Analysts' Overconfidence and the Usefulness of Their Information to Firm Managers

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Abstract

This study finds that corporate investments are more sensitive to information produced by analysts who have predicted earnings more accurately than the median analyst in previous four quarters. This finding suggests that analysts who have experienced short-lived success become overconfident in their forecasting ability. Hence, they overweight private information, which is unknown to firm managers. In turn, these managers benefit from information produced by such overconfident analysts. The implications are twofold: (a) analyst overconfidence has a bright side and (b) firm managers learn from analysts' information when making real decisions.

Keywords: analyst, overconfidence, real efficiency

Classification codes: G14, G31, M41

1. Introduction

As one of the most important information intermediaries in the financial market, analysts spend significant time and resources collecting and analyzing information. Existing literature primarily focuses on the usefulness of analysts' information to investors. On one hand, there is ample evidence showing that analysts' information is useful to investors. On the other hand, many studies find that analysts are subject to various cognitive biases, which can impair the usefulness of their information to investors.[1] One of these cognitive biases is overconfidence. In particular, Hilary and Menzly (2006) find that an overconfident analyst overweights private information and, as a result, s/he is less accurate and further from the consensus in her/his earnings prediction. This finding suggests a detrimental effect of analyst overconfidence in reducing the usefulness of analysts' information to investors.

This study departs from the existing literature by evaluating analysts' information from another perspective, specifically, its usefulness to firm managers. This study finds that as an analyst's overconfidence increases, corporate investments become more sensitive to the analyst's information, suggesting that when making real decisions, the firm's manager becomes more dependent on the analyst's information. Thus, this finding suggests the bright side of analyst overconfidence, as it increases the usefulness of analysts' information to firm managers. More broadly, this study suggests that because firm managers also learn from analysts, evaluating their information solely from the perspective of investors is incomplete.

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[1] See a review of the literature on financial analysts in Ramnath, Rock, and Shane (2008) and Bradshaw, Ertimur, and O'Brien (2017).

Overconfidence is one of the most robust cognitive biases found in experimental studies, and one of its manifestations is overweighting private information. [2] According to Kraemer et al. (2006, p. 424), because overconfident subjects believe their private information is more accurate than it is, they "put too much weight on their private information." In the financial analyst setting, Hilary and Menzly (2006) find that an analyst who forecasts earnings more accurately than the median analyst in the previous four quarters tends to be relatively less accurate and further from the consensus forecast in her/his subsequent earnings prediction. Hilary and Menzly (2006) interpret this finding as being consistent with an analyst becoming more overconfident after experiencing a short series of successes in forecasting. Particularly noteworthy is that Hilary and Menzly (2006) control an analyst-firm (i.e., the combination of analyst and firm) fixed effect in their study. Thus, their study focuses not on the cross-sectional difference in overconfidence between analysts or between firms but on the time-series dynamic of overconfidence in a given analyst for forecasting a particular firm.

The finding of Hilary and Menzly (2006) suggests that from an investor's perspective, overconfidence negatively affects the usefulness of an analyst's information. However, from a firm manager's perspective, the effect of overconfidence could be positive. Although much of the literature assumes that managers know more than analysts, several empirical studies cast doubt on this presumption. For example, Ruland (1978) and Hutton and Stocken (2009) find that approximately only 50% of managers' earnings forecasts are more accurate than analysts'. Hutton,

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[2] See, for example, Alpert and Raiffa (1982), Lichtenstein, Fischhoff, and Phillips (1982), and Gervais and Odean (2001). Odean (1998) provides a review of literature on overconfidence.

Lee, and Shu (2012) further find that analysts have a macroeconomic information advantage over managers, suggesting that managers could learn from analysts. If this is the case, and if overconfident analysts overweight private information unknown to firm managers (this point is discussed in greater detail in Section 3.2), it is expected that managers will be more likely to learn from overconfident analysts.

This expectation is tested in three ways. In a sample of analyst-firm-year observations, the first test examines the effect of analyst overconfidence on the sensitivity of corporate investments to analysts' long-term growth forecasts (henceforth, investment-*GF* sensitivity). As discussed in Section 3.2, among all forms of predictions an analyst makes, the growth forecast is likely to have the most significant influence on a firm manager's investment decisions. Following Hilary and Menzly (2006), an analyst-firm fixed effect is controlled. Thus, the result from this test shows that regarding a particular firm, the dynamic nature of an analyst's overconfidence affects, over time, the usefulness of the analyst's growth forecasts to the firm's manager. As an analyst becomes more overconfident, corporate investments become more sensitive to the analyst's growth forecasts. This result is robust in controlling various analyst/forecast characteristics, in particular, the analyst ability as measured by forecast accuracy. Furthermore, in a placebo test, an analyst's overconfidence is purposely mismatched with the growth forecast of another analyst. Although corporate investments are found to respond positively to growth forecasts, overconfidence is not found to affect investment-*GF* sensitivity. Thus, the result from the placebo test confirms that increased investment sensitivity regarding an analyst's growth forecast is due to this particular analyst's increased overconfidence.

The second test examines the effect of analyst overconfidence on the sensitivity of corporate investments to stock prices, as measured by Tobin's Q (henceforth, investment-*Q* sensitivity). This test is based on the first test, that is, it is based on a sample of analyst-firm-year observations with the control of the analyst-firm fixed effect. As an analyst becomes more overconfident, corporate investments become more sensitive to stock prices. This result also suggests that overconfidence positively affects the usefulness of analysts' information to firm managers. Furthermore, this result implies that the positive investment-Q sensitivity is partially resultant from firm managers obtaining information from analysts that is impounded into stock prices. Therefore, the results from the first and second tests suggest that managers learn from analysts through two channels: directly from analysts' outputs (e.g., growth forecasts) and indirectly from stock prices incorporating the information in analysts' outputs.

The third test also examines the effect of analyst overconfidence on investment-Q sensitivity, but it is based on a sample of firm-year observations. The test methods include a pooled regression with firm-fixed and year-fixed effects and a Fama–MacBeth regression. The main finding from this test is that as the average overconfidence of analysts covering a firm increases, investment-Q sensitivity increases. This result confirms the finding from the second test using a different sample and a different regression specification.

In summary, this study tests and finds robust evidence to support the joint hypothesis that (a) information produced by overconfident analysts is more useful to firm managers and (b) when making investment decisions, firm managers learn from analysts' information.

This study makes the following contributions to existing literature. First, this study confirms the conclusion by Hilary and Menzly (2006) that overconfidence affects the production of analysts' information by leading them to overweight their private information. Although from the investor perspective the finding suggests the dark side of analyst overconfidence, the findings of this study show the bright side from the perspective of firm managers.

