THE INFORMATIONAL ROLE OF SELL-SIDE ANALYSTS' FORECAST HORIZON

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ABSTRACT

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This dissertation explores the informational role of sell-side analysts' change in forecasting horizon. I find that portfolios formed by buying stocks with large increase in analyst horizon and shorting stocks with large decrease in analyst horizon generate superior future return. Horizon change has information incremental to analyst earnings forecast and recommendation revisions, as well as firm fundamentals. Large increase in horizon mainly drives the result. I find that analysts who contribute to strong horizon increase are associated with higher forecast accuracy. This increase is likely associated with the career concerns of inexperienced analysts. The return predictability associated with analyst forecast horizon change exists in the information environment of high liquidity and low volatility, at the times when analyst forecasts are the most accurate. Moreover, analyst forecast horizon is partially related to analysts' profitability prediction and firm risk assessment, although the horizon change, the component predictable by firm fundamentals notwithstanding, is still able to predict return in the short-run.

Overall, the findings reported in this dissertation support the view that sell-side analysts are important rational-information providers in the financial industry.

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1. Introduction

Sell side analysts issue annual earnings forecasts for the firms they follow, sometimes up to about five years ahead of the estimated fiscal-year ending date. As the estimated fiscal-year end approaches, analysts revise their estimates based on newly arrived information. Previous literature has found evidence that early estimates—the estimates issued a long time before the estimated fiscal-year end date—are generally more biased and dispersed and are a relatively inaccurate reflection of true analysts' expectation based on consistent cash flow forecasting rules (Brown, 1991; Abarbanell and Bernard, 1992; Lim, 2001). As a result, most empirical research emphasizes the recency of short-term forecasts and includes in hypothesis tests only the forecasts for an event date issued several months or days before the estimated fiscal-period end arrives. Such design ensures that the information in the forecasts is incorporated in a timely manner. To name a few, Ivković and Jegadeesh (2004) use one-quarter-ahead earnings forecasts revisions around the earnings announcement date to study the informational role of analysts. Loh and Mian (2006) also employ the cut-off rule of keeping the forecasts of the current year issued after last year's earnings announcement. Da and Warachka (2011) use the consensus annual earnings forecasts for the previous and current fiscal year to back up the short-term growth forecast for a firm. Keskek, Senyo, and Tucker (2014) analyze the timing of analysts' annual forecasts using the forecasts for the current year.

This dissertation explores why analysts issue forecasts so early and, relatedly, whether early forecasts present a new dimension of information relevant for understanding and forecasting stock prices. This dissertation takes a first step toward evaluating critically the extant assumption that early estimates are too biased and stale to be informationally relevant. The dissertation starts by analyzing whether the change in analysts' earnings forecasting horizon can predict returns. The analysts' coverage has long been recognized as discretional (e.g., McNichols and O'Brien, 1997). Thus, it appears natural also to hypothesize that, aside from the very choice to cover the stock in the first place, the choice of the number of forward-looking forecasting periods, or the horizon of their earnings forecasts, is discretionary too, and that an important component of that decision may reflect the analysts' future cash-flow expectation. The dissertation proposes the use of the longest annual earnings forecasting horizon an analyst issues for a stock to proxy for the analyst's forecasting horizon. As an empirical matter, the annual earnings forecasting horizons have richer cross-sectional variation than the quarterly earnings forecasting horizons do. The dissertation provides a thorough analysis of the relation between monthly stock returns and monthly changes in average analyst horizon.

I commence with the study the univariate portfolio performance by sorting on the change in horizon at the end of each month. I find that the portfolio of stocks with large increases in analyst horizon outperforms the portfolio of stocks with large decreases in analyst horizon. The result is robust throughout time, both before and after the passage of Reg FD, a rule that improves capital market transparency by requiring firm managers to disclose information equally to all market participants. The short-lasting predictability is strongest in the first month, and dissipates three months after portfolio formation. Subsequent analyses indicate that the predictability lasts for about 18-21 weeks. This evidence indicates that it is unlikely that the information contained in the change in horizon is related to a risk-based explanation.

Next, the dissertation explores whether analyst forecast horizon change has information incremental to that already embedded in other analysts' variables and related firm fundamentals. There are three types of analyst variables that most likely correlate with horizon change in their information content: analyst short-term earnings forecast revisions, the level and revision of analyst recommendations, and the level and revision of long-term growth (LTG) forecasts. To address the above concerns, I perform bi-variate portfolio analyses by sorting on the variable of concern and horizon change. The resulting finding that the horizon change is still able to predict returns, along with controlling for the variables of concern, suggests that horizon change adds information beyond other analyst variables.

To understand further the return predictability of horizon change, I carry out a sequence of panel tests that regress one-month stock returns on lagged horizon change, controlling for analyst variables and other firm-level confounding factors such as size, book-to-market ratio, momentum, idiosyncratic volatility, institutional ownership, turnover, sales growth, and total accrual. The panel analysis is also a convenient tool for studying whether the return predictability of horizon change stems from the lengthening of horizon or the prolonged silence. Throughout the panel specifications, horizon change positively predicts future return, and the horizon lengthening appears to be a main driver of the result.

The next section studies further the relation between the increase of horizon and future return. By design, the largest increase in average forecasting horizon is contributed by a group of analysts who issue far-end forecast for the firm that exceeds the forecasting horizon of all other analysts who cover that particular firm at the time. I pinpoint the issuance dates of these forecasts as the event days if there are no other earnings-forecast revisions for the current fiscal year or the current quarter. The cumulative abnormal return (CAR) analysis for a three-trading-day window is substantially higher than the CARs of the stocks that have not experienced analyst horizon jumps on the event days. Such CARs persist for long periods of time; they still exists after 45 trading days.

To ascertain whether the return predictability of horizon change is associated with information environment, I continue to analyze the performance of horizon change portfolios in different liquidity and volatility circumstances. The results indicate that the predictability is strong in high liquidity and low volatility environments. The time-series average of analyst forecast error and differences in opinion are high when liquidity is low and when volatility is high, indicating that the quality of analyst forecasts declines in such information environments, which may explain why the message embedded in horizon change is not put to the market participants in these circumstances.

In the next section of the dissertation, I explore whether horizon change is associated with analysts' level estimate of firms' future profitability and their risk-assessment activities. To obtain the relevant estimates, I regress horizon change on the group of firm fundamental variables that are most relevant, as shown by past literature. I find that the profitability and risk-estimating activity is only partially related to horizon change. Further, the residuals from the analysis, or the component of horizon change orthogonal to the information available from firm fundamentals, is still able to predict short-run return, with an even stronger effect.

Lastly, I explore whether the return predictability of horizon change comes from its predictability of firm fundamentals. I find that horizon change positively predicts the FSCORE in the next four quarters, which indicates that horizon jump is associated with improvements in firm fundamentals. The horizon-change premium is a firm-level phenomenon that does not exhibit cyclical or counter-cyclical properties.

This dissertation contributes to two strands of literature. First, it contributes to the literature studying analyst forecasts and return predictability. There have been debates whether analysts are important information providers who matter for the investment universe. Many researchers have argued that analysts only reiterate what is already available in the public domain and do not add value to the price-discovery process (e.g. Altınkılıç et al. 2013; Kim and Song, 2014). This dissertation argues against this line of literature by finding that analyst average-horizon change does contain information relevant for future expected returns. Second, the dissertation is in line with the literature studying analysts' forecast timing and forecasting ability. Previous literature has focused on the analysts' role in information production close to the release of quarterly financial statements (Ivković and Jegadeesh, 2004; Chen, Cheng, and Lo, 2010; Keskek, Senyo, and Tucker, 2014). This dissertation also provides evidence that analysts' information production role is related to early provision of cash-flow expectations.

2. Data and definitions

Analyst data are collected from the I/B/E/S unadjusted detail historical file. Stock data is from CRSP monthly and daily files, and firm fundamental variables are from Compustat Annual and Quarterly files. Common shares held by institutional investors are from the Thomson Reuters Institutional Holdings (13f) files. Further details concerning variable definitions and data sources are presented in Appendix B of this dissertation.

A. Analyst forecasting horizon

Ideally, an individual analyst's forecasting horizon would be a function of time and information available, depicting the length of time of the analyst's farthest earnings prediction, at a high-frequency level. In reality, such a convenient horizon function is not readily available. In I/B/E/S, earnings predictions are discrete and rather sparse, with months of silence before new forecasts with the same or a similar horizon are issued. This dissertation proposes the use of the analyst's maximum forecasting horizon for a stock over the past year as a convenient substitute measure. This monthly analyst-level measure is constructed by first calculating the largest number of months of outlook of a firm covered by the analyst in a certain month, and then taking the maximum value of the largest number of months of outlook over the past year. Thus, this measure of horizon reflects not only the visible horizon in a month, but also the *inferred* longest horizon from the past longest analyst horizon information.

In the I/B/E/S detail file, each entry of individual analysts' forecasts has its announcement date and review date, allowing the econometrician to back out the range of months in which the value is considered outstanding. Each month, an analyst may have several outstanding forecasts for the same firm, concerning its several future fiscal period ending dates. The calculation of the longest horizon then includes the number of months every outstanding forecast is removed from the current month, and finding the longest outstanding month for the same analyst regarding the same firm. The possibility that the largest forecasting horizons might be subject to data error in I/B/E/S motivates winsorization of the maximum outstanding months at the 99.5 percentile level. Average analysts' annual forecasting horizon for a firm varies from 1 to 69 months, a figure larger than the variation of the analysts' average quarterly forecasting horizon.

A more detailed insight into the analysts' change in horizon is presented in Panel A of Table 1.1. Of the 10,329,019 annual forecasts from June of 1982 to December of 2016, 4,822,044 forecasts have the longest forecasting horizon for the same firm an analyst covers in a month. Finding the longest forecasting horizon and the average annual earnings forecast horizon of an analyst for a firm in each year results in 1,382,400 observations. For a firm-year, analyst longest horizon varies from 105 months after the fiscal year ending to 148 months prior to the fiscal year ending. On average, an analyst farthest outlook for a firm in a year is 22 months ahead, 5 months more than the average horizon of all annual earnings forecasts.

To analyze the time variation of analyst horizon, I summarize the average horizon change of the longest horizon of all annual earnings forecast an analyst makes for the firm in 3 months, 6 months, 9 months, and 12 months relative to the longest horizon of the current month. The summary statistics indicate that the longest horizon, on average, gets back to the current longest horizon in about 12 months. Moreover, the last column of Panel A ("Recovery") summarizes the number of months it takes for an analyst to issue a forecast that has the horizon as far as, or farther than, the first longest horizon for a firm. The first largest horizon appears as the first annual earnings forecast whose horizon is farther than all annual earnings forecasts in the previous year and the analyst has at least one annual earnings forecast made in the preceding year. 301,247 analyst forecasts' first longest horizon meet the above requirement, and 142,466 first longest horizon forecasts do not have future forecasts whose horizon is farther than, or equal to, their own horizon. Among the first longest horizons that have successor annual earnings forecasts of equal or farther horizon, fewer than 1% takes 1 month for the successor to arrive, and about one-half of the successors arrive in about a year.

For the same fiscal-period ending date, analyst forecasting horizon over a year decreases mechanically as time passes from one month to another unless a new long horizon forecast is issued. After an analyst makes a farthest forecast at time 0, the horizon naturally decreases in the months following, as time approaches the forecast ending period with which the forecast is associated. An analyst renews the farthest-horizon on a yearly basis, so after a steady decrease of horizon for a year, the horizon increases as the analyst makes another longest-horizon forecast. Such visible horizon variation does not reflect the true analyst horizon because it does not take the problem of sparse data into consideration. This issue can be mitigated by using the *inferred* longest horizon, the maximum forecasting horizon over the past year. Because the analysts' forecasting horizon is mostly renewed on a yearly basis, in the period during which analysts are silent and are waiting to announce a new farthest-horizon forecast, the appropriate inferred horizon is the longest horizon in the past year.

