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Two essays on information ambiguity and informed traders' trade-size choice

Ziwei Xu
University of South Florida

Two Essays on

Information Ambiguity and Informed Traders' Trade-Size Choice

by

Ziwei Xu

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Department of Finance
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Major Professor: Christos Pantzalis, Ph.D.
Delroy Hunter, Ph.D.
Jianping Qi, Ph.D.
Ninon Sutton, Ph.D.

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ABSTRACT

Defining ambiguity as investor's uncertainty about the precision of the observed information, Chapter One constructs an empirical measure of ambiguity based on analysts' earnings forecast information, and finds that the market tends to react more negatively to highly ambiguous bad news, while it tends to be less responsive to highly ambiguous good news. This result supports the theoretical argument of Epstein and Schneider (2003, 2008) that ambiguity-averse investors take a worst-case assessment of the information precision, when they are uncertain about the information precision. In addition, Chapter One shows that returns on stocks exposed to highly ambiguous and intangible information are more negatively skewed.

Chapter Two finds that certain traders are informed about either the forthcoming analysts' forecasts or long-term value of the stock, and informed traders prefer to use medium-size trades to exploit their private information advantage. Specifically, medium-size trade imbalance prior to the forecast announcements is positively correlated with the nature of forecast revisions, while in the days immediately after the forecasts medium-size trade imbalance is positively correlated with future stock returns for up to four months. Small-size trade imbalance is also positively correlated with future returns but only following downward revisions. In contrast, it is also shown that large trades placed right after the forecasts are unprofitable and generate slightly negative profits in the long run. Overall, our results are consistent with the "stealth trading hypothesis" proposed by Barclay and Warner (1993).

Chapter 1
Market Response to Ambiguous Good and Bad News

1.1 Introduction

This paper examines whether in the presence of information ambiguity investors react differently to firm-specific good and bad news. Following Epstein and Schneider (2008), this study defines information ambiguity as investor's uncertainty about the precision of observed information. Mathematically, suppose that investors want to estimate a parameter θ , and what they can observe is a signal s , which equals to:

$$s = \theta + \varepsilon, \varepsilon \sim N(0, \sigma_s^2), \sigma_s^2 \in \left[\underline{\sigma}_s^2, \overline{\sigma}_s^2 \right] \qquad (1)$$

Here, ε is the noise in the signal s , and information precision (IP) is measured by the inverse of the standard deviation of the noises $1/\sigma_s^2$, whereas information ambiguity (IA) is captured by the range of possible information precisions $[1/\underline{\sigma}_s^2, 1/\overline{\sigma}_s^2]$.

Prior studies have found that the market tends to be more responsive to news with high levels of IP. In particular, several empirical studies focusing on analysts' forecasts have shown that the magnitude of investors' responses to forecast revisions increases with the expected accuracy of the forecasts (see Stickel (1992), Park and Stice (2000), and Clement and Tse (2003)). On the other hand, Epstein and Schneider (2003, 2008) have shown, theoretically, that

IA also matters in terms of the market response to news. Inspired by the experimental evidence that is typified by the Ellsberg Paradox, they argue that an ambiguity-averse agent behaves as if he maximizes expected utility under a worst-case scenario. Since when observing a bad (good) signal with uncertainty about its precision, the worst-case scenario is that the signal is precise (imprecise), agents are expected to take ambiguous bad news seriously and ignore ambiguous good news. As a result, upon the arrival of ambiguous information, the market is expected to react more strongly to bad news than to good news.

To date, there is little empirical evidence documenting the effect of IA on market reactions to firm-specific news and whether the reactions to good and bad news are asymmetric as suggested by the theory. One of the challenging obstacles to testing IA effects on market reaction to corporate news is to empirically measure the level of IA. This study fills the gap in the literature and is the first to provide a measure of IA and show evidence in support of the theoretical arguments of Epstain and Schneider (2003, 2008). Similar to prior studies, this paper focuses on analysts' earnings forecasts as the source of firm-specific news. There are several advantages of doing so. First, analyst forecasts are ambiguous information. Unlike actual earnings which are required to be accurate by law, the market is usually not sure about the precision of earnings forecasts. Second, the forecasts are quantitative information, which enables us to quantitatively measure IA. While using other ambiguous information sources, such as the news from the press that offer qualitative assessments of the firms, make it not only hard to determine the ambiguity level of these news but also difficult to classify them into good and bad news, analyst forecast revisions can be readily sorted into good- or bad- news groups based on their signs.

This paper constructs a measure of IA that is specific to each analyst forecast and based on the forecast history of the analyst following a particular firm. To measure IA in a manner that is consistent with our definition, we first estimate a model that predicts the IP (measured by the historical absolute forecast errors) of each forecast. If investors observe that it is hard to predict the IP of a certain analyst's forecast based on the historical accuracy and other ex ante information, then by definition, they should perceive the forecast by this analyst as highly ambiguous information. Therefore, we measure IA for each analyst-firm pair as the amount of historical variations in the portion of actual IPs of this analyst-firm pair that is left unexplained by a predictive model of IP, i.e., the variations in the unpredictable portion of the actual IPs.

Based on the tests utilizing the above mentioned IA measure, this paper finds evidence largely supporting the theoretical predictions of Epstein and Schneider (2003, 2008). In particular, we find that, among downward forecast revisions (i.e. bad news), highly ambiguous forecasts are associated with more negative market responses during the forecast announcement period. Meanwhile, among upward forecast revisions that are also higher than the historical trend (i.e. good news), highly ambiguous forecasts are associated with a less positive market response. Overall, the results suggest that the market is taking ambiguous bad news more seriously than ambiguous good news. Consistent with prior studies (Stickel (1992), Park and Stice (2000), and Clement and Tse (2003)) that focus on the effect of IP, we also find that the market chooses to ignore the forecasts with high expected forecast errors, regardless of whether the news is good or bad.

A corollary of the asymmetric response to highly ambiguous good and bad news found above, is that stocks with high level of IA should be associated with more negatively skewed stock returns. Therefore, we further test if the IA measure aggregated at firm-level can explain cross-sectional variations in stock return skewness. This test also serves the purpose of validating whether the IA measure estimated based on analysts' forecast information can be used as a general proxy for the average ambiguity level of various types of information about a firm during a certain time period. Epstein and Schneider (2008) argue that the arrival of tangible signals tend to "correct" the prior reactions to intangible signals, which is assumed to be ambiguous information. It follows that the skewness of stocks' returns during a certain period should also be influenced by the relative arrival rates of tangible and intangible information about the firm during that period. Firms exposed to highly ambiguous information coupled with high relative arrival frequency of intangible information are expected to have more negatively skewed returns. We use the proportion of intangible assets (plus good-wills) as a proxy for the relative arrival rates of tangible and intangible information for the firm. Consistent with the theory, we find that stocks with high level of IA *and* intangible assets have more negatively skewed returns.

This study makes several contributions to the literature. First, this paper constructs a novel measure of IA and, to our knowledge, is the first to provide empirical support for the theory of Epstein and Schneider (2003, 2008). Second, this paper adds a new dimension in explaining market response to analyst forecasts. Prior studies (see Park and Stice (2000), Clement and Tse (2003), among others) focus on the effect of expected forecast errors (or expected IP), while our study suggests that the market response is also influenced by expected IA. Third, this study also contributes to the existing literature that documents an asymmetric market response to the firm-specific good and bad news. Xu (2007) studies market reaction to actual earnings announcements and finds that stock prices display a stronger reaction to positive than to negative earnings surprises of equal magnitudes, which induces, on average, a positive market response during the earnings announcement period. He suggests that the asymmetric market response is due to short sale constraints suppressing pessimistic investors from expressing their views. Our findings also show that the average market response during the analyst forecast announcement period is positive, but becomes less positive when the forecasts are more ambiguous. Finally, we find that, in addition to the factors suggested by Xu (2007), IA is an important determinant of stock return skewness.

The reminder of the paper is organized as follows. In Section II, we introduce our IA measure. Section III contains the performance of the model predicting the forecast errors and our main results on how market response to news with differing level of IA. In Section IV, we present the results of the IA effect on stock return skewness. Section V concludes the paper.

1.2 Existing Literature and Hypotheses

A large body of literature studying analyst earnings forecasts has shown that the magnitude of market reaction to forecast announcement increases with the expected accuracy (IP) of the forecasts or analyst characteristics that is positively related to forecast accuracy. For example, Stickel (1992) finds that All American Analysts selected by Institutional Investors supply more accurate forecasts than other analysts, and their forecast announcements have greater price impact, especially following large upward forecast revisions. Similarly, Park and Stice (2000) show that for analysts with superior tracking record, i.e., a history of providing accurate forecasts, their forecast revisions are associated with stronger market reaction. Finally, Clement and Tse (2003) construct a predictive model for forecast accuracy based on various analyst and forecast characteristics, and find that the price response coefficient increases with the predicted accuracy estimated from the model. It is also shown that although all of the characteristics in the model are correlated with future forecast accuracy investors are only responsive to a subset of the characteristics, suggesting that investors fail to extract all the information that has predictive power for forecast accuracy.

On the other hand, little is known on how the market responds to forecasts whose accuracy is unknown, i.e., highly ambiguous (high-IA) forecasts.

Theoretically, Epstein and Schneider (2003, 2008) argue that an ambiguity-averse agent behaves as if he maximizes expected utility under a worst-case scenario, which is consistent with the experimental evidence typified by Ellsberg Paradox[1]. Since when observing a bad (good) signal with uncertainty about its precision, the worst-case scenario is that the signal is precise (imprecise), agents are expected to take ambiguous bad news seriously and ignore ambiguous good news. Applying this prediction to analysts' forecasts, it follows that:

Hypothesis (1): Among the high-IA forecasts, the market reacts more strongly to downward revisions than to upward revisions.

Empirically, a more general test is to examine how market reactions vary across forecasts with different levels of IA. This study predicts that this relation depends on the nature of the news. In particular, among bad-news (downward-revision) forecasts, the market responds more negatively to high-IA forecasts than to low-IA forecasts, whereas among good-news (upward-revision) forecasts, the market responds less positively to high-IA forecasts than to low-IA forecasts. This prediction can be inferred from prior findings of an IP effect on forecast announcement and Hypothesis (1) above. To illustrate this, here is a numerical example (see Figure 2). Assume that there are two types of forecast revisions: low-precision revisions (LPRs) and high-precision revisions (HPRs). The arrival rate of each type of revisions is 50%. Based on prior studies' findings that the market responds more strongly to news of higher expected accuracy, we can also assume that the market reaction is -1% for the downward HPRs, 1% for

[1] See Ellsberg (1961) for details.

upward HPRs, and 0% for LPRs revisions regardless of the direction of the revision. Since the investors can almost always tell which forecasts are LPRs or HPRs it follows that if they are low-IA forecasts, the average reaction to this group should be close to -0.5% for downward revisions and 0.5% for upward revisions. On the other hand, in the case of high-IA forecasts, it is impossible for investors to differentiate HPRs from LPRs. If the investors are ambiguity-averse, they will act assuming the worst-case assessment about the precision, i.e., treat all the downward (upward) revisions as HPRs (LPRs). Consequently, the average reaction to high-IA downward forecasts should be close to -1%, while the average reaction to high-IA upward forecasts should be close to 0%. These predictions can be summarized in the following hypothesis.

Hypothesis (2): Among downward-revision forecasts, on average, the market response more negatively to high-IA forecasts than to low-IA forecasts, whereas among upward-revision forecasts, on average, the market response less positively to high-IA forecasts than to low-IA forecasts.

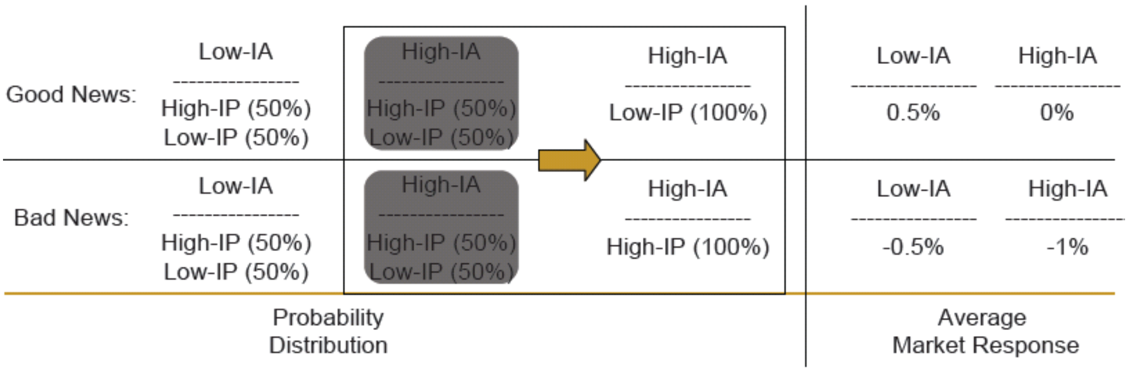

Figure 1.1 Numerical Example

Following Hypothesis (1), it is expected that stocks that are exposed to high-IA news should have more negatively skewed returns. In addition, Epstein and Schneider (2008) argue that the stock return skewness for a firm measured during certain time period is not only determined by the average level of IA for the news announced during the period, but also by the arrival frequency of the ambiguous news relative to the unambiguous news. They show that the arrival of tangible signals (e.g., dividend or earnings announcements), which are assumed to be unambiguous information, tend to "correct" the prior market reactions to intangible signals (e.g., the press articles speculating the firm's prospects), which are assumed to be ambiguous information. So a firm should have more negatively skewed returns during certain period, only if it is exposed to signals with high level of IA *and* relatively more ambiguous signals. The third hypothesis is summarized as following:

Hypothesis (3): Firms exposed to signals with high level of IA and relatively more ambiguous signals are expected to have more negatively skewed returns.

1.3 The Information Ambiguity Measure

To get a measure of IA that is consistent with our definition of IA as the range of possible values of IP, we first need to estimate a model that predicts the IP of each analyst's forecast. One widely used *ex post* measure of analyst forecast IP is the absolute forecast error (FCST_ERR). There is a large body of studies that find associations between FCST_ERR and several *ex ante* forecast and analyst characteristics: forecast timeliness, analyst experience, broker size, and so on (see Mikhail, et al. (1997); Clement (1999); Jacob, et al. (1999) among others). This study incorporates all these formerly identified variables to a prediction model for FCST_ERR. By definition, when the forecast information is highly ambiguous, it should be difficult to get an accurate estimate of the expected information precision, i.e., it is expected that for high-IA analyst forecasts, their predicted IPs should be less accurate than those of low-IA forecasts. Therefore, we can measure IA as the amount of variation in the portion of actual IP left unexplained by the model. In particular, our IA measure for the forecast of certain analyst following certain firm equals to the standard deviation of the historical residuals from the prediction model of the same analyst following the same firm.

The intuition behind the IA measure can be illustrated using a numerical example. Suppose that analyst A1 following firm F1 has a track record of (scaled) FCST_ERRs of 10%, 10%, 10%, 10% and 10% over the past 5 years, while analyst A2 following firm F2 has a track record of FCST_ERRs of 10%, 10%, 0%, 0%, and 10% during the same period. Investors following these analysts should feel quite confident that the FCST_ERR for the forecast issued by analyst A1 this year will still be around 10%. On the other hand, for analyst A2, the expected probability of her issuing a very accurate forecast (FCST_ERR=0%) is similar to the probability of her issuing an inaccurate forecast (FCST_ERR=10%). So the uncertainty about Analyst A2's forecast accuracy (i.e., the information ambiguity, IA) should be much higher than that of Analyst A1. Furthermore, simply using the standard deviation of the historical FCST_ERRs is problematic. Since certain forecast and analyst characteristics can change over time, part of the changes in the FCST_ERRs should be predictable. For example, if an analyst this year makes a forecast later in the fiscal year period, i.e., closer to the actual earnings announcement date, than he did last year, investors should expect this year's forecast to be more accurate. Thus, we calculate IAs as the standard deviations of the residuals from a prediction model for the FCST_ERR that accounts for all the potential changes in various relevant characteristics[2].

Specifically, in a given year *t,* we run the following pooled OLS regression across all analyst-firm pairs for the past *n* years (from year *t-n* to year *t-1*).

$$\begin{aligned} Ln(FCST\_ERR_{ijt}) = {} & \beta_0 + \beta_1 Ln(FCST\_ERR_{ij(t-1)}) + \beta_2 Ln(FCST\_HRZN_{ijt}) + \beta_3 HERD\_DUM_{ijt} \\ & + \beta_4 Ln(DAYS\_ELPS_{ijt}) + \beta_5 Ln(EXPRNCE_{ijt}) + \beta_6 Ln(BROKER\_SIZE_{ij(t-1)}) \\ & + \beta_7 Ln(FCST\_FREQ_{ij(t-1)}) + \beta_8 Ln(COMP\_NUM_{i(t-1)}) + \beta_9 Ln(IND\_NUM_{i(t-1)}) \\ & + \beta_{10} Ln(SIZE_{ijt}) + \beta_{11} M/B_{ijt} + \beta_{12} Ln(BUSSEG\_NUM_{j(t-1)}) + \beta_{13} Ln(VAR\_EPS_{jt}) + \varepsilon_{ijt} \end{aligned} \quad (2)$$

This model is an augmented version of the Clement and Tse (2003) model with additional controls for firm characteristics. We predict that the absolute forecast error for analyst i following firm j during year t ($FCST\_ERR_{ijt}$) should increase with prior absolute forecast error ($FCST\_ERR_{ij(t-1)}$) and forecast horizon (FCST_HRZN). Mikhail, et al. (1997) and Jacob, et al. (1999) find that FCST_ERR decreases as analysts gain more firm-specific experience (EXPRNCE). Clement (1999) and Jacob, et al. (1999) find that analysts from brokerage firms that employ many analysts (BROKER_SIZE) issue forecasts

[2] We do not use the *average* of historical residuals, because rational investors will adjust their forecast by the mean of historical residuals, if the residuals are always maintained at certain level. E.g., if the residuals from the model are always 10% for analyst A1 in the past 5 years, investors should realize that this model always underestimates the FCST_ERR by 10% for analyst A1. So they should feel confident that the FCST_ERR of analyst A1 this year should be somewhere near the predicted value of FCST_ERR from the model plus 10%.

with less FCST_ERRs. Jacob, et al. (1999) document that FCST_ERR decreases with the analysts' forecast frequency during each fiscal year (FCST_FREQ), which is considered to be a proxy of the amount of effort that the analysts apply in analyzing the firm. Jacob, et al. (1999) and Clement (1999) also find that FCST_ERR tends to increase with the, number of companies and industries followed by the analyst (COMP_NUM, IND_NUM), since additional forecasting tasks may reduce the amount of research effort the analyst allocates to each firm being followed. It is also expected that the FCST_ERR is high when the analysts are more likely to be herding (see, for example, DeBond and Forbes (1999)).1F[3] The herding dummy here equals to one when the forecast is *not* the first one among all the analysts following the firm during the fiscal year, and it equals to zero otherwise. It is unlikely for the first forecasters to herd, because no other forecasts have been made for the current fiscal year. We also expect the FCST_ERR to decrease with days elapsed from the most recent forecast (DAYS_ELPS), since there may be more firm-specific information made available to the analysts during the period. The model also controls for other firm characteristics. We predict that the FCST_ERR is higher when the firm is small, has more business segments, and has more volatile earnings. The market-to-book ratio, as a proxy for firm's growth opportunities, is also included, although the predicted coefficient sign of this variable is unclear given existing theories. The detailed definitions of all variables are shown in Table I, Panel A.

[3] Herding is not directly observable, Therefore, studies like Olsen (1996), DeBondt and Forbes (1999) and Kim and Pantzalis (2003) operationalized the definition of herding among security analysts as excessive agreement among analysts that produce estimates with large errors.

