stock recommendations are more likely to be attributable to greater brand recognition, but unfavorable stock recommendations are more likely to be due to factors other than brand recognition. In addition, the three-day *BHAR* for recommendation downgrades ranges from -2.04% to -

2.8% while the five-day *BHAR* for recommendation downgrades ranges from -1.51% to -3.08%. The difference of three-day *BHAR* between the highest and the lowest brand-capital-intensity groups is -0.3% which is weakly significant, while the difference of five-day *BHAR* is 0.87% which is non-significant. There are also no significant differences of the three-day *BHAR* and the five-day *BHAR* between the highest and the lowest brand-capital-intensity groups for recommendation upgrades. This finding indicates that the short-term market reactions centered in recommendation revisions, although are significant on average, do not differentiate much in terms of brand capital intensity and that the initial market reactions are incomplete.

The three-day, five-day and post-revision *BHAR*s for earnings forecast downgrades are mostly monochronically decreasing and the *BHAR*s for earnings forecast upgrades are mostly monochronically increasing from the lowest brand-capital-intensity groups to the highest brand-capital-intensity groups. The differences of all *BHAR*s between the lowest brand-capital-intensity groups and the highest brand-capital-intensity groups are statistically significant, even for the three-day and five-day *BHAR*s. These findings are consistent with hypothesis 3.2 that analysts' forecast revisions are more informative for firms with comparatively greater brand capital. Also, these findings are more robust than those from the recommendation revision sample, suggesting that firms' brand recognition is more considered in analysts' earnings forecasts than in stock recommendations.

[Insert Table 3.6 here]

The results of short-term *BHAR*s differentiated based on recommendation revision paths and forecast revision magnitudes are documented in Table 3.7. Panel A of Table 3.7 shows that the market reactions to recommendation downgrades, although do not follow a strictly monochronic pattern across different brand-capital-intensity groups, are negative across all revision paths and brand-capital-intensity groups on average, suggesting that investors on average trade on analysts' recommendations within a short period. Similar to the results in Panel A in Table 6, there are no significant differences of three-day and five-day *BHAR*s between the highest and the lowest brand-capital-intensity groups across all revision paths, except the three-day *BHAR* of "*SB-B*" in which the *BHAR* of the highest brand-capital-intensity group is 1.46% less than that of the lowest brand-capital-intensity group. In addition, Panel B of Table 3.7 also shows that three-day and five-day *BHAR*s for recommendation upgrades are not significantly different between the highest and the lowest brand-capital-intensity groups across all revision paths, except the three-day *BHAR* for "*B-SB*" and the five-day *BHAR*s for "*S-H*" and "*H-B*" which are only weakly significant. These findings further suggest that the absence of difference of short-term market reactions centered in recommendation revisions among different brand-capital-intensity groups are not due to the effect of revision paths but are general in almost all revision paths.

The one-day post-revision *BHAR*s for recommendation downgrades are significant smaller for the highest brand-capital-intensity group than for the lowest brand-capital-intensity group for small revision magnitudes ("*H-S*", "*B-H*" and "*SB-B*") by 0.48%, 0.47% and 0.59% respectively. Similar results are also found from the five-day, ten-day and twenty-day post-revision *BHAR*s for recommendation downgrades for small revision magnitudes, except for the twenty-day post-revision *BHAR*s for "*H-S*" and "*B-H*", where the differences are insignificant 0.55% and 0.33%. The post-revision *BHAR*s for recommendation downgrades for large revision magnitudes ("*B-S*", *SB-S*" and "*SB-H*"), however, are mostly statistically indifferent between the highest and the lowest brand-capital-intensity groups, except for the ten-day post-revision *BHAR*s for "*SB-H*" in which the *BHAR*s are only weakly different by 0.44%. The short-term post -revision *BHAR*s for recommendation upgrades also show similar pattern. The distinguishing effects of brand capital intensity on market reactions to small recommendation revisions and to large recommendation revisions might be due to the long-term nature of brand building that will more likely to cause gradual shift of recommendations than rapid change of recommendations. In other words, since the effect of brand building takes time to gradually manifest which would only impact stock prices moderately but not rapidly, large recommendation revisions are less likely to be related to brand recognition but rather related to other factors that would affect stock prices to a greater extent in a short period. Another explanation is that the cases of large recommendation revisions are comparatively rare in the sample, especially for "*SB-S*" which only has less than 100 observations in both downgrades sample and upgrades sample, a situation that may result in overestimated standard error due to outliers. Interestingly, the post-revision *BHAR*s for recommendation upgrades for "*B-SB*" are mostly smaller for the highest brand-capital-intensity groups than for the lowest brand-capital-intensity groups and the ten-day post-revision *BHAR*s for the highest brand-capital-intensity group is even statistically smaller by 0.69% than for the lowest brand-capital-intensity group. This finding implies that brand-capital-intensity might have negative effect on the market reactions to recommendation upgrades from "buy" to "strong buy". Overall, analyzing market reactions to different recommendation paths suggests the weak effect of brand capital intensity on market reactions to stock recommendation revisions is partially due to the absence of relationship between brand capital intensity and large recommendation revisions and that there is observable incremental effect of brand capital intensity on market reactions to small recommendation revisions.

[Insert table 3.7 here]

Table 3.8 shows the short-term market reactions to forecast revisions differentiated based on revision magnitudes. Expectedly, *BHAR*s are negative for all forecast downgrades and positive for all forecast upgrades and the absolute values of *BHAR*s are increasing in the magnitudes of forecast revisions. Unlike stock recommendation revisions, forecast revisions are accompanied by significantly different three-day *BHAR*s and five-day *BHAR*s between the lowest and the highest brand-capital-intensity groups, suggesting the market reactions to forecast revisions are more prompt than those to recommendation revisions. Furthermore, the significance of the differences of *BHAR*s between the highest and the lowest brand-capital-intensity groups increases in forecast revision magnitudes. For example, the t-value for the difference of three-day *BHAR*s for forecast upgrades between the highest and the lowest brand-capital-intensity groups increases from 8.3 for small revisions to 13.21 for large revisions. This finding suggests that the effect of brand capital intensity on market reactions to forecast revisions also increases in revision magnitudes. Overall, the relationship between brand capital intensity and the informativeness of forecast revisions is general across different forecast revision magnitudes.

[Insert table 3.8 here]

3.4.3 Portfolio analysis

The results of the calendar-time portfolio analysis are documented in Table 3.9. The raw return, market-adjusted return and annualized alpha from the four-factor model are reported for the long, short and long-short portfolios respectively. The raw returns, market-adjusted returns and annualized alphas are increasing gradually from the lowest brand-capital-intensity groups to the highest brand-capital-intensity groups and they are all significantly larger for the highest brand-capital-intensity groups than for the lowest brand-capital-intensity groups, except for the annualized alpha in the short portfolio, which is not significantly different. We base our argument mainly on the annualized long-short portfolio because the it controls the commonly accepted pricing factors and is able to in a way neutralize the brand-capital-related pricing factors that may not be captured by the factors in the pricing model. In the long-short portfolio, the annualized alphas range from 12% to 20% and the annualized alpha for the highest brand-capital-intensity group is 19% which is significantly larger than 12% for the lowest brand-capital-intensity group. This finding suggests that the effect of brand capital intensity on the informativeness of analysts' recommendations is not temporary and that the initial manifestation of the effect of brand capital intensity on market reactions may be incomplete.

[Insert table 3.9 here]

3.4.4 Regression analysis

The results of the main regression analysis are documented separately for recommendation revisions and forecast revisions in Table 3.10. Expectedly, *BRANDCAP* is significantly positively related to *BHAR (0, +2)* in all four model specifications which coefficient estimates of 2.26, 1.42, 3.60 and 2.12 respectively, suggesting the main result that the informativeness of analysts' signals increases in brand capital intensity is robust after controlling for other commonly accepted determinants of short-term analysts-revision *BHAR*. Also, market reactions to analysts' signals increase in book-to-market ratio, the existence of accompanying forecasts or recommendations, revision magnitudes and analyst boldness and decrease in firm size and analyst coverage.

In addition, model specification 2 and 4 show that the coefficient estimates of *CONFLICT* are -0.79 for the recommendation revisions sample and -0.13 for the forecast revisions sample and both coefficient estimates are statistically significant, suggesting that the situation of conflicting analysts' signals against news sentiment results in weaker market reactions compared with non-conflicting analysts' signals. Also, the coefficient estimates for *CONFLICT* × *CSS* are all significantly negative in both model specifications, suggesting conflicting analysts' signals weaken market reactions to news sentiment. The coefficient estimates for *BRANDCAP* × *CSS* are significantly positive in both model specifications, which implies that market reactions to news sentiment are stronger when firms have relatively more brand capital. This could be because investors rely more heavily on publicly available news when they are facing higher information asymmetry stemmed from firms' brand capital investments. Finally, the coefficient estimates for *CONFLICT* ×

BRANDCAP are insignificantly -1.81 for recommendation revision samples and significantly 3.36 for forecast revision samples. We also applied *BHAR (0, +1)* and *BHAR (0, +5)* as dependent variables and found similar results. This finding suggests that forecasts revisions dominate news sentiment in terms of market reactions when they are on the opposite direction of news sentiments, while recommendation revisions and news sentiment are likely to be equally valued by investors when they conflict each other, rendering the market reactions insignificant. This finding also enhances the results in the univariate analyses that the effect of brand capital intensity on market reactions to forecast revisions is stronger and more prompt than to recommendation revisions.