Next, to get the average analyst forecasting horizon of a firm, the calculation takes the arithmetic average over the analyst forecasting horizon of all analysts covering that firm in that month. This calculation excludes the analysts whose forecasts feature the value of 0 because 0 is a code that indicates an I/B/E/S error. Moreover, to ensure that an analyst's forecasting horizon is more a reflection of their expectation concerning the firm rather than a reflection of their individual habit, the calculations demean an analyst's forecasting horizon by the analyst's average forecasting horizon over the analyst's lifetime activity across all the firms that the analyst covers. The results reported in this dissertation remain the same even in the absence of such career-wide horizon adjustment. Furthermore, the sample is restricted to the firms followed by at least two analysts. This restriction alleviates the concern that the results are driven by thinly-covered stocks. Past literature has found that changes in analyst coverage have stock price implications (Kecskes and Womack, 2007; Kelly and Ljungqvist, 2011; Mola, Rau, and Khorana, 2012). To rule out this contaminating factor, the analysis is limited to the sub-sample of firm-months during which analyst coverage remains the same. The final sample includes a total of 22,823 analysts and 17,852 firms, and 843,040 firm-months having average analyst forecasting horizon, covering the period from September of 1981 to December of 2016.

B. Change in forecast horizon and returns

To assess whether analyst forecasting horizon is informationally relevant, I inquire whether future returns are related to the change in forecast horizon. If forecasting horizon contains price information and the market incorporates the information in the change of horizon only gradually, the magnitude of horizon change should be associated with future returns. This leads toward the following hypothesis:

Hypothesis 1: The change in forecast horizon does not predict future return.

To test the hypothesis, I form in every month 10 decile portfolios based on the change of average forecasting horizon.[1] The average forecasting horizon is the average maximum forecasting horizon over the past year of all the analysts following the firm. To reject the hypothesis, we should observe that the resulting portfolio returns vary across change-in-horizon-sorted portfolios. Further, if the return of the portfolio with large change in horizon differentiates from the return of the portfolio with smallest change in horizon in a positive direction, the result is consistent with the market favoring the positive change in forecasting horizon and, conversely, not favoring the negative change in forecasting horizon.

[1] In robustness checks, to rule out the possibility that the results are driven by extreme percentiles, I replicate the univariate portfolio analysis after formation of quintile portfolios. At the end of each month, I form five quintile portfolios based on average change in horizon over the past month. The zero-cost portfolio of buying quintile 5 (largest increase in horizon) and selling quintile 1 (largest decrease in horizon) stocks, generates on average 0.21% return in raw in the first month, with a t-statistic of 3.03, an abnormal return of 0.20% after adjusting by Fama-French three factors, with a t-statistic of 2.81, and abnormal return of 0.12% after adjusting by Carhart four factors, with a t-statistic of 1.75.

3. Horizon change and expected returns

A. Univariate portfolio analysis

Panel B of Table 1.1 reports the characteristics of the 10 decile portfolios formed every month based on the change in average analysts' forecasting horizon, and the average analysts' forecasting horizon calculated over the window of the past year.[2] Portfolio decile 1 is the group of stocks with the lowest change in horizon, with the smallest change (typically a decrease in horizon of about 1 months), while portfolio decile 10 is the group of stocks with the highest change in horizon, with the largest change (typically an increase in horizon of about 2 months). On average, there are 213 stocks in each decile and the stocks are highly comparable in the dimensions of average forecasting horizon, size, book-to-market ratio, and the raw return in the past year.

Table 1.2 reports the result of the portfolio test of Hypothesis 1. Panel A presents the monthly average return of the decile portfolios formed at the end of each month based on horizon change sorts and the stocks are equal weighted.[3] The first three columns in Panel B presents the average monthly return of the zero-cost portfolio of shorting the decile 1 portfolio and buying the decile 10 portfolio. The returns are in raw, risk-adjusted, and characteristics-adjusted forms. For risk adjustment, I use the Carhart (1997) four-factor model and for characteristics adjustment I use the DWTG (1997) characteristics. The samples are then split into subperiods, with cutoff imposed by Reg FD. The portfolios are

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[2] In the main analysis the change in horizon is measured by the change over the past month. In unreported results, the horizon change is also measured over the past three months. Such a variation of definition does not affect the results.

[3] In unreported results, portfolios are also formed using market capitalization weight at the end of each month. The results generally have the same sign, but lose some of the statistical significance. The statistical difference between value-weighted and equal-weighted returns implies that the change-in-horizon predicts returns not just for large capitalization stocks.

formed either right after the sort or after waiting for 1 month, to account for slow information incorporation. Panel C reports the return results of portfolios held with overlaps over the next 3 or 6 months after portfolio formation.

B. Incremental role of horizon change

Analysts presumably revise their short-term forecasts downward or upward when they are pessimistic or optimistic about the firm's near future. This section first addresses the concern that analysts might be lengthening or shortening their forecasting horizon in light of their changes in expectation for the firm in the short-run.

I perform a portfolio analysis by first double sorting on the short-run mean revision and then sorting on the change in horizon at the end of each month. The short-run mean revision, $FREV_{i,t}$, is constructed as the rolling sum of monthly consensus forecast revision for the current fiscal year over the past half year, scaled by price of the stock i in the prior month.. Past literature calculates the forecast error relative to the corresponding actual earnings figure, and the forecast is considered pessimistic if the forecast error is negative and optimistic if the forecast error is positive. The short-run mean revision measures the change of analyst expectation relative to their consensus expectation of last month. The consensus is pessimistic if it is adjusted downward and optimistic if it is adjusted upward. At the end of each month, I first sort on short-run mean revision into five quintiles from pessimistic to optimistic(Q1 to Q5), and then sort on the change in horizon into five quintiles, where quintile 1 has largest decrease in horizon and quintile 5 has largest increase in horizon. I form the portfolios by using equal weighting and I hold it for one month. In the Panel A of Table 1.3, I present the average return of the portfolios and the zero-cost portfolio that takes long positions in the stocks with largest increases in horizon and short positions in the stocks with largest decreases in horizon.

The predictive power of horizon change persists throughout all quintiles of short-run consensus forecast revision. The return spread by quintile 5-1 is quite large for Quintile 4 of forecast revision and, particularly, for Quintile 5. The spread also increases almost monotonically, indicating that analysts change their horizon not only as a reflection of their short-term pessimism or optimism. The zero-cost portfolio in the top short-run consensus forecast revision quintile earns 0.41% more in the first month than the zero-cost portfolio in the bottom short-run consensus forecast revision quintile, with a t-statistic of 2.18. The difference remains at 0.46% after adjusting by Carhart's four-factor model, with a t-statistic of 2.32.

Analyst recommendation revision has been shown to have more predictive power than its level (Jegadeesh et. al, 2004). To purge the effect of recommendation revision on return from horizon change, I perform a double sorting, first on the recommendation revision, and then on the change in horizon at the end of each month. Specifically, at the end of each month, I first sort on recommendation revision into five quintiles, from pessimistic to optimistic (Q1 to Q5), and then sort on the change in horizon into five quintiles, where quintile 1 has the largest decrease in horizon while quintile 5 has the largest increase in horizon. I form the portfolios using equal weighting and hold them for one month. Panel B of Table 1.3 reports the portfolio analysis results, revealing that horizon changes also possess an orthogonal component to recommendation revisions that explain future returns.[4]

[4] In the first month, the zero-cost portfolio in the top recommendation revision quintile, on average, is 0.85% more in the first month than the zero-cost portfolio in the bottom recommendation revision quintile (*t* =

LTG revision is strongly related to contemporaneous returns, which, in turn, subsumes the effect of short-run earnings forecast revisions (Copeland et. al., 2004). Because horizon changes reflect analysts' changing expectations for a distant fiscal end, it is possible that such changes correlate with the decisions to revise LTG forecasts. Therefore, I also perform a portfolio analysis regarding whether horizon change adds information in a dimension different from the revision of LTG forecast. At the end of each month, I first sort on LTG revision into five quintiles from pessimistic to optimistic (Q1 to Q5), and then sort on the change in horizon into five quintiles, where quintile 1 has the largest decrease in horizon while quintile 5 has the largest increase in horizon. I form the portfolios using equal weights and rebalance them monthly. Panel C of Table 1.3 reports the portfolio analysis results, indicating that the relation between returns and horizon changes is not subsumed by LTG revisions.[5]

C. Panel analysis

We proceed by regressing returns on the horizon change (variable Chghor) and other controls in a panel setting. Such a test represents a more direct and comprehensive way of studying whether horizon change is incrementally informationally relevant for returns, controlling for a myriad of other, well known factors that predict returns and are potentially correlated with analysts' horizon change Chghhor. I estimate the pooled firm-level regression of monthly returns on the raw change in horizon and other confounding factors:

4.23). The difference is 0.87% after adjusting by Carhart's four-factor model (*t* = 4.25).

[5] The zero-cost portfolio in the top LTG revision quintile, on average, is 0.31% more in the first month than the zero-cost portfolio in the bottom recommendation revision quintile (*t* = 1.63). The difference is 0.41% after adjusting by Carhart's four-factor model, with a t-statistic of 2.08.

$$
\begin{aligned}
r_{i,t+1} = {} & \alpha + \beta_1 Chghor_{i,t} + \beta_2 Horizon_{i,t} + \beta_3 FREV_{i,t} \\
& + \beta_4 RecRev_{i,t} + \beta_5 RecRlev_{i,t} + \beta_6 Dispersion_{i,t} + \beta_7 SUE_{i,t} \\
& + \beta_8 IO_{i,t} + \beta_9 Turnover_{i,t} + \beta_{10} Idiovol_{i,t} + \beta_{11} Size_{i,t} + \beta_{12} B/M_{i,t} \\
& + \beta_{13} RETP1_{i,t} + \beta_{14} RETP2_{i,t} + \beta_{15} EP_{i,t} + \beta_{16} LTG_{i,t} + \beta_{17} LTGrev_{i,t} \\
& + \beta_{18} SG_{i,t} + \beta_{19} TA_{i,t} + \beta_{20} CAPEX_{i,t} + Month/Year\ Fixed\ effect \\
& + Industry\ Fixed\ effect + Month/Year \times Industry\ Fixed\ effect + \varepsilon_{i,t+1}
\end{aligned}
\tag{1}
$$

The set of control variables is largely drawn from Jegadeesh et al.(2004), Diether et al.(2002), Fama and French(1992,1993), and Ang et al.(2006). $Jump_{i,t}$ is an indicator variable that equals 1 if firm *i* experienced a sharp increase in analysts' horizon in month *t* (where sharp increase is defined as belonging to the top decile of horizon changes in month *t*), and equals 0 otherwise.