Table 1.1
Definitions of Variables

Variables		Definition
Panel A: Variables for the Absolute Forecast Error Model [Model (1)]		
Absolute Forecast Error	$FCST\_ERR_{ijt}$	It is the absolute value of the difference between the forecasted EPS value by analyst i following firm j in year t and the actual EPS value for the corresponding fiscal year, scaled by the stock closing price two days prior to the analyst's forecast announcement.
Days Elapsed	$DAYS\_ELPS_{ijt}$	It is the number of days between the current forecast by analyst i following firm j in year t and the most recent forecast made by any analyst following firm j during the same fiscal year, and it equals to 0 if the current forecast is the first one during the corresponding fiscal year.
Herding Dummy	$HERD\_DUM_{ijt}$	It equals to 0, if the forecast by analyst i is the first one among all the forecasts by the analysts following firm j during the same fiscal year, and it equals to 1 otherwise.
Analyst Experience	$EXPRNCE_{ijt}$	It is the number of years during which analyst i has issued at least one forecast for firm j, as documented by I/B/E/S.
Forecast Horizon	$FCST\_HRZN_{ijt}$	It is the number of days from the current forecast by analyst i following firm j in year t to the corresponding fiscal-year end.
Forecast Frequency	$FCST\_FREQ_{ijt}$	It is the number of forecasts made by analyst i for firm j during the year t.
Broker Size	$BROKER\_SIZE_{ijt}$	It is the number of analysts in year t that are employed by the broker hiring analyst i, as documented by I/B/E/S.
Number of Companies	$COMP\_NUM_{it}$	It is the number of companies followed by analyst i in year t.
Number of Industries	IND_NUM_{it}	It is the number of two-digit SIC industries followed by analyst i in year t.
Firm Size	$SIZE_{ijt}$	It is the market capitalization of firm j two-days prior to analyst i's forecast in year t, scaled by the producer price index of finished goods in the corresponding year-month.
Market-to-book Ratio	M/B_{ijt}	It is the ratio of the market capitalization of firm j two-days prior to analyst i's forecast in year t to the book value of common equity at the end of the fiscal year ending in year t-1.
Earnings Volatility	VAR_EPS_{jt}	It is the sample variance of the annual EPS growth rates of firm j over the past 5 fiscal years. EPS growth rate is calculated as the current EPS less prior-year EPS scaled by the absolute value of prior-year EPS. Here, EPS is the calculated as the operating income before depreciation divided by the number of common shares outstanding at the fiscal-year end.
Number of Business Segments	$BUSSEG\_NUM_{jt}$	It is the number of business segments that the firm j has during the fiscal year ending in year t.
Panel B: Variables for the Market Response Model		
Cummulative Abnormal Return	$CAR3_{ijt}$	It is the three-trading-day cumulative market-adjusted return surrounding analyst i's forecast for firm j in year t. The measurement period starts one trading before the forecast and ends one trading day after the forecast. The market adjusted return is calculated by subtracting the concurrent value-weighted market return from the firm j's daily stock return.

Information Ambiguity (based on *n*-year history)	IAn_{ijt}	To calculate *IAn*, we first run the pooled OLS regression based on Model (1) from year *t-n* to year *t-1*, and then *IAn* is calculated as the sample standard deviation of the regression residuals of analyst i following firm j from year *t-n* to year *t-1.*
Predicted Absolute Forecast Error (based on *n*-year history)	$PRED\_lnERRn_{ijt}$	To calculate *PRED_lnERRn*, we first run the pooled OLS regression based on Model (1) from year *t-n* to year *t-1*, and then *PRED_lnERRn* is calculated as the predicted value of the log of absolute forecast error for analyst i following firm j in year t, based on the coefficients estimated from the prior regression.
Forecast Revision	$FCST\_REV_{ijt}$	It is the forecasted EPS value by analyst i following firm j in year t, less the actual EPS from the last fiscal year, scaled by the stock closing price two days prior to the analyst's forecast announcement.
Adjusted Forecast Revision	$FCST\_REV2_{ijt}$	It is the forecast revision by analyst i following firm j in year t, less the historical average of forecast revisions by analyst i following firm j during the period from year t-3 to year t-1.
Panel C: Variables for the Stock Skewness Model		
Stock Skewness	$SKEW_{jt}$	It is the third-order standardized moment of daily log returns for firm j in year t. Log return is the logarithm of one plus the daily return.
Average IA	AVG_IA5_{jt}	It is the average of *IA5*s estimated for all the analysts following firm j in year t. *IA5* here is estimated using the rolling window from year *t-4* to year *t*.
Intangible Assets	$INTANG_{jt}$	It is the firm j's total intangible assets (reported on the balance sheet) plus the goodwill scaled by total assets at the end of current fiscal year.
Stock Volatility	VOL_RET_{jt}	It is the sample standard deviation of the daily log returns for firm j in year t. Log return is the logarithm of one plus the daily return.
Detrended Turnover	$DETRN\_TO_{jt}$	It is the average of daily turnovers for firm j in year t, and the daily turnover is detrended by a moving average of past 20-trading-day turnover. Daily turnover is calculated as the ratio of daily share volume to total shares outstanding. This measure is calculated for NYSE and AMEX stocks only.
Average Size	AVG_SIZE_{jt}	It is the average of daily market capitalizations of firm j in year t.
Annual Return	$ARET_{jt}$	It is the cumulative stock return for firm j in year t.
Institutional Ownership	INS_OWN_{jt}	It is the average of the quarterly institutional ownerships of firm j in year t, which are the ratios of shares held by 13(f) financial institutions to shares outstanding at the end of the quarter.
Ownership Breadth	OWN_BRD_{jt}	It is the average of the quarterly ownership breadths of firm j in year t, which are the ratios of number of 13(f) financial institutions holding the firm j's shares to total number of 13(f) institutions presenting in Thomason Reuters 13(f) institutional holding data at the end of the quarter.

IA is measured by the sample standard deviation of the FCST_ERR residuals of analyst *i* following firm *j* from Model (1) over the past *n* years (from year *t-n* to year *t-1*). Since the IA measure is limited to use the information only up to year *t-1,* it is insured that the measure is *ex ante* and can be considered as a proxy for the investors' expectation of IA.

$$IAn_{ijt} = \sqrt{\frac{\sum_{k=1}^{n} (\varepsilon_{ij(t-k)} - \bar{\varepsilon}_{ij})^2}{n-1}} \tag{3}$$

The length of the rolling estimation window (n) is reduced to 5 years for some later empirical tests2F[4]. Realizing that this choice is quite *ad hoc*, we also try 7-year and 9-year rolling windows to estimate IA as robustness checks.

1.4 The Ambiguity Effect on Market Reactions to Analyst Forecasts

1.4.1 Data and Sample Selection

Analysts' forecast information is obtained from the Institutional Broker Estimate System (I/B/E/S) Detailed History database[5]. The forecasts are for firms' current fiscal year-end earnings. The initial sample for estimating the model predicting forecast errors (Equation (2)) starts from January 1983 and ends in December 20074F[6]. The sample period for testing the market reaction to analyst forecast announcement starts from January 1994 to December 2007. Clement and Tse (2003) suggest that prior to the early 1990s, the forecast release date recorded in I/B/E/S often differs from the actual forecast date by a few days, but

[4] It is not required that the analyst must have a 5-year full history of following the firm. Obviously, the IA tends to be higher for analysts with short forecasting history, for which we have fewer observations used to calculate sample standard deviation. This feature is actually desirable, since the investors should be more uncertain about the analyst's forecast precision, if they can only observe a short track record for the analyst.
[5] The rounding error problem associated with I/B/E/S adjusted data (Barber and Kang (2002)) is less severe in the case of the detailed history I/B/E/S database, where the estimates are rounded to four decimals, instead of two decimals as is the case in the summary history I/B/E/S database.
[6] The data coverage of I/B/E/S for the U.S. firms is poor prior to 1983 (see Diether et al. (2002)).

the accuracy of the forecast release date is improved after 1994. Since the event study always requires accurate event dates, this paper also estimates IA and conducts the rest of tests starting from 1994. Stock prices and returns data are from the Center for Research in Security Prices (CRSP) database and firms' accounting data are from Compustat North America Fundamentals Annual Files.

We require that forecasts must be made at least 30 days, but no more than 1 year, before the fiscal-year end. Certain observations are also eliminated, if any of the following conditions are met. (1) No valid stock price and accounting information is available from CRSP and Compustat to construct the variables listed in Table 1. (2) The stocks are not ordinary common stocks, i.e., the share code does not equal to 10, 11, or 12. (3) The analyst did not issue a forecast in the prior fiscal year for the firm. This condition is needed, because the prediction model for forecast accuracy requires the prior fiscal-year forecast information. (4) The forecasts are made prior to the announcement of last fiscal year's actual earnings. This requirement is needed to ensure that the forecast revision measure uses ex ante information, since the forecast revision is to compare the current forecasts with the last fiscal-year actual earnings, which has to be available before the current forecasts. The sample is restricted to the first forecast for each analyst-firm pair during the forecast period that also satisfies the above requirements. The first forecasts, which have long forecast horizons, tend to be the most inaccurate ones and, thus, uncertainty about the accuracy of these forecasts should also be high. Consequently, using this sample is expected to generate ample cross-sectional variations in information ambiguity. Effectively, there is only one observation for each analyst-firm pair per fiscal year. After imposing these constraints, we obtain a final sample that contains an average of 1860 firms and 12725 analyst-firm pairs every year during the period of 1994-2007.

The descriptive statistics for the variables used in this paper are presented in Table 1.2. All variables are winsorized at the top and bottom one percentile, and are at annual frequency. Panel A covers the variables used in the model that predicts analyst forecast errors (Equation (2)). Panel B reports the variables in the model that explains the market response to analyst forecasts (Equation (4)). Variables in Panel A and B are at the forecast level or the analyst-firm level. Panel C reports the variables in the model that explains stock return skewness (Equation (5)). The variables in Panel C are aggregated at the firm level. Panel D and E report Pearson correlations among our main variables and the corresponding P-values in parentheses. As shown in Panel D, the IA measure is positively correlated with the expected IP (PRED_lnERR5), which is as expected, since the investors' uncertainty regarding IP should be high when the expected IP is low (or PRED_lnERR5 is high). On the other hand, the correlation of these two variables is not too high, about 6%, suggesting that the IA measure still contains some unique information that is not captured by PRED_lnERR5. After aggregating the IA measure at the firm level in Panel E, we can see that firms with high levels of IA tend to be smaller and their stocks perform poorly in the current year. Meanwhile, Panel E also shows that high-IA stocks have more volatile earnings, less institutional ownership, and lower level of ownership breadth. Although the negative sign of the correlation between IA and the proportion of intangible assets (INTANG) is somewhat not expected, the magnitude is very small, around -1.58%.

Table 1.2
Descriptive Statistics

Here we report the summary statistics of the main variables across all firms and years. All the variables are at the annual frequency. All the variables are winsorized at the top and bottom one percentile.

Panel A: Variables for the Absolute Forecast Error Model [Model (1)] (Analyst-Firm level, 1983-2007)								
	N	Mean	Std. Dev.	1^{st} percentile	25^{th} percentile	Median	75^{th} percentile	99^{th} percentile
FCST_ERR	264928	0.0193	0.0453	0.0000	0.0013	0.0048	0.0159	0.3271
DAYS_ELPS	264928	6.0825	11.9166	0	0	1	7	69
HERD_DUM	264928	0.5624	0.4961	0	0	1	1	1
EXPRNCE	264928	3.4477	2.8130	1	1	3	5	14
FCST_HRZN	264928	271.4521	68.5134	56	243	293	324	348
FCST_FREQ	264928	3.5741	2.0200	1	2	3	5	10
BROKER_SIZE	264928	55.5711	54.6535	1	18	41	66	276
COMP_NUM	264928	18.5507	13.3723	2	11	15	21	80
IND_NUM	264928	4.9693	3.4113	1	3	4	6	18
SIZE	264928	9.6007	1.6802	5.7257	8.4556	9.6096	10.7380	13.6260
M/B	264928	3.4087	3.4492	-2.2366	1.5318	2.3756	3.9628	21.9895
VAR_EPS	264928	19.2161	134.8504	0.0017	0.0426	0.0937	0.3220	1250.3321
BUSSEG_NUM	264928	2.3724	1.6723	1	1	2	3	8
Panel B: Variables for the Market Response Model (Analyst-Firm level, 1994-2007)								
	N	Mean	Std. Dev.	1^{st} percentile	25^{th} percentile	Median	75^{th} percentile	99^{th} percentile
CAR3 (%)	83139	0.1157	5.6564	-19.1273	-2.4856	-0.0044	2.6891	18.3414
IA5	83139	1.1150	0.6680	0.0420	0.6413	1.0107	1.4670	3.4136
IA7	83139	1.1268	0.6503	0.0453	0.6764	1.0370	1.4630	3.3875
IA9	83139	1.1352	0.6465	0.0459	0.6934	1.0498	1.4648	3.3978
PRED_lnERR5	83139	-5.3974	1.0844	-8.0868	-6.1139	-5.3585	-4.6333	-2.9965
PRED_lnERR7	83139	-5.3990	1.1035	-8.1380	-6.1272	-5.3591	-4.6223	-2.9602
PRED_lnERR9	83139	-5.4056	1.1230	-8.1945	-6.1480	-5.3674	-4.6146	-2.9286
FCST_REV	83139	0.0098	0.0334	-0.0764	0.0014	0.0048	0.0106	0.1940
FCST_REV2	82684	0.0002	0.0356	-0.1558	-0.0044	0.0004	0.0048	0.1611
Panel C: Variables for the Stock Skewness Model (Firm level, 1994-2007)								
	N	Mean	Std. Dev.	1^{st} percentile	25^{th} percentile	Median	75^{th} percentile	99^{th} percentile
SKEW	20765	-0.0706	1.1091	-5.0058	-0.3079	0.0861	0.4310	2.8475
AVG_IA5	20765	1.1571	0.5600	0.1423	0.7794	1.0743	1.4387	3.1429
INTANG	20765	0.2059	0.2752	0.0000	0.0000	0.0812	0.3149	1.1724
VOL_RET	20765	0.0279	0.0136	0.0090	0.0181	0.0247	0.0343	0.0766
DETRN_TO	12360	0.0193	0.1289	-0.4192	-0.0289	0.0089	0.0579	0.5664
AVG_SIZE	20765	13.7694	1.6691	10.2659	12.5897	13.6695	14.8547	18.1225
ARET (%)	20765	15.27029	50.68505	-76.3308	-15.3091	8.465608	35.66045	233.8171
INS_OWN (%)	20763	62.06885	23.47481	8.35933	45.4448	64.16467	79.74758	111.1199
OWN_BRD (%)	20763	9.349544	9.400359	0.597627	3.641387	6.434627	11.40103	54.24653

Panel D: Pearson Correlations (P-values) of Variables for the Market Response Model (Analyst-Firm level, 1994-2007)								
	IA5	*IA7*	*IA9*	*PRED_ lnERR5*	*PRED_ lnERR7*	*PRED_ lnERR9*	*FCST_ REV*	*FCST_ REV2*
CAR3	-0.01118 (0.0013)	-0.01107 (0.0014)	-0.01154 (0.0009)	0.00016 (0.9643)	-0.00007 (0.9831)	-0.00056 (0.8708)	0.04071 (<.0001)	0.04828 (<.0001)
IA5		0.96841 (<.0001)	0.95624 (<.0001)	0.06149 (<.0001)	0.06099 (<.0001)	0.06026 (<.0001)	0.03416 (<.0001)	-0.00896 (0.0099)
IA7			0.98822 (<.0001)	0.06838 (<.0001)	0.06789 (<.0001)	0.06728 (<.0001)	0.03631 (<.0001)	-0.00951 (0.0063)
IA9				0.06974 (<.0001)	0.06928 (<.0001)	0.06875 (<.0001)	0.03713 (<.0001)	-0.00962 (0.0057)
PRED_lnERR5					0.99880 (<.0001)	0.99773 (<.0001)	0.25479 (<.0001)	0.04339 (<.0001)
PRED_lnERR7						0.99929 (<.0001)	0.25461 (<.0001)	0.04258 (<.0001)
PRED_lnERR9							0.25443 (<.0001)	0.04229 (<.0001)
FCST_REV								0.69831 (<.0001)

Panel E: Pearson Correlations (P-values) of Variables for the Stock Skewness Model (Firm level, 1994-2007)								
	AVG_IA5	*INTANG*	*VOL_RET*	*AVG_SIZE*	*ARET*	*Ln(INS_ OWN)*	*Ln(OWN_ BRD)*	*DETRND_ TO*
SKEW	-0.03766 (<.0001)	-0.05396 (<.0001)	-0.13254 (<.0001)	-0.03727 (<.0001)	0.29196 (<.0001)	-0.08622 (<.0001)	-0.04927 (<.0001)	-0.06305 (<.0001)
AVG_IA5		-0.01580 (0.0228)	0.08360 (<.0001)	-0.10778 (<.0001)	-0.04933 (<.0001)	-0.04680 (<.0001)	-0.08958 (<.0001)	-0.00760 (0.3983)
INTANG			-0.09919 (<.0001)	0.11319 (<.0001)	-0.04054 (<.0001)	0.20996 (<.0001)	0.07194 (<.0001)	-0.00929 (0.3016)
VOL_RET				-0.43947 (<.0001)	-0.05422 (<.0001)	-0.15606 (<.0001)	-0.41036 (<.0001)	0.06743 (<.0001)
AVG_SIZE					0.04132 (<.0001)	0.37177 (<.0001)	0.92498 (<.0001)	0.01191 (0.1856)
ARET						0.02364 (0.0007)	0.03522 (<.0001)	0.03870 (<.0001)
Ln(INS_ OWN)							0.48475 (<.0001)	0.08413 (<.0001)
Ln(OWN_ BRD								0.00043 (0.9620)

1.4.2 Performance of the Prediction Model for Absolute Forecast Errors

In Table 1.3, we report the results of the model predicting absolute forecast errors (Equation (2)). As suggested by Petersen (2009), for panel regressions when the dependent variable is highly persistent, the correlation of residuals within a firm across years (time-series dependence) is of great concern. Petersen (2009) suggests two types of regression models to address for this type of dependence: a) pooled OLS regressions with standard errors clustered by firm, and b) firm fixed-effect regressions. The regressions are performed for the whole sample period (1983-2007)5[7]. To ensure that only ex-ante information is used for the prediction of IA, we lag certain variables by one year. These variables, like brokerage firm size, forecast frequency, etc, require the full-year information and thus are not observable until the end of a year.

The signs of the variables' coefficients are largely consistent with our expectations. The current absolute forecast error is highly correlated with the absolute forecast error from last year, which also confirms that the dependent variable is persistent and the regressions accounting for the time-series dependence are appropriate. The result shows that inaccuracy is high, for analysts with long forecast horizon (FCST_HRZN) and short firm experience (EXPRNCE). It is also shown that the effort the analyst allocates to the firm also influences the forecast accuracy. When the analyst issues fewer forecasts for the firm during the fiscal year (FCST_FREQ) and is following large number of other

[7] For constructing the IA measure, the prediction model is estimated based on a historical rolling window of 5, 7, or 9 years to avoid any look-ahead bias, and we use pooled OLS regression to obtain the residuals of the model, since the residuals from the firm fixed-effect regression are demeaned within the firm across years, which make the residuals not comparable across firms.

firms at the same time (COMP_NUM), her forecast accuracy tends to be lower6F [8]. Also as expected, analysts from larger brokerage houses (BROKER_SIZE) issue more accurate forecasts. Forecasts that are not the first ones among all analysts' forecasts for the current fiscal period (HERD_DUM) are associated with lower accuracy, consistent with the notion that they are indicative of herding behavior. The forecasts that are issued long after the last forecast (DAYS_ELPS) have higher accuracy, consistent with the explanation that more information regarding the firm may be made available to analysts during the period between two forecasts. Besides the analyst characteristics, firm characteristics also play an important role in determining absolute forecast errors. Forecast inaccuracy is lower for firms with larger size (SIZE), more growth opportunities (M/B), fewer business segments (BUSSEG_NUM) and less volatile earnings (VAR_EPS)7F [9]. Overall, the model encompasses almost all the variables that are known to have predictive power for analyst forecast accuracy. The high adjusted R-square (39% for the clustered regression) also confirms that the model can capture a substantial portion of the predictable variations in actual absolute forecast errors.