Second and relatedly, this study suggests that analysts' information is useful to not only investors but also firm managers. Most literature on analysts is concerned with how the information they provide is useful to investors. Few empirical studies have directly examined the usefulness of analysts' information for firm managers when making real decisions. This study fills this research gap. The results in this study suggests that a new definition of usefulness is needed to account for the extent to which analysts' information is useful for real decision efficiency. This new definition could assist regulators to comprehensively consider the effects of a policy. For example, much of the debate on Regulation FD (a regulation that prohibits selective disclosure, promulgated by the U.S. Securities and Exchange Commission in August 2010) focused on how it would affect the information available to investors; how it would affect firm managers was only minimally considered (Regulation FD could encourage analysts to conduct independent research, thus enhancing the usefulness of their information to firm managers).

Third, most studies on analysts examine their short-term earnings forecasts or stock recommendations; in contrast, this study focuses on analysts' long-term growth forecasts. This study finds that managers learn directly from analysts' growth forecasts, complementing the conclusion in Jung et al. (2012) that these forecasts signify an analyst's effort and ability to analyze a firm's long-term prospects.

Finally, this study provides additional supporting evidence that is unique to the managerial-learning interpretation of investment-*Q* sensitivity. Although it is an intuitive and long-standing notion that managers learn from stock prices, finding conclusive supporting empirical evidence is difficult because of competing explanations, including that *Q* is a proxy for the marginal cost of capital and that *Q* contains a mispricing component (Tobin, 1969; von Furstenberg, 1977; Baker, Stein, and Wurgler, 2003). One approach to distinguish competing explanations is to focus on cross-sectional predictions that are unique to the managerial-learning channel as, for example, in Chen et al. (2007). In this study, the effect of analyst overconfidence on investment-*Q* sensitivity (both the time-series effect within a given analyst-firm and the cross-sectional effect between firms) is unique to the managerial-learning interpretation, thus adding empirical evidence to support this interpretation. Furthermore, this study uncovers one source of information in stock prices that directs managers' investment decisions: overconfident analysts.

The remainder of this study proceeds as follows: Section 2 describes the data and the sample; Section 3 presents the empirical results; and Section 4 concludes the study.

2. Data and sample

Analyst forecast data are retrieved from I/B/E/S, stock return data from CRSP, and accounting information from Compustat.

In each year t, we retain the last growth forecast of an analyst i for a given firm j (denoted as $GF_{i,j,t}$), and we require this growth forecast to fall within July to December of year t.[3] This is to ensure that when the senior manager of firm j makes investment decisions for year t + 1, information from analyst i's most updated growth forecast is not stale.

Following Hilary and Menzly (2006), we use two measures−*FREQ* and *STREAK*− to capture the notion that an analyst becomes more overconfident after a short-term sequence of good predictions. $FREQ_{i,j,t}$ is defined as the number of superior quarterly forecasts issued by analyst i for firm j in the preceding four quarters before the issuance of $GF_{i,j,t}$. Alternatively, $STREAK_{i,j,t}$ is

[3] The average number of growth forecasts issued by an analyst for a firm in each year is 1.67.

defined as the number of consecutive superior quarterly forecasts issued by analyst *i* for firm *j* in the preceding four quarters before the issuance of $GF_{i,j,t}$.[4] A quarterly forecast is considered superior if its error is below the median error of all analysts covering the same firm in that particular quarter. To ensure that $FREQ_{i,j,t}$ and $STREAK_{i,j,t}$ are available before this issue date, earnings announcement dates of all four quarters (or, equivalently, the earnings announcement date of the last quarter) must be before the date that $GF_{i,j,t}$ is issued. The same criteria as those in Hilary and Menzly (2006) are adopted to measure *FREQ* and *STREAK*: (1) only the first forecast from an analyst for a firm-quarter is included; (2) at least four analysts cover a firm-quarter; (3) to be included in the sample, an analyst needs to have made at least four predictions for a given firm in the preceding quarters; and (4) only firms with a December fiscal year-end are included.

As noted in Hilary and Menzly (2006), these overconfidence measures implicitly assume that an analyst treats each firm independently. As we match growth forecasts with the overconfidence calculated from quarterly forecasts, we further assume that an analyst's overconfidence is manifested not only in the subsequent prediction of quarterly earnings but also

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[4] In Hilary and Menzly (2006), *STREAK* is defined as "*the number of consecutive superior predictions before the current prediction is made*." Therefore, their *STREAK* measure is *not* restricted to the preceding four quarters. Hilary and Hsu (2011) applies the same concept, using corporate managers' earnings forecasts, to construct a measure of manager overconfidence. They define *STREAK* as "*the number of consecutive accurate predictions for a given firm in the last four quarters before the current prediction is made*." The second definition of *STREAK* is preferred because it is (1) not dependent on the total number of predictions made by an analyst, and (2) more consistent with the conceptual underpinning of overconfidence given that it focuses on a *short* time-series of success.

in other predictions (e.g., growth forecasts). This assumption is plausible because when an analyst produces predictions for a given firm, the amount of public and private information available is the same, regardless of the form of the prediction. Additionally, the weight the analyst assigns to public *versus* private information is also likely to be identical for different forms of predictions. This is because the weight depends on the analyst's perception of personal ability, which is likely analyst-specific as opposed to forecast-specific.

After calculating $FREQ_{i,j,t}$ ($STREAK_{i,j,t}$) for each $GF_{i,j,t}$, $GF_{i,j,t}$ is matched with investments of firm j in year $t + 1$ (denoted as $I_{i,j,t+1}$). Because we control the analyst-firm fixed effect, at least two years of observations for each analyst-firm are required. The final sample includes 28,305 analyst-firm-year observations from 1985 to 2018. This relatively small sample size is the result of matching *FREQ* (*STREAK*) calculated from quarterly forecasts with growth forecasts (the number of quarterly forecasts is approximately 5.6 times the number of growth forecasts in I/B/E/S). Because quarterly earnings forecasts for a large number of firms were first available in 1984, the sample starts from 1985, and it ends in 2018, because to calculate post-investment stock returns, at least one year of return data is required.

The empirical analyses in Sections 3.1–3.3 (subsequently described) are based on this sample of analyst-firm-year observations. In these analyses, an analyst-firm fixed effect is controlled. Thus, the results in these sections focus on an analyst's dynamic overconfidence for forecasting a given firm and how this affects the usefulness of the analyst's information to the manager of said firm. Controlling the analyst-firm fixed effect has the advantage of controlling omitted variables, such as cross-sectional differences in characteristics from firms and analysts.

As subsequently explained in detail, the empirical analysis in Section 3.4 is based on a sample of 35,382 firm-year observations from 1985 to 2018. This sample is used to examine how the average overconfidence of all analysts covering a firm affects the usefulness of their information to managers across firms and across time.

The summary statistics of the variables in the sample of analyst-firm-year observations are provided in Panel A of Table 1. Panel B provides the summary statistics of the variables in the sample of firm-year observations. In Section 3, these variables are defined and explained in each regression.