[Insert table 3.10 here]

Table 3.11 shows the regression results of the additional tests. Model specifications 1, 2, 3 and 4 documents the regression results of the relationship between revision and brand capital intensity. The coefficient estimates for BRANDCAP are significantly positive for both recommendation revision frequency and forecast revision frequency, suggesting the time it takes for analysts to issue recommendations and forecasts increases in firms' brand capital intensity. This could be because more brand capital investments increase the amount and complexity of information that analysts need to interpret in order to deliver valuable signals to the market. Model specifications 5 and 6 document the regression results of the relationship between forecast accuracy and brand capital intensity. Expectedly, the average forecast accuracy decreases in brand capital intensity after controlling for news sentiment related factors. This finding implies that the greater information asymmetry and information complexity introduced by brand building activities result in greater bias in analysts' forecasts. Overall, the regression analysis provides supportive evidences to the hypothesis that brand capital intensity increases the informativeness of analysts' signal, as well as additional hypotheses about news sentiment, revision frequency and forecast accuracy.

[Insert table 3.11 here]

3.5 Conclusion

This paper reveals a positive relationship between the informativeness of financial analysts' signals and firms' brand capita intensity using textual analysis, univariate analysis, portfolio analysis and regression analysis. More specifically, both short-term and long-term event day abnormal returns to analysts' stock recommendations and earnings forecasts increase in the capitalized advertising expenses scaled by total assets after controlling for generally accepted pricing factors as well as firm-specific and analyst-specific factors. The results link the existing financial intermediary literature to the existing marketing literature by showing that financial analysts reduce information asymmetry between firms and investors from various aspects including information asymmetry introduced by marketing activities.

There are also several limitations in this paper. First, although textual analysis was applied to provide evidence that analysts discuss brand-capital-related topics in their reports, it is still unclear how and to what extent investors understand the information and incorporate the information in their trading strategies. Thus, further analyses are required to reveal more evidence on the value-creating mechanism from analysts' information role on brand capital intensity. Second, although advertising expense is the most widely accepted determinant of brand capital, such brand capital created by firms' advertising activities might be different from the brand capital perceived by investors. It is unclear whether the market reaction to analysts' signal is due to a shift of investors' original valuation of brand capital to the valuation signaled by the firm or to the valuation from analysts' own perception. Consequently, the results could be biased if analysts' own perception failed to capture the actual value of brand capital but only shift investors' belief to another biased end. Further research could be conducted to construct a more inclusive measure of brand capital that mitigates the conflict between firms' signal of brand capital resulting from advertising activities and investors' perception of brand capital from other determinants such as product quality.

TABLE 3.1.
Descriptive statistics for textual analyses

Panel A. Brand-capital-related topics

Brand-capital-related topics (equally weighted)	
Topic 1	"unilever" "consume" "**brand**" "coke" "portfolio" "volume" "drink" "cola" "coca" "spend"
Topic 2	"consume" "ship" "cruise" "capacity" "royal" "roic" "Caribbean" "global" "**brand**" "concern"
Topic 3	"user" "**advertise**" "online" "search" "mobile" "internet" "yahoo" "google" "platform" "network"
Topic 4	"digit" "agency" "**advertise**" "publish" "educ" "media" "group" "bro" "public" "online"
Topic 5	"vehicle" "dealer" "dealership" "repair" "**brand**" "Asbury" "auto" "gross" "part" "group"
Topic 6	"restaurant" "**brand**" "digit" "chain" "view" "consume" "food" "effort" "location" "single"
Topic 7	"beer" "volume" "**brand**" "Phillipe" "craft" "Morgan" "brewer" "premium" "amber" "beverage"
Topic 8	"toll" "**brand**" "room" "green" "franchise" "owner" "properties" "own" "supplies" "pinnacle"
Topic 9	"**brand**" "consume" "categories" "apparel" "retail" "point" "premium" "distribution" "gross" "adjust"
Brand-capital-related topics (tf-idf)	
Topic 1	"cable" "television" "content" "media" "**advertise**" "internet" "audience" "entertain" "subscribe" "video"
Topic 2	"store" "**brand**" "retail" "regular" "utility" "insurance" "energies" "consume" "fiscal" "segment"
Topic 3	"yahoo" "**advertise**" "user" "online" "search" "chines" "Alibaba" "TenCent" "internet" "mobile"

Panel B. Descriptive statistics for selected variables

	BRANDCAP ($M)	Advertising expense ($M)	Price ($)	Number of topics (equally weighted)	Number of topics (tf-idf)
1 (Low Brand Cap)	0.00	0.00	61.58	11.26	5.02
2	0.00	0.00	58.94	10.42	4.92
3	0.95	0.07	330.73	11.17	5.22
4	338.52	174.53	52.17	10.75	5.07
5 (High Brand Cap)	1330.13	704.77	75.59	10.83	4.79

Panel B (continued)

	Intangible assets ($M)	Depreciation expense (%)	Sales ($M)	R&D expense (%)	Number of analyst reports	Analysts following
1 (Low Brand Cap)	4,976	0.06	21,357	0.05	38.23	17.82
2	4,648	0.06	25,412	0.02	35.98	22.47

3	7,431	0.06	21,511	0.04	37.4	19.5
4	7,640	0.05	22,846	0.04	35.69	22.09
5 (High Brand Cap)	6,788	0.06	22,801	0.06	37.87	25.26

This table summarizes the brand-capital-related topics in analyst reports and descriptive statistics for selected variables in the textual analyses sample. Panel A shows the key words in brand-capital-related topics for LDA topic modeling using both equal-weighting and tf-idf methods. 100 mostly discussed topics in 35,992 analysts reports from 2001 – 2018 were generated for each method, 9 topics were identified as brand capital related in the equal-weighting method and 3 topics were identified as brand capital related in the tf-idf method. Panel B shows the mean of selected variables in the textual analyses sample based on the brand capital intensity quintile groups. BRANDCAP is the unscaled measure of capitalized and amortized advertising expenses. Advertising expense, Intangible assets, Depreciation expense, sales and R&D expense are from COMPUSTAT North America Fundamentals Annual Database, where Depreciation expense and R&D expense are scaled by Sales. Price is the closing price at the end of the fiscal year. Number of topics is the average number of topics discussed in analyst reports in the quintile group. Number of analyst reports is the average number of analyst reports issued for all firm-year observations in the quintile group. Analyst following is the average number of analysts that issued at least one earnings forecasts or stock recommendations for the firm in the quintile groups.

TABLE 3.2.
Descriptive statistics for selected variables for univariate tests

Panel A. Recommendation revision sample

	BRANDCAP ($M)	Advertising expense ($M)	Price ($)	Size ($M)	Intangible assets ($M)	Sales ($M)	R&D expense (%)	Analyst following
1 (Low Brand Cap)	0	27.69	37.24	25,372	1,373	8,817	0.02	16.1
2	0	115.95	33.79	33,376	953	5,285	0.04	15.71
3	0.02	122.02	36.67	25,901	2,105	7,780	0.04	16.42
4	82.99	66.59	34.11	59,108	2,940	6,365	0.05	17.31
5 (High Brand Cap)	536.59	317.82	37.75	11,955	3,155	10,611	0.06	20.44

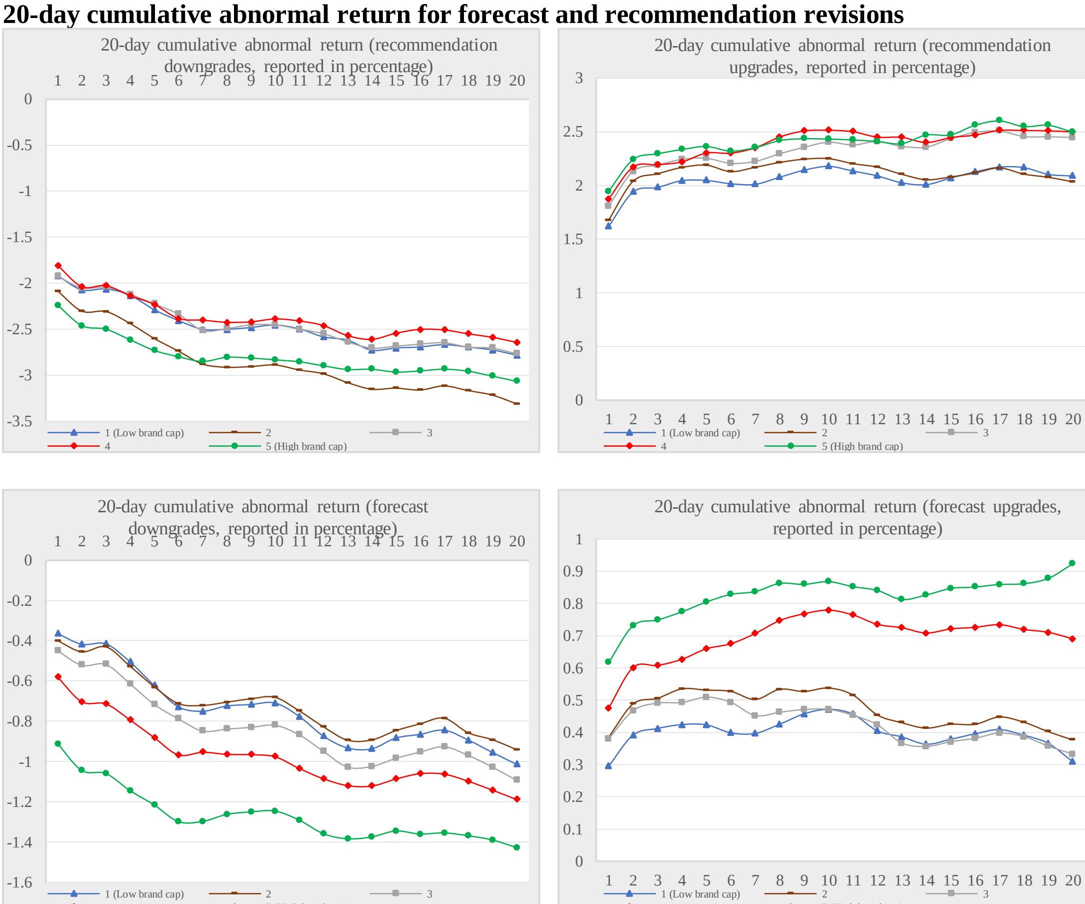
Panel B. Forecast revision sample

	BRANDCAP ($M)	Advertising expense ($M)	Price ($)	Size ($M)	Intangible assets ($M)	Sales ($M)	R&D expense (%)	Analyst following
1 (Low Brand Cap)	0	28.39	44.47	27,521	1,994	14,884	0.02	19.57
2	0	90.37	40.41	50,616	1,353	7,115	0.05	18.94
3	0.15	246.56	41.99	32,492	2,892	11,360	0.04	18.71
4	158.46	110.45	37.93	103,017	4,544	10,848	0.04	18.58
5 (High Brand Cap)	780.36	448.89	44.15	16,921	4,484	15,015	0.05	22.32