Also, to understand further whether there is an asymmetry between horizon increase and horizon decrease in terms of its ability to predict returns, I decompose the change in horizon into *the horizon lengthening component* $Chghor^{+}_{i,t}$ = max(0, $Chghor_{i,t}$) and the *horizon shortening component* $Chghor^{-}_{i,t}$ = –min(0, $Chghor_{i,t}$). $\text{Horizon}_{i,t}$ is the level of the horizon for the firm with a one-month lag, and this variable is included to account for the mean-reversion pattern of the change in horizon variable. The corresponding regression model is provided in Equation (1)':

$$
\begin{aligned}
r_{i,t+1} = {} & \alpha + \beta_1 Chghor^{+}_{i,t} + \beta_2 Chghor^{-}_{i,t} + \beta_3 Horizon_{i,t} \\
& + \beta_4 FREV_{i,t} + \beta_5 RecRev_{i,t} + \beta_6 RecRlev_{i,t} + \beta_7 Dispersion_{i,t} + \beta_8 SUE_{i,t} \\
& + \beta_9 IO_{i,t} + \beta_{10} Turnover_{i,t} + \beta_{11} Idiovol_{i,t} + \beta_{12} Size_{i,t} + \beta_{13} B/M_{i,t} \\
& + \beta_{14} RETP1_{i,t} + \beta_{15} RETP2_{i,t} + \beta_{16} EP_{i,t} + \beta_{17} LTG_{i,t} + \beta_{18} LTGrev_{i,t} \\
& + \beta_{19} SG_{i,t} + \beta_{20} TA_{i,t} + \beta_{21} CAPEX_{i,t} + Month/Year\ Fixed\ effect \\
& + Industry\ Fixed\ effect + Month/Year \times Industry\ Fixed\ effect + \varepsilon_{i,t+1}
\end{aligned}
\tag{1'}
$$

$\text{FREV}_{i,t}$ measures consensus annual earnings forecast revision over the past half year; it is scaled by price. $\text{RecRev}_{i,t}$ measures the revision of consensus recommendation over the past quarter. The level of Recommendation is also included as $\text{Reclev}_{i,t}$. $\text{Dispersion}_{i,t}$

measures the differences of opinion; it is defined as the standard deviation of analysts' current annual earnings forecasts scaled by the absolute value of the consensus annual forecast for the same fiscal year. $SUE_{i,t}$, or the standardized unexpected earnings, is defined as the difference between the actual earnings from the past quarter and the earnings from the same quarter in the last fiscal year, scaled by the standard deviation of the quarterly earnings over the past two years. $IO_{i,t}$ and $Turnover_{i,t}$ are important analyst incentive variables that have been shown to influence analysts coverage decision. Also, the institutional ownership $IO_{i,t}$ measures the level of short-sale constraints and is constructed as the fraction of common shares owned by institutional investors as reported in the Institutional Holdings (13f) file. $Turnover_{i,t}$ is the share volume divided by the number of shares outstanding, and is related to overvaluation. $Idiovol_{i,t}$ is the standard deviation of the daily excess return from Fama-French three factors benchmark; it captures cash-flow uncertainty. $Size_{i,t}$, $BtoM_{i,t}$, and $Mom_{i,t}$ are the commonly used factors to control firm risk characteristics. The remaining control variables are constructed following the same steps as in Jegadeesh et al. (2004). LTGrev is the revision of long-term growth forecasts; it has been shown in Copeland et al. (2004) that it has a strong effect on the contemporaneous stock returns. The correlations between the independent variables are presented in Table 1.4.

All regressions in the Panel A of Table 1.5 include either year or month fixed effect along with industry fixed effects, with all standard errors clustered on the year and industry interaction level or month and industry interaction level correspondingly. The year and industry interaction fixed effects are not included together with year fixed effects and industry fixed effects because the year and industry fixed effects are omitted.

Panel B addresses the concern that unobservable industry-year or industry-month component might drive the results by controlling for such fixed effects using the same set of independent variables. All standard errors are also clustered on the year and industry interaction level or month and industry interaction level correspondingly.[6] The economic magnitude is not tremendous, with a one-standard-deviation increase in horizon shifting the return by 13.6 bp in column (1) of Panel A, and 13.42 bp in column (3) of Panel A.

[6] In unreported results, I replace the independent variable Chghor with RChghor, defined as Chghor relative to the average horizon of the past month. The coefficient associated with RChghor increases considerably in terms of its economic magnitude. For example, the coefficient of RChghor corresponding to the specification (1) from Panel A is 0.0139, with a t-statistic of 1.93, implying that a one-month increase in relative horizon is associated with a 139 basis-point increase in one-month returns. Moreover, the coefficient associated with RChghor corresponding to the specification (3) from Panel A is 0.0413, with a t-statistic of 4.46, implying that a one-month increase in relative horizon is associated with a 413 basis-point increase in one-month returns.

4. Horizon jumps and return predictability

A. Timing of horizon jumps

A strand of the literature reports that analyst revisions of earnings and recommendations are the most active around the quarterly earnings announcement dates (Ivković and Jegadeesh, 2004; Keskek et al., 2014; Kim and Song, 2014). If active revision is an indicator that analysts generate efforts in information gathering and interpretation, it's legitimate to posit that the horizon jump may also exhibit such clustering feature around quarterly earnings announcements (QEA hereafter).

In this section, I analyze the timing of horizon jumps relative to the quarterly earnings announcement dates. The sample includes all 150,707 analysts' far-horizon annual earnings forecasts issued in the month during which the firm is ranked in the top decile of analyst horizon change. Figure 1 summarizes the frequency of trading days the jumps are prior to or after the event day of QEA. Each analyst forecast is matched to the closest earnings announcement and the sample is winsorized at the 99% level, resulting ultimately in 149,212 earnings forecasts in the period from July 1982 July to December 2016. The figure indicates that 28.44% of the far-horizon forecasts are made within the three days of the QEA. The rest of the far-horizon forecasts are made evenly throughout the days from 31 days pre-QEA to 31 days post-QEA, at about 1% per day.

B. Short-term stock price reaction to horizon jumps

Previous analyses have demonstrated that the relation between future stock returns and changes in analyst average horizon appears to be short-lived, with effects dissipating in less than three month. Moreover, consistent with an agency issue explanation, increases in analyst average forecast horizon appear to contain more information than decreases in analyst average forecast horizon. In an effort to probe more deeply into the predictability of returns from positive horizon changes, this part of the analysis studies the cumulative abnormal returns in the three-day windows surrounding horizon jumps. A stock is regarded to have a horizon jump in a month it its change in horizon belongs to the top decile that month. The jumps take place when an analyst issues a new forecast for a far-off fiscal period ending date that incurs a jump in horizon compared with the longest horizon in the past year. The top decile of horizon change is sorted on a monthly basis, yet the jumps take place on the days on which at least one analyst gives a forecast for a far-off fiscal year. The forecast having the largest number of months till its forecast ending period is identified as the forecast causing the jump. If more than one analyst has a forecast identified as a horizon jump in a month, all the forecasts made by the identified analysts for that particular firm on the forecast announcement days on which jumps take place are retained. To purge the effect of current annual or quarterly earnings forecast revisions, I exclude the horizon jumps that take place five days before or after analyst forecast revision announcements for the current fiscal year or quarter.

If analysts' large increases of horizon indeed present a surprise to the market because they convey incremental information, the three-day cumulative abnormal returns (thereafter CARs) surrounding the event days of horizon jumps should be significantly positive. Table 1.6 summarizes the three-day CARs of stocks with horizon jumps, in comparison with the average three-day CARs of stocks over the same periods but without horizon jumps. The CARs are calculated by adding the difference between the raw return and value-weighted market portfolio return including distributions of all stocks traded on

NYSE, AMEX and NASDAQ (Item vwretd in CRSP daily stock market indexes file) over event day *t*, day *t*+1, and day *t*+2. The event days are the first trading days on or before which the horizon-changing announcements are made. Column (1) presents the average CARs of 15,830 jumps and column (2) reports the average CARs of all other stocks over the same time periods but without analysts' average horizon jumps. The evidence in Table 1.6 shows that there is a significant difference between the CARs produced by the groups of stocks with horizon jumps and those without horizon jumps, suggesting that analyst forecast horizon jumps convey value-relevant information that surprises the market.

To better understand the superior returns by the groups of stocks that have experienced a horizon jump, in Figure 1.2 I present the time variation of the average CARs over a 45-trading-day window following the horizon jump, in comparison with the average CARs of all other stocks that did not experience horizon jumps on the event days. As the figure shows, the CARs of the stocks with horizon jumps continue to outperform the stocks without horizon jump over the next several weeks.

C. Horizon change and weekly returns

This section explores the return horizon over which analyst forecast horizon changes predict returns. Figure 3 presents the results of estimating the panel regression specified in equation (1) for weekly returns over increasingly longer return horizons. The results indicates that the predictive power persists for 18-21 weeks.

5. Horizon change and information environment

A. Horizon change and liquidity

Liquidity decreases with information asymmetry between informed traders and noise traders, who are interpreted as market makers (Kyle, 1985). When liquidity is low, new information is hard to be incorporated into prices and mispricing tends to persist (Sadka and Scherbina, 2007). On the other hand, when liquidity is high, or when noise trading is more active, stock price reaction is larger when analysts' new forecasts convey information (Ivković and Jegadeesh, 2004). If analysts increase or decrease their forward-looking earnings forecasting period because they received or are lacking private information, a natural conjecture is that the degree of stock-price reactions to horizon changes should be affected by the liquidity of the individual stock. Therefore, I propose the following hypothesis:

Hypothesis 2: In the cross-section, analysts' horizon changes are associated with larger stock-price reactions when liquidity is high and smaller stock-price reactions when liquidity is low.

To test this hypothesis, I perform a portfolio analysis by double sorting, first on liquidity and then on the change in horizon. I employ the Amihud (2002) illiquidity as the first measure for liquidity. The Amihud (2002) illiquidity measure is calculated as the ratio of the monthly average daily absolute return and the dollar trading volume, subsequently multiplied by 10^6, where the volume is positive. The measure is one of the most valid low frequency price impact proxies (Goyenko et al., 2009). The second measure is the bid-ask spread, the ratio of the monthly average absolute difference between ask and bid prices and the average of ask and bid prices (Modh, 2005; Fu et. al., 2012). Bid-ask spread has been used as a measure for information asymmetry; the higher the bid-ask spread, the more information asymmetry there is, or the lower the liquidity is.

At the end of each month, I first partition the stocks into three groups based on monthly liquidity of individual stocks using the Amihud (2002) illiquidity measure. The sample pertaining to liquidity includes all stocks traded on NYSE and AMEX, whereas the sample pertaining to the bid-ask spread measure includes all stocks traded on NYSE, AMEX, and Nasdaq. Then, I form five quintiles based on the change in analyst horizon within each liquidity quintile. Quintile 1 has the largest decrease in analyst horizon and quintile 5 has the largest increase in analyst horizon. The portfolios use equal weights and are held for either one, or with three, six, or nine month overlaps with monthly rebalancing.

The portfolio analysis, presented in Table 1.7, generally confirms the hypothesis. For low illiquidity stocks (i.e., high liquidity stocks), the zero-cost portfolio of buying the stocks with large increases in analyst horizon and selling the stocks with large decreases in analyst horizon generates positive and statistically significant returns. However, when stocks are rather illiquid, such a zero-cost portfolio generates a profit close to 0. This is consistent with the conjecture that stocks' illiquidity prevents the information contained in the signal of analyst horizon change from being revealed in the stock price. The results persist in the specifications featuring the Fama French 3 factors or the Carhart 4 factors. Moreover, consistent with previous results, the market reaction to the changes in analyst horizon are rather short-lived because the returns of the zero-cost portfolios held for more than 6 months decrease. Overall, the evidence suggests that there indeed is price-relevant information contained in the changes of analyst forecasting horizons and that such information is more easily incorporated into stock prices when liquidity of the stocks is high.

B. Horizon change and volatility

Excess stock return volatility is associated with learning and resolving cash flow uncertainty (Timmerman, 1993; Pastor and Veronesi, 2003). Stock return volatility is high when uncertainty is high, while learning the true value of the fundamentals lowers return volatility. Moreover, in the cross-section, the expected future return is larger if uncertainty is higher, and the shift of information from private to public lowers equilibrium expected excess return (Easley and O'hara, 2004). If analysts' change in horizon indeed carries cash-flow-related information, the change in horizon should predict lower future returns when stock volatility is high. Also, the change in horizon is conjectured to have more information pounded into prices by the market when the overall uncertainty is low, when active learning is low, and the analysts' future projection are more accurate.