3. Empirical results

3.1 Effect of analyst overconfidence on forecast error and deviation from the consensus

Using the sample in this study, this section replicates the findings of Hilary and Menzly (2006), where the analyst forecast data are retrieved from the Zacks database for the period 1980–1997. As mentioned in Section 2, the analyst forecast data used in this study are retrieved from I/B/E/S, and the sample period covers years 1985–2018. Furthermore, this study's sample is restricted to quarterly forecasts issued by analysts who also issue growth forecasts. Therefore, it is interesting to determine whether the results still hold when using data from another source in a restricted sample and for an extended period.

Specifically, the following regression (1) is used to examine whether an analyst, who has predicted quarterly earnings more accurately than the median analyst in the previous four quarters, tends to be less accurate and further from the consensus forecast in the subsequent quarterly earnings prediction.

$$DEV_{i,j,t}(ERROR_{i,j,t}) = \alpha + \beta Overconfidence_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

The dependent variable is either deviation from consensus forecast ($DEV_{i,j,t}$) or forecast error ($ERROR_{i,j,t}$). The dependent variable is based on analyst *i*'s first quarterly forecast for firm *j* after issuing a growth forecast (i.e., $GF_{i,j,t}$). In this way, $DEV_{i,j,t}$ and $ERROR_{i,j,t}$ do not overlap with quarterly forecasts used to measure $FREQ_{i,j,t}$ and $STREAK_{i,j,t}$. *DEV* is calculated as the distance (i.e., in absolute value) between analyst *i*'s forecast and the median forecast of all analysts covering the same firm for the same quarter. If an analyst issues more than one forecast for this firm-quarter, the one closest to analyst *i*'s forecast is selected. *ERROR* is calculated as the distance (i.e., in absolute value) between analyst *i*'s forecast and the actual earnings-per-share announced by firm *j* for that quarter. Both *DEV* and *ERROR* are scaled by the stock price at the end of June in year *t*. As explained in Section 2, $FREQ_{i,j,t}$ and $STREAK_{i,j,t}$ capture analyst *i*'s dynamic overconfidence. The analyst-firm fixed effect is controlled, and test statistics are based on standard errors clustered by year.[5] In all the tables, the estimated coefficients for the explanatory variables are multiplied by 100 to ensure that they do not appear to be 0.00.

Table 2 reports the results of regression (1). When the dependent variable is *DEV*, the coefficients on both *FREQ* and *STREAK* are positive and significant, suggesting that as overconfidence increases, an analyst's forecast moves further away from the consensus forecast.

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[5] Hilary and Menzly (2006) use standard errors clustered by both firm and time (i.e., quarter in their study). When this two-way clustering approach is used in this study, the coefficient on the explanatory variable is unavailable. The reason might be as follows. In the two-way clustering approach, the variance-covariance matrix is calculated as: *variance of firm and time* = *variance of firm* + *variance of time* – *variance of white*. *Variance of firm* (*time*) is the variance-covariance matrix clustered by firm (time), and *variance of white* is the diagonal of the variance-covariance matrix. If *variance of white* is relatively large, then *variance of firm and time* have negative elements on the diagonal; as a result, the standard errors cannot be obtained. Cameron et al. (2011) suggest that "*this issue is most likely to arise when clustering is done over the same groups as the fixed effects*." (The working-paper version in 2006 also suggested that this issue usually occurs when clustering in more than one dimension is unnecessary.)

When the dependent variable is *ERROR*, the coefficient on *FREQ* remains positive and significant, but the coefficient on *STREAK* is insignificant. This result suggests that when gauging analyst overconfidence by the number of superior forecasts in the preceding four quarters, overconfidence negatively affects forecast accuracy; however, the effect of overconfidence on forecast accuracy is not significant when overconfidence is gauged by the number of consecutive superior forecasts in the preceding four quarters. One possible reason is that *DEV* is better than *ERROR* at capturing the consequence of overconfidence. Nevertheless, taken together, these results are consistent with those of Hilary and Menzly (2006), which confirms their conclusion that an analyst with short-lived success becomes overconfident, resulting in overweighting private information.

Note that the dependent variable in this test (i.e., *DEV* or *ERROR*) is based on an analyst's subsequent prediction for quarterly earnings. Even though one main test of our hypothesis is based on the analyst's growth forecast, the dependent variable is not calculated from an analyst's subsequent prediction for earnings growth. The reason is that it is difficult to measure *DEV* and *ERROR* for a growth forecast because (1) different analysts define growth in different ways and deviation from the consensus might simply result from a different definition and (2) actual earnings growth is calculated by I/B/E/S, which is less objective than firms' actual quarterly earnings announcements.[6] In other words, concerning the consequence of overconfidence, dependent

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[6] According to the manuals provided by I/B/E/S, "*Long term growth rate forecasts are received directly from contributing analysts; they are not calculated by Thomson Reuters. While different analysts apply different methodologies, the Long Term Growth Forecast generally represents an expected annual increase in operating earnings over the company's next full business cycle. In general, these forecasts refer to a*

variables based on quarterly forecasts provide more objective evidence than variables based on growth forecasts. However, as discussed in Section 2, our empirical design implicitly assumes that overconfidence is analyst-specific rather than forecast-specific. In other words, the effect of overconfidence spills over to the analyst's other predictions and is not restricted to quarterly forecasts.

3.2 Effect of analyst overconfidence on investment-GF sensitivity

The hypothesis in this study is that as an analyst's overconfidence increases in making predictions for a given firm, the analyst's information becomes more useful to the manager of that firm. The reasoning is as follows.

An analyst uses both public and private information to make a prediction. Public information is available to all parties, including investors, the analyst, and the firm manager. One example of public information is the announcement of an interest rate. Note that a better interpretation of public information (e.g., better interpretation of the announced interest rate) results from possessing private information. From the investor perspective, an analyst's private information

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period of three to five years. Due to the variance in methodologies for Long Term Growth calculations, Thomson Reuters recommends (and uses as its default display) the median value for Long Term Growth Forecast as opposed to the mean value. The median value (defined as the middle value in a defined set of values) is less affected by outlier forecasts." (Reuters, 2009) IBES calculates the actual growth rate as follows: "*The average annualized earnings per share growth for a company over the past five years. The average annualized growth in EPS for the past five years is calculated by measuring the slope of a least squares curve fit to the logarithm of the reported earnings (a log-linear curve) and is expressed as a percent*." (Financial, 2008) consists of information obtained from the firm's manager and independent research. From the firm manager's perspective, an analyst's private information consists only of information from independent research.