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[8] Unlike the effect of COMP_NUM on forecast accuracy, we find that accuracy increases with the number of industries the analyst follows (IND_NUM), which is not consistent with the findings of Clement (1999). One possible explanation for this effect is that brokers prefer to assign their best analysts to cover more industries. Another explanation is that analysts covering several industries can take advantage of information spillover effect across industries.

[9] The sign of the earnings volatility variable is positive, as we expected, in the clustered regression. However, the sign switches to negative in the firm fixed-effect regression. This is likely due to certain econometric imperfections.

Table 1.3
Predicting the Analysts' Absolute Forecast Errors

This table reports results of regressions of the log of absolute forecast errors for analyst *i* following firm *j* in year *t* on various ex ante variables that capture both analyst and firm characteristics. Variables are defined in Table I. The clustered regression is the pooled OLS regression where the standard errors are clustered by firm. Both year dummies and industry dummies are included in all the regressions. Industry dummies are defined using Fama-French 12-industry classifications. The sample period is from 1983 to 2007. The t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dependent Variable: $Ln(FCST\_ERR_{ijt})$	
	Clustered Regression (by Firm)	Firm Fixed-Effect Regression
$Ln(FCST\_ERR_{ij(t-1)})$	0.43481***	0.13200***
	(53.76)	(66.78)
$Ln(FCST\_HRZN_{ijt})$	0.71277***	0.68303***
	(53.58)	(95.6)
$HERD\_DUM_{ijt}$	0.07148***	0.02765***
	(6.35)	(3.39)
$Ln(DAYS\_ELPS_{ijt})$	-.05374***	-.02944***
	(-10.99)	(-8.79)
$Ln(EXPRNCE_{ijt})$	-.02658***	-.01162**
	(-3.16)	(-2.3)
$Ln(BROKER\_SIZE_{ij(t-1)})$	0.00058	-.00976***
	(0.16)	(-3.99)
$Ln(FCST\_FREQ_{ij(t-1)})$	-.13579***	-.06018***
	(-14.24)	(-13.44)
$Ln(COMP\_NUM_{i(t-1)})$	0.02587**	0.04423***
	(2.35)	(8.35)
$Ln(IND\_NUM_{i(t-1)})$	-.04391***	-.02142***
	(-3.37)	(-3.82)
$Ln(SIZE_{ijt})$	-.18224***	-.15569***
	(-19.49)	(-30.3)
M/B_{ijt}	-.05614***	-.04898***
	(-16.57)	(-46.32)
$Ln(BUSSEG\_NUM_{j(t-1)})$	0.01916	0.06541***
	(0.99)	(9.07)
$Ln(VAR\_EPS_{jt})$	0.05242***	-.00860***
	(11.19)	(-5.3)
Adjusted R-square	38.92%	54.00%
Industry and Year Dummies	Yes	Yes
Num of Observations	264928	264928

1.4.3 Event Returns by Information Ambiguity

The first set of empirical tests examines the cross-sectional variations in market responses across forecasts with differing levels of IA. The market response is measured as the three-trading-day cumulative abnormal return (CAR3) over the period surrounding the analyst's forecast announcement date, i.e., from day t-1 to t+1. We compute the abnormal return by subtracting the concurrent value-weighted market return from the firm's daily returns. In Table IV, Panel A, Part I, forecasts are sorted into IA quintiles every year. CAR3s for analysts' forecasts are generally positive. This is consistent with the findings of Xu (2007) that the market response to actual earnings announcement is on average positive. More interestingly, we find that CAR3 is less positive for highly ambiguous forecasts. One potential explanation for this pattern is that the market is responding to bad news more strongly relative to good news when facing ambiguous information, as predicted by Epstein and Schneider (ES 2003, 2008).

To confirm this prediction, we first classify forecasts into good- and bad-news groups based on the direction of forecast revisions, and then within each news group forecasts are further sorted into IA quintiles every year. Since we are using the first forecast of each analyst during the fiscal year, the most relevant benchmark for calculating the revision should be the actual earnings of the last fiscal year8F[10]. Therefore, the forecast revision (FCST_REV) is calculated as the

[10] Gleason and Lee (2003) recommend using the analyst's own prior forecast as a benchmark. For the first forecasts, these prior forecasts should be the analyst's final forecasts for the last fiscal-year earnings. Since we require that the forecasts must be made after the announcement of last-fiscal-year earnings, this benchmark is likely to be outdated information and the market must have updated its expectation based on the announced earnings.

forecast less the actual earnings of the last fiscal year scaled by the end-of-day stock price two days before the forecast date. Table IV, Panel A, Part II shows that for downward revisions high-IA forecasts are associated with stronger negative reactions than low-IA ones, which is consistent with the ES theory. The average CAR3 of the highest-IA bad-news quintile is -1.13%, which is 0.37% lower than the CAR3 of the lowest-IA bad-news quintile.

However, from Table 1.4 Panel A Part II, we cannot observe any significant pattern across IA quintiles for upward revisions. This is likely due to the problem associated with classifying upward revisions as good news. It is well-known that the first forecasts tend to be overly optimistic and thus are more likely to be higher than last-fiscal-year earnings. For example, Richardson, et al. (2004) document that the median consensus forecasts tend to be initially positively biased. Subsequently, analysts gradually “walk down” the forecasts to a level that is beatable by the actual earnings. Our result also shows that around 83% of the first forecasts are upward revisions relative to last-fiscal-year earnings. Given this fact, rational investors should systematically discount the upward revisions. To account for the systematic optimistic bias in the first forecasts, we use a trend-adjusted forecast revision measure (FCST_REV2), which is the forecast revision by analyst i following firm j in year t less the historical average of forecast revisions by analyst i following firm j during the period from year t-3 to year t-1, and we classify the forecasts with positive FCST_REV2 as good news. After this adjustment, as shown in Table 1.4 Panel A Part III, the size of the good-news group becomes more reasonable and is reduced to 56% of the total sample. For the revised good-news group, we find that the market is responding less positively when the forecasts are ambiguous, as predicted by the ES theory. On average, the good-news high-IA forecasts have an event return of 0.45%, compared to 0.69% for good-news low-IA forecasts. Instead of classifying all the negative trend-adjusted revisions as bad news, we keep the prior definition that downward revisions are bad news, and classify forecasts that are higher than last-fiscal-year earnings (FCST_REV > 0) but lower than the previous three-year average (FCST_REV2 < 0) into a neutral-news group. Market reactions to the neutral-news forecasts are generally weak and close to 0. More importantly, the nature of these forecasts is mixed. For example, the average CAR3 is positive for the highest-IA quintile but it is negative for other quintiles. Therefore, any attempt to classify this group as either good or bad news will be associated with a great deal of noise. Interestingly, we can see that for the neutral-news group there is little response to forecasts with highest IAs (mean CAR3 equals to 0.07%) whereas for other IA quintiles the average market reaction is slightly negative, suggesting that the market tends to adopt a more optimistic view when the news is neutral and ambiguous[11].

In order to compare the IA effect with the IP effect on the market's response to forecast revisions, we also sort forecasts by their expected IP every year. Following Clement and Tse (2003), we use the predicted values (PRED_lnERR) from the model predicting forecast errors (Equation (2)) to proxy for the market's expectation of forecast errors. Table IV Panel B shows that

[11] Since the existing theories, to our best knowledge, offer few predictions on how the market should react to the neutral news, we leave the interpretation on this result for future studies.

compared with IA, IP has a distinctive effect on the event returns, especially on the bad-news side. For the bad-news, the highest-PRED_lnERR forecasts are associated with an average CAR3 of -0.65%, which is far less than the response to bad-news lowest-PRED_lnERR forecasts where mean CAR3 equals to -1.34%. Overall, the results for sorting on PRED_lnERR suggest that the market takes *both* highly inaccurate good and bad news less seriously. This is consistent with prior findings of Stickel (1992), Park and Stice (2000), and Clement and Tse (2003).

Table 1.4
Market Reaction to Analysts' Forecasts across IA Quintiles

In Panel A, the reported are means and standard deviations (in parentheses) of the cumulative 3-day abnormal returns surrounding forecast announcements (CAR3) across years and analyst-firm pairs. In Panel A-Part I, The observations are sorted into quintiles based on IA5 every year. In Panel A-Part II, Good (bad) news is defined as an upward (downward) forecast revision, i.e., FCST_REV > (<) 0. The observations are first sorted into good/bad news groups every year, and within each news group we further sort the stocks into quintiles based on IA5. In Panel A-Part III, Good news is defined as an upward adjusted forecast revision, i.e., FCST_REV2 > 0, whereas bad news is defined as a downward forecast revision, i.e., FCST_REV < 0. The observations are first sorted into three groups (good, bad and neutral news) every year, and within each news group they are further sorted the stocks into quintiles based on IA5. In Panel B, Good news is defined as an upward adjusted forecast revision, i.e., FCST_REV2 > 0, whereas bad news is defined as a downward forecast revision, i.e., FCST_REV < 0. The observations are first sorted into three groups (good, bad and neutral news) every year, and within each news group they are further sorted the stocks into quintiles based on the predicted forecast errors (PRED_lnERR5). Variables are defined in Table I. T-statistics for the group mean differences are reported in brackets. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Mean CAR3 Surrounding Forecast Announcements (in %)							
Panel A. Across *IA5* Quintiles							
Part I. Univariate Sorting							
		IA5					Q5– Q1
	N	Q1(low)	Q2	Q3	Q4	Q5 (High)	[t-stat]
All stocks	83139 (100%)	0.1942 (5.682)	0.1592 (5.586)	0.1209 (5.468)	0.0806 (5.636	0.0238 (5.901)	-0.1705*** [2.68]
Part II. Good or Bad News based on Raw Forecast Revision							
		IA5					Q5– Q1
	N	Q1(low)	Q2	Q3	Q4	Q5 (High)	[t-stat]
FCST_REV > 0 (Good News)	67969 (82.5%)	0.3987 (5.554)	0.3835 (5.466)	0.3368 (5.370)	0.3298 (5.456)	0.3113 (5.802)	-0.0873 [1.27]
FCST_REV < 0 (Bad News)	14454 (17.5%)	-.7570 (6.180)	-.9027 (5.931)	-.8742 (5.864)	-1.081 (6.240)	-1.130 (6.140)	-0.3728** [2.30]

		Part III. Good or Bad News based on Raw & Adjusted Forecast Revision					
		IA5					Q5– Q1
	N	Q1(low)	Q2	Q3	Q4	Q5 (High)	[t-stat]
FCST_REV2 > 0	43813	0.6890	0.6574	0.5851	0.5852	0.4534	-0.2356***
(Good News)	(55.7%)	(5.576)	(5.536)	(5.447)	(5.571)	(5.870)	[2.72]
FCST_REV < 0	14454	-.7570	-.9027	-.8742	-1.081	-1.130	-0.3728**
(Bad News)	(18.4%)	(6.180)	(5.931)	(5.864)	(6.240)	(6.140)	[2.30]
Others	20392	-.1696	-.1738	-.1285	-.1386	0.0708	0.2400**
(Neutral News)	(25.9%)	(5.524)	(5.223)	(5.271)	(5.275)	(5.675)	[2.14]

Panel B. Across *PRED_lnERR5* Quintiles

		PRED_lnERR5					Q5– Q1
	N	Q1(low)	Q2	Q3	Q4	Q5 (High)	[t-stat]
FCST_REV2 > 0	43813	0.6190	0.6671	0.6444	0.6517	0.3879	-0.2312***
(Good News)	(55.7%)	(4.959)	(5.173)	(5.329)	(5.701)	(6.680)	[2.60]
FCST_REV < 0	14454	-1.3365	-0.8596	-0.9049	-0.9974	-0.6475	0.689***
(Bad News)	(18.4%)	(5.793)	(5.794)	(5.599)	(6.011)	(7.045)	[4.06]
Others	20392	-0.3847	-0.2029	-0.0572	0.1291	-0.0244	0.360***
(Neutral News)	(25.9%)	(4.957)	(5.065)	(5.012)	(5.488)	(6.325)	[3.16]

1.4.4 Regression Analysis

In this section, we examine whether the ambiguity effect can be explained by other factors that are known to influence market responses to forecast revisions. For example, if the highly ambiguous bad news were to be associated with more negative forecast revisions, the more negative response to this type of news may simply be a manifestation of this correlation. However, as shown in Table 1.2 Panel D the correlation between IA and FCST_REV is not very high, equal to 3.4%. Here, we control for all the factors that are suggested by Clement and Tse (2003), and the market response to forecast revisions is modeled as:

$$\begin{aligned} CAR3_{ijt} = {} & \gamma_0 + \gamma_1 FCST\_REV2_{ijt} + \gamma_2 BAD\_NEWS_{ijt} + \gamma_3 GOOD\_NEWS_{ijt} \\ & + \gamma_4 BAD\_NEWS_{ijt} \cdot IA5_{ijt} + \gamma_5 GOOD\_NEWS_{ijt} \cdot IA5_{ijt} + \gamma_6 NEUTRAL\_NEWS_{ijt} \cdot IA5_{ijt} \\ & + \gamma_7 FCST\_REV2_{ijt} \cdot PRED\_\ln ERR5_{ijt} + (\sum_n \gamma_n FCST\_REV2_{ijt} \cdot Other\ Controls_n) + \varepsilon_{ijt} \end{aligned} \tag{4}$$

where BAD_NEWS is a dummy variable that equals to one if the raw revision is downward (FCST_REV < 0), and GOOD_NEWS is also a dummy variable that equals to one if the revision is above the three-year trend (FCST_REV2 > 0). We expect the coefficient for the GOOD_NEWS (γ_3) to be positive and for the BAD_NEWS (γ_2) to be negative. Our main prediction is that the coefficients for the two interaction terms with IA5 (γ_4 and γ_5) are both negative, because we expect that the response to good news $(\gamma_3 + \gamma_5 \cdot IA5_{ijt})$ will be less positive when the IA is higher, whereas the response to bad news $(\gamma_2 + \gamma_4 \cdot IA5_{ijt})$ will be more negative when the IA is higher. Since the prior studies suggest that expected forecast error will reduce the market response for any given level of forecast revision ($\gamma_1 + \gamma_7 \cdot PRED\_\ln ERR5_{ijt}$) regardless of the nature of news, it is also expected that the coefficient for the interaction term with PRED_lnERR (γ_7) will be negative.

Since the dependent variable in this model is stock return, which is more correlated across firms within each period than across time within each firm, we follow the suggestions of Petersen (2009) and estimate Equation (4) by Fama-MacBeth year-by-year cross-sectional regressions and pooled OLS regressions with standard errors clustered by year to account for the cross-sectional dependency. As shown in Table V, the coefficients for interaction terms with IA5 (γ_4 and γ_5) are always negative, as we expected, under the two types of regressions. Also consistent with our hypothesis, we find that the market is less responsive when the expected forecast errors are high, as shown by the significantly negative γ_7. Similar to the prior sorting results, it is also shown that investors tend to respond more favorably to highly ambiguous neutral news than other neutral news, as reflected by significantly positive γ_6.

Table 1.5 Regression Analysis of Market Reaction to Analysts' Forecasts

This table reports results of regressions of the cumulative abnormal announcement returns for the forecasts made by analyst *i* following firm *j* in year *t* on various variables. Variables are defined in Table I. The clustered regression is the pooled OLS regression where the standard errors are clustered by year. For the Fama-MacBeth regression, the coefficients are the mean of coefficients from year-by-year cross-sectional regressions, while the standard errors are adjusted by New-West procedure with a lag of three years. The sample period is from 1994 to 2007. The t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dependent Variable: $CAR3_{ijt}$ (in %)							
	Fama-MacBeth Regressions					Clustered Regressions (by Year)		
Intercept	0.1331**	-0.0876**	-0.2180***	-0.2052***	-0.2149***	-0.2202**	-.0762	-0.2119**
	(2.21)	(-2.76)	(-5.08)	(-4.69)	(-4.86)	(-2.84)	(-1.14)	(-2.64)
$FCST\_REV2_{ijt}$	7.6677***	-0.5592	-0.4699	-12.727***	11.0672	-0.0901	-11.150***	9.5198
	(6.52)	(-0.61)	(-0.5)	(-3.27)	(0.87)	(-0.08)	(-3.35)	(0.83)
BAD_NEWS_{ijt}		-0.9699***	-0.5835***	-0.5677***	-0.5676***	-0.5347***	-.6353***	-0.5066**
		(-5.48)	(-3.16)	(-3.12)	(-3.19)	(-3.07)	(-4.4)	(-2.9)
$GOOD\_NEWS_{ijt}$		0.7296***	0.9724***	0.9453***	0.9629***	0.9289***	0.7746***	0.9123***
		(4.36)	(5.63)	(5.64)	(5.62)	(6.31)	(5.3)	(6.11)
$BAD\_NEWS_{ijt} \cdot IA5_{ijt}$			-0.2247***	-0.2052***	-0.2054***	-0.2199***	-.2069***	-0.1998**
			(-4.56)	(-4.44)	(-4.09)	(-3.12)	(-3.04)	(-2.85)
$GOOD\_NEWS_{ijt} \cdot IA5_{ijt}$			-0.1071***	-0.1166***	-0.1211***	-0.1104**	-.1179**	-0.1216**
			(-3.72)	(-3.94)	(-3.97)	(-2.29)	(-2.36)	(-2.45)
$NEUTRAL\_NEWS_{ijt} \cdot IA5_{ijt}$			0.1222**	0.1324***	0.1342***	0.1119**	0.1232**	0.1245**
			(2.97)	(3.21)	(3.08)	(2.51)	(2.64)	(2.75)
$FCST\_REV2_{ijt} \cdot PRED\_lnERR5_{ijt}$				-3.1615***			-2.8756***	
				(-3.14)			(-3.16)	
$FCST\_REV2_{ijt} \cdot HERD\_DUM_{ijt}$					-8.3780***			-8.2676***
					(-3.49)			(-3.63)
$FCST\_REV2_{ijt} \cdot Ln(DAYS\_ELPS_{ijt})$					0.8446			0.8815
					(1.13)			(1.13)
$FCST\_REV2_{ijt} \cdot Ln(FCST\_HRZN_{ijt})$					-3.5515			-3.3662
					(-1.63)			(-1.6)
$FCST\_REV2_{ijt} \cdot Ln(FCST\_ERR_{ij(t-1)})$					-1.5046**			-1.7754**
					(-2.95)			(-2.75)
$FCST\_REV2_{ijt} \cdot Ln(BROKER\_SIZE_{ij(t-1)})$					2.0097***			1.9526**
					(4.07)			(2.4)
Adjusted R-square	0.26%	1.25%	1.29%	1.34%	1.45%	1.07%	1.08%	1.15%
Num of Observations	82684	82684	82684	82684	82684	82684	82684	82684

1.4.5 Robustness Analysis

1.4.5.1 Other Controls

Clement and Tse (2003) find that investors seem to be unable to condition their responses to forecasts on all the information that the analyst characteristics provide about future forecast accuracy. In particular, when investors respond to forecasts, they are more concerned with a subset of the variables that predicts the forecast accuracy, such as broker size, days elapsed from the last forecasts, lagged forecast error, and forecast horizon. So instead of using PRED_lnERR which is based on the full information, we also try to interact the forecast revision with each of these variables that investors deem to be important. From Table 1.5, we can see that including these interaction terms does not alter our main results.