To test these hypotheses, I perform a portfolio analysis by double-sorting, first on stock volatility and then on changes in analyst horizon. The stocks are first sorted into three groups of low, medium, and high volatility, respectively. The stocks are then divided into five quintiles within each volatility group based on the changes in analyst horizon, where quintile 1 has the largest drop in analyst horizon and quintile 5 has the largest increase in analyst horizon. To reiterate, stocks with higher volatility as associated with lower future expected return. If analysts change in horizon do carry information, the portfolio of stocks with high volatility in both quintiles should earn lower expected return than the respective portfolios with low volatility. Further, the zero-cost portfolio of buying the quintile 5 and short selling quintile 1 stocks will generate higher profit when stock return volatility is lower, if the information signal makes more marginal contribution to the information environment at times of lower uncertainty.

In performing these tests, I employ both idiosyncratic volatility and total realized return volatility. Following the literature (e.g., Chen et. al., 2012), I construct the idiosyncratic volatility in three steps: (1) regress the monthly return over the past 60 months on the three Fama-French factors and retain the loadings; (2) use the loadings for the daily returns of the current month to get the daily excess return; and (3) calculate the standard deviation of the excess return in the current month. Total realized return volatility is the standard deviation of the realized return over the current month. Such a measure is especially suitable when the sample studied is small and around 100 (Timmerman, 1993). The sample includes all stocks traded on NYSE, AMEX, and Nasdaq exchanges in the period from June 1982 June to December 2016.

The results of the analysis are presented in Table 1.8. The basic portfolio characteristics presented in Panel A. Consistent with prior literature (Ang et al., 2006), returns of the high-volatility portfolios are lower than the corresponding returns of the low-volatility portfolios throughout Panels B in C. Panel B and C also reveal that change in analyst horizon indeed carries value-relevant information in the condition of high information asymmetry conveyed through low volatility and over a one-month horizon (Panel B) because high horizon change portfolios (Q5) outperform low horizon change portfolios (Q1) by 15-17 basis points per month for both idiosyncratic and total volatility measures. Results carry over, though with a decreased magnitude for the three-month overlapping portfolios (the first segment of Panel C), but not for longer period overlaps of six or nine months.

Table 1.9 explores whether analysts' forecasting efficiency varies across different information environments. I sort the stocks into terciles based on the measures of illiquidity, uncertainty, and overvaluation every month and calculate the time-series average of the analysts' equally-weighted forecasting error and differences in opinion. The forecasting error is the absolute difference between the consensus quarterly earnings forecast for the current quarter and the actual earnings, normalized by the price of the current month. The difference of opinion is measured by the standard deviation of analysts' current-quarter forecasts scaled by the absolute value of the mean forecast. The results indicate that both analysts' forecast error and difference in opinion increase when liquidity is low and when uncertainty is high. Moreover, forecast error is low in the environment of overvaluation as measured by P/E ratio.

6. Horizon change and firm fundamental risks

This section explores whether analyst horizon change is associated with the analysts' assessment of firms' fundamental payoff uncertainty. I check whether the cross-sectional variation of horizon change is related to a set of selected firm attributes commonly employed as measures of risks and also related to analysts risk ratings (Lui et al., 2007; Joos et al., 2016). To control for the information in horizon change associated with level estimates of firms' future prospects, I also include a set of firm characteristics that are likely the most important factors that feed into an analyst's earnings forecasts. Second, I form decile portfolios based on the residuals of the regressions above. After extracting the component predictable by publicly available firm characteristics, the residual change in horizon component reflects price-influential analysts' superior knowledge of other aspects of the firms they cover. If the change in horizon variable indeed contains information other than assessment of risk or profitability, the portfolios formed on the basis of such residuals should predict future returns.

Past literature has discovered that the firm characteristics of Fama and French (1992, 1993), idiosyncratic risk, leverage, accounting loss, and earnings volatility together reflect analysts' assessment of firms' future fundamental uncertainty (Lui et al., 2007; Joos et al., 2016). I also include into the specification the set of firm variables associated with analysts' prediction of firms' earnings (Fama and French, 2006; So, 2013). The cross-sectional model is:

$$
\begin{aligned}
Chghor_{i,t} = {} & \alpha + \beta_1 Size_{i,t-1} + \beta_2 MktBeta_{i,t-1} + \beta_3 Idiovol_{i,t-1} + \beta_4 B/M_{i,t-1} \\
& + \beta_5 B/M \times NegBV_{i,t-1} + \beta_6 NegBV_{i,t-1} + \beta_7 Leverage_{i,t-1} \\
& + \beta_8 Leverage \times NegBV_{i,t-1} + \beta_9 NegEarn_{i,t-1} + \beta_{10} Earnvol_{i,t-1} \\
& + \beta_{11} ACC^{+}_{i,t-1} + \beta_{12} ACC^{-}_{i,t-1} + \beta_{13} Assetgrowth_{i,t-1} \\
& + \beta_{14} Dividend_{i,t-1} + \beta_{15} Shareprice_{i,t-1} \\
& + Month\ Fixed\ effects + Industry\ Fixed\ effects + \zeta_{i,t}
\end{aligned} \tag{2}
$$

Here, $size_{i,t}$ is the natural logarithm of monthly market capitalization, $beta_{i,t}$ is the market factor loading of the regression of monthly firm stock return on the 3-factor model of Fama and French (1992, 1993) over the past 60 months, $Ivol_{i,t}$ is the standard deviation of daily excess return in the current month; $BtoM_{i,t}$ is the ratio of the book value of equity for the most recent fiscal year divided by the market capitalization in December of the last fiscal year; $NegBV_{i,t}$ is an indicator variable that equals one if the book equity of the last fiscal year is negative, and equals zero otherwise; $leverage_{i,t}$ is the ratio of long- and short- term debt-to-book equity, where the long- and short-term debt come from the quarter at least three months before the current month; $Earnvol_{i,t}$ is the standard deviation of the quarterly income before extraordinary items over the preceding five years, with a minimum requirement of 10 quarters. $NegEarn_{i,t}$ is an indicator variable that equals one if the sum of income before extraordinary items over the past four quarters is negative, and equals zero otherwise. A firm is deemed riskier if it has small size, high beta or idiosyncratic volatility, high book-to-market ratio, high leverage, more volatile earnings, and accounting loss.

The regression tests vary in the set of independent variables included; the results are presented in Table 1.10. The first specification includes only the market risk exposure $Beta_{i,t}$ and firm specific risk $Ivol_{i,t}$. The second specification includes the Fama and French (1992, 1993) factors $Beta_{i,t}$, $size_{i,t}$, $BtoM_{i,t}$ together with idiosyncratic risk. The third specification includes all the variables associated with analyst risk assessments. In the fourth model, the firm characteristics related to analyst earnings forecasts are selected. Lastly, all variables in previous specifications are included as the independent variables. The industry and month fixed effects are included in all specifications.

The coefficients associated with idiosyncratic risk exposure are negative in all specifications, as are all the coefficients associate with negative earnings. Firms with negative earnings are related to an increase of future risks and associated with shortening of forecasting horizon, which is in line with the reasoning that change in horizon is negatively associated with firm risk. The evidence is mixed, however, because market capitalization is also negatively related to horizon change. Asset growth is associated with lengthening of horizon, which indicates that horizon change is associated with level prediction of future profitability.

Next, I perform portfolio analyses based on the residuals from all five estimations based on equation (5). I sort on the residuals and form 10 decile portfolios (1-10 from low to high) at the end of each month, and either holding the equally-weighted portfolio for one month or holding three overlapping portfolios formed in successive months. Table 1.11 reports the performance of decile 1 and decile 10 portfolios, as well as the performance of the long-short portfolio of of the two. For all five residual specifications, the monthly average return of the long-short portfolio held for 1 month after formation is positive and statistically significant for both raw and risk-adjusted terms. However, the superior return vanishes when the holding period are extended to three months. The evidence suggests that the component of change in horizon after extracting the information of firm fundamental risks can predict future stock return in the short-run, with even larger magnitude, but not in the longer run. Therefore, analyst change in horizon contains both firm fundamental risk information and other information related to the expected returns.

7. Horizon change and future performance

This section continues to explore whether the relation between returns and horizon change partially stems from the ability of analysts' horizon changes to predict firms' performance-related fundamentals. The hypothesis is that if analysts increase their forecasting horizon because they anticipate improvement in firms' fundamentals, there should be a positive relation between fundamental variables associated with better future performance and horizon change.

Here, I employ the Piotroski (2000) FSCORE as the measure of firms' future financial performance. FSCORE aggregates nine key financial performance indicators that summarize firm performance along three dimensions: profitability, solvency, and operating efficiency. The four profitability indicators are ROA, cash flow form operation (CFO), change in net income (ΔNI), and accrual adjustment (ACC). The three solvency indicators are change in leverage ratio (ΔLEVER), change in current ratio (ΔLIQUID), and equity issuance (ISS). The two operating efficiency indicators are change in gross margin ratio (ΔMARGIN) and change in turnover ratio (ΔTURN). Firms' performance in profitability improves when ROA is positive (ROA > 0), cash flow from operation is positive (CFO > 0), net income is larger than it was during the last period (ΔNI > 0), and accrual adjustment is negative (ACC < 0). Firms' solvency abilities improves when long-term debt ratio decreases (ΔLEVER < 0), the current ratio is larger than it was during the last period (ΔLIQUID > 0), and when the firm does not issue more common equity (ISS ≤ 0). Firms' operating efficiency improves when the current gross margin ratio is larger than it was during the last period (ΔMARGIN > 0) and when the current asset turnover ratio is larger than it was during the last period (ΔTURN > 0). The details of the variable construction and the Compustat items used follow Piotroski and So (2012) and Hou et al. (2012). I define nine indicator variables based on these accounting variables and set the indicators to one if the performance is improved, and to zero otherwise. The FSCORE is the sum of the nine indicators.

At the end of each month, I sort the firms into 10 decile portfolios based on the ranking of the raw change in horizon or the fundamental-adjusted change in horizon variable. To ensure that the change in horizon is most relevant to analysts' information discovery efforts, the firms are sampled if the earnings announcement takes place in the upcoming month. Table 1.12 presents the equal-weighted monthly average of the FSCORE and the component individual indicators for the portfolio of the largest drop in horizon portfolio (decile 1) and the largest increase in horizon portfolio (decile 10). Along these performance dimensions, if the difference between the top and bottom decile portfolio is positive, the change in horizon variable predicts performance improvement; if the difference is negative, the change in horizon predicts performance deterioration.

I analyze the performance of the FSCORE and its component indicators over 1-4 quarters after portfolio formation. In the process, I ensure that the last period variables do not contain information available after portfolio formation. Across all forecasting period portfolios, the ROA of the top horizon change decile consistently outperforms that of the bottom horizon change decile. As the forecasting period extends, the FSCORE of the top horizon change decile starts to outperform the FSCORE of the bottom horizon change decile. This may be partially related to the fact that horizon change forecasts a larger positive cash flow in the future year than it does in the upcoming quarter. The results are robust to firm fundamentals adjustment. For the indicators of accrual, change in liquidity and change in turnover, the negative difference between the top and bottom horizon change portfolio is attenuated as the forecasting period extents. For the indicators of change in leverage and change in margin, the difference between the top and bottom horizon change portfolio is larger and positive as forecasting period expands, although the statistical significance may not be overwhelming. Overall, firms with largest increase in forecasting horizon are more profitable and has smaller debt obligations in the future year than the firms with largest decrease in forecasting horizon do. It is unclear, though, why the change in horizon is negatively associated with the issuance indicator. Because the magnitude of the mean issuance indicator is much smaller than the others, it may be that analysts' change in forecasting horizon is related more strongly to their role in profitability forecasting.

8. Time variation in horizon change premium

This section analyzes whether the premium of horizon change has a time-varying feature associated with the business cycle. In the subsections below, I perform time series regressions to test whether horizon change premium is cyclical (or counter-cyclical). Indeed, if the return of the long-short portfolio can be predicted by state variables, the horizon change premium has a cyclical feature.