The findings in Hilary and Menzly (2006) suggest that an overconfident analyst overweights private information. Such overweighting is more likely to occur for private information obtained from independent research than for information obtained from the firm manager, for the following reasons. First, the weight placed on private information depends on how the analyst perceives the precision of the private signal, which in turn depends on the perceived ability of the person generating the signal. The analyst is the source of the private signal from independent research, whereas the firm manager is the source of the private signal for any information offered to the analyst. In other words, an analyst overweights private information from the firm manager if the analyst has an incorrect perception of the manager's ability, whereas an analyst overweights private information from independent research if the analyst has an incorrect perception of personal ability. The overconfidence measures used in this study capture an analyst's perception of personal ability. Second, experimental studies suggest that overconfidence increases with the difficulty of the task and the intensity of the subject's ego-involvement (Miller, 1976; Klayman et al., 1999). Independent research is a more difficult task, involving an analyst's ego to a greater degree than conversing with a firm's manager.

An analyst obtaining private information from independent research versus from the firm manager is analogous to a student solving a math problem alone versus learning the answer from a classmate; the latter is not likely to affect the perception of personal ability. Therefore, an overconfident analyst only overweights private information from independent research, which is likely unknown to and more useful for a firm manager.

Nevertheless, if an overconfident analyst overweights the private information obtained from a firm manager, the finding should reflect that the more overconfident an analyst becomes, the less useful the analyst's information will be to the firm manager. Although this finding is believed to be implausible, whether overconfidence has a positive or negative effect on the usefulness of an analyst's information to the firm manager is ultimately an empirical question.

The test in this section examines how analyst overconfidence affects the sensitivity of corporate investments to growth forecasts (i.e., investment-*GF* sensitivity). Among all forms of predictions an analyst makes, for the following reasons, the growth forecast is the one most likely to influence a firm manager's investment decisions. First, the growth forecast focuses on a long horizon of three–five years, and the information advantage that managers have over analysts becomes smaller as the forecast horizon lengthens. Second, because analysts specialize in forecasting earnings, their earnings growth forecasts likely contain information that is more useful than other long-horizon outputs, such as price forecasts and stock recommendations. Third, corporate investments are long-term decisions made by a firm manager; therefore, a manager is more likely to learn from an analyst's long-term rather than short-term earnings forecasts, such as quarterly or annual earnings forecasts. In particular, Jung et al. (2012) find that growth forecasts issued by analysts signal their effort and ability to analyse a firm's long-term prospects. If firm managers are aware of this signal, they will learn directly from analysts' growth forecasts.

This test uses the following regression (2):

$$I_{i,j,t+1} = a + b_1 GF_{i,j,t} + b_2 GF_{i,j,t} \times Overconfidence_{i,j,t} + b_3 Overconfidence_{i,j,t}$$
$$+ c_1 Q_{i,j,t} + c_2 CF_{i,j,t} + c_3 FRET_{i,j,t} + d_k GF_{i,j,t} \times Controk^{k}_{i,j,t} + e_k Control^{k}_{i,j,t} + \epsilon_{i,j,t+1} \quad (2)$$

The dependent variable ($I_{i,j,t+1}$) is the investment of firm j in year t +1, measured as capital expenditure (Compustat annual item CAPX), plus R&D (item XRD, 0 if missing), scaled by beginning-year-assets (item AT). $GF_{i,j,t}$ is the last growth forecast for firm j issued by analyst i in year t. $Overconfidence_{i,j,t}$ measures analyst i's overconfidence at the time $GF_{i,j,t}$ is issued; $Overconfidence_{i,j,t}$ is proxied by either $FREQ_{i,j,t}$ or $STREAK_{i,j,t}$. $GF_{i,j,t} \times Overconfidence_{i,j,t}$ is the interaction between $GF_{i,j,t}$ and $Overconfidence_{i,j,t}$. The coefficient on the interaction term is of primary interest, and it (i.e., b_2) is expected to be positive and significant.

The following variables, commonly included in a regression involving corporate investments, are controlled: $Q_{i,j,t}$ is Tobin's Q for firm j at the end of the year t, measured as the market value of equity (item PRCC_F multiplied by item CSHO), plus the book value of assets (item AT), minus the book value of equity (item CEQ), scaled by the book value of assets (item AT); $CF_{i,j,t}$ is the cash flow of firm j in year t, measured as net income before extraordinary items (item IB), plus depreciation and amortization expenses (item DP), plus R&D expenses (item XRD, 0 if missing), scaled by beginning-of-year assets (item AT); $FRET_{i,j,t}$ is the future stock returns of firm j after year t, measured as the adjusted buy-and-hold return for the three years following an investment (i.e., from year $t + 1$ to $t + 3$), with the adjustment based on value-weighted market returns. As in regression (1), the analyst-firm fixed effect is controlled, and test statistics are calculated using standard errors clustered by year.

These variables constitute the baseline regression, and the result is reported in Table 3 under the column header "*baseline result*." Consistent with our expectation, the coefficient on $GF \times Overconfidence$ is significantly positive under both proxies, suggesting that analyst overconfidence has a positive effect on investment-GF sensitivity.

To ensure that the coefficient for $GF \times Overconfidence$ is not the result of several analyst/forecast characteristics, these characteristics and their interactions with GF are further controlled, and the results are reported under the column header "*additional controls.*" Specifically, analyst i's experience in making predictions for firm j ($EXP_{i,j,t}$) and its interaction with $GF_{i,j,t}$ are controlled; $EXP_{i,j,t}$ is measured as the number of quarterly forecasts made by analyst i for firm j before the issuance of $GF_{i,j,t}$. The number of days between the issue date of $GF_{i,j,t}$ and the ending date (i.e., December 31) of year t—denoted as $Day_{i,j,t}$—and its interaction with $GF_{i,j,t}$ are also controlled. Finally, analyst i's forecast accuracy for firm j ($ACC_{i,j,t}$) and its interaction with $GF_{i,j,t}$ are controlled. $ACC_{i,j,t}$ is based on the same quarterly forecast as the dependent variable in regression (1), that is, $ACC_{i,j,t} = (-1) \times ERROR_{i,j,t}$. Recall that the forecast that $ERROR_{i,j,t}$ is based on is the first quarterly forecast immediately following analyst i's issuance of $GF_{i,j,t}$; thus, $ACC_{i,j,t}$ captures analyst i's ability when issuing the growth forecast for firm j. The manager of firm j likely relies more on analyst i's growth forecast because of the perception that analyst i is more able (after a series of successful predictions) rather than more overconfident; $GF \times ACC$ is included to control this factor. The result shows that the coefficient on $GF \times ACC$ is significantly positive. However, the coefficients on $GF \times Overconfidence$ continue to be positively significant, suggesting that the effect of overconfidence on investment-*GF* sensitivity is not the result of these control variables.