This table shows the mean of selected variables in the univariate analyses sample based on the brand capital intensity quintile groups. BRANDCAP is the unscaled measure of capitalized and amortized advertising expenses. Advertising expense, Size (total assets), Intangible assets, sales and R&D

expense are from COMPUSTAT North America Fundamentals Annual Database, where Depreciation expense and R&D expense are scaled by Sales. Price is the closing price at the end of the fiscal year. Analyst following is the average number of analysts that issued at least one earnings forecasts or stock recommendations for the firm in the quintile groups.

FIGURE 3.1.
20-day cumulative abnormal return for forecast and recommendation revisions



These figures show 20-day cumulative abnormal returns for forecast and recommendation revisions based on brand capital intensity quintile groups. Cumulative abnormal return is the raw buy-and-hold return minus the cumulative value-weighted market return.

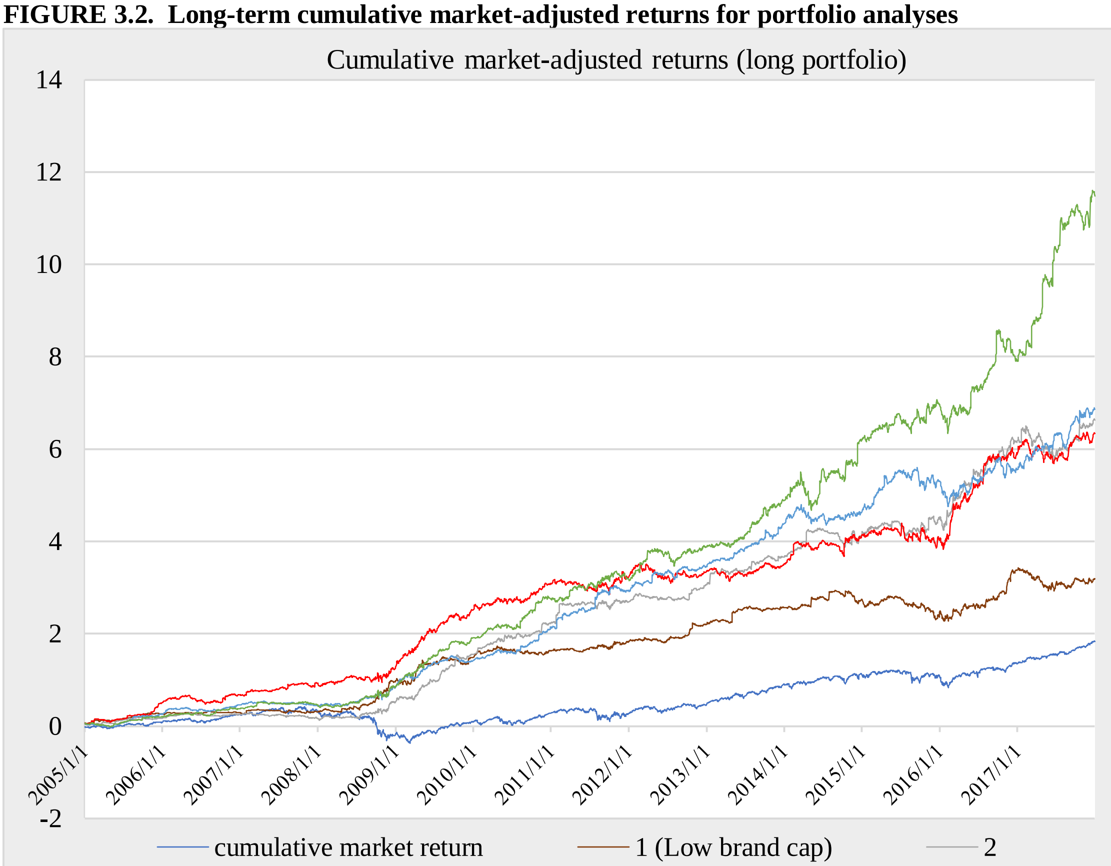
TABLE 3.3.
Descriptive statistics for portfolio analyses sample