1.4.5.2 Alternative Measurement Windows for IA Estimates

To check if the results are sensitive to the length of rolling window used in the estimation of IAs, we re-estimate IAs using seven- and nine-year rolling windows and then repeat the regression tests. From Table 1.2 Panel D, we can see that IA5 is highly correlated with IA7 and IA9 and the correlations are hovering around the 95% level. In Table 1.6 where IA5 and PRED_lnERR5 are replaced by the corresponding variables estimated over seven- or nine-year windows, the regression results are virtually the same as those in Table V. Therefore, our result is robust to the alternative length of the estimation rolling window.

1.4.5.3 Sub-period Analysis

Here, we examine if the previously discovered relation between IA and market reaction is consistent over time. Since our sample period is surrounding the Tech Bubble period, it is divided into four sub-periods accordingly: pre-bubble (1994-1998), bubble (1999-2000), bubble-bursting (2001-2002), and post-bubble periods (2003-2007). From Table 1.7, the signs for coefficients of the interaction terms between IA and good/new news are fairly consistent and remain negative for most sub-periods, similar to what we find in Table V. The only exception is the sign for $\boldsymbol{GOOD\_NEWS_{ijt} \cdot IA5_{ijt}}$ during bubble-bursting period. Overall, the result is much weaker for bubble-bursting period, but stronger for post-bubble and bubble period. One possible explanation is that when Tech Bubble bursted, the market is in panic mood and investors simply treated all bad news seriously and ignored all good news, regardless of the IA level of the news.

Table 1.6
Robustness Analysis I: Alternative Measurement Windows for IA Estimates

This table reports results of regressions of the cumulative abnormal announcement returns for the forecasts made by analyst *i* following firm *j* in year *t* on various variables. Variables are defined in Table I. For the Fama-MacBeth regression, the coefficients are the mean of coefficients from year-by-year cross-sectional regressions, while the standard errors are adjusted by New-West procedure with a lag of three years. The sample period is from 1994 to 2007. The t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dependent Variable: $CAR3_{ijt}$ (in %)			
	Fama-MacBeth Regressions			
Intercept	-.22818***	-.23649***	-.22485***	-.23364***
	(-5.15)	(-5.3)	(-5.09)	(-5.28)
$FCST\_REV2_{ijt}$	-11.721***	11.2208	-11.722***	11.1619
	(-3.5)	(0.88)	(-3.5)	(0.88)
BAD_NEWS_{ijt}	-.55417***	-.55173***	-.55700**	-.55398***
	(-3.11)	(-3.19)	(-3.01)	(-3.08)
$GOOD\_NEWS_{ijt}$	0.98804***	1.00280***	0.99109***	1.00725***
	(5.59)	(5.6)	(5.63)	(5.63)
$\boldsymbol{BAD\_NEWS_{ijt} \cdot IA7_{ijt}}$	-.19843***	-.19929***		
	(-4.26)	(-3.96)		
$\boldsymbol{GOOD\_NEWS_{ijt} \cdot IA7_{ijt}}$	-.13314***	-.13728***		
	(-4.52)	(-4.64)		
$\boldsymbol{NEUTRAL\_NEWS_{ijt} \cdot IA7_{ijt}}$	0.15059***	0.15248***		
	(3.28)	(3.14)		
$\boldsymbol{BAD\_NEWS_{ijt} \cdot IA9_{ijt}}$			-.19662***	-.19802***
			(-4.14)	(-3.91)
$\boldsymbol{GOOD\_NEWS_{ijt} \cdot IA9_{ijt}}$			-.13848***	-.14273***
			(-4.47)	(-4.55)
$\boldsymbol{NEUTRAL\_NEWS_{ijt} \cdot IA9_{ijt}}$			0.14744***	0.14921***
			(3.31)	(3.18)
$FCST\_REV2_{ijt} \cdot PRED\_lnERR7_{ijt}$	-2.9283***			
	(-3.32)			
$FCST\_REV2_{ijt} \cdot PRED\_lnERR9_{ijt}$			-2.9463***	
			(-3.36)	
$FCST\_REV2_{ijt} \cdot HERD\_DUM_{ijt}$		-8.3778***		-8.3724***
		(-3.47)		(-3.48)
$FCST\_REV2_{ijt} \cdot Ln(DAYS\_ELPS_{ijt})$		0.83528		0.83259
		(1.12)		(1.12)
$FCST\_REV2_{ijt} \cdot Ln(FCST\_HRZN_{ijt})$		-3.5742		-3.5606
		(-1.65)		(-1.64)
$FCST\_REV2_{ijt} \cdot Ln(FCST\_ERR_{ij(t-1)})$		-1.5047**		-1.5023**
		(-2.93)		(-2.92)
$FCST\_REV2_{ijt} \cdot Ln(BROKER\_SIZE_{ij(t-1)})$		2.00857***		2.00836***
		(4.05)		(4.05)
Adjusted R-square	1.33%	1.45%	1.33%	1.45%
Num of Observations	82684	82684	82684	82684

Table 1.7
Robustness Analysis II: Sub-period Analysis

This table reports results of regressions of the cumulative abnormal announcement returns for the forecasts made by analyst *i* following firm *j* in year *t* on various variables. Variables are defined in Table I. The regression used is the pooled OLS regression where the standard errors are clustered by year. The sample period is from 1994 to 2007. The t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dependent Variable: $CAR3_{ijt}$ (in %)			
	Pre-bubble Period (1994-1998)	Bubble Period (1999-2000)	Bubble-bursting Period (2001-2002)	Post-bubble Period (2003-2007)
Intercept	-0.3004***	0.1141	-0.5942	-0.1228
	(-8.47)	(1.02)	(-1.36)	(-0.87)
$FCST\_REV2_{ijt}$	-3.2919	-27.679**	-9.0422	-16.997**
	(-0.41)	(-2.49)	(-0.74)	(-4.36)
BAD_NEWS_{ijt}	-0.2893	-0.5163	-0.2230	-0.8532*
	(-1.32)	(-0.54)	(-0.36)	(-2.77)
$GOOD\_NEWS_{ijt}$	0.5725**	0.7841***	1.5838***	1.1121***
	(3.18)	(8.44)	(6.33)	(3.81)
$\boldsymbol{BAD\_NEWS_{ijt} \cdot IA5_{ijt}}$	-0.1152	-0.5006***	-0.0113	-0.2788**
	(-1.39)	(-4.79)	(-0.05)	(-3.42)
$\boldsymbol{GOOD\_NEWS_{ijt} \cdot IA5_{ijt}}$	-0.0636	-0.2670	0.0567	-0.1664***
	(-0.72)	(-1.47)	(1.28)	(-2.57)
$\boldsymbol{NEUTRAL\_NEWS_{ijt} \cdot IA5_{ijt}}$	0.1521**	0.1275	0.3727	0.0250
	(2.24)	(0.83)	(1.49)	(0.99)
$FCST\_REV2_{ijt} \cdot PRED\_lnERR5_{ijt}$	-0.8694	-8.6567**	-1.0151	-3.9576***
	(-0.45)	(-2.39)	(-0.27)	(-3.99)
Adjusted R-square	32371	11985	9417	28911
Num of Observations	0.5591%	1.141%	1.076%	1.872%

1.5 The Ambiguity Effect on Stock Return Skewness

1.5.1 Data and Measures

In this section, we aggregate analyst-firm-level IA at the firm level and examine whether firm-level IA can explain cross-sectional variations in stock return skewness. This test also serves the purpose of validating whether the IA measure estimated based on analysts' forecast information can be used as a general proxy for the average ambiguity level of various information that a firm is exposed to during a certain time period. Skewness is calculated using daily log returns10F[12], i.e., ln(1+r), from CRSP data. Although we would prefer a short measurement period for skewness as it may vary over time, we also need sufficient observations to ensure a reliable estimate of skewness. As a compromise, we follow Xu (2007) and measure skewness over a one-year period, starting from Jan 1st to Dec 31st. We exclude the firm-year observations where less than 40 valid daily return observations are available. Skewness is defined as the third-order decentralized moment:

$$SKEW = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^3}{n} \bigg/ \hat{\sigma}_x^3 \tag{5}$$

where $\bar{x}$ and $\hat{\sigma}_x$ are sample mean and standard deviation respectively. Since skewness is measured at the firm level, we also need to aggregate the prior IAs estimates for each analyst forecast to the firm level. So IA for firm j in year t (AVG_IA5) is calculated as the average of IAs for the forecasts that are made by all the analysts following firm j during year t11F[13].

As discussed earlier, the ambiguity level for a firm during a one-year period is not only determined by the average level of IA for each piece of news but also by the arrival frequency of the ambiguous news relative to the unambiguous news. We use the current fiscal-year-end intangible assets plus goodwill scaled by total assets (INTANG)12F[14] as a proxy for the relative arrival

[12] Since raw returns are left censored at -100% and thus more positively skewed, following Xu (2007) we use log returns.

[13] Here, we are still limiting the forecasts to be the first one made by each analyst during the fiscal year.

[14] We assume the intangible asset and goodwill to be zero, if a firm does not report these items. The main results are qualitatively the same, if we treat these values as missing.

rates of tangible and intangible signals for the firm. For firms with many intangible assets, the true value of their intangible assets is a major focus for investors. It is expected that there will be more speculative information regarding the value of those intangible assets (intangible signals) for these firms. Moreover, it is hard for the periodical disclosures in firms' financial statements (tangible signals) to fully resolve the ambiguity in those intangible signals, since the true value of intangible assets can only be revealed in the long run. Therefore, the "corrections" resulted from the announcement of tangible signals should also be weaker for firms with more intangible assets. Overall, we expect that the firms with high level of IA *and* high level of intangible assets have more negatively skewed stock returns.

The empirical test is based on the following model of the stock return skewness:

$$\begin{aligned} SKEW_{jt} &= \eta_0 + \eta_1 AVG\_IA5_{jt} + \eta_2 (AVG\_IA5_{jt} \cdot INTANG_{jt}) + \eta_3 DETRN\_TO_{jt} \\ &\quad + \eta_4 ARET_{jt} + \eta_5 ARET_{j(t-1)} + \eta_6 ARET_{j(t-2)} + \eta_7 ARET_{j(t-3)} + \eta_8 VOL\_RET_{jt} \\ &\quad + \eta_9 AVG\_SIZE_{jt} + \eta_{10} INS\_OWN_{jt} + \eta_{11} OWN\_BRD_{jt} + \varepsilon_{jt} \end{aligned} \tag{6}$$

Since our main purpose here is to explain, rather than predict, the stock return skewness, the dependent and independent variables (except for the lagged annual returns) are measured contemporaneously. Accordingly, the IA5 measure is constructed using the rolling window of the previous four years plus the current year, instead of the rolling window of the previous five years.

The control variables are the determinants of skewness suggested by Xu (2007). Specifically, he argues that when investors face short-sale constraints and disagree on the precision of public signals, the equilibrium stock price is a convex function of the public signal, which induces stock returns to be positively skewed. To proxy for short-sale costs, we use the average market capitalization (AVG_SIZE), institutional ownership (INS_OWN), and ownership breadth (OWN_BRD). AVG_SIZE is defined as the annual average of daily market capitalizations from CRSP13F[15]. INS_OWN is measured as the proportion of shares outstanding that are held by financial institutions recorded in Thomson Reuters 13(f) Institutional Holding Database. D'Avolio (2002) shows that large stocks and stocks with high institutional ownership are easier to be short. OWN_BRD is the number of 13(f) financial institutions holding the stock scaled by total number of 13(f) financial institutions at that time14F[16]. More institutions holding the stock usually means more competitions among the stock lenders and thus lower short-sale costs (Xu (2007)). To proxy for investors' disagreement, we use the detrended turnover ratio (DETRND_TO) (see Varian (1989), Harris and Raviv (1993) among others), constructed as the annual average of daily detrended turnovers. The daily detrended turnover is the ratio of daily share volume to total shares outstanding and detrended by a moving average of past 20-trading-days' turnover. Since the volume data for NASDAQ stocks are partially double-counted and thus incomparable with the volume data for stocks from other exchanges, we only estimate DETRND_TO for NYSE and AMEX stocks. Consequently, the regression of Equation (6) is performed only for the

[15] We measure market capitalization over a period, instead of on a certain day, because skewness is also constructed in a similar manner.
[16] Both INS_OWN and OWN_BRD are available at quarterly frequency from Thomson Reuters 13(f) Institutional Holdings Database, and are calculated as the annual average of quarterly data.

NYSE and AMEX subsample, when DETRND_TO is included. Current and lagged annual returns are also included, because Xu (2007) shows that a) price convexity increases stock return skewness and contemporaneous expected market return simultaneously, which causes skewness to be positively correlated with current returns, and b) lagged returns are expected to be negatively correlated with skewness due to corrections to previous over- or under-reaction.

1.5.2 The Results

Table 1.8 reports the regression estimates of the stock return skewness model (Equation (6)). The model is estimated using the pooled OLS regression with standard errors clustered by firm. To account for potential correlations of skewness across firms within a certain year, we also include year (and industry) dummies. In Table 1.8, Column (1), as we expected, the stock return is shown to be more negatively skewed if the average level of IA during the year is high. Also consistent with our hypothesis, Column (2) shows that the interaction term of AVG_IA5 and INTANG is significantly negative. In other words, when firm-specific news is highly ambiguous *and* the arriving frequency of such ambiguous news relative to unambiguous news is high, the stock return is more negatively skewed. It is also shown that the interaction term is more accurately capturing the ambiguity effect on skewness. After other control variables are included, AVG_IA5 is no longer significant but the interaction term retains its explanatory power.

Most of the signs for the control variables are consistent with the findings of Xu (2007). Stock return skewness increases with current annual return while it decreases with previous annual returns. Stock returns are more negatively skewed when the short-sale constraints for the stock are less binding (for example, in the case of large firms, firms with high institutional ownership, and firms with high ownership breadth). We also find that the return is more negatively skewed when stock volatility is high, which can be attributed to the asymmetric volatility effect. Previous studies (see Black (1976), Christie (1982), and Glosten, et al. (1993)) have documented that stocks tend to have higher volatilities following negative returns than following positive returns, therefore negative skewness is expected be associated with higher volatilities. The only result that is not consistent with the findings of Xu (2007) is that skewness is negatively associated with detrended turnover. It is possible that detrended turnover is not a good proxy for disagreement.

Table 1.8
The Determinants of Stock Return Skewness

This table reports results of regressions of the skewness of the daily stock returns on firm *j* in year *t* on various variables. Variables are defined in Table I. The clustered regression is the pooled OLS regression where the standard errors are clustered by firm. The sample period is from 1994 to 2007. The t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dependent Variable: $SKEW_{jt}$				
	Clustered Regression (by Firm)				
	(1)	(2)	(3)	(4)	(5)
$Intercept_{jt}$	0.1385***	0.1411***	-0.9434***	-2.1073***	-2.2867***
	(3.29)	(3.32)	(-8.61)	(-6.54)	(-5.51)
AVG_IA5_{jt}	-0.0795***	-0.0550***	-0.0220	-0.0235	-0.0132
	(-5.1)	(-3.37)	(-1.44)	(-1.56)	(-0.63)
AVG_IA5_{jt} $\cdot INTANG_{jt}$		-0.1205*** (-4.14)	-0.1548*** (-5.53)	-0.1363*** (-4.95)	-0.1773*** (-4.97)
$ARET_{jt}$			0.6578***	0.6581***	0.7125***
			(37.15)	(37.19)	(25.95)
$ARET_{j(t-1)}$			-0.1027***	-0.0977***	-0.1029***
			(-6.82)	(-6.45)	(-4.64)
$ARET_{j(t-2)}$			-0.0624***	-0.0580***	-0.0745***
			(-4.3)	(-4.02)	(-3.4)
$ARET_{j(t-3)}$			-0.0325**	-0.0289**	-0.0636***
			(-2.55)	(-2.28)	(-3.23)
$Ln(VOL\_RET_{jt})$			-0.5723***	-0.5849***	-0.5619***
			(-18.65)	(-18.89)	(-13.72)
AVG_SIZE_{jt}			-0.0886***	-0.0314*	-0.0140
			(-15.59)	(-1.74)	(-0.6)
$Ln(INS\_OWN_{jt})$				-0.1474***	-0.0762**
				(-5.85)	(-2.22)
$Ln(OWN\_BRD_{jt})$				-0.0831**	-0.1347***
				(-2.38)	(-2.9)
$DETRN\_TO_{jt}$					-0.4916***
					(-5.55)
Adjusted R-square	1.442%	1.561%	13.48%	14.00%	14.09%
Industry and Year Dummies	Yes	Yes	Yes	Yes	Yes
Num of Observations	20765	20765	20765	20763	12359 (NYSE & AMEX only)

1.6 Conclusion

Defining ambiguity as investor's uncertainty about the precision of observed information, this paper constructs an empirical measure of ambiguity based on analysts' earnings forecast information, and finds that the market tends to react more negatively to highly ambiguous *bad* news, while it tends to be less responsive to highly ambiguous *good* news. This result supports the theoretical findings by ES (2003, 2008), who argue that ambiguity-averse investors take a worst-case assessment of the information precision when the information precision is unknown. In addition, this paper shows that for the stocks exposed to highly ambiguous and intangible information, their returns are more negatively skewed.

Chapter 2
Informed Investors' Trade-Size Choice:
Evidence from Analysts' Earnings Forecast Announcements

2.1 Introduction

This paper investigates trade-size choice by informed investors. Barclay and Warner (1993) argue that the informed, who tend to trade large amount of shares to fully take advantage of their private information, should prefer breaking up the trade into medium-size orders. Compared to one large trade, several medium trades are less likely to be noticed by the uninformed and/or regulators. Furthermore, as suggested by Seppi (1990), large trades (or block trades) are usually executed through negotiations with dealers in the "upstairs market". Therefore, there is no anonymity and the party initiating such block trades subjects to "no-bagging-the-street" commitment[17]. Given these constraints and the assumption that the size of block trades is capped at a relatively low level, Seppi (1990) shows that it is optimal for informed traders to avoid block trades and use smaller trades executed by the market specialists instead, since informed investors can accumulate much larger positions through a series of smaller trades than through "one-shot" block trade, and hence higher trading profits. On the other hand, using too small trades is both costly and slow. There is usually a fixed transaction cost associated with each trade. Moreover, the informed run the risk that their private information may be detected by market

[17] This commitment requires that the traders using dealers' block trades cannot trade the stock again in the near future.

makers or revealed by other informed traders, prior to establishing desirable positions. Consistent with this "stealth trading" hypothesis, Barclay and Warner (1993) find that during the preannouncement periods for tender offer targets medium-size trades drive a disproportionally large amount of the cumulative stock-price changes relative to their transaction number and volume. Furthermore, Chakravarty (2001) uses the TORQ Database and finds that the medium trades that have large price impacts are primarily initiated by institutions.

However, these studies' evidence only provides indirect support for the hypothesis that investors using medium-size trades are informed, since their conclusions are based on the assumption that cumulative stock-price movements are largely due to informed trading. Although several papers have documented that trading on private information, rather than public information, is largely driving cumulative stock-price changes (see French and Roll (1986), Barclay, Litzenberger, and Warner (1990)), there is no guarantee that the private information is correct, i.e., that investors trading on private information are indeed informed. Those results could also be due to the overconfidence of medium-size traders who pay too much attention on their private information, which may not be correct, and trade excessively on it[18]. To address this concern, this paper compares the direction of order flow imbalance across different trade-size groups

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[18] Daniel, Hirshleifer, and Subrahmanyam (1998) propose a theory where investors are overconfident about the precision of their private information and the bias leads to long-term return reversal and excessive stock volatility.

with the direction of actual news[19]. If investors are informed, they should trade in the same direction of the news prior to its announcement.