A placebo test is conducted to reinforce confidence in the baseline result. Specifically, in regression (2), analyst i's growth forecast for firm j in year t (i.e., $GF_{i,j,t}$) is replaced with another analyst's (called k, and $k \neq i$) forecast for firm j in year t (denoted as $GF_{k,j,t}$). If more than one $GF_{k,j,t}$ exists, the one closest to the issue date of $GF_{i,j,t}$ is selected. Hence, in this placebo test, $GF_{i,j,t}$ is purposely mismatched with $Overconfidence_{i,j,t}$; that is, analyst k, who issues $GF_{k,j,t}$ is not actually overconfident but rather assigned to be overconfident. The coefficient on $GF_{k,j,t} \times Overconfidence_{i,j,t}$ is expected to be *insignificant* if, as was assume, the baseline result reflects the effect of overconfidence on investment-*GF* sensitivity.

In Table 3, the result of the placebo test is reported under the column headed "*placebo test.*" Consistent with our expectation, we find the coefficient on $GF_{k,j,t} \times Overconfidence_{i,j,t}$ is insignificant under both proxies of overconfidence, which reinforces the interpretation from the baseline result; the reason investments are more sensitive to analyst *i*'s growth forecast is that analyst *i* becomes more overconfident.

Furthermore, the coefficient on $GF_{k,j,t}$ is significantly positive in the result of the placebo test, suggesting that even after controlling for firm fundamentals (*CF*), mispricing (*FRET*), and information incorporated into stock prices (*Q*), corporate investments respond positively to growth forecasts from analysts. Therefore, even in the presence of stock prices that incorporate the information in these forecasts, managers learn directly from analysts' growth forecasts, which is plausible because the information set possessed by managers is different from that of investors. Accordingly, managers and investors use analysts' information differently. For example, analysts' information that is useless to investors (hence, not incorporated into stock prices) could be of potential use to managers.

This argument also suggests that because stock prices reflect the combined information of analysts and investors, even after directly observing analysts' growth forecasts, managers can still learn indirectly from stock prices that incorporate these forecasts. Furthermore, analysts issue predictions in forms other than growth forecasts, such as price forecasts, stock recommendations, and short-term earnings forecasts. When examined individually, these predictions may not have a significant impact on corporate investments. However, the collective information contained in these predictions could significantly influence corporate investments, and stock prices comprehensively capture the collective information from analysts' various predictions. Both arguments suggest that through stock prices, managers could indirectly learn from analysts' information. Therefore, in the next section, the effect of analyst overconfidence on investment-*Q* sensitivity is examined.

3.3 Effect of analyst overconfidence on investment-Q sensitivity

This section examines whether analyst overconfidence affects the sensitivity of corporate investments to stock prices (i.e., investment-*Q* sensitivity). A well-documented result is that corporate investments respond positively to stock prices. One interpretation of this result is that stock prices incorporate information from various sources collected by traders, some of which might be unknown to firm managers. Hence, firm managers can learn from stock prices (e.g., Chen et al., 2007). Because analysts are one of the most important information sources for investors, stock prices naturally incorporate analysts' information. As discussed at the end of Section 3.2, in addition to learning directly from analysts' growth forecasts, managers might also indirectly learn from analysts through stock prices, because stock prices (a) comprehensively incorporate analysts' information released in all forms of predictions and (b) combine analysts' information with investors' information. Therefore, the positive investment-*Q* sensitivity might partially be the result of managers learning from analysts' information that is impounded into stock prices. If this is the case and if overconfidence increases an analyst's reliance on private information that is unknown to the firm manager, overconfidence is expected to have a positive effect on investment-*Q* sensitivity.

This expectation is tested using the same regression (2), except that the interactions of *Q* with analyst overconfidence (i.e., $Q_{i,j,t} \times Overconfidence_{i,j,t}$) and with other control variables (i.e., $Q_{i,j,t} \times Controls_{i,j,t}$) are included in the regression. Two sets of results are reported in Table 4, shown in the columns headed "*only Q*" and "*Q and GF*," respectively. For the results of "*only Q*," *GF* or its interaction with *Overconfidence* is not included in the regression. The coefficient on *Q*

× *Overconfidence* is significantly positive, suggesting that overconfidence has a positive effect on investment-Q sensitivity. For the results of "*Q* and *GF*," *GF* and its interactions with *Overconfidence* and other control variables are added to the regression. The significantly positive coefficients on both *Q* × *Overconfidence* and *GF* × *Overconfidence* suggest that overconfidence has a positive effect on both investment-*GF* and investment-*Q* sensitivities.

Overall, these results provide further supporting evidence for the hypothesis that analysts' overconfidence enhances the usefulness of their information for firm managers. Moreover, these results suggest that managers learn from analysts through two channels: (a) directly from analysts' outputs and (b) indirectly from stock prices that incorporate the information in analyst' outputs.

3.4 Effect of analyst overconfidence on investment-Q sensitivity in a firm-year panel

The results in Sections 3.1–3.3 are based on a sample of analyst-firm-year observations with the control of the analyst-firm fixed effect. This section examines the average overconfidence of all analysts covering a firm and how this average overconfidence affects investment-*Q* sensitivity in a sample of firm-year observations. This test is motivated by the following. First, Chen et al. (2007) find that in a panel of firm-year observations, analyst coverage (i.e., the number of analysts covering a firm) negatively affects investment-*Q* sensitivity. Their result can be interpreted as analysts largely transferring information from managers to investors, which seems to contrast the results inferring that managers learn from analysts. Second, although it is interesting to investigate the time-series effect of dynamic overconfidence in a given analyst for forecasting a given firm, it is also interesting to observe how the average overconfidence of analysts covering a firm affects corporate investments across firms and across time. Third, this test does not rely on analysts' growth forecasts, the availability of which rendered a small sample size in previous tests. Fourth, the test specification is different and serves as a robustness check of previous results.

Specifically, the effect that the average overconfidence of analysts covering a firm has on investment-Q sensitivity is tested using the following regression (3):

$$I_{j,t+1} = \alpha_0 + \beta_1 Q_{j,t} + \beta_2 Q_{j,t} \times AvOverconfidence_{j,t} + \beta_3\, AvOverconfidence_{j,t} + \beta_4 Q_{j,t} \times Coverage_{j,t} + \beta_5\, Coverage_{j,t} + \beta_6 Q_{j,t} \times AvEXP_{j,t} + \beta_7\, AvEXP_{j,t} + \gamma_1 CF_{j,t} + \gamma_2 FRET_{j,t} + \epsilon_{i,j,t+1} \quad (3)$$

The dependent variable $I_{j,t+1}$ denotes the investment of firm j in year $t + 1$. $Q_{j,t}$ denotes Tobin's Q of firm j at the end of year t; $CF_{j,t}$ denotes the cash flow of firm j in year t; and $FRET_{j,t}$ denotes the future market-adjusted stock return of firm j during the three years after investment in year t. The definitions for these variables are identical to those in regression (2). $AvOverconfidence_{j,t}$ denotes average analyst overconfidence, calculated as the average of available $FREQ_{i,j,t}$ or $STREAK_{i,j,t}$ across all analysts covering firm j in year t. In turn, $FREQ_{i,j,t}$ ($STREAK_{i,j,t}$) is calculated as the number of (consecutive) superior quarterly forecasts issued by analyst i for firm j in the preceding four quarters before the end of year t. $Coverage_{j,t}$ denotes analyst coverage for firm j in year t, calculated as the number of analysts issuing at least one quarterly forecast for firm j in year t. $AvEXP_{j,t}$ denotes average experience, calculated as the average $EXP_{i,j,t}$ across all analysts covering firm j in year t. $EXP_{i,j,t}$ is calculated as the total number of quarterly forecasts issued by analyst i for firm j by the end of year t. $Q_{j,t} \times AvOverconfidence_{j,t}$, $Q_{j,t} \times Coverage_{j,t}$, and $Q_{j,t} \times AvEXP_{j,t}$ are the interactions of Q with these three variables, respectively.