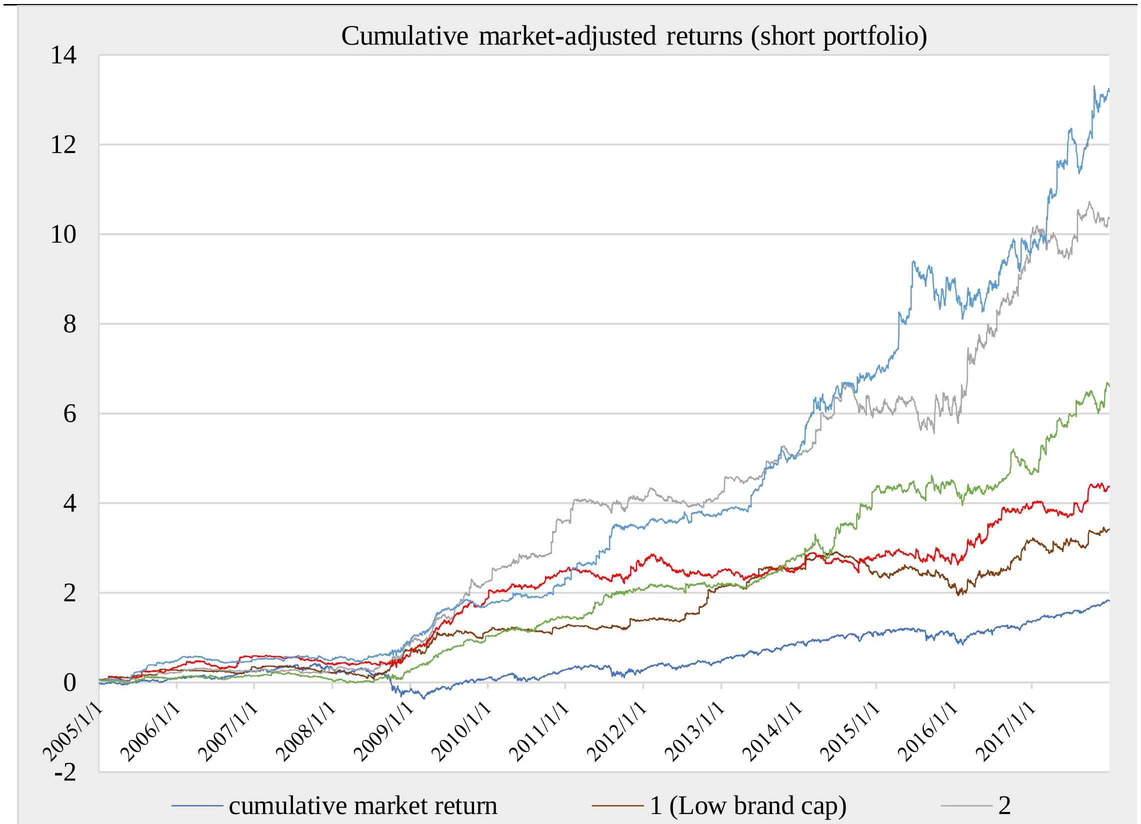
Number of securities in the portfolios

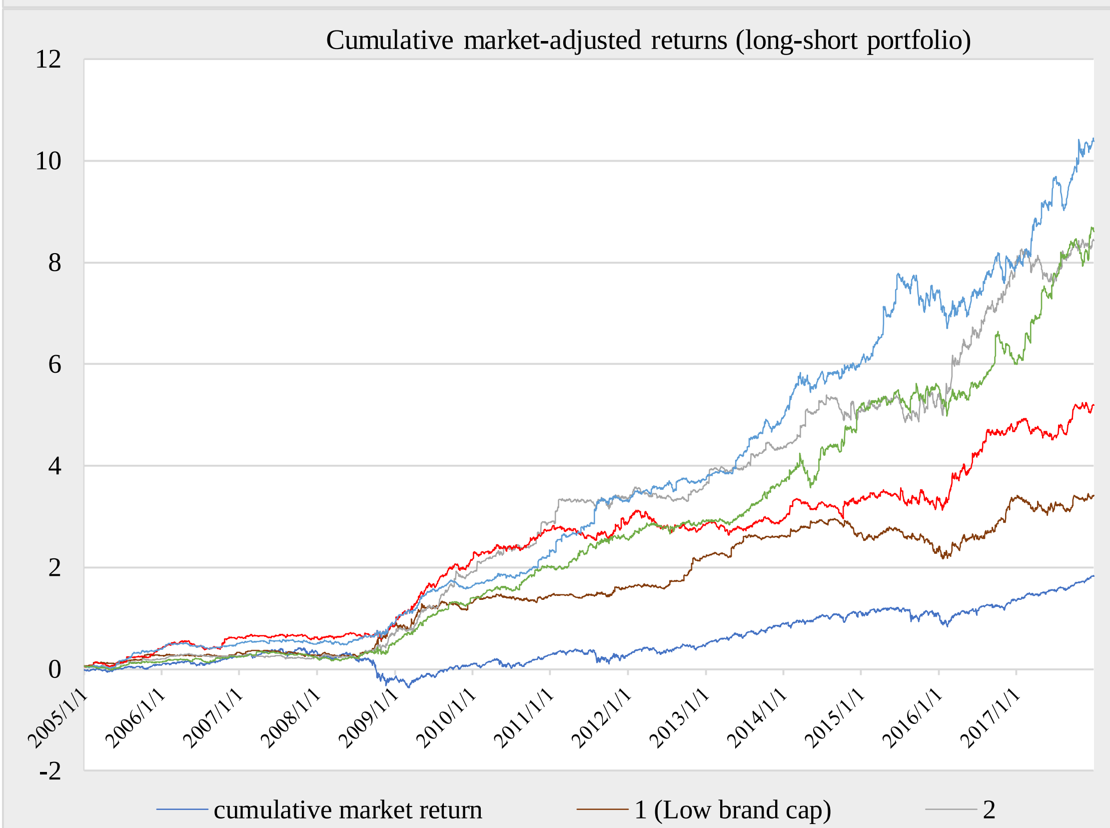
	Long portfolio			Short portfolio		
	min	mean	max	min	mean	max
1 (Low Brand Cap)	646	1,123	1,494	700	1,273	1,608
2	748	1,191	1,545	811	1,321	1,592
3	624	1,384	2,023	678	1,610	2,241
4	509	869	1,196	605	1,073	1,309
5 (High Brand Cap)	516	951	1,379	575	1,124	1,519

This table shows the minimum, average and maximum number of securities in both long and short portfolios in each brand capital intensity quintile groups. Portfolios were constructed over 2005 – 2018.

FIGURE 3.2. Long-term cumulative market-adjusted returns for portfolio analyses







These figures show the long-term cumulative market-adjusted returns for each portfolio and the long-term cumulative value-weighted market return over 2005 – 2018. Cumulative market-adjusted return is the raw return minus the cumulative value-weighted market return. Returns are reported in absolute values.

TABLE 3.4.
Descriptive statistics for regression analyses sample

	N	Mean	25%	Median	75%
Panel A. Recommendation revision sample					
BHAR (0, +2)	50,277	2.33	-0.23	1.44	3.84
REC_FREQ	50,277	0.94	0.25	0.61	1.25
SIZE	50,277	26994.6	894.35	3249	12408.27
B/M	50,277	0.48	0.23	0.39	0.62
COVER	50,277	20.49	12	19	28
AMIHUD	50,277	0.01	0	0	0
FOR	50,277	0.6	0	1	1
REV_MAG	50,277	1.4	1	1	2
BOLDNESS	50,277	0.86	0.33	0.78	1.25
CONFLICT	50,277	0.16	0	0	0
CSS	50,277	0.39	0	0.2	0.6
BRANDCAP	50,277	0.02	0	0	0.01
Panel B. Forecast revision sample					
BHAR (0, +2)	633,118	0.58	-1.03	0.31	1.85
FOR_FREQ	633,118	0.16	0.07	0.14	0.22
FOR_ACCU	633,118	0.65	0.04	0.14	0.42
SIZE	633,118	47866.53	1615.5	5735.45	21532
B/M	633,118	0.54	0.26	0.45	0.73
COVER	633,118	21.21	11	20	29
AMIHUD	633,118	0.01	0	0	0
REC	633,118	0.07	0	0	0
REV_MAG	633,118	0.25	0.02	0.04	0.13
BOLDNESS	633,118	0.21	0.02	0.06	0.16
CONFLICT	633,118	0.26	0	0	1
CSS	633,118	0.21	0	0.13	0.39
BRANDCAP	633,118	0.02	0	0	0.01

This table shows descriptive for all variables in the regression analyses. Panel A shows the descriptive statistics for the recommendation revision sample. *BHAR (0, +2)* is the 2-day recommendation revision buy-and-hold abnormal return. *BHAR (0, +2)* for recommendation downgrades was multiplied by -1. *REC_FREQ* is the number of days between the current revision and the last revision scaled by 365. *SIZE* is the nature logarithm of firm size at fiscal yearend. *B/M* is the book-to-market ratio at fiscal yearend. *COVER* is the number of analysts following the firm during that fiscal year. *AMIHUD* is the Amihud (2002) illiquidity ratio. *FOR* is an indicator variable equal to one if the recommendation revision is accompanied by earnings forecast revisions made by the same analyst within the three-day period around the recommendation revision date, and zero otherwise. *REV_MAG* is calculated as the absolute value of the new recommendation minus the previous recommendation made by the same analyst. *BOLDNESS* is calculated as the absolute value of the difference between the new recommendation minus the previous recommendation consensus. *CONFLICT* is an indicator variable equal to one if the forecast or recommendation revision is on the opposite direction of daily news sentiment, and zero otherwise. *CSS* is the composite sentiment score, a measure of daily news sentiment from RavenPack Database. *CSS* is adjusted by using 50 minus *CSS* for all *CSS* below 50 and using *CSS* minus 50 for all *CSS* above or equal to 50 so that a larger value indicates more divergence of market sentiment from the neutral sentiment. *BRANDCAP* is the measure of brand capital calculated as the capitalized and amortized advertisement expenses scaled by total assets. Panel B shows the descriptive statistics for the forecast revision sample. *FOR_FREQ* is the number of days between the current revision and the last revision scaled by 365. *FOR_ACCU* is the absolute value of the difference between earnings forecasts and actual earnings, scaled by the absolute value of the actual earnings. *REC* is an indicator variable equal to one if the forecast revision is accompanied by recommendation revisions made by the same analyst within the three-day period around the forecast revision date, and zero otherwise. *REV_MAG* is calculated as the absolute value of the difference between the new forecast and the previous forecast made by the same analyst divided by the previous forecast. *BOLDNESS* is calculated as the absolute value of the difference between the new forecast and the previous forecast consensus divided by the previous forecast consensus.

TABLE 3.5.
Brand capital intensity and brand-capital-related topics

	Equally weighted		Tf-idf	
	TOPIC_TOTAL	*TOPIC_SCALED*	*TOPIC_TOTAL*	*TOPIC_SCALED*
1 (*Low brand cap*)	0.5823*** (41.23)	0.0502*** (40.27)	1.0835*** (207.33)	0.2276*** (155.84)
2	0.5123*** (38.91)	0.0444*** (39.6)	1.0943*** (193)	0.2415*** (118.32)
3	0.7111*** (45.47)	0.0587*** (45.04)	1.1295*** (177.2)	0.23*** (139.41)
4	0.8525*** (51.38)	0.0745*** (51.1)	1.2374*** (137.41)	0.2528*** (147)
5 (*High brand cap*)	1.7718*** (80.24)	0.1664*** (78.59)	1.3838*** (130.16)	0.2997*** (136.8)
5 - 1	**1.1895*** (45.38)**	**0.00309*** (47.26)**	**0.3003*** (25.35)**	**0.0721*** (27.4)**

This table shows the relationship between brand capital of firms and the frequency in which analysts raised brand-capital-related topics in their reports. Firms are divided into 5 groups based on the measure *BRANDCAP* with group 1 containing firms with the smallest *BRANDCAP* and group 5 with firms containing the largest *BRANDCAP*. 35,992 analysts' reports from 2001 – 2018 were collected from Morningstar, a financial service company that provides a variety of investment-research-related data. Latent Dirichlet Allocation (LDA) approach was applied to model the topics of these reports. Two sets of mostly discussed topics in these reports were generated using equal weighting and tf-idf weighting schemes, respectively, with each set containing 100 topics. Topics with the words "brand" and "advertise" were identified as brand-capital-related topics. With this approach, 9 topics were identified as brand-capital-related topics in the equally weighted set and 2 topics were identified as brand-capital-related topics in the tf-idf weighted set. These topic sets were then used to identify the total number of all topics and the number of brand-capital-related topics in each analyst report. *TOPIC_TOTAL* is the absolute number of brand-capital-related topics in each report and *TOPIC_SCALED* is the absolute number of brand-capital-related topics divided by the total number of all topics in each report. The last row labeled "5-1" shows the difference of the number of topics between the low brand capital group and the high brand capital group.