The news source used here is the set of analysts' annual earnings forecast announcements. There are several advantages of doing so. First, the public generally does not know the timing of forecast announcement beforehand. For the news with pre-announced release date, like earnings announcements, it is hard to differentiate the trades from "informed" traders, who know the nature of the news, and from "skillful" traders, who correctly bet on the direction of the news prior to its release based on their own judgment and publicly available information. In contrast, the "correct" trades placed right before forecast announcements are more likely to come from informed traders, because those investors have to know not only the nature of the news but also its timing, and the latter is very difficult to gauge. Second, our samples are more representative. Compared to other news whose timing is unknown to the public in advance, like tender offers, analysts' forecast announcements are more frequent and more pervasive across different types of firms. Third, sell-side analysts' information is prone to leakage. For example, a recent article from *Wall Street Journal*[20] reveals that Goldman Sachs research analysts disseminated their trading tips to their own traders first, and then to their top-priority clients before finally making them

[19] Similar approach has been used in several other papers. For example, Kaniel, Liu, Saar, and Titman (2008) use it to examine whether investors are informed prior to earnings announcement. However, their focus is on trades from individual investors, rather than trades across different trade-size groups.

[20] See "Goldman's Trading Tips Reward its Biggest Clients" from *Wall Street Journal* Page A1 on August 24, 2009.

public. To our knowledge, this paper is the first to examine order flow imbalance surrounding analysts' earnings forecast announcements.

Prior to the announcement of earnings forecasts, there could exist two types of informed traders. The first type (Type-I) informed traders know the nature of earnings forecasts, and should be buyers (sellers) prior to the announcements of positive (negative) forecast revisions. The second type (Type-II) informed traders know the long-term value of the stock, and will react after the forecast announcements. For example, assuming an investor is informed about the actual earnings the analyst is forecasting, rather than the analyst's forthcoming forecast, she can always compare the analyst's forecast (once it is made to the public) with her private information and determine whether the forecast is too optimistic or pessimistic. If the overly optimistic (pessimistic) forecasts induce significant market reaction, she will sell (buy) after the forecasts. Empirically, for each stock, we examine the abnormal order flow imbalance of different trade-size groups to determine whether a certain trade-size group is net buyer or net seller for this stock. Suggesting the existence of Type-I informed traders and their preference to use medium trades, we find that medium-size traders tend to be net buyers prior to very positive forecast revisions and net sellers prior to very negative forecast revisions. But we cannot observe such pattern for large-size or small-size traders. This result provides strong support for the "stealth trading" hypothesis. We also find that during the announcement all trade-size groups are trading in the direction of the news. However, after the announcement, large traders keep trading in the direction of the news ("news momentum traders"), whereas medium and small traders are trading against the direction of news ("news contrarian traders")

In support of the existence of Type-II informed traders and their preference to use medium trades, our results show that the stocks medium-size traders buy immediately after the forecast announcements significantly outperform the stocks they sell in the future up to four months. We also find similar patterns for small traders, but only following *downward* revisions. Moreover, we find that large trades placed immediately following the forecasts are unprofitable and generate, on average, slightly negative profits in the long run. Specifically, the post-event trade imbalance of large trades is weakly negatively related to future long-run returns. This result suggests that large trades are more likely to be used to meet immediate liquidity needs where the execution speed of the trade is more important than the profitability of the trade. We also show that our results hold for two different trade-size classification methods: a method based on static dollar-based cutoff points and a method based on firm-size- and stock-price-specific cutoff points.

This study makes several contributions to the literature. First, it provides further support for the "stealth trading hypothesis" proposed by Barclay and Warner (1993), who argue that informed investors prefer to use medium-size trades. Our empirical framework allows us to directly test whether the private information possessed by medium-size traders is correlated with future public information. While existing literature on "stealth trading hypothesis" (Barclay and Warner (1993) and Chakravarty (2001)) exclusively focus on pre-event trading activities, we also examine post-event trading activities and address the question of whether medium-size traders have superior skills in interpreting public signals. Furthermore, by focusing on analysts' forecast announcements, we are able to differentiate informed investors from skillful speculators while maintaining a broader sample. Second, this study provides additional empirical evidence that certain investors possess analysts' information before it is made available to the public. Christophe, Ferri, and Hsieh (2009) document that stocks tend to experience abnormally high levels of short-selling activity in the three days prior to announcements of analysts' downgrades. While Christophe, et al. (2009) only examine short sellers and their trading activities prior to analysts' downgrades, this paper looks at the order flow imbalance induced by all investors and both positive and negative news as reflected in earnings forecast announcements. Third, this paper extends the studies examining order flow imbalance and its implications. Some of these studies investigate trade imbalance's effects on cross-sectional returns (See Hvidkjaer (2006, 2008), Barber and Odean (2008), Barber, Odean and Zhu (2009), Kaniel, Saar, and Titman (2009), etc.), while some of them examine its relation to earnings announcements (See Bhattacharya (2001), Battalio and Mendenhall (2005), Shanthikumar (2004), Kaniel, Liu, Saar, and Titman (2008), Campbell, Ramadorai, and Schwartz (2009), etc.). These studies either focus on the large or small trades, which are used as proxies for institutional or individual trades, or look directly at the institutional or individual trades. However, medium-size trades are usually omitted from their analysis, since it is difficult to separate these trades into institutional and retail trades. Our results suggest that medium-size trades, which could be initiated by either individuals or institutions, contain very important information about forthcoming public announcements and future long-run stock returns.

The rest of this paper is organized as follows. Section II describes the data and the construction of the order flow imbalance variables. Section III analyses the trading imbalance of different trade-size groups before, during, and after the announcement of analysts' forecasts, and examine the relation between the trading imbalance and the nature of the news. Section IV investigates the predictive power of order flow imbalance from different trade-size groups for future long-run returns. We check our results' robustness to an alternative trade-size classification scheme in Section V. Section VI concludes the paper.

2.2 Data and Construction of Variables

2.2.1 Sample Selection

The sample in this paper includes all ordinary common stocks listed on New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) during the period from January 1994 to December 2000. We exclude NASDAQ stocks, because their trading volumes are partially double-counted and thus are not comparable with NYSE and AMEX. The sample period begins at 1994 when the forecast announcement dates recorded in I/B/ES start to become reliable, as suggested by Clement and Tse (2003). Similar to Barber, Odean, and Zhu (2009), the sample period stops at 2000, because the introduction of decimalization in 2000 and the widespread use of computerized algorithm trading to break up institutional trades create a structural change in the distribution of trade sizes[21]. Therefore, the trade size cutoff points, suggested by earlier studies, may no longer be valid after 2000.

Analysts' forecast information is obtained from the Institutional Broker Estimate System (I/B/E/S) Detailed History database[22]. The forecasts are for firms' current fiscal year-end earnings. To insure that the analysts' forecast announcements are not contaminated by other concurrent events, we require that there is no quarterly/annual earnings announcement made 10 days prior to or after the forecasts, and there is no other forecast announcement made 5 days prior to or after the forecasts. We also require that forecasts must be made at least 30 days, but no more than 1 year, before the fiscal-year end. The forecast-horizon requirement of at least 30 days is needed, since Clement and Tse (2003) show that the market tends to be less responsive to late forecasts, i.e., those made closer to the fiscal-year end, and thus informed traders may not find it profitable to trade before the late forecasts. The forecast-horizon requirement of less than 1 year excludes stale forecasts.

Stock transaction data are obtained from the Trade and Quote (TAQ) database. Only NYSE/AMEX quotes and trades reported within the opening hours (from 9:30AM to 4PM) of the exchanges are included. We also eliminate

[21] For example, Hvidkjaer (2008) has found that there is a huge increase in the number of small trades after 2000.

[22] The rounding error problem associated with I/B/E/S adjusted data (Barber and Kang (2002)) is less severe in the case of the detailed history I/B/E/S database, where the estimates are rounded to four decimals, instead of two decimals as is the case in the summary history I/B/E/S database.

the opening trades, which are aggregated orders from a call auction process for NYSE/AMEX stocks. The trades and quotes data are run through a filter, suggested by Hvidkjaer (2006), to exclude erroneous observations. Specifically, we exclude quote observations with condition codes of "4, 5, 7-9, 11, 13-17, 19, 20" and trade observations with condition codes of "A, C, D, G, L, N, O, R, X, Z, 8, 9". In addition, quotes are deleted if the ask price is not greater than the bid price, or the bid-ask spread is greater than 75% of the quote midpoint, or the ask/bid price is more than double or less than half of the previous ask/bid price. Trades are deleted if the correction code is greater than 1, or the trade price is more than double of less than half of the previous trade price. Following Lee and Ready (1991), the trade report times are lagged by five seconds when we merge trade and quote data, and the trades are classified into buyer- or seller-initiated trades by using the quote rule first and then the tick rule. In particular, the trade is buyer (seller) initiated, if the trade price is above (below) the midpoint of the most recent quotes. If the trade price equals the quote midpoint, we use the tick rule, i.e., the trade is buyer (seller) initiated, when the trade price is above (below) the previous trade price.

Finally, we require that stocks simultaneously have trade information from TAQ, prices information from CRSP, and accounting information from Compustat Fundamentals Annual Files during the periods surrounding forecast announcements. After all the requirements, we have 28409 valid analyst-forecast observations and on average about 338 observations per month. In addition, our sample covers about 276 different firms every month.

2.2.2 The Trade-size Classification and Order Flow Imbalance Measure

Following Lee and Radhkrishna (2000) and Barber, et al. (2009), we partition the trades into three trade-size groups based on the dollar size (T) of the trades:

1. T <= $5,000 (Small Trades)
2. $5,000 < T <= $50,000 (Medium Trades)
3. T > $50,000 (Large Trades)

Dollar-based cutoff points are more accurate than share-based ones, since the latter are likely to be biased when the stock price per share is unusually high or low. For example, the share-based approach used in Barclay and Werner (1993) and Chakravarty (2001) classifies all the trades with more than 10,000 shares as large trades. However, for “penny” stocks, 10,000 shares could hardly be considered as large trades. Lee and Radhkrishna (2000), using TORQ data, find that these cutoff points perform very well in differentiating individual trades from institutional trades, i.e., small trades are more likely to come from individuals while large trades are more likely to come from institutions. Although there is still an ongoing debate on the suitability of this proxy[23], it should have little impact on our study. This paper focuses on investigating which trade size the informed investors prefer to use, regardless of the informed traders’ characteristics (e.g., institutions or individuals). This classification scheme is adopted, because it provides an objective way to separate the trades based on their economic significance. The cutoff points are proposed based on the TORQ

[23] For example, Campbell, Ramadorai, and Schwartz (2007) conclude that the smallest trades (below $2000) are actually more likely to come from institutions rather than individuals.

data covering the period from November 1990 to January 1991. To account for the inflation effect on trade sizes, all the trades' dollar sizes are converted to 1991 dollars using annual CPI level before comparing them to the cutoff points. In response to possible concerns regarding the appropriateness of our trade-size classification method, in Section V we will repeat our analysis using an alternative trade-size classification method in which cutoff points are specific to firm size and stock prices. We show that our results are quite robust to different trade-size classification methods.

To detect investors' unusual trading activities, we use cumulative abnormal order flow imbalance. For each stock i on day t, the daily abnormal order flow imbalance (ABN_DOFI) for trade-size group j is defined as:

$$DOFI_{i,j,t} = \begin{cases} \dfrac{Buy_{i,j,t} - Sell_{i,j,t}}{(Buy_{i,j,t} + Sell_{i,j,t})/2}, & if\ Buy_{i,j,t} \neq 0\ or\ Sell_{i,j,t} \neq 0 \\ 0, & otherwise \end{cases}$$

$$ABN\_DOFI_{i,j,t} = DOFI_{i,j,t} - \overline{DOFI_{i,j,}}_{\ in\ the\ prior\ year}$$

Here, Buy (Sell) is the daily dollar volume of buyer- (seller-) initiated trades. Daily order flow imbalance is subtracted by the average daily imbalance in the prior year to get the abnormal measure. And the cumulative abnormal order flow (ABN_OFI) over the period from t1 to t2 is defined as:

$$ABN\_OFI_{i,j,t1,t2} = \sum_{t=t1}^{t2} ABN\_DOFI_{i,j,t}$$

Table 2.2 reports the summary statistics of this measure. It is shown that large traders are, on average, net buyers before [t-5, t-2], during [t-1, t+1], and after the forecast announcements [t+2, t+5]. The evidence is inconclusive for medium and small traders, since the sign of means and medians are inconsistent.

Table 2.1
Definitions of Variables

Variables		Definition
Abnormal Order Flow Imbalance of Large/ Medium/ Small Trades	$ABN\_OFI_{Large/Med/Small,\ t1,\ t2}$	It is the cumulative abnormal order flow imbalance (OFI) during the period from relative trading day t1 to t2 for the trades on a stock that belongs to certain size group. E.g., large trades are defined as the trades with size greater than $50,000 (in terms of 1991 dollars); medium trades are the trades with size between $5,000 and $50,000; small trades are the trades with size below $5,000. The daily abnormal OFI on day t is calculated as: $DOFI_t = \frac{buy_t - sell_t}{(buy_t + sell_t)/2}$ $ABN\_DOFI_t = OFI_t - \overline{OFI}_{in\,the\ prior\ year}$ where buy_t ($sell_t$) is dollar volume of all buyer (seller) initiated trades on day t. And the cumulative abnormal OFI from t1 to t2 is defined as: $ABN\_OFI_{t1,t2} = \sum_{t=t1}^{t2} ABN\_DOFI_t$
Mean Abnormal Order Flow Imbalance of Size-B/M-sorted Benchmark Portfolio	$MABN\_OFI_{Large/Med/Small,\ t1,\ t2}$	It is the cumulative daily averages of abnormal OFIs for all the stocks in the same size-B/M-sorted benchmark portfolio from relative trading day t1 to t2. Every July, we sort all the stocks that have OFI information from TAQ database into size quintiles based on the market value of equity at the end of June. Within each size quintile, we further sort the stocks into B/M quintiles. The Book-to-market ratio is the book value of common equity at the end of fiscal year ending anywhere in the previous calendar year divided by the market value of equity at the end of previous calendar year. The benchmark portfolio is equally weighted.
Short-term Cummulative Abnormal Return	$CAR_{t1,t2}$	It is the cumulative market-adjusted return during the periods surrounding analyst's forecast announcement date. The measurement period starts on relative trading day t1 and ends on t2. The market adjusted return is calculated by subtracting the concurrent value-weighted market return from the firm j's daily stock return.
Long-term Post-event Cumulative DGTW Characteristic-adjusted Abnormal Returns	$LTCAR\_DGTW_{t1,t2}$	$LTCAR\_DGTW = \sum_{t=t1}^{t2} (R_{it} - R_t^{dgtw\_bench})$, where R_{it} is the raw daily return and $R_t^{dgtw\_bench}$ is the daily return on size-B/M-momentum sorted benchmark portfolio. The universe for benchmark portfolios include all stocks listed in NYSE, AMEX and NASDAQ.

Long-term Post-event Cumulative Size-B/M-adjusted Abnormal Returns	$LTCAR\_SBM_{t1,t2}$	$LTCAR\_SBM_{t1,t2} = \sum_{t=t1}^{t2}(R_{it} - R_t^{sbm\_bench})$, where R_{it} is the raw daily return and $R_t^{sbm\_bench}$ is the daily return on size-B/M sorted benchmark portfolio. The universe for benchmark portfolios include all stocks listed in NYSE, AMEX and NASDAQ.
Long-term Post-event Cumulative DGTW Characteristic-adjusted Abnormal Returns (With NYSE-and-AMEX Benchmark Universe)	$LTCAR\_DGTW\_NA_{t1,t2}$	The construction of this variable is similar to $LTCAR\_DGTW_{t1,t2}$, except that the universe for benchmark portfolios include only stocks listed in NYSE and AMEX.
Forecast Revision	FCST_REV	It is the EPS forecast minus the prior EPS forecast from the same analyst, scaled by the stock closing price two days prior to the analyst's forecast announcement date.
Pre-event Momentum	MOMEN	It is the six-month cumulative return during the period ending six trading days before the forecast announcement (t-6).
Forecast Innovation Signal	INNOV_SIG	Following Gleason and Lee (2003), it equals to 1 (highly-innovative good-news forecasts), if the forecast is above the prior consensus and analyst's own prior forecast; equals to 0 (low-innovative forecasts), if the forecast falls between the prior consensus and analyst's own prior forecast; equals to -1 (highly-innovative bad-news), if the forecast is below the prior consensus and analyst's own prior forecast. The prior consensus is the mean of forecasts for the same firm in the previous month obtained from I/B/E/S summary database.

Table 2.2
Descriptive Statistics

Here we report the descriptive statistics of the main variables at the forecast level. The sample consists of the analysts' forecasts for current fiscal year-end earnings announced between 1994 and 2000 and documented in I/B/E/S Adjusted Detail History Database. We require that forecasts must be made at least 30 days, but no more than 1 year, before the fiscal-year end. We also eliminate the forecasts that have a quarterly/annual earnings announced during the period of t-10 to t+10, or have other earnings forecasts announced during the period of t-5 to t+5. The stocks covered by the analysts are required to be traded in NYSE/AMEX and have available trade and quote information in TAQ database during the sample period. All the variables are winsorized at the top and bottom one percentile. Table I has the definition of all variables.