Two regression methods are used: pooled regression with both firm-fixed and year-fixed effects, and Fama–MacBeth regression. The pooled regression captures both cross-firm and within-firm effects, whereas the Fama–MacBeth regression captures only cross-firm effects. Following Chen et al. (2007), test statistics are calculated using standard errors clustered by firm in the pooled regression. Test statistics in the Fama–MacBeth regression are calculated using standard errors adjusted for heteroscedasticity and autocorrelations.

The results from the pooled and Fama–MacBeth regressions are reported in Table 5, and they are qualitatively similar. For each regression, we report two sets of results: with and without controlling the effect of the average analyst experience. When the effect of the analyst experience is not considered, the coefficient on $Q \times Coverage$ is found to be significantly negative, which is consistent with the result in Chen et al. (2007). However, after controlling for the effect of the analyst experience, the coefficient on $Q \times Coverage$ becomes insignificant, and the coefficient on $Q \times AvEXP$ is significantly negative. These results suggest that the negative effect of analyst coverage on investment-Q sensitivity can be mainly attributed to the average experience of analysts covering the firm: the more experienced the analyst is, the less sensitive the corporate investments are to stock prices. One potential reason for this result is that through a longer period of relationship cultivation, more experienced analysts have better relationships with firm managers. Hence, they are more likely to rely on firm managers for information (rather than independent research); in turn, these analysts' information is less useful to firm managers.

More important to this study, the coefficient on $Q \times AvOverconfidence$ is found to be significantly positive, regardless of whether the effect of the average analyst experience is considered. This result suggests that investments become more sensitive to stock prices as the average confidence of analysts increases. This suggestion is consistent with the hypothesis that as analysts' overconfidence increases, their information becomes more useful to managers. These results also suggest that the effect of analyst coverage on investment-Q sensitivity depends on the characteristics of the analysts covering the firm; whereas overconfidence heightens the sensitivity, experience weakens it.

4. Conclusion

This study finds evidence that suggests that analyst overconfidence has a positive effect on the usefulness of their information to firm managers. Specifically, within a given analyst firm, as an analyst's overconfidence increases, corporate investments become more sensitive to the analyst's growth forecast and the firm's stock price. Moreover, across firms (and across time), as the average overconfidence of analysts covering a firm increases, corporate investments become more sensitive to stock prices.

The implications are twofold and related. First, when viewed from the perspective of firm managers, analysts' overconfidence has a bright side. Second, evaluating the usefulness of analysts' information needs to account for how managers put the information to use to make real decisions.

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Table 1: Summary statistics

This table shows the summary statistics of the variables in the two different samples used in this study. The first sample (in Panel A) comprises analyst-firm-year observations based on the last growth forecast issued by an individual analyst between July and December of each year. This sample is used in the empirical analyses of Tables 2–4. The second sample (in Panel B) comprises firm-year observations that do not involve analysts' growth forecasts. This sample is used in the empirical analysis of Table 5.

The variables in the first sample are defined as follows. *GF* is an individual analyst's long−term growth rate forecast (in percentage). *FREQ* (*STREAK*) is the number of (consecutive) superior quarterly forecasts issued by an analyst for a given firm in the preceding four quarters before the issuance of a growth forecast for this firm. A superior forecast is one in which the error is less than the median error for all analysts covering the same firm in that particular quarter. *EXP* denotes analyst experience, measured as the number of quarterly forecasts issued by an analyst for a given firm before the analyst issues a growth forecast for this firm. *Days* is calculated as the number of days between the issue date of an analyst's growth forecast and the year−end (i.e., December 31). *I* is a firm's investment in the following year, after an analyst issues the growth forecast for this firm. *I* is calculated as capital expenditures (Compustat annual item CAPX), plus R&D (item XRD, 0 if missing), scaled by beginning−year assets (item AT); *Q* is Tobin's *Q* of a firm at the end of the year in which an analyst issues a growth forecast for this firm; *Q* is calculated as the market value of equity (item PRCC_F multiplied by item CSHO), plus the book value of assets (item AT), minus the book value of equity (item CEQ), scaled by the book value of assets (item AT). *CF* is the cash flow of a firm in the year during which an analyst issues a growth forecast for the firm. *CF* is calculated as net income before extraordinary items (item IB), plus depreciation and amortization expenses (item DP), plus R&D expenses (item XRD, 0 if missing), scaled by beginning−of−year assets (item AT). *FRE*T denotes future stock returns measured as the adjusted stock returns for a firm during the three years following an investment, and the adjustment is based on value−weighted market returns. *DEV* and *ERROR* denote deviations from the consensus forecast and forecast error, respectively; both are based on the first quarterly forecast issued by an analyst for a given firm, following the issuance of a growth forecast for this firm. *DEV* is calculated as the absolute value of the difference between an analyst's forecast and the median forecast of all analysts covering the same firm for the same quarter, scaled by stock price. *ERROR* is calculated as the absolute value of the difference between an analyst's forecast and the corresponding actual earnings−per−share, scaled by stock price. *DEV* and *ERROR* are multiplied by 100.

In the second sample, the variables are defined as follows. *AvFREQ* (*AvSTREAK*) is the average *FREQ* (*STREAK*) of all analysts covering a firm in the year before the firm's investment; *FREQ* (*STREAK*) is calculated as the number of (consecutive) superior quarterly forecasts issued by an analyst in the four quarters before year−end. *AvExp* is the average *EXP* of all analysts covering a firm in the year before the firm's investment; *EXP* is calculated as the number of all preceding quarterly forecasts issued by an analyst before year−end. *Coverage* denotes analyst coverage, calculated as the number of analysts who had issued at least one quarterly forecast for a firm in the year before the firm's investment. The definitions of the other variables are the same as those in Panel A.