TABLE 3.6.
Short-term market reactions on recommendation and forecast revisions

Brand capital quintile group	Recommendation revisions						Earnings forecast revisions					
	(-1, +1)	(-2, +2)	(0, +1)	(0, +5)	(0, +10)	(0, +20)	(-1, +1)	(-2, +2)	(0, +1)	(0, +5)	(0, +10)	(0, +20)
Panel A. Downgrades and *BHAR* (reported in percentages)												
1 (*Low brand cap*)	-2.5***	-2.38***	-1.92***	-2.29***	-2.46***	-2.78***	-0.74***	-0.95***	-0.29***	-0.55***	-0.63***	-0.93***
	(-22.11)	(-14.5)	(-31.13)	(-29.48)	(-25.38)	(-23.11)	(-30.42)	(-34.89)	(-23.82)	(-30.61)	(-25.42)	(-28.43)
2	-3.03***	-3.08***	-2.09***	-2.6***	-2.89***	-3.31***	-0.83***	-1.03***	-0.37***	-0.6***	-0.6***	-0.86***
	(-26.29)	(-24.42)	(-33.04)	(-33.13)	(-29.85)	(-27.65)	(-27.49)	(-31.39)	(-29.58)	(-32.74)	(-24.11)	(-26.41)
3	-2.37***	-2.44***	-1.93***	-2.22***	-2.45***	-2.77***	-0.94***	-1.14***	-0.42***	-0.68***	-0.8***	-1.07***
	(-18.47)	(-17.61)	(-32)	(-29.88)	(-26.77)	(-24.24)	(-38.5)	(-42.04)	(-35.72)	(-40.12)	(-34.2)	(-35.24)
4	-2.04***	-2***	-1.81***	-2.23***	-2.39***	-2.64***	-1.26***	-1.51***	-0.56***	-0.89***	-0.96***	-1.12***
	(-20.71)	(-18.24)	(-32.19)	(-32.18)	(-27.47)	(-24.35)	(-52.76)	(-56.26)	(-42.7)	(-48.99)	(-39.26)	(-35.03)
5 (*High brand cap*)	-2.8***	-1.51	-2.24***	-2.73***	-2.83***	-3.07***	-1.72***	-1.85***	-0.86***	-1.2***	-1.19***	-1.36***
	(-27.76)	(-1.11)	(-36.63)	(-36.55)	(-30.57)	(-26.74)	(-70.48)	(-19.63)	(-62.13)	(-63.72)	(-47.16)	(-41.62)
5 - 1	**-0.3****	**0.87**	**-0.32*****	**-0.44*****	**-0.38*****	**-0.28***	**-0.98*****	**-0.9*****	**-0.56*****	**-0.66*****	**-0.57*****	**-0.44*****
	(-1.97)	**(0.64)**	**(-3.65)**	**(-4.07)**	**(-2.8)**	**(-1.69)**	**(-28.51)**	**(-9.19)**	**(-30.61)**	**(-25.24)**	**(-16.04)**	**(-9.43)**
Panel B. Upgrades and *BHAR* (reported in percentages)												
1 (*Low brand cap*)	2.41***	2.35***	1.62***	2.05***	2.18***	2.09***	0.72***	0.83***	0.29***	0.39***	0.37***	0.1***
	(28.53)	(23.85)	(35.26)	(32.05)	(25.8)	(18.35)	(29.46)	(29.85)	(25.16)	(22.45)	(15.02)	(2.93)
2	2.45***	2.37***	1.68***	2.19***	2.25***	2.03***	0.86***	0.99***	0.36***	0.47***	0.4***	0.16***
	(25.2)	(21.58)	(36.12)	(32.95)	(25.05)	(17.42)	(32.96)	(33.33)	(29.8)	(26.64)	(16.11)	(4.79)
3	2.53***	2.45***	1.81***	2.25***	2.4***	2.45***	0.78***	0.92***	0.34***	0.42***	0.31***	0.07**
	(23.57)	(21.19)	(40.25)	(36.46)	(28.91)	(22.3)	(35.36)	(33.56)	(30.27)	(25.48)	(13.4)	(2.38)
4	2.56***	2.47***	1.87***	2.3***	2.52***	2.5***	1.18***	1.37***	0.51***	0.67***	0.71***	0.64***
	(29.04)	(25.08)	(41.92)	(37.59)	(30.47)	(23.14)	(48.21)	(49.2)	(43.92)	(40.09)	(30.59)	(20.8)
5 (*High brand cap*)	2.55***	2.55***	1.94***	2.36***	2.43***	2.5***	1.23***	1.53***	0.63***	0.85***	0.82***	0.87***
	(29.89)	(25.63)	(40.7)	(36.37)	(28.74)	(22.52)	(56.02)	(15.05)	(52.51)	(49.83)	(35.49)	(28.56)
5 - 1	**0.14**	**0.2**	**0.33*****	**0.32*****	**0.25****	**0.41****	**0.51*****	**0.7*****	**0.34*****	**0.45*****	**0.45*****	**0.77*****
	(1.19)	**(1.44)**	**(4.91)**	**(3.45)**	**(2.11)**	**(2.57)**	**(15.67)**	**(6.61)**	**(20.21)**	**(18.54)**	**(13.4)**	**(17.29)**

This table shows the mean value-weighted market-adjusted buy-and-hold returns around recommendation and forecast revisions with a window of (-1, +1), (-2, +2), (0, +1), (0, +5), (0, +10) and (0, +20), respectively. Brand capital intensity quintile groups were based on the annual ranking of firms with the capitalized and amortized advertising expenses scaled by total assets. Panel A reports negative recommendation and forecast revisions and Panel B reports positive recommendation and forecast revisions. The last row in each panel labeled "5-1" shows the difference of returns between the low brand capital group and the high brand capital group. ***, ** and * denote significance at the 1, 5 and 10 percent significance levels, respectively.

TABLE 3.7.
Short-term market reactions on recommendation revisions with different revision magnitudes

Brand capital quintile group	(-1, +1)						(-2, +2)					
	H-S	B-S	SB-S	B-H	SB-H	SB-B	H-S	B-S	SB-S	B-H	SB-H	SB-B
Panel A. Stock recommendation downgrades and *BHAR* (reported in percentages)												
1 (*Low brand cap*)	-2.74*** (-7.09)	-5.46*** (-4.45)	-5.58** (-2.54)	-2.59*** (-14.73)	-2.45*** (-10.58)	-1.29*** (-5.99)	-2* (-1.72)	-5.19*** (-3.98)	-7.03*** (-2.96)	-2.54*** (-12.88)	-2.44*** (-9.69)	-1.07*** (-4.2)
2	-3.3*** (-11.15)	-4.82*** (-3.98)	-1.47 (-1.39)	-3.17*** (-16.62)	-3.19*** (-12.68)	-1.81*** (-8.44)	-3.5*** (-10.87)	-4.61*** (-3.66)	-1.7 (-1.6)	-3.16*** (-14.94)	-3.16*** (-11.71)	-2.14*** (-8.77)
3	-2.71*** (-11.94)	-4.67*** (-4.31)	-3.72* (-2.58)	-2.2*** (-8.57)	-2.43*** (-10.1)	-1.89*** (-8.63)	-2.85*** (-11.23)	-4.39*** (-3.7)	-3.79** (-2.25)	-2.2*** (-8.09)	-2.56*** (-10.05)	-2.03*** (-7.7)
4	-2.81*** (-11.4)	-1.2 (-0.94)	-3.6*** (-3.05)	-1.91*** (-11.36)	-2.01*** (-10.09)	-1.67*** (-9.12)	-2.83*** (-10.52)	-0.88 (-0.64)	-3.93*** (-3)	-1.82*** (-9.76)	-1.87*** (-8.53)	-1.83*** (-8.42)
5 (*High brand cap*)	-3.13*** (-12.79)	-4.03*** (-5.57)	-5.85*** (-5.3)	-2.86*** (-17.29)	-2.59*** (-12.82)	-2.75*** (-11.61)	-3.24*** (-11.92)	-3.86*** (-5.23)	-6.27*** (-5.5)	-2.98*** (-16.26)	-2.48*** (-11.06)	5.64 (0.66)
5 - 1	**-0.39 (-0.84)**	**1.44 (1.01)**	**-0.27 (-0.11)**	**-0.27 (-1.11)**	**-0.14 (-0.47)**	**-1.46*** (-4.56)**	**-1.24 (-1.04)**	**1.33 (0.89)**	**0.76 (0.29)**	**-0.44 (-1.62)**	**-0.05 (-0.14)**	**6.71 (0.78)**
	(0, +1)						(0, +5)					
	H-S	B-S	SB-S	B-H	SB-H	SB-B	H-S	B-S	SB-S	B-H	SB-H	SB-B
1 (*Low brand cap*)	-2.07*** (-12.09)	-3.58*** (-5.5)	-4.24*** (-4.07)	-1.89*** (-19.39)	-2.02*** (-16.04)	-1.04*** (-7.68)	-2.53*** (-11.15)	-4.43*** (-5.69)	-4.04*** (-3.42)	-2.24*** (-18.27)	-2.44*** (-15.72)	-1.26*** (-7.08)
2	-2.18*** (-12.52)	-3.24*** (-5.23)	-1.71*** (-2.84)	-2.31*** (-22.24)	-2.19*** (-16.73)	-1.06*** (-8.33)	-2.7*** (-12.6)	-3.53*** (-4.37)	-1.83** (-2.1)	-2.77*** (-21.81)	-2.87*** (-17.87)	-1.27*** (-7.51)
3	-2.17*** (-14.91)	-3.4*** (-5.68)	-2.81*** (-3.69)	-1.85*** (-18.36)	-2.05*** (-17.18)	-1.25*** (-9.11)	-2.56*** (-13.36)	-4.42*** (-6.3)	-2.77*** (-2.97)	-2.1*** (-17.02)	-2.45*** (-16.88)	-1.23*** (-6.83)
4	-2.03*** (-13.43)	-1.68*** (-2.75)	-2.36*** (-3.48)	-1.83*** (-19.48)	-1.99*** (-17.76)	-1.11*** (-9.31)	-2.65*** (-14.39)	-2.49*** (-3.29)	-2.89*** (-3.53)	-2.18*** (-19.14)	-2.47*** (-17.98)	-1.28*** (-8.04)
5 (*High brand cap*)	-2.55*** (-16.14)	-2.6*** (-5.58)	-4.33*** (-5.15)	-2.36*** (-23.24)	-2.3*** (-19.17)	-1.63*** (-11.24)	-3.03*** (-15.27)	-2.86*** (-4.61)	-5.41*** (-5.21)	-2.78*** (-22.96)	-2.78*** (-19.13)	-2.18*** (-11.45)
5 - 1	**-0.48** (-2.08)**	**0.98 (1.22)**	**-0.09 (-0.06)**	**-0.47*** (-3.32)**	**-0.28 (-1.59)**	**-0.59*** (-2.99)**	**-0.5* (-1.67)**	**1.57 (1.58)**	**-1.37 (-0.87)**	**-0.55*** (-3.19)**	**-0.34 (-1.59)**	**-0.92*** (-3.53)**
	(0, +10)						(0, +20)					
	H-S	B-S	SB-S	B-H	SB-H	SB-B	H-S	B-S	SB-S	B-H	SB-H	SB-B
1 (*Low brand cap*)	-2.7*** (-9.84)	-4.23*** (-4.57)	-5.09*** (-4.04)	-2.42*** (-15.84)	-2.55*** (-13.34)	-1.4*** (-5.88)	-2.96*** (-8.05)	-5.12*** (-5.06)	-6.41*** (-3.72)	-2.87*** (-15.16)	-2.78*** (-11.71)	-1.41*** (-4.8)