I run the time-series regression of monthly long-short portfolio returns of different holding periods $R_{t,t+h}$ on various state variables proxies z_t and focus on the sign of the coefficient β_h.

$$R_{t,t+h} = \alpha_h + \beta_h z_t + \varepsilon_{t,t+h} \tag{3}$$

For procyclical state variables, the horizon change premium is procyclical if β_h is positive and is countercyclical if β_h is negative; for countercyclical state variables, the horizon change premium is procyclical if β_h is negative and is countercyclical if β_h is positive.

The state variables I utilize have been commonly used ones in the literature: dividend yield (DY), default spread (DS), and term spread (TS). State variables data, available with monthly frequency, come from the FRED database. I construct the dividend yield of the CRSP value-weighted index as in Fama and French (1988). Default spread is the yield difference between Moody's seasoned corporate Baa and Aaa bonds. Term spread is the yield difference between the 10-year and 1-year constant maturity Treasury bonds. Aside from these state variables, I also follow Petkova (2006) by adding the 3-month T-bill rate (RF) to the set of state variables above, so that RF and TS capture the level and slope of the yield curve. The literature has found that RF and DS negatively predict macroeconomic changes while DY and TS positively predict macroeconomic changes (Campbell and Vuolteenaho, 2004; Petkova, 2006). The results are presented in Table 1.13. All *t*-statistics are adjusted for heteroskedasticity and autocorrelation by the Newey and West (1987) method with lag of *h*. The results suggest that the horizon change premium is not likely to be related to macroeconomic state variables (although, in unreported results, the single variable regression with DS as the independent variable has a negative and statistically significant coefficient).

9. Conclusion

This dissertation analyzes sell-side analysts' change in forecasting horizon. I discover that portfolios formed by horizon change deciles generate superior returns not explained by risk models. Such return predictability is robust after controlling for various confounding factors that are likely correlated with analysts' horizon change. The relation between returns and horizon change is more pronounced in the information environments of high liquidity and low volatility, the conditions under which analysts' forecast might be the most informative. Moreover, horizon change is partially related to analysts profitability and firm-risk assessment, although portfolio formation based on horizon change, when excluding the component predictable by firm fundamentals, is still able to predict return in the short-run, and with an even larger magnitude. Horizon change is associated with FSCORE, an index that measures firm future fundamental profitability and growth. Horizon change premium is not associated with macroeconomic variables that predict business cycles.

CHAPTER 2

HORIZON JUMPS, FORECASTING ACCURACY, AND CAREER CONCERNS

1. Introduction

The average analyst forecasting horizon of a firm varies throughout the year. For the purposes of my analysis, the stock of a firm is defined to experience an analyst horizon jump if the analyst horizon—the average longest annual forecast horizon over the past 12 months of all individual analysts issuing annual forecasts for the firm—has a large increase from the last month, and the horizon increase belongs to the top decile of all horizon changes. Horizon jumps take place primarily because some analysts issue annual earnings forecasts with horizons much farther than both the horizon the same analyst had featured in the past and other analysts' forecast horizon for the same stocks. Horizon jumps increase in frequency as the date draws nearer to the date of the quarterly earnings announcement, potentially a sign that horizon jumps may involve analysts' active information-related efforts.

The question remains, however, what is the likely reason why some analysts make far-end horizon forecasts while others do not. Is horizon jump a manifestation of information advantage or forecasting skill? This chapter of the dissertation attempts to address this inquiry by analyzing the difference of forecasting accuracy, measured by the relative forecast error, between the group of analysts who contribute to horizon jump and the group of analysts who do not.

I find that, on the event day of the horizon jump, the forecasts issued by the group of analysts who contribute to average horizon jump is more accurate than the forecasts issued by the analysts who do not. The difference does not persist for long, though. It is gone by the end of the month, indicating that there is information dissemination between the two groups of analysts. The difference in accuracy resurfaces at the end of the second month, however, reflecting the notion that there is also a component of skill associated with analysts who issue far-end horizon forecasts.

Next, I explore the underlying motivation for the existence of such skill by studying the analyst characteristics associated with individual horizon jumps, and the associated analysts' career outcomes. I find that analysts less experienced with the firm or the broker, analysts from more reputable broker houses, and analysts who issue more accurate forecasts are more likely to issue far-horizon forecasts. Moreover, the act of issuance of far-horizon annual earnings forecast is likely to result in a favorable career outcome, with little possibility of getting a demotion. That noted, there is still a chance of departure associated with issuing far-horizon forecasts.

This chapter is related to the literature studying analysts' rationality. Although the forecasts far from its associated forecast period ends tend to be more biased and inaccurate, analysts who issue them are more likely to receive favorable career outcomes.

2. Forecasting accuracy and horizon jumps

Analysts strive to improve forecasting accuracy, with higher estimation precision indicating the ability to generate more value-relevant information, which, in turn, may lead to favorable career outcomes (Mikhail et al., 1999; Hong and Kubik, 2003; Loh and Mian, 2006; Altınkılıç et al. 2013; Hugon et al. 2016). This section analyzes the accuracy of the forecasts conditional on the analysts making horizon jumps, identified as the top decile of horizon change in a month. The analysts' annual earnings forecasts issued over the horizons farther than any other annual forecasts made in the same month are considered as the forecasts leading to the jump. If analysts' issuance of far-horizon forecast coincides with active information gathering efforts, the analysts who contribute to the horizon jump should be more accurate than those who do not contribute to the horizon jump.

I follow Ivković and Jegadeesh (2004) and use the relative forecasting error between the absolute error of most recently issued forecast and absolute error of the consensus estimate a day before as the measure of accuracy for the new estimates made on the day on which the jump occurs. The absolute forecasting error is defined as the absolute value of the difference between the annual earnings forecast and the actual annual earnings, standardized by the absolute value of the actual annual earnings. The data come from the Compustat variable earnings per share excluding extraordinary items EPSPX or EPSFX, depending on whether the earnings forecast is primary or diluted.

The relative forecasting error is negative if the new forecast is more accurate than the consensus forecast (the latter summarizes the information available before the new forecast). If the jump in horizon reflects analysts' superior information, the forecasts conditional on horizon jump should be more precise in comparison with the forecasts issued on the same days for the same firm, but without horizon jumps. Therefore, I perform *t*-tests for the differences of relative forecasting error of the forecasts conditional on horizon jump. The difference tested is between E(relative forecast error$_{i,j,t}$|jump$_{i,t}$ = 1) and E(relative forecast error$_{i,k,t}$|jump$_{i,t}$ = 1), where analyst j issues a far-horizon forecast that causes the jump and analyst k issues a new forecast that does not lead to horizon jump. The relative forecast error is at the analyst level. If there is more than one forecast that an analyst makes on the same day, I calculate the arithmetic average relative forecast error for the analyst. The results are presented in the first row of Table 2.1. On the day of the average horizon jump, the analysts contributing to the jump are on average 7.88% more accurate than the consensus forecast is, and are about 1% more accurate than the group of analysts not contributing to the jump is.

If analysts who contribute to jumps are systematically more skillful than the analysts who do not contribute to jumps while other analysts do, the earnings forecast errors of the two groups will continue to differ after the horizon-jump occurrence. To test this hypothesis, I compare the forecast errors across the two groups of analysts over time, after the horizon jump takes place. The time points included are the end of the month of the outstanding forecasts of the same analysts for the same firm, but before the arrival of the associated forecast period end. The results are presented in the remaining rows in Table 2.1.

The second row in Table 2.1 shows that, at the end of the first month, the earnings forecast error of the group of analysts who do not contribute to the jump is already comparable to that of the analysts who affect the jump, implying that the former are herding towards the analysts who made the jump. To address the concern that far-end forecasts are more biased and may bias upwards the relative forecast error, in column (2) I include the forecast whose related forecasting period-ends are comparable with those of the no-jump analysts. This step does not affect the results. However, the forecast error difference persists at the end of the second month, as the analysts who lead the jumps are more resourceful and outperform those who do not. In sum, analysts who contribute to the jump showcase both superior knowledge and higher skill levels than other analysts do.

3. Horizon jump and analyst characteristics

Analyst characteristics such as experience, workload, broker reputation, accuracy, and boldness captures the analysts' major career and reputational concerns (Hong et. al., 2000; Hong and Kubik, 2003). In this section, I analyze whether such concerns are related to the horizon jump decisions. Specifically, I estimate the following logit model:

$$\begin{aligned} Jump_{i,j,t} = {} & \alpha + \beta_1 General\ Experience_{j,t} + \beta_2 Firm\ Experience_{i,j,t} + \beta_3 Tenure_{j,t} \\ & + \beta_4 Workload_{j,t} + \beta_5 Broker\ Reputation_{j,t} + \beta_6 Accuracy_{j,t} \\ & + \beta_7 Boldness_{j,t} + Industry\ Fixed\ effects + Year\ Fixed\ effects \\ & + Broker\ Fixed\ effects + \eta_{i,j,t} \end{aligned} \tag{4}$$

where $Jump_{i,j,t}$ is an indicator variable that equals 1 if analyst j makes a jump for firm i in year t, and equals 0 otherwise. The raw (upper triangle) and rank-adjusted (lower triangle) correlations of the independent variables are presented in Table 2.2.

Table 2.3 shows that analysts' characteristics are strongly associated with horizon jump. Analysts with less experience for a particular firm and broker are more likely to jump, and analysts who work for more reputed broker houses and exhibit relatively higher forecast accuracy tend to issue far-end earnings forecasts.

4. Horizon jump and career outcomes

This section assesses the relation between the likelihood that an analyst will experience a favorable career outcome over the next year and making at least one jump in the current year. Formally, I estimate the coefficients for the logit model

$$\begin{aligned} Career\ Outcome_{j,t+1} = {} & \alpha + \beta_1 Jump_{j,t} + \beta_2 General\ Experience_{j,t} \\ & + \beta_3 Tenure_{j,t} + \beta_4 Workload_{j,t} + \beta_5 Broker\ Reputation_{j,t} + \beta_6 Accuracy_{j,t} \\ & + \beta_7 Boldness_{j,t} + Year\ Fixed\ effects + Broker\ Fixed\ effects + \eta_{j,t+1} \end{aligned} \quad (5)$$

where $Jump_{j,t}$ is an indicator variable that equals 1 if analyst j makes at least one jump in year t, and equals 0 otherwise. Three types of career outcomes are analyzed: favorable movement and unfavorable movement among brokers, and departure, where an analyst disappears from the I/B/E/S sample in the next year. I refrain from using the terminology "termination" because leaving the analyst job career does not necessarily imply negative utility for the analyst. The career outcomes are measured by the reputation of the broker house for which the analyst works. The reputation ranking is generated on a yearly basis and broker reputation is ranked by the number of analysts they hire in the year. If an analyst works for the same broker and the broker's reputation has improved from last year, such an outcome is considered as favorable because the analyst has chosen not to leave for another broker. To sharpen the test, I also include two cases of promotion: (1) the analyst's new associated broker house reputation is one quintile higher than the current broker house; (2) the analyst's new associated broker house is 2 decile more reputed than the current one. Also, I consider the case of demotion, in which the analyst's new broker is ranked one quintile lower below the current one, as well as departure.

The test results are presented in Table 2.4. Analysts who jump are more likely both to receive promotion and to depart, but they are less likely to get a demotion. Therefore, conditional upon remaining in the industry, there is a positive relation between a favorable career outcome and affecting at least one horizon jump.

5. Conclusion

This chapter used horizon jumps as an identifying tool to explore the analysts' forecasting quality and their incentives. I find that analysts who contribute to horizon jumps of a stock generally have higher forecast accuracy than the analysts who do not. Such differences in forecasting accuracy can be attributed to both informational advantage and analyst skills. The analysts contributing to horizon jumps tend to be less experienced with the firm or the broker, work for more reputable broker houses, and issue more accurate forecasts. Conditional on remaining in the industry, analysts who give far-end horizon forecasts have a higher chance to receive better career outcome in the next year, with low possibility of receiving a demotion.