Table 1 Continued

Panel A: Analyst-firm-year observations						
	Number	*Mean*	*Std. Dev*	*P25th*	*P50th*	*P75th*
GF	28305	13.94	31.05	8.00	12.00	18.00
FREQ	28305	1.47	1.04	1.00	1.00	2.00
STREAK	28305	0.50	0.79	0.00	0.00	1.00
EXP	28305	14.47	10.18	7.00	12.00	19.00
Days	28305	80.70	49.84	46.00	67.00	125.00
I	28305	9.35	9.01	3.28	7.15	12.67
Q	28305	2.04	1.43	1.18	1.57	2.31
CF	28305	0.14	0.11	0.07	0.12	0.19
FRET	28305	0.05	0.75	−0.36	−0.02	0.33
ERROR	26750	0.31	0.74	0.30	0.12	0.04
DEV	26547	0.11	0.21	0.00	0.04	0.11

Panel B: Firm-year observations						
	Number	*Mean*	*Std. Dev*	*P25th*	*P50th*	*P75th*
AvFREQ	35382	1.48	0.48	1.20	1.51	1.79
AvSTREAK	35382	0.50	0.34	0.29	0.50	0.67
AvEXP	35382	8.77	6.12	4.00	7.00	12.00
Coverage	35382	11.50	5.69	7.00	10.45	15.00
I	35382	0.10	0.12	0.02	0.06	0.13
Q	35382	1.92	1.48	1.11	1.44	2.13
CF	35382	0.11	0.13	0.04	0.10	0.17
FRET	35382	0.03	0.88	−0.45	−0.07	0.33

Table 2: Effect of analyst overconfidence on forecast error and deviation from consensus

This table reports the results of the following regression in a sample of analyst-firm-year observations (as described in Table 1): $DEV_{i,j,t}\left(ERROR_{i,j,t}\right) = \alpha + \beta Overconfidence_{i,j,t} + \varepsilon_{i,j,t}$. The dependent variable is either the deviation from the consensus forecast ($DEV_{i,j,t}$) or the forecast error ($ERROR_{i,j,t}$). It is based on analyst *i*'s first quarterly forecast for firm *j* after the issuance of a growth forecast for firm *j* in year *t*. $Overconfidence_{i,j,t}$ denotes analyst *i*'s overconfidence in making forecasts for firm *j* in year *t*, which is proxied by $FREQ_{i,j,t}$ and $STREAK_{i,j,t}$. The detailed definitions of these variables are in Table 1. An analyst-firm fixed effect is controlled, and test statistics (in parentheses) are calculated using standard errors clustered by year.

Overconfidence proxied by:	*FREQ*		*STREAK*	
	DEV	*ERROR*	*DEV*	*ERROR*
Intercept	0.00	2.01	0.00	2.01
	(0.00)	(3.81)	(0.00)	(3.80)
Overconfidence	0.57	0.97	0.26	−0.22
	(3.84)	(4.44)	(2.00)	(−0.49)

Table 3: Effect of analyst overconfidence on investment-*GF* sensitivity

This table reports the results of the following regression in a sample of analyst-firm-year observations (as described in Table 1): $I_{i,j,t+1} = a + b_1 GF_{i,j,t} + b_2 GF_{i,j,t} \times Overconfidence_{i,j,t} + b_3 Overconfidence_{i,j,t} + c_1 Q_{i,j,t} + c_2 CF_{i,j,t} + c_3 FRET_{i,j,t} + d_k GF_{i,j,t} \times Controls^k_{i,j,t} + e_k Controls^k_{i,j,t} + \epsilon_{i,j,t+1}$. $GF_{i,j,t}$ is the last growth forecast issued by analyst *i* for firm *j* in year *t*. $Overconfidence_{i,j,t}$ (proxied by $FREQ_{i,j,t}$ and $STREAK_{i,j,t.}$) denotes the overconfidence of analyst *i* immediately before the issuance of $GF_{i,j,t}$. $GF_{i,j,t} \times Overconfidence_{i,j,t}$ is the interaction of these two variables. $I_{i,j,t+1}$ is the investment of firm *j* in year *t* + 1. $Q_{i,j,t}$ is Tobin's Q of firm *j* at the end of year *t*. $CF_{i,j,t}$ is the cash flow of firm *j* in year *t*. *FRET* is the future stock return of firm *j*, measured during the three years following an investment (i.e., from *t* + 2 to *t* + 4). *Controls* include $EXP_{i,j,t}$ (analyst *i*'s experience in forecasting firm *j* before the issuance of $GF_{i,j,t}$), $ACC_{i,j,t}$ (the accuracy of analyst *i*'s first quarterly forecast for firm *j* after the issuance of $GF_{i,j,t}$), and $Days_{i,j,t}$ (the number of days between the issue date of $GF_{i,j,t}$ and year–end). Also included are the interactions of these control variables with $GF_{i,j,t}$. In the column headed "*placebo test*," $GF_{i,j,t}$ is replaced with the growth forecast issued by another analyst (e.g., analyst *k*) for firm *j* in year *t*, denoted as $GF_{k,j,t.}$ Analyst *k*'s growth forecast interacts with analyst *i*'s overconfidence, that is, the interaction *GF* × *Overconfidence* is $GF_{k,j,t}$ multiplies $Overconfidence_{i,j,t}$. The detailed definitions of these variables are in Table 1. An analyst-firm fixed effect is controlled and test statistics (in parentheses) are calculated based on standard errors clustered by year.

Table 3 Continued

Overconfidence proxied by:		*FREQ*			*STREAK*	
	baseline result	*additional controls*	*placebo test*	*baseline result*	*additional controls*	*placebo test*
Intercept	0.00	0.00	0.00	0.00	0.00	0.00
	(0.02)	(0.04)	(0.01)	(0.02)	(0.05)	(0.01)
GF	−0.05	0.59	0.72	0.12	0.66	0.51
	(−1.05)	(1.68)	(2.37)	(1.48)	(1.84)	(2.52)
GF × Overconfidence	0.34	0.39	−0.17	0.26	0.31	−0.12
	(3.10)	(3.09)	(−1.18)	(1.91)	(2.15)	(−1.48)
Overconfidence	−0.04	−0.04	0.03	0.06	0.05	0.10
	(−1.33)	(−1.18)	(0.83)	(1.65)	(1.40)	(2.61)
Q	1.23	1.22	1.13	1.23	1.22	1.13
	(9.50)	(9.37)	(9.00)	(9.54)	(9.41)	(8.98)
CF	6.88	6.02	7.61	6.90	6.06	7.61
	(4.30)	(3.83)	(4.65)	(4.31)	(3.85)	(4.65)
FRET	−0.27	−0.30	−0.27	−0.27	−0.30	−0.27
	(−3.17)	(−3.46)	(−3.00)	(−3.18)	(−3.46)	(−3.00)
GF × EXP		−0.01			−0.01	
		(−0.53)			(−0.52)	
EXP		−0.07			−0.07	
		(−10.55)			(−10.91)	
GF × ACC		0.32			0.23	
		(4.41)			(2.95)	
ACC		0.03			0.04	
		(0.47)			(0.63)	
GF × Days		−0.01			−0.00	
		(−1.94)			(−1.72)	
Days		0.00			0.00	
		(0.52)			(0.41)	

Table 4: Effect of analyst overconfidence on investment-*Q* sensitivity

This table reports the results of a regression that is similar to that used in Table 2, except that interaction of *Q* with *Overconfidence* (i.e., *Q* × *Overconfidence*) and other control variables are included as explanatory variables in the regression. In the column headed "*only Q*," the growth forecast (i.e., *GF*) or its interaction with *Overconfidence* is not included as an explanatory variable. In the column headed "*Q* and *GF*," both *Q* and *GF* and their interactions with *Overconfidence* (and with other control variables) are included as explanatory variables in the regression.