2	-2.82***	-4.18***	-2.79***	-3.05***	-3.24***	-1.42***	-3.31***	-4.51***	-2	-3.4***	-3.73***	-1.93***
	(-10.64)	(-4.48)	(-2.75)	(-19.81)	(-16.57)	(-6.13)	(-9.94)	(-3.9)	(-1.44)	(-17.9)	(-15.89)	(-6.6)
3	-2.77***	-4.3***	-3.96***	-2.34***	-2.64***	-1.51***	-3.08***	-5.29***	-4.83***	-2.56***	-3.07***	-1.82***
	(-11.13)	(-5.06)	(-3.47)	(-15.92)	(-14.81)	(-6.45)	(-9.91)	(-5.23)	(-3)	(-13.91)	(-13.9)	(-6.26)
4	-2.64***	-3.17***	-3.26***	-2.37***	-2.56***	-1.54***	-2.9***	-3.39***	-2.23**	-2.6***	-2.79***	-1.88***
	(-10.44)	(-3.46)	(-3.37)	(-16.94)	(-15.33)	(-7.19)	(-9.49)	(-3.11)	(-2.08)	(-14.83)	(-13.56)	(-6.71)
5 (*High brand cap*)	-3.39***	-3***	-5.43***	-2.81***	-2.99***	-2.21***	-3.51***	-3.16***	-6.29***	-3.2***	-3.24***	-2.23***
	(-13.08)	(-4.06)	(-5.03)	(-18.59)	(-16.94)	(-9.16)	(-10.76)	(-3.37)	(-4.32)	(-17.09)	(-15.36)	(-7.22)
5 - 1	**-0.69***	**1.23**	**-0.34**	**-0.39***	**-0.44***	**-0.81****	**-0.55**	**1.96**	**0.12**	**-0.33**	**-0.46**	**-0.82****
	(-1.82)	**(1.04)**	**(-0.2)**	**(-1.8)**	**(-1.67)**	**(-2.39)**	**(-1.12)**	**(1.42)**	**(0.05)**	**(-1.23)**	**(-1.44)**	**(-1.92)**

	(-1, +1)						(-2, +2)					
	S-H	S-B	S-SB	H-B	H-SB	B-SB	S-H	S-B	S-SB	H-B	H-SB	B-SB
Panel B. Stock recommendation upgrades and *BHAR* (reported in percentages)												
1 (*Low brand cap*)	2.08***	2.97***	3.37**	2.54***	2.56***	2.42***	1.65***	2.62***	2.98**	2.53***	2.67***	2.22***
	(8.03)	(5.29)	(2.52)	(18.01)	(16.77)	(11.46)	(5.93)	(3.4)	(2.34)	(15.16)	(14.76)	(9.38)
2	1.86***	1.78**	2.8***	2.74***	2.97***	1.79***	1.71***	1.67**	3.46***	2.76***	2.87***	1.46***
	(7.28)	(2.41)	(3.1)	(15.95)	(15.57)	(8.97)	(5.66)	(2.07)	(2.86)	(14.21)	(13.78)	(6.19)
3	2.27***	3.22***	3.09***	2.66***	2.93***	1.89***	2.28***	3.04***	3.8***	2.6***	2.93***	1.72***
	(8.21)	(5.34)	(3.34)	(22.69)	(9.56)	(8.99)	(7.49)	(4.07)	(3.79)	(19.19)	(9.16)	(7.28)
4	1.9***	2.84***	3.97***	2.7***	3.16***	1.98***	1.46***	3.23***	4.29***	2.74***	3.07***	1.79***
	(6.08)	(3.79)	(4.3)	(20.07)	(17.78)	(9.35)	(4.52)	(4)	(4.1)	(17.72)	(15.35)	(7.6)
5 (*High brand cap*)	2.57***	2.71***	3.94***	2.81***	2.76***	1.89***	2.66***	2.78***	4.69***	2.94***	2.64***	1.73***
	(8.26)	(3.9)	(4.08)	(19.54)	(19.52)	(9.06)	(7.7)	(3.59)	(4.23)	(18.24)	(16.44)	(6.01)
5 - 1	**0.5**	**-0.26**	**0.57**	**0.26**	**0.2**	**-0.52***	**1.01****	**0.16**	**1.71**	**0.41***	**-0.03**	**-0.49**
	(1.22)	**(-0.29)**	**(0.35)**	**(1.31)**	**(0.95)**	**(-1.76)**	**(2.29)**	**(0.15)**	**(1.01)**	**(1.77)**	**(-0.12)**	**(-1.32)**

	(0, +1)						(0, +5)					
	S-H	S-B	S-SB	H-B	H-SB	B-SB	S-H	S-B	S-SB	H-B	H-SB	B-SB
1 (*Low brand cap*)	1.21***	1.68***	3.61***	1.6***	1.83***	1.74***	1.34***	2.27***	3.89***	1.96***	2.42***	2.26***
	(9.71)	(4.98)	(4.83)	(22.26)	(19.97)	(14.25)	(7.67)	(4.71)	(4.08)	(19.66)	(19.43)	(13.18)
2	1.1***	1.61***	1.73***	1.77***	2.04***	1.51***	1.63***	1.79***	3.09***	2.27***	2.6***	1.95***
	(8.62)	(4.29)	(2.94)	(23.85)	(21.76)	(12.74)	(8.7)	(3.25)	(2.73)	(21.48)	(20.51)	(11.39)
3	1.51***	2.15***	1.99***	1.92***	1.99***	1.53***	1.95***	2.58***	2.23***	2.2***	2.68***	1.94***
	(10.52)	(5.91)	(4.07)	(27.3)	(23.63)	(12.41)	(10.12)	(5.12)	(3.33)	(23.38)	(23.22)	(11.06)
4	1.27***	1.64***	2.53***	1.89***	2.26***	1.67***	1.59***	2.15***	3.2***	2.35***	2.76***	2.07***
	(9.38)	(4.84)	(5.43)	(26.9)	(25.77)	(14.13)	(8.43)	(4.77)	(5.87)	(24.73)	(23.45)	(12.38)
5 (*High brand cap*)	1.92***	2.06***	3.05***	2.01***	2.22***	1.48***	2.07***	2.55***	3.52***	2.4***	2.79***	1.9***

	(12.55)	(4.85)	(4.96)	(24.63)	(27.17)	(12.3)	(10.27)	(4.27)	(4.8)	(22.23)	(24.2)	(11.05)
5 - 1	**0.7*** (3.57)**	**0.38 (0.71)**	**-0.57 (-0.58)**	**0.41*** (3.76)**	**0.39*** (3.16)**	**-0.26 (1.49)**	**0.73*** (2.73)**	**0.28 (0.36)**	**-0.36 (-0.3)**	**0.45*** (3.04)**	**0.38** (2.21)**	**-0.37 (-1.52)**
	(0, +10)						(0, +20)					
	S-H	S-B	S-SB	H-B	H-SB	B-SB	S-H	S-B	S-SB	H-B	H-SB	B-SB
1 (*Low brand cap*)	1.29*** (5.35)	2.38*** (3.95)	4.37*** (3.15)	2.03*** (15.46)	2.52*** (15.44)	2.65*** (11.65)	0.94*** (2.86)	2.37*** (2.98)	5.61*** (3.02)	2.07*** (11.6)	2.59*** (11.93)	2.31*** (7.58)
2	1.43*** (5.73)	1.92*** (2.71)	2.38 (1.62)	2.46*** (17.21)	2.68*** (15.69)	2.12*** (8.92)	1.27*** (3.92)	2.82*** (2.87)	2.85 (1.61)	2.54*** (13.74)	2.35*** (10.54)	1.43*** (4.6)
3	2.1*** (8.33)	2.41*** (3.48)	2.51*** (3.21)	2.3*** (18.3)	2.9*** (18.1)	2.12*** (9.2)	2.33*** (7)	2.66*** (2.8)	4.52*** (3.66)	2.2*** (12.74)	2.92*** (13.98)	2.53*** (8.7)
4	1.3*** (5.17)	1.94** (2.56)	2.93*** (3.08)	2.62*** (20.29)	3.06*** (19.44)	2.48*** (11.27)	1.19*** (3.65)	1.15 (1.28)	3.01* (1.99)	2.48*** (14.88)	3.01*** (14.67)	2.9*** (9.85)
5 (*High brand cap*)	1.86*** (7.03)	3.32*** (4.77)	1.88** (2.45)	2.46*** (18)	2.95*** (19.52)	1.95*** (8.27)	2.21*** (6.24)	2.66*** (3.01)	1.31 (1.2)	2.65*** (14.85)	3.08*** (15.64)	1.74*** (5.57)
5 - 1	**0.57 (1.58)**	**0.95 (1.03)**	**-2.5 (-1.58)**	**0.43** (2.27)**	**0.43** (1.92)**	**-0.69** (-2.12)**	**1.27 (2.62)**	**0.3 (0.25)**	**-4.3** (-2)**	**0.58** (2.29)**	**0.49* (1.68)**	**-0.58 (-1.32)**

This table shows the mean value-weighted market-adjusted buy-and-hold returns around recommendation with a window of (-1, +1), (-2, +2), (0, +1), (0, +5), (0, +10) and (0, +20), respectively. Brand capital intensity quintile groups were based on the annual ranking of firms with the capitalized and amortized advertising expenses scaled by total assets. Panel A reports negative recommendation revisions and Panel B reports positive recommendation revisions. The last row in each panel labeled "5-1" shows the difference of returns between the low brand capital group and the high brand capital group. "S-H", "S-B", "S-SB", "H-B", "H-SB" and "B-SB" denote "sell to hold", "sell to buy", "sell to strong buy", "hold to buy", "hold to strong buy" and "buy to strong buy", respectively. ***, ** and * denote significance at the 1, 5 and 10 percent significance levels, respectively.