	N	Mean	Std. Dev.	25^{th} percentile	Median	75^{th} percentile
$ABN\_OFI_{Large,\ t-5,\ t-2}$	27993	0.0428	2.2289	-1.3269	0.0730	1.4114
$ABN\_OFI_{Large,\ t-1,\ t+1}$	28003	0.0326	1.8941	-1.1238	0.0521	1.2117
$ABN\_OFI_{Large,\ t+2,\ t+5}$	28006	0.0188	2.2137	-1.3556	0.0470	1.4263
$ABN\_OFI_{Med,\ t-5,\ t-2}$	27993	0.0080	1.6093	-0.9088	0.0299	0.9606
$ABN\_OFI_{Med,\ t-1,\ t+1}$	28003	-0.0188	1.3467	-0.7779	0.0090	0.7673
$ABN\_OFI_{Med,\ t+2,\ t+5}$	28006	-0.0160	1.6195	-0.9523	0.0144	0.9426
$ABN\_OFI_{small,\ t-5,\ t-2}$	27993	-0.0093	2.0681	-1.2268	0.0000	1.2502
$ABN\_OFI_{small,\ t-1,\ t+1}$	28003	-0.0185	1.6555	-1.0169	0.0000	1.0095
$ABN\_OFI_{small,\ t+2,\ t+5}$	28006	-0.0520	2.0702	-1.2780	0.0000	1.2191
$MABN\_OFI_{Large,\ t-5,\ t-2}$	26825	0.0219	0.3717	-0.2157	0.0346	0.2749
$MABN\_OFI_{Large,\ t-1,\ t+1}$	26836	0.0105	0.3083	-0.1853	0.0184	0.2181
$MABN\_OFI_{Large,\ t+2,t+5}$	26836	0.0158	0.3730	-0.2236	0.0272	0.2653
$MABN\_OFI_{Med,\ t-5,\ t-2}$	26825	-0.0167	0.3855	-0.2419	0.0101	0.2450
$MABN\_OFI_{Med,\ t-1,\ t+1}$	26836	-0.0225	0.3147	-0.2085	-0.0025	0.1891
$MABN\_OFI_{Med,\ t+2,\ t+5}$	26836	-0.0301	0.3872	-0.2575	-0.0079	0.2349
$MABN\_OFI_{small,\ t-5,\ t-2}$	26825	-0.0424	0.4189	-0.3102	-0.0243	0.2401
$MABN\_OFI_{small,\ t-1,\ t+1}$	26836	-0.0395	0.3316	-0.2558	-0.0235	0.1833
$MABN\_OFI_{small,\ t+2,\ t+5}$	26836	-0.0576	0.4191	-0.3257	-0.0360	0.2278
$CAR_{t-5,\ t-2}$ (%)	28409	-0.0992	3.8626	-2.1214	-0.2220	1.8004
$CAR_{t-1,\ t+1}$ (%)	28409	-0.2140	6.4958	-3.7924	-0.4281	3.1926
$CAR_{t+2,\ t+5}$ (%)	28409	-0.2317	6.4986	-3.8204	-0.4622	3.0814
MOMEN (%)	26842	7.5376	27.3527	-8.9677	5.6819	20.5895
FCST_REV	28409	-0.0025	0.0121	-0.0026	-0.0001	0.0011
INNOV_SIG	26145	-0.0568	0.8540	-1.0000	0.0000	1.0000
$LTCAR\_SBM_{t+6,\ t+20}$ (%)	26922	-0.2131	8.6170	-4.8963	-0.3552	4.4140
$LTCAR\_SBM_{t+6,\ t+120}$ (%)	26922	-1.2792	23.9596	-14.8017	-1.3674	11.8968
$LTCAR\_SBM_{t+6,\ t+250}$ (%)	26922	-1.1264	35.6760	-21.2170	-2.0647	18.1661
$LTCAR\_DTGW_{t+6,\ t+20}$ (%)	26922	-0.1754	8.4455	-4.8165	-0.3291	4.3263
$LTCAR\_DTGW_{t+6,\ t+120}$ (%)	26922	-1.0104	23.3865	-13.9985	-1.0681	11.7000
$LTCAR\_DTGW_{t+6,\ t+250}$ (%)	26922	-0.8505	34.4889	-20.1125	-1.7943	17.2726
$LTCAR\_DTGW\_NA_{t+6,\ t+20}$ (%)	26916	-0.0768	8.1872	-4.5549	-0.1414	4.3433
$LTCAR\_DTGW\_NA_{t+6,\ t+120}$ (%)	26916	-0.1754	22.1967	-12.7672	-0.3672	11.9906
$LTCAR\_DTGW\_NA_{t+6,\ t+250}$ (%)	26916	0.8515	32.7871	-18.0684	-0.3912	17.9683

2.3 The Trade Imbalance Surrounding Forecast Announcements

2.3.1 Univariate Analysis

In this section, we examine which trade-size group is informed about the forthcoming forecast announcement. To do this, we report the average cumulative order flow imbalances of the three trade-size groups (large, medium, and small), conditional on the nature of the forecasts. We classify forecasts into five news groups based on the cumulative abnormal returns (STCAR) during the three-day surrounding the forecast announcement [t-1, t+1],: very positive (STCAR > 5%), positive (1% < STCAR <= 5%), neutral (-1% < STCAR <= 1%), negative (-5% < STCAR <= -1%), and very negative news (STCAR < -5%). The daily abnormal returns are calculated as the raw daily returns less the concurrent value-weighted market returns.

From Table 2.3 Panel A, we can see that during the pre-event period order flow imbalances induced by large and small traders are not systematically related to the nature of forthcoming forecasts, suggesting that they are uninformed. In contrast, medium traders seem to know the nature of forecasts in advance; they are net buyers (positive ABN_OFI) for very positive news and net sellers (negative ABN_OFI) for very negative news. To account for the possibility that ABN_OFI may not be normally distributed, which may invalidate the t-test, we also report the medians and test the median difference by non-parametric Wilcoxon rank sum test. It is shown that the medium traders' pre-event ABN_OFI difference between very positive and very negative news is 12.27% and statistically significant both in terms of the mean and median. Since the timing of analysts' forecast announcement is unknown to the public, this result suggests that certain medium traders know not only the nature of the forecast but also the timing of the forecast. Moreover, it is unlikely that medium traders may just be skillful in guessing the direction of the forecast revisions.

Panel B of Table 2.3 shows that during the event period order flow imbalances across all three trade-size groups are monotonically increasing with the event-period CARs. However, since both order flow imbalances and CARs are measured over the period of [t-1, t+1], it is hard to infer the causal direction of this pattern. It is possible that positive (negative) news induce buying (selling) pressure, while it is also likely that buying (selling) pressure itself tends to drive up (down) concurrent stock returns.

In Panel C of Table 2.3, we look at the order flow imbalance during the four days immediately following the announcement of forecasts. Interestingly, we find that large traders tend to be "news momentum" traders, who are buying after good news and selling after bad news. On the other hand, medium and small traders tend to be "news contrarian" traders, who are selling winners and buying losers. These results are similar to the findings from earnings announcements. For example, Shanthikumar (2004) find large traders trade in the direction of earnings surprises for up to one month after the announcement while small traders do not. Kaniel, et al. (2008), who are able to identify individuals' trades using the proprietary Consolidated Audit Trail database, also document a contrarian behavior for individual investors following earnings surprises.

Table 2.3
Order Flow Imbalances during Periods Surrounding Forecast Announcements

The reported are means and medians of the cumulative abnormal OFI of different trade-size groups across various news groups. We sort the forecasts into five news groups, based on the market response during the announcement date. In particular, the forecast is "very-positive" news, if $CAR_{t-1, t+1}$ >= 5%; the forecast is "positive" news, if 1%<= $CAR_{t-1, t+1}$ < 5%; the forecast is "neutral" news, if -1% <= $CAR_{t-1, t+1}$ < 1%; the forecast is "negative" news, if -5% <= $CAR_{t-1, t+1}$ < -1%; the forecast is "very-negative" news, if $CAR_{t-1, t+1}$ <= -5%. Variables are defined in Table I. To test the difference in means, we use two-sided T-test and T-statistics are reported in brackets. To test the difference in medians, we use two-sided Wilcoxon rank sum test and the corresponding p-values are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Panel A. Pre-event Period (t-5, t-2)

		News Nature					
		Very Negative (VN)	Negative	Neutral	Positive	Very Positive (VP)	VP-VN [t-stat] or (Wilcoxon P-value)
	nobs	2194	8571	7861	7142	2225	
Large Trades ABN_OFI	mean	0.0147	0.0731	0.0503	0.014	0.0249	0.0102 [0.15]
	median	0.0321	0.088	0.0845	0.0596	0.0787	0.0466 (0.8298)
Medium Trades ABN_OFI	mean	-0.0487	0.0015	0.0024	0.0187	0.074	0.1227** [2.51]
	median	0.0015	0.0232	0.0343	0.0396	0.0421	0.0406** (0.0204)
Small Trades ABN_OFI	mean	0.0173	-0.0252	-0.0436	-0.0018	0.1186	0.1013* [1.67]
	median	0.0213	0	0	0	0.1427	0.1214 (0.1194)

Panel B. During-event Period (t-1, t+1)

		News Nature					
		Very Negative (VN)	Negative	Neutral	Positive	Very Positive (VP)	VP-VN [t-stat] or (Wilcoxon P-value)
	nobs	2196	8577	7863	7142	2225	
Large Trades ABN_OFI	mean	-0.7441	-0.4312	0.0625	0.5351	0.8792	1.6232*** [30]
	median	-0.715	-0.3338	0.0531	0.4926	0.8208	1.5358*** (<.0001)
Medium Trades ABN_OFI	mean	-0.4041	-0.2441	-0.0264	0.2228	0.4847	0.8889*** [22.48]
	median	-0.3034	-0.1833	0.0133	0.1942	0.4163	0.7197*** (<.0001)
Small Trades ABN_OFI	mean	-0.1329	-0.1197	-0.0813	0.0809	0.3881	0.5211*** [11.06]
	median	-0.0828	-0.0478	0	0.0099	0.3746	0.4574*** (<.0001)

Panel C. Post-event Period (t+2, t+5)

		News Nature					
		Very Negative (VN)	Negative	Neutral	Positive	Very Positive (VP)	VP-VN [t-stat] or (Wilcoxon P-value)
	nobs	2195	8575	7867	7142	2227	
Large Trades ABN_OFI	mean	-0.278	-0.1458	0.0062	0.2222	0.3414	0.6193*** [9.49]
	median	-0.186	-0.0811	0.0491	0.2049	0.3383	0.5243*** (<.0001)
Medium Trades ABN_OFI	mean	0.1897	0.0358	-0.0746	-0.0567	-0.083	-0.2726*** [-5.8]
	median	0.1955	0.0558	-0.0279	-0.0111	-0.0743	-0.2698*** (<.0001)
Small Trades ABN_OFI	mean	0.1847	-0.0722	-0.117	-0.0495	0.0284	-0.1563*** [-2.59]
	median	0.1744	0	0	0	0.048	-0.1264** (0.0168)

2.3.2 Regression Analysis

The results of pre-event trade imbalance are of greater interests to us, since they provide direct support to the stealth trading hypothesis. This section employs a regression framework that enables us to control for other variables that may also affect trade imbalances. The pre-event cumulative order flow imbalance of the trade-size group j for stock i is modeled as:

$$ABN\_OFI_{i,j,t-5,t-2} = \beta_0 + \beta_1 CAR_{i,t-1,t+1} + \beta_2 CAR_{i,t-5,t-2} + \beta_3 MOMEN_{i,t-126,t-6} + \beta_4 MABN\_OFI_{j,t-5,t-2} + \varepsilon_{i,j} \qquad (1)$$

The stealth trading hypothesis predicts that medium traders are informed about the nature of upcoming forecasts, i.e., event-period market response CAR $_{i,\ t-1,\ t+1}$ should be positively related to pre-event trade imbalance ABN_OFI $_{i,\ j,\ t-5,\ t-2}$ for only medium-size trade group. Since pre-event trade imbalance could also be trigged by other news that is announced over the period of [t-5, t-2] and not captured by our sample selection filter[24], we control for this potential bias by including the pre-event market response CAR $_{i,\ t-5,\ t-2}$. If any pre-event news is significant enough to trigger trade imbalance, it must also have similar effect on concurrent stock returns. We also control for the stock return momentum, which is measured as the past 6-month stock return up to day t-6. Hvidkjaer (2006) finds that small traders tend to buy past 6-month losers and reduce the purchase of past 6-month winners, whereas large traders are largely momentum traders who buy past winners and sell past losers. It is also possible that there exists cross-sectional dependence in order flow imbalances for stocks with similar characteristics. For example, if investors engage in style investing as suggested by Barberis and Shleifer (2003), then on a certain day all stocks in one asset class, e.g. small-value stocks, may experience the same buying or selling pressure. These buying or selling pressures are not due to investors' trading on firm-specific information and thus need to be controlled for. To achieve this goal, we include the contemporaneous order flow imbalance of an equally-weighted benchmark portfolio. The benchmark portfolio for a stock I includes all the stocks in NYSE/AMEX that are in the same size and book-to-market bin as stock i.[25]

Table 2.4 reports the coefficient estimates of model (1) for each trade-size group. To further account for the cross-sectional dependency in the dependent variable, we use the Rogers standard errors that are clustered by month, as

[24] Our sample selection procedure has eliminated the possibility that earnings or analysts' forecast announcements can be made during that period.

[25] Specifically, at the beginning of each July we sort the stocks into five size groups based on size-quintile cutoff points obtained from NYSE stocks only. The size is measured as the market capitalization at the end of June. Within each size group, we further sort the stocks into B/M quintiles based on their industry-adjusted book-to-market ratios.

suggested by Petersen (2009). Consistent with the stealth trading hypothesis, only medium-size trade imbalances are positively related to event-period market responses. Based on the regression estimation, a 10% increase in event-period CAR $_{i,\ t-1,\ t+1}$ is associated with an 8% increase in pre-event net buying pressure from medium traders ABN_OFI $_{med,\ t-5,\ t-2}$. The signs of the control variables' coefficients are also largely as expected. The pre-event order flow imbalance is significantly positively related to the pre-event CAR and the order flow imbalance of the benchmark portfolio. Similar to the findings of Hvidkjaer (2006), the negative sign of β_3 for small traders suggest that they are contrarians who trade in the opposite direction of the past six-month price movement, while the positive sign of β_3 for large traders suggest that they are momentum traders. Interestingly, medium traders display a similar contrarian trading pattern as the small traders during the post-event period. In addition, we find that individual stocks' trade imbalance is positively related to the trade imbalance of benchmark portfolios, suggesting that stocks with similar characteristics tend to experience the same buying or selling pressures during certain periods.

Table 2.4
Regression Analysis of Abnormal Order Flow Imbalances during the Pre-event Period

This table reports the regression results of the cumulative abnormal OFIs of different trade size during the pre-event period [t-5, t-2] on various variables. Variables are defined in Table I. The regressions are the pooled OLS regression where the standard errors are clustered by month. The t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dependent Variables:					
	Large Trades $ABN\_OFI_{Large,\ t-5,\ t-2}$		*Medium Trades* $ABN\_OFI_{Med,\ t-5,\ t-2}$		*Small* $ABN\_OFI_{small,\ t-5,\ t-2}$	
Intercept	0.0611**	0.0279*	0.0132	0.00951	-.0075	0.0573***
	(2.6)	(1.79)	(0.52)	(0.46)	(-0.24)	(4.41)
$\boldsymbol{CAR_{t-1,\ t+1}}$	0.0010	-.0017	0.0081***	0.0068**	0.0063	0.0056
	(0.32)	(-0.48)	(2.82)	(2.39)	(1.54)	(1.58)
$CAR_{t-5,\ t-2}$	0.07971***	0.0761***	0.0198***	0.0187***	0.0068**	0.0068***
	(21.21)	(20.39)	(11.81)	(10.67)	(2.48)	(2.9)
MOMEN		0.0015**		-.0011**		-.0031***
		(2.59)		(-2.41)		(-5.04)
$MABN\_OFI_{Large,\ t-5,\ t-2}$		0.9045***				
		(22.79)				
$MABN\_OFI_{Med,\ t-5,\ t-2}$				0.4470***		
				(9.43)		
$MABN\_OFI_{small,\ t-5,\ t-2}$						0.99521***
						(28.53)
Num of Observations	27993	26476	27993	26476	27993	26476
Adjusted R-square	5.46%	7.85%	0.68%	1.77%	0.053%	4.41%

2.4 Post-event Trade Imbalance and Future Long-run Stock Performance

In this section, we investigate whether there exist Type-II informed traders who know the long-term value of the stocks and whether they will use medium trades to exploit their informational advantage. For Type-II informed traders, their trades after observing the public signals should be consistent with the stock long-run performance. Thus, we focus on the relation between order flow imbalance immediately following the forecast announcement [t+2, t+5] and stock long-run cumulative abnormal returns over the period of [t+6, t+T].

2.4.1 Long-run Abnormal Return Measure

To measure long-run abnormal returns, we use cumulative size-B/M-adjusted returns and cumulative DGTW characteristics-adjusted returns proposed by Daniel, Grinblatt, Titman, and Wermers (1997). As pointed out by Lyon, Barber, and Tsai (1999), cumulative abnormal returns have better statistical properties and are less subject to the positive skewness bias which could yield mispecified t statistics, compared to buy-and-hold abnormal returns.

In particular, at the beginning of each July we sort all the stocks in NYSE, AMEX, and NASDAQ into 25 size-B/M benchmark portfolios for size-B/M-adjusted returns and 125 size-B/M-momentum benchmark portfolios for characteristics-adjusted returns. For example, the 125 size-B/M-momentum benchmark portfolios are formed by sequentially sorting stocks into size, book-to-market ratio, and momentum quintiles. The size is the stock's market capitalization at the end of June and the breakpoints used for the size sorting are the size-quintile breakpoints of NYSE firms only. The book-to-market ratio is the ratio of book value of common equity at the end of fiscal year ending anywhere in the previous calendar year and the market capitalization at the end of last December. We further adjust the ratio by subtracting the long-term industry[26] average. Finally, the momentum is the past 12-month return excluding the most recent one month, i.e., it is measured from last July to the end of this May.

Since our sample selection criteria limit the universe to NYSE/AMEX stocks, we also re-estimate the DGTW characteristics-adjusted returns using

[26] Industries are defined following Fama-French 48-industry classification.

only NYSE/AMEX stocks for the benchmark portfolios. The long-run cumulative abnormal return is the sum of daily differences of raw return and the contemporaneous return on the corresponding benchmark portfolio. Specifically, for stock i over the period of [t1, t2], its cumulative abnormal return is calculated as:

$$LTCAR_{i,t1,t2} = \sum_{t=t1}^{t2} (R_{i,t} - R_{bench,t}) \qquad (2)$$

In Table V, we compare the appropriateness of the above three measures of long-run cumulative abnormal return by examining the post-forecast-announcement drift. Several papers have documented that stock prices tend to drift in the same direction of forecast revisions for up to nine months (e.g., Stickel (1991), Chan, Jegadeesh, and Lackonishok (1996), and Gleason and Lee (2003)). The forecast revision is measured as the difference between an analyst's current forecast and his/her own prior forecast, scaled by the stock closing price two days prior to the forecast announcement[27].

As shown in Table 2.5, under all the three CAR measures, stocks experiencing negative revisions continue to underperform relative to stocks experiencing positive revisions for up to one year, and the drift is more pronounced during the first six months following forecast revisions. It is also shown that different measures do generate different levels of CARs. The drift magnitude measured by DGTW characteristics-adjusted returns is smaller than

[27] Stickel (1991), Imhoff and Lobo (1984) and Gleason and Lee (2003) all find that analyst's own prior forecast is a better benchmark than the prior consensus forecast for measuring the amount of surprise in analysts' forecasts.

the one measured by size-B/M-adjusted returns. This is not surprising, given the prior finding that the post-forecast-announcement drift can be partially explained by the momentum effect (Chan, et al.(1996)). Although the use of characteristics-adjusted returns may potentially weaken our results, it is preferred to size-B/M-adjusted returns, as it is a more conservative approach and since we know that findings based on this measure are not artifacts of the momentum effect. We also find that the CAR measures using the full universe (NYSE/AMEX/NASDAQ) are systematically biased downward. For example, the medians of long-run CAR for positive-revision stocks tend to be negative. This is likely due to the fact that NASDAQ stocks are performing fairly well during our sample period (1994-2000) which coincides with the technology-bubble period. More specifically, our sample filter eliminates NASDAQ stocks but our benchmark portfolios include these stocks. Consequently, the returns on the benchmark portfolios will be, on average, higher than the raw returns on our sample stocks, which yields downwardly biased CAR. Panel C of Table V confirms this argument. Here, the benchmark portfolios consist of only NYSE and AMEX stocks, and the mean and median values of this CAR measure (LTCAR_DGTW_NA) remain positive for stocks following positive revisions. Also, from Table II we can see that LTCAR_DGTW_NA is on average higher than LTCAR_DGTW that includes NASDAQ stocks in the benchmark universe. For the rest of the analysis, we will use LTCAR_DGTW_NA as the long-run abnormal return measure, since results based on it will not affected by our sample selection criteria. However, it should be noted that our results remain qualitatively the same if we use the other two CAR measures.