APPENDICES

APPENDIX A

Tables and Figures

Table 1.1. Summary statistics

This table presents a more detailed characterization of analysts' horizon and change in horizon (Panel A) and the portfolio characteristics at formation (Panel B) along the dimension of average horizon (expressed as the number of months), average change in horizon (expressed as the number of months), average number of stocks, size (in millions), book-to-market ratio, and the raw return over the past year. In Panel A, the cross-sectional variation of horizon change is summarized in the first two columns and the time-series changes over 3, 6, 9 and 12 months are reported in the subsequent four columns. The last column of Panel A summarizes the number of months it takes for an analyst to issue a forecast that has the horizon as far as, or farther than, the first longest horizon for a firm. The first largest horizon is defined as the first annual earnings forecast whose horizon is farther than all annual earnings forecasts in the previous year and the analyst has made at least one annual earnings forecast in the preceding year.

Panel A: Horizon and horizon change

	Cross-sectional horizon variation		Time-series variation of change in horizon				
	Raw	Demeaned	3Mo.	6Mo.	9Mo.	12Mo.	Recovery
Smallest	-105	0	-99	-102	-81	-108	1
1%	1	0	-27	-30	-33	-24	1
25%	17	1	-3	-6	-9	0	9
50%	21	4.5	-3	-6	3	0	11
75%	24	7	9	6	3	0	12
99%	58	21.75	21	30	27	24	80
Largest	148	76.8	105	90	99	96	301
Mean	22	4.9	-0.15	-0.15	-0.05	-0.18	14
No. of Obs	1,382,400	1,382,400	2,191,305	1,941,624	1,749,811	1,735,469	158,781

Table 1.1 (cont'd)

Panel B: Portfolio characteristics by horizon change deciles

	(Low) 1	2	3	4	5	6	7	8	9	(High) 10
Chghor	-1.15	-0.29	-0.13	-0.03	0.00	0.00	0.01	0.06	0.31	1.90
Horizon	23.96	23.57	23.55	22.85	22.48	22.43	22.44	22.64	22.85	21.85
RChghor	-0.05	-0.01	-0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.10
Earnlev	1.67	2.33	1.86	-0.10	2.10	2.11	2.20	2.06	1.99	2.31
Reclev	2.70	2.71	2.72	2.75	2.78	2.79	2.78	2.77	2.75	2.78
LTG	16.88%	16.46%	15.36%	15.45%	15.89%	16.07%	15.95%	15.72%	15.45%	16.18%
Size	4,247.0	3,641.2	5,650.5	5,832.7	2,446.3	1,759.0	2,077.4	3,282.3	5,574.0	4,537.4
B/M ratio	2.66	1.90	1.28	2.13	2.75	3.07	2.71	2.50	1.53	1.97
RETP	3.47%	3.34%	5.94%	9.92%	12.76%	13.23%	12.44%	12.26%	11.04%	15.57%
No. of Stocks	213	213	213	213	213	213	214	213	214	212

Table 1.2. Portfolio sorted by horizon change

This table reports the returns of the portfolios formed every month based on change in average analyst horizon. Panel A presents the result of the equal-weighted monthly average returns of portfolio decile 1 (largest decrease in horizon) to decile 10 (largest increase in horizon) and the zero-cost portfolio of short selling decile 1 and buying decile 10 are reported in Panel B. The average returns are reported in raw, Carhart (1997) -4-factors-adjusted, and DWTG (1997)-characteristics-adjusted terms. The subperiod long-short portfolio performance before and after the promulgation of Reg FD is also reported. The portfolios are formed either right after the sort or after waiting for 1 month, to account for slow information incorporation. Panel C summarizes the return of monthly rebalanced equal-weighted portfolios, holding with overlaps for 3 or 6 months, with portfolios formed 0 or 1 months after sorting on the change in horizon.

Panel A: Portfolio returns by horizon change deciles

	(Low) 1	2	3	4	5	6	7	8	9	(High) 10
No Waiting	0.97%	1.13%	1.21%	1.10%	1.22%	1.19%	1.19%	1.21%	1.21%	1.27%
(t-stat)	3.36	3.39	4.43	3.96	4.21	4.11	4.05	4.23	4.29	4.47
1 Mo. Waiting	1.07%	1.14%	1.18%	1.20%	1.09%	1.21%	1.11%	1.34%	1.19%	1.23%
(t-stat)	3.58	4.00	4.27	4.29	3.82	4.25	3.86	4.52	4.24	4.29

Panel B: Risk- and characteristics-adjusted portfolio returns

	Full Sample			Pre-Reg FD			Post-Reg FD		
	Raw Return	Risk-adj alpha	Char-adj alpha	Raw Return	Risk-adj alpha	Char-adj alpha	Raw Return	Risk-adj alpha	Char-adj alpha
No Waiting	0.30%	0.20%	0.26%	0.28%	0.25%	0.20%	0.33%	0.26%	0.33%
(t-stat)	3.28	2.15	2.92	2.25	1.86	1.71	2.29	1.97	2.42
1 Mo. Waiting	0.16%	0.07%	0.15%	0.00%	-0.07%	0.14%	0.30%	0.27%	0.17%
(t-stat)	1.64	0.68	1.53	0.03	-0.45	1.02	2.17	2.07	1.14

Table 1.2 (cont'd)

Panel C: Portfolio returns, held for multiple months										
	No Waiting					1 Mo. Waiting				
Holding Period	Decile 1(Low)	Decile 10(High)	Long 10 Short 1	FF3 alpha	Carhart alpha	Decile 1(Low)	Decile 10(High)	Long 10 Short 1	FF3 alpha	Carhart alpha
1-months	0.97%	1.27%	0.30%	0.24%	0.26%	1.07%	1.23%	0.16%	0.16%	0.07%
(t-stat)	3.36	4.47	3.28	2.61	2.92	3.58	4.29	1.64	1.63	0.68
3-months	1.05%	1.21%	0.16%	0.15%	0.08%	1.06%	1.17%	0.12%	0.11%	0.03%
(t-stat)	3.62	4.30	2.33	2.19	1.11	3.64	4.16	1.66	1.60	0.46
6-months	1.07%	1.14%	0.07%	0.05%	-0.01%	1.09%	1.10%	0.01%	0.01%	-0.06%
(t-stat)	3.72	4.11	1.09	0.82	-0.25	3.78	3.98	0.18	0.12	-0.98

Table 1.3. Bivariate portfolio analysis

This table present the average return of the portfolios and the zero-cost portfolio after double-sorting on three forms of analyst revisions and on horizon change. Panel A focuses on current-year earnings forecast revision, Panel B studies the recommendation revision and Panel C analyzes the LTG forecast revisions. At the end of each month, first sort on short-run mean revisions into five quintiles from pessimistic to optimistic (Q1 to Q5), and then sort on the change in horizon into five quintiles, where quintile 1 has largest decrease in horizon while quintile 5 has largest increase in horizon. Form the portfolios using equal weight and hold for 1-month.

Panel A: double-sorting on FREV and Chghor

	Horizon change portfolio					Long 5	FF3	Carhart
	1(Low)	2	3	4	5(High)	Short 1	alpha	alpha
1(Sm)	0.10%	0.34%	0.12%	0.34%	0.48%	**0.37%**	**0.35%**	**0.35%**
(t-stat)	0.29	0.97	0.34	0.93	1.34	2.70	2.48	2.43
2	**0.62%**	**0.76%**	**0.62%**	**0.72%**	**0.88%**	**0.27%**	**0.24%**	**0.28%**
(t-stat)	2.11	2.77	2.20	2.45	3.04	2.41	2.14	2.40
3	**0.86%**	**0.95%**	**0.93%**	**0.87%**	**1.23%**	**0.37%**	**0.36%**	**0.36%**
(t-stat)	3.51	4.07	3.78	3.47	5.74	3.94	3.67	3.69
4	**1.26%**	**1.23%**	**1.34%**	**1.33%**	**1.80%**	**0.55%**	**0.52%**	**0.56%**
(t-stat)	4.97	4.88	5.08	5.23	6.91	5.50	5.09	5.39
5(Lg)	**1.72%**	**1.76%**	**1.81%**	**1.94%**	**2.51%**	**0.78%**	**0.76%**	**0.76%**
(t-stat)	5.14	5.46	5.65	6.12	7.51	5.84	5.57	5.44

Panel B: double-sorting on Recrev and Chghor

	Horizon change portfolio					Long 5	FF3	Carhart
	1(Low)	2	3	4	5(High)	Short 1	alpha	alpha
1(Sm)	-0.51%	0.02%	-0.30%	-0.13%	-0.46%	0.05%	0.01%	0.04%
(t-stat)	-1.24	0.06	-0.75	-0.33	-1.17	0.34	0.04	0.26
2	**0.72%**	**0.81%**	**0.78%**	**0.83%**	**1.20%**	**0.48%**	**0.50%**	**0.52%**
(t-stat)	2.02	2.46	2.22	2.35	3.25	3.46	3.50	3.62
3	**0.94%**	**0.93%**	**0.74%**	**1.13%**	**1.33%**	**0.39%**	**0.35%**	**0.36%**
(t-stat)	2.55	2.64	2.10	3.18	3.63	2.31	2.10	2.08
4	**1.23%**	**1.14%**	**1.04%**	**1.26%**	**1.71%**	**0.48%**	**0.47%**	**0.51%**
(t-stat)	3.34	3.44	2.98	3.51	4.83	3.24	3.12	3.37
5(Lg)	**1.85%**	**1.67%**	**1.67%**	**1.76%**	**2.74%**	**0.89%**	**0.87%**	**0.90%**
(t-stat)	4.80	4.66	4.17	4.46	6.85	5.87	5.63	5.77

Table 1.3 (cont'd)

Panel C: double-sorting on LTGrev and Chghor

	Horizon change portfolio					Long 5	FF3	Carhart
	1(Low)	2	3	4	5(High)	Short 1	alpha	alpha
1(Sm)	**0.55%**	**0.75%**	**0.90%**	**0.84%**	**0.88%**	**0.33%**	**0.32%**	**0.26%**
(t-stat)	1.69	2.47	2.86	2.67	2.77	2.45	2.31	1.87
2	**0.84%**	**1.07%**	**1.03%**	**1.03%**	**1.40%**	**0.51%**	**0.50%**	**0.51%**
(t-stat)	3.24	4.20	4.00	3.81	5.28	4.51	4.28	4.27
3	**0.92%**	**1.19%**	**1.00%**	**0.92%**	**1.33%**	**0.41%**	**0.40%**	**0.45%**
(t-stat)	3.04	4.23	3.53	3.24	4.35	3.15	3.04	3.34
4	**1.04%**	**1.16%**	**1.10%**	**1.12%**	**1.59%**	**0.54%**	**0.55%**	**0.57%**
(t-stat)	3.82	4.59	4.19	4.25	6.15	4.46	4.42	4.50
5(Lg)	**1.21%**	**1.13%**	**1.27%**	**1.26%**	**1.85%**	**0.64%**	**0.62%**	**0.67%**
(t-stat)	3.81	3.59	3.82	3.94	5.83	4.59	4.38	4.64