TABLE 3.8.
Short-term market reactions on forecast revisions with different revision magnitudes.

Brand capital quintile group	(-1, +1)			(-2, +2)			(0, +1)		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Panel A. Earnings forecast downgrades and *BHAR* (reported in percentages)									
1 (*Low brand cap*)	-0.44*** (-13.14)	-0.67*** (-18.37)	-1.06*** (-20.76)	-0.57*** (-15.05)	-0.85*** (-20.87)	-1.37*** (-23.94)	-0.15*** (-9.3)	-0.31*** (-16.07)	-0.4*** (-15.54)
2	-0.41*** (-10.41)	-0.83*** (-19.73)	-1.14*** (-17.92)	-0.56*** (-12.63)	-1*** (-21.66)	-1.4*** (-20.54)	-0.21*** (-11.33)	-0.38*** (-19.32)	-0.48*** (-19.78)
3	-0.36*** (-13.12)	-0.87*** (-27.58)	-1.56*** (-26.42)	-0.48*** (-15.04)	-1.04*** (-28.45)	-1.86*** (-29.13)	-0.15*** (-10.5)	-0.41*** (-22.15)	-0.68*** (-26.59)

4	-0.44*** (-16.23)	-1.04*** (-31.18)	-2.38*** (-40.39)	-0.56*** (-18.39)	-1.25*** (-32.97)	-2.81*** (-42.64)	-0.2*** (-13.81)	-0.46*** (23.04)	-1.06*** (-33.31)
5 (*High brand cap*)	-0.82*** (-30.28)	-1.68*** (-44.79)	-3.08*** (-47.28)	-0.88*** (-8.33)	-1.65*** (-6.5)	-3.53*** (-49.43)	-0.4*** (-25.86)	-0.89*** (-38.83)	-1.5*** (-42.05)
5 - 1	**-0.39*** (-9.02)**	**-1.01*** (-19.33)**	**-2.02*** (-24.42)**	**-0.31*** (-2.79)**	**-0.8*** (-3.11)**	**-2.16*** (23.59)**	**-0.25*** (-11.16)**	**-0.57*** (-19.01)**	**-1.1*** (-25.2)**
		(0, +5)			(0, +10)			(0, +20)	
1 (*Low brand cap*)	-0.29*** (-11.63)	-0.52*** (-18.23)	-0.79*** (-21.83)	-0.36*** (-10.23)	-0.61*** (-15.54)	-0.87*** (-17.5)	-0.54*** (-11.52)	-0.87*** (-16.65)	-1.3*** (-20)
2	-0.34*** (-12.8)	-0.58*** (-20.07)	-0.8*** (-22.62)	-0.31*** (-8.17)	-0.56*** (-14.24)	-0.85*** (-17.87)	-0.5*** (-9.86)	-0.8*** (-15.12)	-1.17*** (-19.37)
3	-0.25*** (-11.39)	-0.64*** (-24.21)	-1.13*** (-30.73)	-0.38*** (-11.87)	-0.77*** (-20.91)	-1.22*** (-24.7)	-0.6*** (-13.96)	-0.95*** (-19.32)	-1.65*** (-26.05)
4	-0.36*** (-16.85)	-0.76*** (-26.93)	-1.62*** (-37.62)	-0.44*** (-14.14)	-0.75*** (-19.59)	-1.74*** (-31.37)	-0.54*** (-12.76)	-0.85*** (-16.58)	-2.04*** (-28.67)
5 (*High brand cap*)	-0.56*** (-25.86)	-1.26*** (-40.08)	-2.07*** (-43.3)	-0.57*** (-18.41)	-1.2*** (-28.18)	-2.1*** (-33.63)	-0.65*** (-15.93)	-1.34*** (-24.26)	-2.43*** (-30.5)
5 - 1	**-0.29*** (-11.63)**	**-0.52*** (-18.23)**	**-0.79*** (-21.83)**	**-0.36*** (-10.23)**	**-0.61*** (-15.54)**	**-0.87*** (-17.5)**	**-0.54*** (-11.52)**	**-0.87*** (-16.65)**	**-1.3*** (-20)**
		(-1, +1)			(-2, +2)			(0, +1)	
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
Panel B. Earnings forecast upgrades and *BHAR* (reported in percentages)									
1 (*Low brand cap*)	0.28*** (8.62)	0.71*** (18.76)	1.04*** (21.69)	0.31*** (7.98)	0.81*** (18.67)	1.24*** (22.61)	0.15*** (9.07)	0.28*** (14.57)	0.41*** (18.5)
2	0.42*** (11.05)	0.81*** (19.77)	1.2*** (24.31)	0.46*** (10.4)	0.92*** (19.86)	1.4*** (25.1)	0.22*** (11.92)	0.37*** (18.57)	0.45*** (20.2)
3	0.36*** (11.87)	0.78*** (23.4)	1.17*** (24.73)	0.42*** (8.6)	0.9*** (23.54)	1.43*** (26.18)	0.21*** (13.63)	0.33*** (18.23)	0.48*** (20.16)
4	0.51*** (18.64)	1.15*** (34.22)	1.98*** (31.42)	0.55*** (17.39)	1.27*** (33.49)	2.43*** (33.93)	0.31*** (20.08)	0.53*** (28.27)	0.72*** (27.3)
5 (*High brand cap*)	0.63*** (23.02)	1.4*** (40.04)	2.06*** (34.43)	0.79*** (6.78)	1.82*** (7.02)	2.45*** (36.26)	0.42*** (28)	0.71*** (34.72)	0.91*** (28.52)
5 - 1	**0.35*** (8.3)**	**0.69*** (13.34)**	**1.01*** (13.21)**	**0.48*** (3.95)**	**1.01*** (3.83)**	**1.21*** (13.89)**	**0.27*** (11.95)**	**0.43*** (15.3)**	**0.5*** (12.83)**
		(0, +5)			(0, +10)			(0, +20)	
1 (*Low brand cap*)	0.17***	0.38***	0.57***	0.16***	0.34***	0.54***	-0.07	0.06	0.25***

	(6.74)	(13.01)	(17.25)	(4.5)	(8.55)	(11.73)	(-1.4)	(1.1)	(4.1)
2	0.26*** (9.48)	0.47*** (16.38)	0.62*** (18.93)	0.29*** (7.31)	0.38*** (9.54)	0.48*** (10.7)	0.11** (2.03)	0.14*** (2.63)	0.2*** (3.34)
3	0.22*** (9.37)	0.39*** (14.87)	0.63*** (18.65)	0.09*** (2.61)	0.31*** (8.43)	0.51*** (10.91)	-0.1** (-2.16)	0.08 (1.58)	0.24*** (3.77)
4	0.36*** (16.03)	0.7*** (25.91)	0.99*** (26.45)	0.3*** (8.96)	0.71*** (19.04)	1.18*** (23.34)	0.19*** (4.32)	0.65*** (13.1)	1.13*** (17.08)
5 (*High brand cap*)	0.5*** (23.61)	0.96*** (33.85)	1.3*** (28.97)	0.43*** (14.43)	0.91*** (23.82)	1.38*** (23.09)	0.4*** (9.98)	0.99*** (19.5)	1.53*** (19.76)
5 - 1	**0.33*** (9.97)**	**0.59*** (14.44)**	**0.73*** (13.09)**	**0.27*** (5.73)**	**0.57*** (10.24)**	**0.84*** (11.12)**	**0.47*** (7.37)**	**0.93*** (12.47)**	**1.28*** (13.05)**

This table shows the mean value-weighted market-adjusted buy-and-hold returns around forecast revisions with a window of (-1, +1), (-2, +2), (0, +1), (0, +5), (0, +10) and (0, +20), respectively. Brand capital intensity quintile groups were based on the annual ranking of firms with the capitalized and amortized advertising expenses scaled by total assets. Panel A reports negative forecast revisions and Panel B reports positive forecast revisions. The last row in each panel labeled "5-1" shows the difference of returns between the low brand capital group and the high brand capital group. "Small", "Medium" and "large" denote revision magnitude which is determined based on annual ranking of the absolute value of the difference between the new forecast and the previous forecast made by the same analyst divided by the previous forecast. ***, ** and * denote significance at the 1, 5 and 10 percent significance levels, respectively.