Table 2.5
Post-earnings-forecast Long-term CARs
Sorted by the Signs of Forecast Revisions

The reported are means and medians of the long-term cumulative abnormal returns following earnings forecast announcements. We sort the forecasts into two groups, based on the signs of forecast revision. Variables are defined in Table I. To test the difference in means, we use two-sided T-test and T-statistics are reported in brackets. To test the difference in medians, we use two-sided Wilcoxon rank sum test and the corresponding p-values are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Panel A. Cumulative Size-B/M-adjusted Returns (*LTCAR_SBM*)
(Benchmark Universe: NYSE, AMEX, NASDAQ)

		nobs	[t+6, t+20]	[t+6, t+40]	[t+6, t+80]	[t+6, t+120]	[t+6, t+250]
Positive Revision (FCST_REV >0)	Mean	12461	0.3672	0.3909	0.1788	0.0629	0.3225
	Median		0.1882	0.301	0.1259	-0.276	-0.8023
Negative Revision (FCST_REV <0)	Mean	13893	-0.7009	-1.4124	-2.0148	-2.3497	-2.2785
	Median		-0.8375	-1.364	-2.062	-2.3105	-3.1182
Difference	Mean [t-stat]		1.0680*** [10.06]	1.8411*** [11.44]	2.1935*** [9.16]	2.4126*** [8.18]	2.6010*** [5.92]
	Median (Wilcoxon p-value)		1.0257*** (<.0001)	1.665*** (<.0001)	2.1879*** (<.0001)	2.0345*** (<.0001)	2.3159*** (<.0001)

Panel B. Cumulative DGTW Characteristics-adjusted Returns (*LTCAR_DGTW*)
(Benchmark Universe: NYSE, AMEX, NASDAQ)

		nobs	[t+6, t+20]	[t+6, t+40]	[t+6, t+80]	[t+6, t+120]	[t+6, t+250]
Positive Revision (FCST_REV >0)	Mean	12461	0.3173	0.2828	0.1237	0.0893	0.3072
	Median		0.0954	0.1898	-0.0335	-0.3166	-0.8624
Negative Revision (FCST_REV <0)	Mean	13893	-0.582	-1.1903	-1.6134	-1.8804	-1.7814
	Median		-0.6627	-1.0731	-1.6426	-1.6522	-2.4982
Difference	Mean [t-stat]		0.8993*** [8.64]	1.4731*** [9.29]	1.7371*** [7.42]	1.9697*** [6.84]	2.0886*** [4.91]
	Median (Wilcoxon p-value)		0.7581*** (<.0001)	1.2629*** (<.0001)	1.6091*** (<.0001)	1.3356*** (<.0001)	1.6358*** (<.0001)

Panel C. Cumulative DGTW Characteristics-adjusted Returns (*LTCAR_DGTW_NA*)
(Benchmark Universe: NYSE, AMEX)

		nobs	[t+6, t+20]	[t+6, t+40]	[t+6, t+80]	[t+6, t+120]	[t+6, t+250]
Positive Revision (FCST_REV >0)	Mean	12460	0.4284	0.579	0.6761	0.7939	1.6441
	Median		0.3138	0.4881	0.4641	0.3405	0.3036
Negative Revision (FCST_REV <0)	Mean	13888	-0.4952	-0.9053	-0.9222	-1.8804	0.2331
	Median		-0.5064	-0.7287	-1.0933	-1.6522	-0.9806
Difference	Mean [t-stat]		0.9236*** [9.16]	1.4842*** [9.7]	1.5983*** [7.17]	1.7592*** [6.43]	1.4110*** [3.49]
	Median (Wilcoxon p-value)		0.8202*** (<.0001)	1.2168*** (<.0001)	1.5574*** (<.0001)	1.9927*** (<.0001)	1.2842*** (<.0001)

2.4.2 Univariate Analysis

Table 2.6 reports long-run stock performance after forecast announcements over the periods ranging from one month to one year, conditional on the level of trade imbalances immediately following the forecasts, i.e., from relative trading day t+2 to day t+5. Specifically, every year, for each trade-size group we sort stocks into quintiles based on the post-event trade imbalance. Consistent with prior evidence, medium traders seem to be also informed about the long-term value of the stock and their trades can reliably predict future returns up to six months ahead. For example, in Panel B of Table VI, the stocks heavily bought by medium traders after the forecasts outperform the stocks heavily sold by them by about 1% over the two-month holding period.

Interestingly, there is also evidence suggesting that small-size trade imbalance can predict future returns (See Panel C of Table VI). Stocks that small traders buy outperform the stocks they sell for up to four months following the forecasts. Moreover, the magnitude of the performance difference is similar to that generated by sorting on the medium-trade imbalance. It may be because that Type-II informed traders face less time constraints and more information uncertainty, and thus they use small trade occasionally to trade on their private information. Specifically, compared to Type-I informed traders who have to finish their trades prior to the announcement of forecast revisions, Type-II traders can exploit their private information about stock long-term value over a much longer period, meanwhile they have to take on more risks, in that during this extended period it is more likely that certain exogenous news may move the stock prices in a direction opposite to their initial expectations. Another interesting result is in Panel A of Table VI. Large trades can also predict future returns but in an opposite sense, i.e. the stocks large traders buy right after the analysts' forecasts significantly underperforming those they sell during the holding period of two to six months. Therefore, large traders will lose money if they hold their positions for the long run. Taken together with the evidence in Lee and Radhakrishna (2000) that large trades are more likely to come from institutions, our results here suggest that large trades are likely used by institutions to meet immediate liquidity needs. For example, a mutual fund may use large trades when they experience unexpected large amounts of funds inflows or outflows. Under this scenario, the large traders' top priority is execution speed, rather than profits generated by these trades[28].

[28] Another possible explanation to this finding is that lots of large trades are batched trades that consist of several smaller orders placed for liquidity purposes. Lee and Radhakrishna (2000) find that 56% of the trades involving more than 1900 shares have multiple participants on the active-side. Unfortunately, we cannot tell which trade is batched using the TAQ database.

Table 2.6
Post-earnings-forecast Long-term CARs
Sorted by the Abnormal OFIs during [t+2, t+5]

The reported are means and medians of the long-term cumulative abnormal returns following earnings forecast announcements. We sort the forecasts into quintiles, based on the cumulative abnormal OFIs of different trade sizes measured during the period immediately after the forecast announcement [t+2, t+5]. The long-run CAR is measured using DGTW characteristics-adjusted returns and the benchmark universe includes NYSE and AMEX stocks only. Variables are defined in Table I. To test the difference in means, we use two-sided T-test and T-statistics are reported in brackets. To test the difference in medians, we use two-sided Wilcoxon rank sum test and the corresponding p-values are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Means of Cumulative DGTW Characteristics-adjusted Returns (*LTCAR_DGTW_NA*)
(Benchmark Universe: NYSE, AMEX)
Panel A. Sorted by Large-trade Abnormal OFI ($ABN\_OFI_{Large,\ t+2,\ t+5}$)

		Q1 (Net Sell)	Q2	Q3	Q4	Q5 (Net Buy)	Q5-Q1	[t-stat] or (Wilcoxon P-value)
	Nobs	5313	5316	5316	5315	5316		
1-mon	mean	-0.0017	-0.0811	-0.0671	-0.118	-0.1242	-0.1225	[-0.76]
[t+6, t+20]	median	-0.1276	-0.1378	-0.0718	-0.1759	-0.1959	-0.0683	(0.5618)
2-mon	mean	0.0975	-0.4883	-0.1143	-0.2062	-0.3904	-0.4879**	[-1.97]
[t+6, t+40]	median	0.044	-0.4317	-0.1607	-0.0202	-0.2961	-0.3401*	(0.0607)
4-mon	mean	0.4337	-0.4997	-0.0889	-0.2423	-0.5551	-0.988***	[-2.75]
[t+6, t+80]	median	0.1989	-0.4541	-0.198	-0.3424	-1.0212	-1.220***	(0.0008)
6-mon	mean	0.2158	-0.2582	0.0989	-0.2177	-0.7651	-0.9810**	[-2.22]
[t+6, t+120]	median	-0.2792	-0.3222	0.2043	-0.4416	-1.1409	-0.8617**	(0.0133)
12-mon	mean	1.4007	0.7379	0.9703	0.4429	0.5021	-0.8986	[-1.39]
[t+6, t+250]	median	-0.0569	-0.525	0.0205	-0.5342	-1.0459	-0.989	(0.0856)

Panel B. Sorted by Medium-trade Abnormal OFI ($ABN\_OFI_{Medium,\ t+2,\ t+5}$)

		Q1 (Net Sell)	Q2	Q3	Q4	Q5 (Net Buy)	Q5-Q1	[t-stat] or (Wilcoxon P-value)
	Nobs	5313	5316	5316	5316	5315		
1-mon	mean	-0.3911	-0.1578	-0.0394	-0.0053	0.2014	0.5926***	[3.63]
[t+6, t+20]	median	-0.5294	-0.2576	-0.0545	-0.0015	0.0639	0.5933***	(0.0001)
2-mon	mean	-0.6747	-0.3526	-0.2373	-0.2338	0.3966	1.0713***	[4.32]
[t+6, t+40]	median	-0.4824	-0.3682	-0.1381	-0.1087	0.2895	0.7719***	(<.0001)
4-mon	mean	-0.3081	-0.5569	-0.2763	-0.2733	0.4621	0.7703**	[2.14]
[t+6, t+80]	median	-0.8367	-0.5534	-0.3248	-0.1109	0.118	0.9547***	(0.0085)
6-mon	mean	-0.3268	-0.4635	-0.129	-0.5038	0.4966	0.8234*	[1.85]
[t+6, t+120]	median	-0.8147	-0.4287	-0.1702	-0.8749	0.3563	1.171**	(0.012)
12-mon	mean	1.9452	0.2055	1.0158	-0.5374	1.4253	-0.5199	[-0.79]
[t+6, t+250]	median	-0.1252	-0.8804	-0.0952	-1.4376	0.4166	0.5418	(0.7474)

Panel C. Sorted by Small-trade Abnormal OFI (*$ABN\_OFI_{Small,\ t+2,\ t+5}$*)

		Q1 (Net Sell)	Q2	Q3	Q4	Q5 (Net Buy)	Q5-Q1	[t-stat] or (Wilcoxon P-value)
	Nobs	5313	5311	5321	5316	5315		
1-mon	mean	-0.3173	-0.0794	-0.0896	-0.0223	0.1164	0.4337***	[2.62]
[t+6, t+20]	median	-0.3692	-0.2106	-0.1148	-0.0312	0.0219	0.3911***	(0.0084)
2-mon	mean	-0.7876	-0.3147	-0.2652	0.0052	0.2601	1.0477***	[4.22]
[t+6, t+40]	median	-0.5697	-0.4371	-0.1418	0.0511	0.2511	0.8208***	(<.0001)
4-mon	mean	-0.5407	-0.3258	-0.3307	-0.2534	0.4979	1.0386***	[2.87]
[t+6, t+80]	median	-0.8209	-0.7594	-0.3972	-0.2362	0.4156	1.2365***	0.0002
6-mon	mean	-0.2968	-0.4369	-0.2866	-0.1414	0.2352	0.532	[1.2]
[t+6, t+120]	median	-0.8396	-0.7364	-0.6436	0.0248	0.3513	1.1909**	0.0403
12-mon	mean	1.2541	0.7226	0.3971	0.3684	1.3121	0.0579	[0.09]
[t+6, t+250]	median	-0.6434	-1.0223	-0.1638	-0.2947	0.1972	0.8406	0.2764

2.4.3 Robustness Analysis

2.4.3.1 Non-overlapping observations only

Since analysts' forecast announcements are frequent events, it is very likely that there are overlapping periods when we measure long-run abnormal returns after different forecast announcements for the same firm. The overlapping returns will lead to time-series dependence, i.e., the long-run returns for the same firm at different event dates are highly correlated, and will bias toward rejecting the null hypothesis. Lyon, et al. (1999) argue that it is one of the most severe form of dependence in long-run event studies, and suggest that the only ready solution to this problem is to eliminate observations with overlapping measurement periods. Therefore, in Table 2.7 we repeat our analysis of Table 2.6 for observations without overlapping return measurement periods.[29] Not surprisingly, as we impose this requirement and lengthen the holding periods, the

[29] We keep the earlier sample when two samples have overlapping returns.

sample size drops dramatically. As shown in Table 2.7, the pattern previously observed still holds for the non-overlapping sample subset. The only noticeable difference is that even though the large trades are still unprofitable at any holding horizon, the negative relation between trade imbalance of large trades and future returns is no longer statistically significant.

Table 2.7 Robustness Analysis I:
Post-earnings-forecast Long-term CARs
Sorted by the Abnormal OFIs during [t+2, t+5]
For Non-overlapping Observations Only

Here, we require the observations whose long-run CAR measurement periods do not overlap with those of other observations. In case of an overlapping, we drop the later observations. The reported are means and medians of the long-term cumulative abnormal returns following earnings forecast announcements. We sort the forecasts into quintiles, based on the cumulative abnormal OFIs of different trade sizes measured during the period immediately after the forecast announcement [t+2, t+5]. The long-run CAR is measured using DGTW characteristics-adjusted returns and the benchmark universe includes NYSE and AMEX stocks only. Variables are defined in Table I. To test the difference in means, we use two-sided T-test and T-statistics are reported in brackets. To test the difference in medians, we use two-sided Wilcoxon rank sum test and the corresponding p-values are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Means of Cumulative DGTW Characteristics-adjusted Returns (*LTCAR_DGTW_NA*)
(Benchmark Universe: NYSE, AMEX)
Panel A. Sorted by Large-trade Abnormal OFI (*$ABN\_OFI_{Large,\ t+2,\ t+5}$*)

		Q1 (Net Sell)	Q2	Q3	Q4	Q5 (Net Buy)	Q5-Q1	[t-stat] or (Wilcoxon P-value)
	Nobs	3798	3800	3800	3801	3799		
1-mon	mean	0.0103	0.0571	-0.009	-0.085	-0.1266	-0.1369	[-0.72]
[t+6, t+20]	median	-0.1069	-0.0613	-0.0311	-0.1423	-0.1628	-0.0559	(0.5563)
	Nobs	3075	3077	3075	3078	3074		
2-mon	mean	0.1574	-0.4181	0.0415	-0.2213	-0.3756	-0.533	[-1.64]
[t+6, t+40]	median	0.0773	-0.4471	-0.1511	-0.1843	-0.1514	-0.2287	(0.1576)
	Nobs	2197	2201	2199	2201	2198		
4-mon	mean	0.3254	-0.6752	0.5388	0.0285	-0.0112	-0.3365	[-0.6]
[t+6, t+80]	median	-0.0899	-0.5332	0.3014	-0.3306	-0.4825	-0.3926	(0.2536)
	Nobs	1764	1770	1769	1770	1768		
6-mon	mean	0.6206	-0.7988	0.7464	-0.083	-0.5385	-1.1591	[-1.5]
[t+6, t+120]	median	0.0613	-0.6895	0.2349	-0.4045	-1.231	-1.2923*	(0.0936)

Panel B. Sorted by Medium-trade Abnormal OFI (*$ABN\_OFI_{Medium,\ t+2,\ t+5}$*)

		Q1 (Net Sell)	Q2	Q3	Q4	Q5 (Net Buy)	Q5-Q1	[t-stat] or (Wilcoxon P-value)
	Nobs	3797	3801	3800	3801	3799		
1-mon	mean	-0.3689	-0.1256	0.0454	0.0168	0.2788	0.6478***	[3.37]
[t+6, t+20]	median	-0.6074	-0.235	0.0267	0.0135	0.1687	0.7761***	(0.0001)
	Nobs	3074	3078	3075	3078	3074		
2-mon	mean	-0.8446	-0.0815	-0.2146	-0.1722	0.4967	1.3413***	[4.18]
[t+6, t+40]	median	-0.6239	-0.1914	-0.2009	-0.1401	0.3123	0.9362***	(<.0001)
	Nobs	2197	2201	2199	2201	2198		
4-mon	mean	-0.8015	-0.1011	-0.0132	0.3749	0.7457	1.5473***	[2.77]
[t+6, t+80]	median	-1.286	-0.2424	0.0225	0.1073	0.5162	1.8022***	(0.002)
	Nobs	1764	1770	1769	1770	1768		
6-mon	mean	-0.0146	-0.8808	0.167	-0.2642	0.9384	0.953	[1.25]
[t+6, t+120]	median	-1.4322	-1.0577	-0.0431	-0.7898	0.8234	2.2556**	(0.0318)

Panel C. Sorted by Small-trade Abnormal OFI (*$ABN\_OFI_{Small,\ t+2,\ t+5}$*)

		Q1 (Net Sell)	Q2	Q3	Q4	Q5 (Net Buy)	Q5-Q1	[t-stat] or (Wilcoxon P-value)
	Nobs	3797	3802	3799	3801	3799		
1-mon	mean	-0.3135	0.0074	-0.1096	0.0376	0.2245	0.5380***	[2.76]
[t+6, t+20]	median	-0.3238	-0.1736	-0.0842	0.0016	0.0484	0.3722***	0.0046
	Nobs	3074	3079	3074	3079	3073		
2-mon	mean	-0.7908	-0.1304	-0.2071	0.0978	0.214	1.0048***	[3.13]
[t+6, t+40]	median	-0.6111	-0.4144	-0.0617	-0.075	0.1536	0.7647***	0.0006
	Nobs	2197	2201	2199	2201	2198		
4-mon	mean	-0.7321	0.4608	-0.078	0.2434	0.3102	1.0423*	[1.87]
[t+6, t+80]	median	-1.1485	0.142	-0.0408	-0.1943	0.2277	1.3762**	0.024
	Nobs	1764	1771	1768	1770	1768		
6-mon	mean	-0.6714	1.0437	-0.2801	-0.4523	0.3021	0.9735	[1.27]
[t+6, t+120]	median	-1.4104	0.3357	-0.1582	-0.939	0.1256	1.536*	0.0615

2.4.3.2 Conditioning on the Signs of Forecast Revisions

This section examines if the prior results hold following both positive and negative forecast revisions. Existing studies suggest that the market may react to good and bad news differently. For example, Hong, Lim and Stein (2000) show that the momentum effect is stronger for past losers and they attribute this phenomenon to the slow diffusion of bad news. In Table 2.8, we repeat the analysis separately for stocks experiencing positive revisions and those with negative revisions. We find that the predictive power of medium-size trade imbalance for future returns holds following both positive and negative revisions, although the predictive power extends over a shorter time on the positive side (for about two months). However, small-size trade imbalance can predict future returns only following negative revisions. So far, we do not have a good explanation for this result.