Table 1.4. Correlation table of independent variables

This table presents the Pearson correlation in the lower triangle and the Spearman correlation in the upper triangle, of the independent variables used in panel regression (1). The variables are defined as in the paper and a more details can be found in the Appendix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	Chghor	1	-0.08	0.03	0.01	0.02	-0.02	0.02	0.01	0.03	0.02	0.00	0.02	0.05	0.04	0.01	-0.01	0.01	0.01	0.00	0.02
(2)	Horizon	-0.10	1	0.02	0.01	-0.11	-0.06	0.03	0.30	0.29	-0.31	0.47	-0.06	0.04	0.05	0.00	-0.20	0.00	-0.08	-0.01	-0.09
(3)	FREV	0.02	0.03	1	0.11	0.16	-0.09	0.35	-0.02	0.02	-0.07	0.07	0.01	0.35	0.19	-0.12	0.07	0.08	0.11	-0.03	-0.09
(4)	RecRev	0.01	0.01	0.08	1	0.22	-0.01	0.02	-0.01	-0.02	-0.02	0.03	0.03	0.10	0.04	-0.06	-0.01	0.08	-0.02	-0.01	-0.02
(5)	Reclev	0.02	-0.09	0.12	0.26	1	-0.16	0.12	-0.07	-0.01	0.12	-0.07	-0.16	0.08	0.14	-0.01	0.34	0.05	0.27	0.10	0.04
(6)	Dispersion	0.00	-0.01	-0.06	-0.01	-0.05	1	-0.15	-0.02	0.06	0.31	-0.31	0.22	-0.09	-0.14	-0.27	0.06	-0.01	-0.12	-0.04	0.00
(7)	SUE	0.02	0.02	0.27	0.02	0.11	-0.06	1	-0.01	0.04	-0.06	0.07	-0.04	0.16	0.28	0.01	0.09	0.03	0.21	-0.03	0.00
(8)	IO	0.00	-0.01	-0.01	0.00	-0.02	0.01	0.00	1	0.40	-0.10	0.19	0.00	-0.02	0.00	-0.06	-0.06	-0.02	-0.08	-0.02	-0.13
(9)	Turnover	0.03	0.15	-0.02	-0.03	-0.02	0.02	0.02	0.02	1	0.22	0.22	-0.11	0.01	0.06	-0.09	0.14	-0.03	0.09	0.01	-0.02
(10)	Idiovol	0.01	-0.20	-0.14	-0.05	0.06	0.09	-0.07	0.01	0.29	1	-0.50	-0.01	-0.17	-0.09	-0.19	0.36	-0.03	0.10	0.02	0.04
(11)	Size	0.01	0.43	0.09	0.04	-0.06	-0.08	0.07	0.00	0.10	-0.43	1	-0.21	0.13	0.11	0.12	-0.27	0.02	-0.01	-0.01	0.04
(12)	B/M Ratio	0.00	-0.02	0.00	0.01	-0.02	0.01	-0.01	0.00	0.13	-0.02	-0.07	1	0.07	0.02	0.05	-0.29	0.04	-0.22	-0.08	-0.01
(13)	RETP1	0.03	0.00	0.24	0.10	0.07	-0.02	0.12	0.00	0.05	-0.09	0.06	0.01	1	-0.04	-0.14	0.00	0.12	0.00	-0.05	-0.05
(14)	RETP2	0.03	0.01	0.14	0.03	0.12	-0.02	0.20	0.00	0.07	0.00	0.03	0.00	-0.03	1	-0.05	0.06	0.07	0.11	-0.03	0.00
(15)	E/P Ratio	0.00	0.00	0.03	0.00	0.06	-0.06	0.06	0.00	-0.04	-0.21	0.12	0.00	0.01	0.02	1	-0.29	-0.05	0.04	0.05	0.13
(16)	LTG	0.00	-0.09	0.05	-0.01	0.23	0.02	0.07	-0.01	0.09	0.22	-0.18	-0.04	0.03	0.08	-0.03	1	0.12	0.32	0.08	0.02
(17)	LTGrev	0.00	0.00	0.03	0.03	0.01	0.00	0.01	0.00	-0.01	-0.02	0.02	0.00	0.05	0.02	-0.01	0.35	1	-0.01	-0.01	-0.01
(18)	SG	0.00	0.01	0.01	0.00	0.01	0.02	0.02	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.03	0.00	1	0.22	0.13
(19)	TA	0.00	0.00	-0.01	-0.02	0.09	-0.01	-0.03	0.00	0.02	0.02	-0.02	-0.02	-0.03	-0.01	0.03	0.06	0.00	0.02	1	0.04
(20)	CAPEX	0.02	-0.08	-0.04	-0.02	0.05	0.00	-0.02	0.01	0.04	0.06	-0.01	0.03	-0.04	-0.01	0.03	0.05	-0.01	0.01	0.05	1

Table 1.5. Panel regression

This table presents the coefficients of the panel analysis of equation (1) and (1)'. In panel A, either year or month fixed effect along with industry fixed effects, with all standard errors clustered on the year and industry interaction level or month and industry interaction level correspondingly. Panel B addresses the concern that unobservable industry-year or industry-month component might drive the results by controlling for such fixed effects using the same set of independent variables. All standard errors clustered on the year and industry interaction level or month and industry interaction level correspondingly. (Unit: # of months×1,000, for the easy of presentation.)

	Panel A				Panel B			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chghor	1.7***	1.0***			1.7***	0.9**		
Chghor+			2.2***	0.8**			2.1***	0.9**
Chghor-			-1.0	-1.3**			-0.9	-0.8
Horizon	0.3***	0.2**	0.2***	0.2**	0.3***	0.3***	0.3***	0.3***
FREV	-43.8**	-15.6	-43.9**	-15.5	-47.7**	-15.5	-47.8**	-15.5
RecRev	4.3***	3.0***	4.3***	3.0***	4.1***	4.1***	4.1***	4.1***
Reclev	-0.2	-0.3	-0.2	-0.3	0.3	-0.5	0.3	-0.5
Dispersion	-0.8**	-1.0***	-0.8**	-1.0***	-0.6[a]	-0.8**	-0.6[a]	-0.8**
SUE	0.6*	0.3	0.6*	0.3	0.8**	0.5	0.8**	0.5
IO	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Turnover	-0.4	-0.2	-0.4[a]	-0.2	-0.2	0.1	-0.2	0.1
Idiovol	110.1**	-12.1	108.9**	-11.6	107.1**	-129.7**	105.8**	-129.9**
Size	-1.0***	-1.0***	-1.0***	-1.0***	-1.2***	-1.5***	-1.2***	-1.5***
B/M Ratio	-25.4	-27.7	-25.7	-27.6	-13.0	-13.9	-13.4	-14.0
RETP1	-8.8***	3.4**	-8.8***	3.4**	-14.5***	3.1*	-14.5***	3.1*
RETP2	-2.6*	0.8	-2.6*	0.8	-4.1***	0.3	-4.1***	0.3
EP	-0.8	-1.2	-0.8	-1.2	-0.8	-1.3	-0.8	-1.3
LTG	-0.2***	-0.1***	-0.2***	-0.1***	-0.2***	-0.1**	-0.2***	-0.1***
LTGrev	0.1*	0.1	0.1***	0.1	0.1*	0.1	0.1*	0.1
SG	-0.1***	-0.1	-0.1***	-0.1	-0.1***	-0.1	-0.1***	-0.1
TA	-15.7***	-13.2***	-15.7***	-13.2***	-14.4***	-12.8***	-14.4***	-12.9***
CAPEX	28.0***	-1.3	27.8***	-1.2	33.4***	-4.9	33.2***	-4.9
Year FE	Y		Y					
Month FE		Y		Y				
Industry FE	Y	Y	Y	Y				
Yr×Ind FE					Y		Y	
Mo×Ind FE						Y		Y
No. of Obs.	239,929	239,929	239,929	239,929	254,809	254,809	239,929	239,929
Adj R-2	0.0096	0.1638	0.0096	0.1638	0.0076	0.1626	0.0096	0.1638

Table 1.6. CAR analysis

The table presents the three-day cumulative abnormal returns (CARs), expressed in basis points, over the event days on which there are horizon jumps. Column (1) is the average CARs of stocks with jumps and column (2) reports the average CAR of all other stocks on the same even day but don't have an analyst incurring average horizon jump. The difference between the stocks with horizon jumps and those without is presented in the last column. The CARs are presented in basis points.

	Horizon Jump stocks	Other stocks	difference
CAR	38	6	32
(t-stat)	8.13	24.67	6.92
No. of Obs.	15,830	6,331,855	

Table 1.7. Illiquidity and horizon change portfolios

The table presents the characteristics and return results of the portfolios double-sorted on liquidity and then on change in horizon. The stocks are sorted into low (L), medium (M) and high (H) quintiles based on liquidity and then sorted into 5 horizon change quintiles, where quintile 1 is the largest decrease in analyst horizon and quintile 5 is the largest increase in horizon. The portfolios are formed each month using equal weight and overlapping portfolios are rebalanced monthly. The liquidity measures used are Amihud (2002) illiquidity and the bid-ask spread. Panel A summarizes the average liquidity, average horizon change, average size (in millions) and average number of stocks at formation of each portfolio. Panel B reports average monthly returns of the portfolios held for a month while panel C reports average monthly return of the portfolios held for 3,6, or 9 months overlappingly. Panel B and C report the average return of the quintile 1 and quintile 5 portfolios and average returns of the zero-cost portfolios of buying quintile 5 and short selling quintile 1 stocks, and the zero-cost portfolio returns are further adjusted by Fama-French 3 factors or Carhart 4 factors. Returns are expressed in percent per month.

Panel A: Portfolio Characteristics at formation

	Amihud (2002) illiquidity				Bid-ask spread		
		Chghor				Chghor	
		Q1(L)	Q 5(H)			Q1(L)	Q5(H)
	illiquidity	0.0043	0.0058		BA spread	0.0183	0.0187
L	Chghor	-0.56	0.89	L	Chghor	-0.61	0.97
	Size (in mi)	6682.2	7161.0		Size (in mi)	5094.6	6235.2
	no. of stocks	90	91		*no. of stocks*	124	124
	illiquidity	0.0535	0.0701		BA spread	0.0349	0.0347
M	Chghor	-0.65	1.13	M	Chghor	-0.62	1.07
	Size (in mi)	743.5	808.1		Size (in mi)	2347.0	3180.6
	no. of stocks	87	88		*no. of stocks*	174	172
	illiquidity	1.0959	0.7455		BA spread	0.0692	0.0662
H	Chghor	-0.73	1.09	H	Chghor	-0.76	1.24
	Size (in mi)	179.4	200.3		Size (in mi)	611.7	891.2
	no. of stocks	34	35		*no. of stocks*	107	107

Table 1.7 (cont'd)

Panel B: Portfolio returns after formation, holding for 1 month

	Amihud (2002) illiquidity					Bid-ask spread				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.04***	1.27***	**0.25***	**0.23***	**0.25***	1.12***	1.25***	**0.14***	**0.12**	**0.11**
M	1.14***	1.43***	**0.26***	**0.24**	**0.21**	1.18***	1.36***	**0.18**	**0.16*	0.10
H	1.09***	1.11***	0.01	0.09	0.01	0.50	0.43	0.00	-0.04	-0.13

Panel C: Portfolio returns after formation, overlapping holding period

Holding for 3 months

	Amihud (2002) illiquidity					Bid-ask spread				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.02***	1.22***	**0.20***	**0.18***	**0.19***	1.16***	1.28***	**0.11***	**0.11***	**0.11***
M	1.20***	1.36***	**0.16**	**0.14**	0.11	1.10***	1.25***	**0.15***	**0.13**	0.08
H	1.30***	1.41***	0.11	0.11	0.09	0.50	0.52	0.01	-0.03	-0.07

Holding for 6 months

	Amihud (2002) illiquidity					Bid-ask spread				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.05***	1.17***	**0.12***	**0.10**	**0.10**	1.15***	1.19***	0.04	0.03	0.02
M	1.18**	1.31**	**0.09*	0.07	0.04	1.06***	1.13***	0.06	0.04	0.00
H	1.22***	1.29***	0.07	0.07	0.07	0.52	0.55	0.03	0.03	0.00

Holding for 9 months

	Amihud (2002) illiquidity					Bid-ask spread				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.01***	1.07***	**0.06*	0.05	0.04	1.12***	1.15***	0.03	0.03	0.01
M	1.11***	1.13***	0.02	0.01	-0.02	1.06***	1.07***	0.01	0.00	-0.04
H	1.08***	1.17***	0.08	0.07	0.07	0.67	0.60	-0.07	-0.07	-0.11

Table 1.8. Volatility and horizon change portfolios

The table presents the characteristics and return results of the portfolios double-sorted on volatility and then on change in horizon. The stocks are sorted into low (L), medium (M) and high (H) quintiles based on volatility and then sorted into 5 horizon change quintiles, where quintile 1 is the largest decrease in analyst horizon and quintile 5 is the largest increase in horizon. The portfolios are formed each month using equal weight and overlapping portfolios are rebalanced monthly. The volatility measures used are idiosyncratic volatility and total realized volatility. Panel A summarizes the average volatility, average horizon change, average size (in millions) and average number of stocks at formation of each portfolio. Panel B reports average monthly returns of the portfolios held for a month while panel C reports average monthly return of the portfolios held for 3,6, or 9 months overlappingly. Panel B and C report the average return of the quintile 1 and quintile 5 portfolios and average returns of the zero-cost portfolios of buying quintile 5 and short selling quintile 1 stocks, and the zero-cost portfolio returns are further adjusted by Fama-French 3 factors or Carhart 4 factors. Returns are expressed in in percent per month.