TABLE 3.9.
Portfolio analyses

Brand capital quintile group	Raw return	Market-adj. return	Annualized alpha	MKT - R_f	SMB	HML	UMD	R^2
Panel A. Long portfolios								
1 (Low brand cap)	0.21*** (57.93)	0.11*** (39.68)	0.11*** (4.75)	0.88*** (105.3)	0.34*** (20.82)	0.46*** (26.84)	-0.08*** (-6.64)	0.85
2	0.29*** (52.88)	0.17*** (51.57)	0.16*** (6.49)	0.93*** (109.94)	0.51*** (31)	0.22*** (12.84)	-0.12*** (-10.12)	0.85
3	0.27*** (59.75)	0.16*** (59.21)	0.15*** (5.44)	0.96*** (101.85)	0.54*** (29.18)	-0.04* (-1.85)	-0.09*** (-6.48)	0.81
4	0.29*** (73.28)	0.18*** (77.87)	0.17*** (7.88)	0.87*** (118.52)	0.6*** (42.2)	-0.12*** (-7.94)	-0.07*** (-6.9)	0.86
5 (High brand cap)	0.35*** (75.01)	0.22*** (89.17)	0.21*** (8.47)	0.93*** (110.57)	0.62*** (37.32)	-0.19*** (-10.96)	-0.08*** (-6.76)	0.83
5 - 1	**0.14***** **(51.66)**	**0.11***** **(47.77)**	**0.1***** **(2.86)**	0.06*** (5.14)	0.28*** (12.75)	-0.65*** (-28.35)	0.00 (-0.16)	0.28
Panel B. Short portfolios								
1 (Low brand cap)	0.22*** (50.57)	0.12*** (35.74)	0.12*** (4.33)	0.84*** (85.23)	0.36*** (18.78)	0.44*** (21.81)	-0.15*** (-10.98)	0.79
2	0.33*** (53.53)	0.21*** (48.25)	0.19*** (5.93)	0.91*** (83.55)	0.54*** (25.45)	0.21*** (9.38)	-0.19*** (-12.49)	0.77
3	0.25*** (45.19)	0.14*** (38.33)	0.13*** (4.41)	0.92*** (92.23)	0.58*** (29.84)	-0.01 (-0.49)	-0.13*** (-9.73)	0.79
4	0.35*** (73.48)	0.22*** (72.77)	0.23*** (7.48)	0.83*** (82.92)	0.61*** (31.23)	-0.11*** (-5.12)	-0.14*** (-9.86)	0.76
5 (High brand cap)	0.31*** (59.55)	0.19*** (58.33)	0.18*** (6.23)	0.88*** (90.34)	0.66*** (34.85)	-0.14*** (-6.76)	-0.15*** (-10.82)	0.79
5 - 1	**0.09***** **(23.14)**	**0.07***** **(21.31)**	**0.06** **(1.37)**	0.04*** (3.17)	0.3*** (11.69)	-0.58*** (-21.15)	0.00 (0.19)	0.2

Panel C. Long-short portfolios								
1 (Low brand cap)	0.22*** (54.79)	0.12*** (38.77)	0.12*** (4.94)	0.86*** (101.67)	0.35*** (21.35)	0.45*** (26)	-0.12*** (-9.84)	0.84
2	0.31*** (53.47)	0.19*** (49.93)	0.18*** (6.58)	0.92*** (101.18)	0.53*** (29.69)	0.22*** (11.59)	-0.16*** (-12.35)	0.83
3	0.26*** (51.58)	0.15*** (47.18)	0.14*** (5.15)	0.94*** (102.38)	0.56*** (31.34)	-0.02 (-1.13)	-0.11*** (-8.75)	0.82
4	0.33*** (75.22)	0.2*** (78.57)	0.2*** (8.45)	0.85*** (105.15)	0.61*** (38.67)	-0.11*** (-6.71)	-0.11*** (-9.57)	0.83
5 (High brand cap)	0.33*** (66.74)	0.21*** (71.87)	0.19*** (7.69)	0.91*** (106.12)	0.64*** (38.52)	-0.16*** (-9.09)	-0.12*** (-9.75)	0.83
5 - 1	**0.11*** (34.69)**	**0.09*** (32.12)**	**0.08** (2.12)**	0.05*** (4.25)	0.29*** (13.15)	-0.61*** (-26.27)	0.00 (-0.02)	0.26

This table shows the results of the portfolio analyses. Panel A shows the results of long portfolios, Panel B shows the results of short portfolios and Panel C shows the results of long-short portfolios. Brand capital intensity quintile groups were based on the annual ranking of firms with the capitalized and amortized advertising expenses scaled by total assets. Raw return is the mean annualized cumulative buy-and-hold return and market-adjusted return is the raw return minus the annualized cumulative value-weighted market return. Annulized alpha is the annualized intercept of Fama-French 4 factor model. MKT - R_f is the market return less the risk-free rate, SMB is the size factor, HML is the book-to-market factor and UMD is the premium on winners minus losers. The last row in each panel labeled “5-1” shows the difference between the low brand capital group and the high brand capital group. ***, ** and * denote significance at the 1, 5 and 10 percent significance levels, respectively.

TABLE 3.10.
Short-term market reaction, brand capital intensity and news sentiment

	Prediction	BHAR (0, +2)			
		Recommendation revisions		Forecast revisions	
Intercept	+	2.0872*** (11.91)	1.8502*** (10.53)	0.5935*** (23.36)	0.6685*** (23.61)
SIZE	-	-0.4989*** (-29.72)	-0.4873*** (-29.27)	-0.1251*** (-38.55)	-0.1418*** (-40.89)
B/M	+	0.3563*** (4.56)	0.3335*** (4.3)	0.0788*** (5.79)	0.1021*** (6.91)
COVER	-	-0.7251*** (-3.87)	-0.6141*** (-3.3)	-0.185*** (-5.39)	-0.2653*** (-7.26)
AMIHUD	+	4.1094*** (3.69)	3.9052*** (3.53)	-1.8868*** (-8.19)	-0.9872*** (-3.46)
FOR	+	0.8485*** (15.79)	0.8137*** (15.27)		
REC	+			0.5518*** (28.13)	0.4428*** (21.31)
REV_MAG	+	0.3672*** (6.87)	0.3262*** (6.16)	0.171*** (11.4)	0.1879*** (11.4)
BOLDNESS	?	0.1349*** (3.34)	0.1154*** (2.88)	0.0191* (1.74)	0.0171 (1.42)
CONFLICT	-		-0.7894*** (-7.74)		-0.1327*** (-7.36)
CONFLICT × *BRANDCAP*	?(+/-)		**-1.8141 (-1.1)**		**3.3616*** (10.53)**
CSS	+		1.196*** (18.7)		1.1763*** (62.33)
CONFLICT × *CSS*	-		-1.6715*** (-9.66)		-1.8790*** (-54.48)
BRANDCAP × *CSS*	+		**2.6514** (2.07)**		**1.4125*** (4.34)**
BRANDCAP	+	**2.2562*** (3.65)**	**1.4217* (1.68)**	**3.6042*** (27.43)**	**2.1208*** (12.18)**
Year fixed effect		Yes	Yes	Yes	Yes
Adj. R^2		0.0403	0.0567	0.0108	0.0248
N		50,277	50,277	633,118	633,118

This table shows the results of regression models using OLS estimates. ***, ** and * denote significance at the 1, 5 and 10 percent significance levels, respectively.

TABLE 3.11.
Revision frequency, forecast accuracy, brand capital intensity and news sentiment.

	REC_FREQ		*FOR_FREQ*		*FOR_ACCU*	
Intercept	1.1615*** (39.86)	1.1356*** (38.57)	0.1962*** (256.5)	0.1941*** (232.6)	0.1261*** (11.48)	0.1102*** (9.31)
SIZE	0.0366*** (13.13)	0.0371*** (13.29)	-0.0018*** (-18.87)	-0.0018*** (-17.57)	-0.0638*** (-45.43)	-0.0619*** (-42.7)
B/M	-0.1115*** (-8.58)	-0.1108*** (-8.53)	-0.0082*** (-19.91)	-0.0092*** (-21.07)	0.3779*** (64.2)	0.3849*** (62.32)
COVER	0.0484 (1.55)	0.0528* (1.7)	-0.0851*** (-82.35)	-0.0783*** (-72.71)	0.3612*** (24.35)	0.3456*** (22.62)
AMIHUD	0.0379 (0.2)	0.0286 (0.15)	0.1513*** (21.81)	0.1479*** (17.55)	0.6285*** (6.31)	0.7334*** (6.14)
FOR	0.097*** (10.85)	0.0964*** (10.79)				
REC			0.0592*** (100.29)	0.0582*** (95.07)	-0.0385*** (-4.53)	-0.0359*** (-4.13)
REV_MAG	0.1225*** (13.8)	0.121*** (13.63)	0.0204*** (45.22)	0.0206*** (42.44)	0.0821*** (12.66)	0.0848*** (12.3)
BOLDNESS	-0.0918*** (-13.65)	-0.0912*** (-13.56)	-0.0169*** (-51.13)	-0.0173*** (-48.75)	0.5848*** (122.93)	0.5899*** (116.98)
CONFLICT		0.0928*** (5.43)		0.0062*** (11.63)		0.0339*** (4.5)
CONFLICT × *BRANDCAP*		**-0.4711*** **(-1.71)**		**0.0014** **(0.15)**		**0.2376*** **(1.78)**
CSS		0.0678*** (6.33)		-0.0676*** (-12.15)		0.2393*** (3.03)
CONFLICT × *CSS*		-0.2399*** (-8.28)		-0.0303*** (-2.98)		-0.5423*** (-3.76)
BRANDCAP × *CSS*		**-0.5176****		**-0.3903*****		**0.0691**

		(-2.41)		**(-4.07)**		**(0.05)**
BRANDCAP	**0.4***** **(3.89)**	**0.6982***** **(4.93)**	**0.0392***** **(9.91)**	**0.0545***** **(10.63)**	**-0.9289***** **(-16.35)**	**-0.9981***** **(-13.71)**
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0687	0.0703	0.0451	0.0428	0.0622	0.0636
N	50,277	50,277	633,118	633,118	633,118	633,118

This table shows the results of regression models using OLS estimates. ***, ** and * denote significance at the 1, 5 and 10 percent significance levels, respectively.

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