Table 2.8 Robustness Analysis II:
Post-earnings-forecast Long-term CARs
Sorted by the Signs of Forecast Revisions and Abnormal OFI during [t+2, t+5]

The reported are means and medians of the long-term cumulative abnormal returns following earnings forecast announcements. Every year, we first sort the forecasts into two groups, based on the signs of forecast revision. Within each revision group, the forecasts are further sorted into quintiles based on abnormal OFIs of different trade sizes immediately after forecast announcements [t+2, t+5]. The long-run CAR is measured using DGTW characteristics-adjusted returns and the benchmark universe includes NYSE and AMEX stocks only. Variables are defined in Table I. To test the difference in means, we use two-sided T-test and T-statistics are reported in brackets. To test the difference in medians, we use two-sided Wilcoxon rank sum test and the corresponding p-values are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Means of Cumulative DGTW Characteristics-adjusted Returns (*LTCAR_DGTW_NA*)
(Benchmark Universe: NYSE, AMEX)
Panel A. Following Positive Revisions (FCST_REV>0)

Sorted By $ABN\_OFI_{t+2,\ t+5}$		nobs	[t+6, t+20]	[t+6, t+40]	[t+6, t+80]	[t+6, t+120]	[t+6, t+250]
Large Trades	Q1 (Net Sell)	2456	0.724	0.7707	1.1499	1.3536	2.6857
	Q5 (Net buy)	2456	0.394	0.6355	0.8572	0.7062	2.276
	Q5-Q1		-0.33	-0.1352	-0.2927	-0.6473	-0.4097
	[t-stat]		[-1.42]	[-0.39]	[-0.57]	[-1.02]	[-0.43]
	(Wilcoxon p-value)		0.1798	0.7447	0.3201	0.3184	0.4285
Medium Trades	Q1 (Net Sell)	2456	0.299	0.312	0.6101	0.7073	2.5741
	Q5 (Net buy)	2456	0.7263	1.0507	1.1901	1.2161	2.1462
	Q5-Q1		0.4273*	0.7387**	0.58	0.5087	-0.4279
	[t-stat]		[1.84]	[2.11]	[1.13]	[0.79]	[-0.45]
	(Wilcoxon p-value)		0.0403	0.1067	0.2381	0.2875	0.7034
Small Trades	Q1 (Net Sell)	2456	0.4376	0.5151	0.6502	1.3455	2.6521
	Q5 (Net buy)	2456	0.4556	0.6383	0.8607	0.4534	1.7654
	Q5-Q1		0.018	0.1232	0.2106	-0.892	-0.8866
	[t-stat]		[0.08]	[0.35]	[0.4]	[-1.38]	[-0.91]
	(Wilcoxon p-value)		0.7133	0.562	0.44	0.5125	0.9291

Panel B. Following Negative Revisions (FCST_REV<0)

Sorted By $ABN\_OFI_{t+2,\ t+5}$		nobs	[t+6, t+20]	[t+6, t+40]	[t+6, t+80]	[t+6, t+120]	[t+6, t+250]
Large Trades	Q1 (Net Sell)	2741	-0.6195	-0.6317	-0.1756	-0.55	0.8447
	Q5 (Net buy)	2744	-0.6119	-1.3659	-1.8883	-2.1293	-1.1109
	Q5-Q1		0.0076	-0.7342**	-1.7126***	-1.5792**	-1.9556**
	[t-stat]		[0.03]	[-2.07]	[-3.34]	[-2.5]	[-2.17]
	(Wilcoxon p-value)		0.8388	0.0312	0.0001	0.0046	0.0284
Medium Trades	Q1 (Net Sell)	2741	-0.8866	-1.4578	-1.1166	-1.1149	1.4407
	Q5 (Net buy)	2744	-0.1677	-0.1068	-0.0698	-0.0091	1.1483
	Q5-Q1		0.7189***	1.3510***	1.0468**	1.1059*	-0.2924
	[t-stat]		[3.1]	[3.81]	[2.04]	[1.76]	[-0.32]
	(Wilcoxon p-value)		0.0007	<.0001	0.0109	0.0196	0.8229
Small Trades	Q1 (Net Sell)	2741	-0.9397	-1.8096	-1.3818	-1.4771	-0.0434
	Q5 (Net buy)	2744	-0.1383	-0.0638	0.2254	0.2679	1.1414
	Q5-Q1		0.8014***	1.7458***	1.6072***	1.7450***	1.1848
	[t-stat]		[3.42]	[4.98]	[3.14]	[2.82]	[1.27]
	(Wilcoxon p-value)		0.0001	<.0001	0.0001	0.0008	0.0735

2.4.3.3 Regression Analysis

In this section, we use the regression framework to control for other factors that may potentially influence the long-run post-forecast-announcement returns. Specifically, we model the long-run DGTW characteristics-adjusted returns (LTCAR_DGTW) of stock i over the post-event period of [t+6, t+T] as:

$$\begin{aligned} LTCAR\_DGTW_{i,t+6,t+T} = \beta_0 + \beta_1 ABN\_OFI_{i,large,t+2,t+5} + \beta_2 ABN\_OFI_{i,medium,t+2,t+5} \\ + \beta_3 ABN\_OFI_{i,small,t+2,t+5} + \beta_4 POS\_REV_i \cdot ABN\_OFI_{i,small,t+2,t+5} \\ + \beta_5 FCST\_REV_i + \beta_6 CAR_{i,t-1,t+1} + \beta_7 INNOV\_SIG_i + \varepsilon_i \qquad (3) \end{aligned}$$

To avoid the serious time-series dependence issue caused by overlapping observations (discussed in Section IV-C-C1), this regression is performed only based on observations that do not have overlaps during the measurement period of the long-run CARs. If a certain trade-size group has superior skills in interpreting the forecasts, we expect its cumulative order imbalance (ABN_OFI) right after the forecasts to be positively related to subsequent long-run stock performance (LTCAR_DGTW). As we have shown, in Table VIII, that the predictability of small-trade imbalance for future returns depends on the direction of forecast revision, we also include the interaction term between the positive revision dummy (POS_REV) and small-trade imbalance. Here, the predictive power of small-trade imbalance is captured by β_3 following downward revisions and ($\beta_3 + \beta_4$) following positive revisions. To account for the well-known post-forecast-revision drift effect, we include the signed level of forecast revision (FCST_REV). We also include the event-period market response (CAR) to control for the part of the announcement surprise that may not be captured by forecast revisions. In addition, we include the indicator variable for high-innovative forecasts, which equals one (highly-innovative good-news forecasts) if the forecast is above the prior consensus and analyst's own prior forecast, zero (low-innovative forecasts) if the forecast falls between the prior consensus and analyst's own prior forecast, or negative one (highly-innovative bad-news) if the forecast is below the prior consensus and analyst's own prior forecast. Gleason and Lee (2003) show that the post-forecast-revision drifts are stronger following highly innovative forecasts. They argue that these forecasts are more accurate and less likely to be the product of analysts' herding, but their importance tends to be overlooked by the investors.

Table 2.9 reports the coefficient estimates of Equation (3) estimated using Fama-MacBeth regressions. In particular, we perform month-by-month cross-sectional regressions and report the averages of the monthly estimates. The standard errors are adjusted for potential serial correlations using the Newey-West procedure with three-month lags. Consistent with the univariate sorting results, medium-trade imbalance can predict long-run post-event returns for up to three months. For small trades, the order imbalance variable is not significant by itself, but when we condition its effect on the revision direction, it is clear that small-trade imbalance can only predict long-run returns following downward revisions as reflected by the positive coefficient for ($ABN\_OFI_{small,\ t+2,\ t+5}$). Moreover, it has little predictive power following upward revisions, since the sum of the coefficients of $ABN\_OFI_{small,\ t+2,\ t+5}$ and its interaction term with positive-revision dummy ($\beta_3 + \beta_4$) is close to zero. Similar to the findings of Gleason and Lee (2003), stocks associated with high-innovation forecasts experience stronger post-event drifts and this effect lasts for up to six months.

Table 2.9
Regression Analysis of Post-earnings-forecast Long-term CARs
(For Non-overlapping Observations Only)

This table reports the regression results of the post-earnings-forecast long-term CARs on the abnormal OFIs of different trade sizes immediately after forecast announcements [t+2, t+5] and other controls. The abnormal return is measured using DGTW characteristics-adjusted approach and the benchmark universe includes NYSE and AMEX stocks only. Fama-MacBeth Regressions are month-by-month cross-sectional regressions, and the coefficient estimates are the average of monthly estimates. The standard errors of the coefficients are adjusted for the serial correlation using Newey-West procedure with three lags. POS_REV is a dummy variable and equals to one if the forecast revision is positive. Other variables are defined in Table I. The t-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dependent Variables: *LTCAR_DGTW_NA*									
	Fama-Macbeth Regressions									
LTCAR_DGTW Period:	[t+6, t+20]	[t+6, t+40]	[t+6, t+60]	[t+6, t+80]	[t+6,t+120]	[t+6, t+20]	[t+6, t+40]	[t+6, t+60]	[t+6, t+80]	[t+6,t+120]
Intercept	0.04532	-.05464	0.16748	0.20305	0.26877	0.04912	-.06845	0.14472	0.19024	0.25120
	(0.51)	(-0.31)	(0.57)	(0.69)	(0.62)	(0.55)	(-0.38)	(0.5)	(0.64)	(0.56)
$ABN\_OFI_{Large,\ t+2,\ t+5}$	-.01509	-.11243	-.03943	-.04553	-.15555	-.01497	-.12117*	-.03342	-.04643	-.11661
	(-0.49)	(-1.59)	(-0.52)	(-0.5)	(-1.25)	(-0.48)	(-1.73)	(-0.44)	(-0.52)	(-1)
$ABN\_OFI_{Med,\ t+2,\ t+5}$	0.09527**	0.14557**	0.21915**	0.06595	0.16392	0.10447**	0.15037**	0.21976**	0.09209	0.20163
	(1.99)	(2.05)	(2.1)	(0.48)	(1.04)	(2.16)	(2.17)	(2.03)	(0.68)	(1.21)
$ABN\_OFI_{small,\ t+2,\ t+5}$	0.04754	0.09041	0.22436**	0.25655	0.11167	0.09133*	0.25300***	0.38145**	0.35053*	0.25284
	(1.3)	(1.15)	(2.06)	(1.62)	(0.79)	(1.67)	(2.75)	(2.34)	(1.9)	(1.38)
POS_REV $ABN\_OFI_{small,\ t+2,\ t+5}$*						-.14849**	-.37514***	-.33016*	-.20605	-.38772
						(-2.01)	(-4.11)	(-1.77)	(-0.95)	(-1.49)
FCST_REV	1.79545	15.7894	12.8548	-.15086	6.55526	0.66883	12.9075	9.13438	-.86989	9.53901
	(0.17)	(1.24)	(0.61)	(-0.01)	(0.15)	(0.06)	(0.98)	(0.45)	(-0.04)	(0.21)
$CAR_{t-1,\ t+1}$	-.01740	0.01259	-.01861	0.05594	0.04020	-.01902	0.01213	-.02044	0.06248	0.04471
	(-0.73)	(0.31)	(-0.34)	(0.71)	(0.43)	(-0.81)	(0.3)	(-0.38)	(0.76)	(0.47)
INNOV_SIG	0.41288***	0.67385***	0.99182***	1.00334***	1.41940***	0.42638***	0.68188***	1.01575***	1.00443***	1.39622***
	(3.84)	(3.68)	(4.41)	(3.41)	(3.94)	(4.06)	(3.77)	(4.48)	(3.48)	(3.65)
Num of Observations	17841	14429	11983	10281	8264	17841	14429	11983	10281	8264
Adjusted R-square	1.182%	1.518%	1.913%	2.081%	1.966%	1.415%	1.540%	2.056%	2.178%	2.401%

2.5 Using Alternative Trade-size Cutoff Points

So far, all our empirical results are based on a trade-size classification scheme that uses the same cutoff points for all the trades and is purely based on the dollar value of the trades. Prior studies have raised concerns over this approach. Lee and Radhakrishna (2000) show that both institutional and retail traders scale down their trade sizes when trading in smaller firms. Hence, informed traders may also reduce their trades for smaller firms in order to effectively "hide" their trades. Consequently, the static classification scheme could induce systematic measurement errors that are correlated with firm size. For example, many medium trades (trades with dollar value between $5,000 and $50,000) for small firms may actually be considered as large trades by informed traders, and thus could be avoided when informed traders are aiming at exploiting their private information. In addition, Lee (1992) notes that although a dollar-based size proxy is conceptually superior to a share-based size proxy, the dollar-based proxy is sensitive to small price changes, due to the "round-lot" recording mechanism used by the TAQ database[30].

To address the above two concerns and check the sensitivity of our results to an alternative trade-size classification method, we rerun the analysis using a firm-size- and stock-price-specific trade-size classification method that is

[30] In particular, TAQ data only report the number of shares traded in hundreds. For instance, if the cutoff point for small and medium trades is $10,000 and the current stock price is $25, then all the trades with size of 100-400 shares are classified as small trades. However, even if the stock price increases just by $0.01, only trades with size of 100-300 shares would be classified as small trades.

similar to the method used by Lee and Radhakrishna (2000) and Hvidkjaer (2006). The details of the method are described as follows:

(1) In each month t, we sort all firms into size quintiles based on their market capitalization at the end of the previous month.

(2) Within each size quintile, we identify the 25th and 75th percentiles of dollar trade size for month t, and use them as the dollar-based cutoff points for all the firms in this size quintile[31].

(3) We compare the month t opening price (first-trade price) for stock i to the dollar-based cut-off points calculated in Step (2) and determine the smallest (largest) number of round-lot shares that is greater (smaller) than or equal to the 75th percentile (25th percentile) of the dollar trade size. This number of round-lot shares will be the share-based trade-size cutoff point for stock i in month t. For example, trades with number of shares greater than or equal to the share-based 75th percentile cutoff point are defined as large trades.

The main results based on the above classification method are reported in Table 2.10. As we can see, the results are very similar to the prior results. Specifically, the medium-trades group is still the only group that is trading in the same direction as upcoming forecast revisions. The medium-trade imbalance immediately after the forecast announcements can predict future long-run stock performances, following both positive and negative forecast revisions. Small-

[31] This step is different from the approach used by Lee and Radhakrishna (2000), who suggest to use \$100/\$200 multiplied by 99th percentile of the stock price within each size quintile as the cutoff points. They argue that this approach maximizes the institution trades in the large trade-size group. Nonetheless, our purpose is simply to identify if a trade is large or small, relative to all the other trades within the same size quintile. Therefore, we believe this approach is more appropriate.

trade imbalance also possesses predictive power for future long-run stock performance, but only following the negative forecast revisions.

Table 2.10
Results using Alternative Trade-size Classification Method

In Panel A, the reported are means of the cumulative abnormal OFI of different trade-size groups across various news groups. We sort the forecasts into five news groups, based on the market response during the announcement date. In particular, the forecast is “very-positive” news, if $CAR_{t-1, t+1}$ >= 5%; the forecast is “positive” news, if 1%<= $CAR_{t-1, t+1}$ < 5%; the forecast is ”neutral” news, if -1% <= $CAR_{t-1, t+1}$ < 1%; the forecast is “negative” news, if -5% <= $CAR_{t-1, t+1}$ < -1%; the forecast is “very-negative” news, if $CAR_{t-1, t+1}$ <= -5%. In Panel B, the reported are means of the long-term CARs following earnings forecast announcements. Every year, we first sort the forecasts into two groups, based on the signs of forecast revision. Within each revision group, the forecasts are further sorted into quintiles based on abnormal OFIs of different trade sizes immediately after forecast announcements [t+2, t+5]. The long-run CAR is measured using DGTW characteristics-adjusted returns and the benchmark universe includes NYSE and AMEX stocks only. To test the difference in means, we use two-sided T-test and T-statistics are reported in brackets. To test the difference in medians, we use two-sided Wilcoxon rank sum test and the corresponding p-values are reported in parentheses. *, ** and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Panel A. Pre-event Period (t-5, t-2) and the Nature of Upcoming Forecast Revisions

				News Nature			
		Very Negative	Negative	Neutral	Positive	Very Positive	VP-VN [t-stat]
	nobs	2191	8551	7847	7131	2221	
Large Trades ABN_OFI	mean	0.0207	0.0602	0.0317	0.0183	0.0284	0.0077 [0.13]
Medium Trades ABN_OFI	mean	-0.056	-0.0197	-0.0203	0.0095	0.0498	0.1057** [2.03]
Small Trades ABN_OFI	mean	-0.0196	-0.0269	-0.0294	-0.0034	0.0753	0.0949 [1.54]

Panel B. Post-event Trading and Long-run Cumulative Abnormal Returns
B-1. Following Positive Revisions (FCST_REV>0)

Sorted By *ABN_OFI* $_{t+2, t+5}$		nobs	[t+6, t+20]	[t+6, t+40]	[t+6, t+80]	[t+6, t+120]	[t+6, t+250]
Large Trades	Q1 (Net Sell)	2461	0.8525	0.9393	1.0466	1.0099	2.3382
	Q5 (Net buy)	2467	0.6924	0.7489	1.2862	1.5214	2.9835
	Q5-Q1		-0.1601	-0.1904	0.2395	0.5115	0.6453
	[t-stat]		[-0.68]	[-0.53]	[0.46]	[0.79]	[0.65]
	(Wilcoxon p-value)		0.383	0.6881	0.6491	0.4711	0.8568
Medium Trades	Q1 (Net Sell)	2468	0.2337	0.3276	0.5571	1.1367	3.4348
	Q5 (Net buy)	2452	0.9443	1.0939	1.814	1.884	2.3806
	Q5-Q1		0.7106***	0.7663**	1.2569**	0.7474	-1.0543
	[t-stat]		[2.99]	[2.12]	[2.37]	[1.13]	[-1.07]
	(Wilcoxon p-value)		0.003	0.0345	0.014	0.1007	0.6796
Small Trades	Q1 (Net Sell)	2471	0.3187	0.606	0.6949	1.6451	3.445
	Q5 (Net buy)	2471	0.6528	0.9663	1.0599	0.6493	2.3208
	Q5-Q1		0.3341	0.3603	0.365	-0.9958	-1.1242
	[t-stat]		[1.37]	[0.97]	[0.67]	[-1.49]	[-1.12]
	(Wilcoxon p-value)		0.362	0.5664	0.4543	0.3825	0.5295

B-2. Following Negative Revisions (FCST_REV<0)

Sorted By *ABN_OFI* $_{t+2,\ t+5}$		nobs	[t+6, t+20]	[t+6, t+40]	[t+6, t+80]	[t+6, t+120]	[t+6, t+250]
Large Trades	Q1 (Net Sell)	2749	-0.5429	-0.7364	-0.2045	-0.3455	2.0714
	Q5 (Net buy)	2758	-0.6267	-1.1753	-1.367	-1.638	-1.5371
	Q5-Q1		-0.0838	-0.4389	-1.1626**	-1.2925**	-3.6085***
	[t-stat]		[-0.36]	[-1.22]	[-2.23]	[-2.03]	[-3.88]
	(Wilcoxon p-value)		0.74	0.1951	0.0065	0.0078	0.0004
Medium Trades	Q1 (Net Sell)	2745	-1.0927	-1.5342	-1.0907	-1.3485	0.4875
	Q5 (Net buy)	2753	-0.4247	-0.1188	0.1485	0.2355	0.9647
	Q5-Q1		0.6679***	1.4154***	1.2392**	1.5840**	0.4772
	[t-stat]		[2.82]	[3.95]	[2.41]	[2.51]	[0.51]
	(Wilcoxon p-value)		0.0002	<.0001	0.0022	0.0015	0.4347
Small Trades	Q1 (Net Sell)	2726	-0.954	-1.8715	-1.4119	-1.2762	0.8981
	Q5 (Net buy)	2763	-0.2846	-0.2304	0.2758	0.0959	1.5672
	Q5-Q1		0.6694***	1.6411***	1.6877***	1.3722**	0.6691
	[t-stat]		[2.75]	[4.47]	[3.18]	[2.11]	[0.7]
	(Wilcoxon p-value)		0.0006	<.0001	0.0001	0.0059	0.2798

2.6 Conclusions

This paper examines the order flow imbalance of different trade-size groups surrounding analysts' forecast announcements. We find evidence suggesting that certain traders are informed about either the forthcoming analysts' forecasts or long-term value of the stock, and informed traders prefer to use medium-size trades to exploit their private information advantage. Specifically, medium-size trade imbalance prior to the forecast announcements is positively correlated with the nature of forecast revisions, while in the days immediately after the forecasts medium-size trade imbalance is positively correlated with future stock returns for up to four months. Small-size trade imbalance is also positively correlated with future returns but only following downward revisions. In contrast, it is also shown that large trades placed right after the forecasts are unprofitable and generate slightly negative profits in the long run. Overall, our results are consistent with the “stealth trading hypothesis” proposed by Barclay and Warner (1993).

One puzzling finding of this paper is that the predictability of small trades for long-run stock returns only exists during the periods following downward revisions. Further studies may explore potential explanations for this phenomenon. Subject to the data availability, another interesting line of research is to explore which type of medium-size traders, institutions or individuals, are more likely to be informed before the analysts’ forecast announcements. If the informed are institutions, do they tend to have an existing business relationship with the analysts’ brokerage house?

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About the Author

Ziwei Xu received a B.Eng. in Management Information System from Tianjin University (China) in 2003 and a M.S. in Statistics from University of Illinois at Chicago in 2005. He is also a certified Financial Risk Manager (FRM) and has passed all three levels of the Chartered Financial Analyst (CFA) exams.

While in the Ph.D. program at the University of South Florida, Mr. Xu was an instructor teaching “Principle of Finance” and “Money and Banking”. He also has coauthored two papers with Dr. Christos Pantzalis and made several presentations at the annual meetings of Financial Management Association and Southern Finance Association. During the summers of 2008 and 2009, Mr. Xu was working for the Advanced Research Center of State Street Global Advisors as a Quantitative Analyst Intern.