Overconfidence proxied by:	*FREQ*		*STREAK*	
	only Q	*Q and GF*	*only Q*	*Q and CF*
Intercept	0.01	0.01	0.01	0.01
	(0.09)	(0.08)	(0.09)	(0.08)
Q	1.30	1.30	1.35	1.34
	(7.42)	(7.38)	(8.50)	(8.40)
GF		0.52		0.53
		(1.60)		(1.65)
Q × *Overconfidence*	0.07	0.06	0.08	0.08
	(2.24)	(1.94)	(2.13)	(2.01)
GF × *Overconfidence*		0.38		0.32
		(3.05)		(3.05)
Overconfidence	−0.12	−0.15	−0.06	−0.08
	(−1.87)	(−2.21)	(−0.83)	(−1.02)
Q × *EXP*	−0.01	−0.01	−0.01	−0.01
	(−2.24)	(−2.27)	(−2.21)	(−2.24)
GF × *EXP*		−0.00		−0.00
		(−0.10)		(−0.11)
EXP	−0.04	−0.04	−0.04	−0.04
	(−4.01)	(−3.83)	(−4.07)	(−3.89)

Q× ACC	−13.70	−16.62	−13.58	−16.29
	(−2.51)	(−3.10)	(−2.51)	(−3.05)
GF × ACC		44.09		42.09
		(5.24)		(4.83)
ACC	20.19	19.28	20.16	19.42
	(2.73)	(2.64)	(2.73)	(2.66)
GF × Days		−0.01		−0.01
		(−1.88)		(−1.84)
Days		0.00		0.00
		(0.58)		(0.56)
CF	6.29	6.20	6.28	6.21
	(3.92)	(3.89)	(3.92)	(3.89)
FRET	−0.32	−0.32	−0.32	−0.32
	(−3.51)	(−3.51)	(−3.52)	(−3.54)

Table 5: Effect of *average* analyst overconfidence on investment-*Q* sensitivity

This table reports the results of the following regression in a sample of firm-year observations: $I_{j,t+1} = \alpha_0 + \beta_1 Q_{j,t} + \beta_2 Q_{j,t} \times AvOverconfidence_{j,t} + \beta_3\, AvOverconfidence_{j,t} + \beta_4 Q_{j,t} \times Coverage_{j,t} + \beta_5\, Coverage_{j,t} + \beta_6 Q_{j,t} \times AvEXP_{j,t} + \beta_7\, AvEXP_{j,t} + \gamma_1 CF_{j,t} + \gamma_2 FRET_{j,t} + \epsilon_{i,j,t+1}$. $I_{j,t}$ is the investment of firm *j* in year t + 1. $AvOverconfidence_{j,t}$ is the average overconfidence of all analysts covering firm *j* at the end of year *t*, which is proxied by the average of *FREQ* or *STREAK* (i.e., *AvFREQ* or *AvSTREAK* described in Table 1). $Coverage_{j,t}$ is the number of analysts covering firm *j* in year *t*. $AvEXP_{j,t}$ is the average experience of all analysts covering firm *j* in year *t*. These three variables interact with $Q_{j,t}$. $CF_{j,t}$ is the cash flow of firm *j* in year *t*, and $FRET_{j,t}$ is the future stock returns for firm *j* in the three years following an investment. The detailed definitions of these variables are in Table 1. In the column headed "*pooled regression*," pooled regression is used with the control of both firm-fixed and year-fixed effects, and test statistics are calculated using standard errors clustered by firm. In the column headed "*Fama-MacBeth regression,*" the Fama-MacBeth regression is used; test statistics are calculated using standard errors adjusted for heteroskedasticity and autocorrelations.

Table 5 Continued

	pooled regression				Fama-MacBeth regression			
AvOverconfidenced proxied by:	*AvFREQ*		*AvSTREAK*		*AvFREQ*		*AvSTREAK*	
Intercept	−1.08	−0.29	−1.07	−0.28	2.92	2.11	2.13	1.46
	(−7.77)	(−1.96)	(−7.72)	(−1.90)	(6.01)	(2.32)	(5.08)	(1.73)
Q	1.29	1.42	1.63	1.79	1.53	3.02	2.51	3.95
	(5.86)	(6.17)	(9.23)	(9.12)	(3.56)	(4.94)	(5.97)	(7.12)
Q × *AvOverconfidence*	0.43	0.49	0.50	0.57	1.06	0.99	0.69	0.70
	(3.12)	(3.64)	(2.62)	(3.04)	(5.57)	(4.62)	(3.16)	(3.01)
AvOverconfidence	−1.00	−1.02	−0.86	−0.93	−0.99	−0.75	−0.67	−0.57
	(−3.71)	(−3.93)	(−2.51)	(−2.78)	(−3.59)	(−2.39)	(−1.83)	(−1.47)
Q × *Coverage*	−0.03	−0.01	−0.03	−0.01	−0.08	0.01	−0.07	0.00
	(−2.42)	(−0.79)	(−2.39)	(−0.82)	(−4.04)	(0.24)	(−3.67)	(0.19)
Coverage	−0.13	−0.13	−0.13	−0.13	0.15	0.10	0.14	0.11
	(−4.32)	(−3.83)	(−4.52)	(−3.95)	(5.22)	(2.23)	(4.78)	(2.72)
Q × *AvEXP*		−0.05		−0.04		−0.28		−0.28
		(−3.10)		(−2.86)		(−3.62)		(−3.63)
AvEXP		−0.04		−0.05		0.20		0.21
		(−1.50)		(−1.82)		(1.47)		(1.50)
CF	7.19	7.10	7.21	7.09	21.87	23.08	21.67	22.86
	(8.24)	(8.22)	(8.24)	(8.17)	(5.37)	(5.92)	(5.25)	(5.78)
FRET	−0.20	−0.23	−0.20	−0.24	−0.62	−0.59	−0.63	−0.59
	(−2.76)	(−3.21)	(−2.81)	(−3.25)	(−3.23)	(−3.27)	(−3.22)	(−3.24)