Panel A: Portfolio Characteristics at formation

	Idiosyncratic volatility				Total realized volatility		
		Chghor				Chghor	
		Q1(L)	Q5(H)			Q1(L)	Q5(H)
	idio stdev	0.0128	0.0128		realized stdev	0.0154	0.0156
L	Chghor	-0.57	0.83	L	Chghor	-0.61	0.94
	Size (in mi)	6902.2	8479.1		Size (in mi)	4976.0	6232.6
	no. of stocks	99	100		*no. of stocks*	135	136
	idio stdev	0.0232	0.0230		realized stdev	0.0273	0.0272
M	Chghor	-0.62	0.98	M	Chghor	-0.64	1.09
	Size (in mi)	2337.6	3452.3		Size (in mi)	2190.2	3177.8
	no. of stocks	96	98		*no. of stocks*	143	145
	idio stdev	0.0452	0.0440		realized stdev	0.0527	0.0507
H	Chghor	-0.74	1.19	H	Chghor	-0.76	1.28
	Size (in mi)	906.4	1362.5		Size (in mi)	788.5	1241.7
	no. of stocks	56	57		*no. of stocks*	90	91

Table 1.8 (cont'd)

Panel B: Portfolio returns after formation, holding for 1 month

	Idiosyncratic volatility					Total realized volatility				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.16***	1.33***	**0.17****	**0.15****	**0.15****	1.16***	1.32***	**0.15****	**0.14****	**0.13****
M	1.28***	1.42***	0.14	0.14	0.08	1.18***	1.39***	**0.21****	**0.20****	0.12
H	0.86**	1.03***	0.17	0.19	0.16	0.68	0.68	0.00	0.03	-0.05

Panel C: Portfolio returns after formation, overlapping holding period

Holding for 3 months

	Idiosyncratic volatility					Total realized volatility				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.21***	1.30***	**0.09****	**0.09***	**0.08***	1.20***	1.32***	**0.12*****	**0.13*****	**0.11*****
M	1.25***	1.33***	0.08	0.08	0.04	1.14***	1.26***	**0.12***	**0.10***	0.05
H	0.86**	1.11***	**0.25***	0.20	0.21	0.67	0.74*	0.07	0.07	0.04

Holding for 6 months

	Idiosyncratic volatility					Total realized volatility				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.19***	1.23***	0.04	0.03	0.03	1.18***	1.23***	0.05	0.04	0.03
M	1.20***	1.24***	0.04	0.03	-0.01	1.14***	1.21***	0.07	0.05	0.01
H	0.92**	1.09***	0.17	0.15	0.13	0.79*	0.77*	-0.01	0.00	-0.03

Holding for 9 months

	Idiosyncratic volatility					Total realized volatility				
	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha	Q1 (Low)	Q5 (High)	Long5 Short1	FF3 alpha	C4 alpha
L	1.17***	1.20***	0.02	0.01	0.01	1.14***	1.16***	0.02	0.02	0.00
M	1.19***	1.18***	-0.01	-0.02	-0.05	1.10***	1.12***	0.01	0.01	-0.03
H	0.94**	1.05***	0.11	0.11	0.07	0.81*	0.77*	-0.05	-0.03	-0.05

Table 1.9. Forecast efficiency and information environment

This table presents the check results on time serial average of analyst forecast efficiency measures in different illiquidity, volatility and overvaluation environment. Panel A summarizes average forecast error, which is the absolute difference between the consensus quarterly earnings forecast for the current quarter and the actual earnings, normalized by the price of the current month. Panel B summarizes the difference of opinion, which is measured by the standard deviation of analysts current-quarter forecasts scaled by the absolute value of the mean forecast. The results are presented in percent per month.

Panel A: Analyst forecast error

Amihud Illiquidity			Bid-ask spread		
L	M	H	L	M	H
3.38***	6.06***	21.70***	3.07***	3.29***	15.54***
Idiosyncratic volatility			**Total volatility**		
L	M	H	L	M	H
2.96***	4.07***	20.17***	3.20***	4.89***	21.47***
P/E ratio			**P/B ratio**		
L	M	H	L	M	H
17.69***	8.82***	2.29***	6.04***	5.18***	10.70***

Panel B: Analyst difference in opinion

Amihud Illiquidity			Bid-ask spread		
L	M	H	L	M	H
19.52***	31.21***	47.12***	13.31***	20.38***	41.91***
Idiosyncratic volatility			**Total volatility**		
L	M	H	L	M	H
15.17***	27.52***	48.03***	17.48***	28.03***	46.02***
P/E ratio			**P/B ratio**		
L	M	H	L	M	H
53.65***	16.26***	21.63***	26.14***	20.13***	34.07***

Table 1.10. Firm characteristics and horizon change

This table presents the coefficients of the estimation of equation (2). The dependent variable, $Chghor_{i,t}$, is the raw change in the analyst horizon. The independent variables are defined in the Appendix. All specifications feature month and industry fixed effects. The industry classification uses the Fama and French (1997) 49-industry scheme. The t-statistics are reported below the coefficients and are clustered at the firm level. For readability, the coefficients are multiplied by a thousand.

	(1)	(2)	(3)	(4)	(5)
Size		-3.6^{***}	-4.6^{***}		-5.2^{***}
MktBeta	3.1	3.3	5.1^{*}		
Ivol	-505.2^{***}	-643.3^{***}	-520.1^{***}		-520.7^{***}
BtoM		-0.3	-0.3	-0.2	-0.3
BtoM×NegBV			0.0068		0.0065
NegBV			-21.4		-20.5
Leverage			8.8		10.9
Leverage×NegBV			1.4		1.0
NegEarn			-17.1^{***}	-17.5^{***}	-14.0^{***}
Earnvol			0.0		0.0
ACC+				23.7	25.8
ACC-				4.2	10.5
Assetgrowth				71.9^{***}	72.7^{***}
Dividend				0.0	0.0
Shareprice				0.0	0.1
Month FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
No. of Obs.	310,309	310,309	310,309	310,309	310,309
Adj R-2	0.0124	0.0125	0.0125	0.0126	0.0127

Table 1.11. Portfolios formed by residuals

This table reports the average monthly return (in percentage per month) and the t-statistics of the portfolios sorted on the residuals from the previous estimations in column (1)-(5) of Table 1.10. The portfolios are formed at the end of each month, and are held for either 1 or are bold-and-held 3 months overlappingly using equal weight. Decile 1-10 are scaled from small to large residuals. Returns of the decile 1 and decile 10 portfolio and the return of the long-short portfolio of decile 10 and decile 1 portfolio are reported. The zero cost portfolio return is further adjusted by the Fama and French three factors and the Carhart four factors. Portfolio returns are presented in percent [er per month form and the t-statistics are below the portfolio returns.)

	Holding for 1 month					Holding for 3 months				
	D. 1 (L)	D. 10 (H)	D. 10- D.1	α-FF3	α-C4	D. 1 (L)	D. 10 (H)	D. 10- D.1	α-FF3	α-C4
(1)	0.87***	1.27***	0.40***	0.40***	0.38***	1.08***	1.18***	0.09	0.10	0.06
(2)	0.90***	1.28***	0.38***	0.38***	0.36***	1.10***	1.18***	0.08	0.09	0.05
(3)	0.92***	1.28***	0.36***	0.36***	0.34**	1.11***	1.18***	0.08	0.08	0.04
(4)	0.89***	1.28***	0.39***	0.39***	0.38***	1.09***	1.18***	0.09	0.10	0.05
(5)	0.90***	1.30***	0.41***	0.41***	0.38***	1.09***	1.19***	0.10	0.11	0.06

Table 1.12. Horizon change and future performance

This table presents the equal-weighted monthly average of the FSCORE and its component individual indicators for the portfolio of the largest drop in horizon (decile 1) and the portfolio of largest increase in horizon (decile 10), and the difference of these variables between decile 10 and decile 1. In Panel A the portfolios are formed by sorting on raw change in horizon variable while in Panel B the portfolios are formed by sorting on the change in horizon adjusted by all firm fundamental risk proxies in Eq (2). The forecasting period are from 1 to 4 quarters immediately after portfolio formation and the last period variables don't contain information available after portfolio formation. The indicators variables are constructed as described in the paper, which equals one for improvement in the performance and 0 otherwise.

Panel A: portfolios sorted by raw change in horizon variable

	Q1				Q1+Q2				Q1+Q2+Q3				Q1+Q2+Q3+Q4			
	D1	D10	diff	t-stat	D1	D10	diff	t-stat	D1	D10	diff	t-stat	D1	D10	diff	t-stat
ROA	0.734	0.805	**0.071**	9.00	0.730	0.808	**0.078**	9.91	0.736	0.808	**0.072**	9.16	0.740	0.809	**0.069**	7.96
CFO	0.615	0.629	**0.015**	1.83	0.646	0.662	**0.018**	2.16	0.651	0.685	**0.033**	4.09	0.655	0.698	**0.042**	5.31
ΔNI	0.496	0.483	-0.012	-1.14	0.482	0.480	-0.004	-0.39	0.483	0.471	-0.012	-1.20	0.473	0.470	-0.00	-0.35
ACC	0.604	0.567	**-0.035**	-4.56	0.644	0.621	**-0.023**	-2.65	0.654	0.659	0.004	0.57	0.662	0.682	**0.019**	2.41
ΔLEVER	0.501	0.507	0.007	0.68	0.502	0.514	0.013	1.51	0.494	0.512	**0.018**	1.87	0.492	0.507	0.016	1.44
ΔLIQUID	0.510	0.507	-0.005	-0.46	0.514	0.519	0.005	0.32	0.514	0.523	0.009	0.57	0.512	0.517	0.006	0.43
ISS	0.298	0.273	**-0.023**	-2.54	0.260	0.228	**-0.032**	-3.50	0.233	0.194	**-0.039**	-4.73	0.215	0.174	**-0.04**	-4.74
ΔMARGIN	0.505	0.498	-0.007	-0.71	0.498	0.503	0.006	0.56	0.492	0.508	0.018	1.78	0.494	0.509	0.012	1.08
ΔTURN	0.509	0.474	**-0.034**	-3.15	0.991	0.969	**-0.022**	-2.14	0.482	0.460	**-0.020**	-1.89	0.460	0.441	**-0.01**	-1.75
FSCORE	4.905	4.846	-0.059	-0.93	4.465	4.487	0.022	0.45	4.847	4.928	0.081	1.62	4.828	4.934	**0.106**	2.06

Table 1.12 (cont'd)

Panel B: portfolios sorted by change in horizon variable ***adjusted by firm fundamental proxies***

	Q1				Q1+Q2				Q1+Q2+Q3				Q1+Q2+Q3+Q4			
	D1	D10	diff	t-stat	D1	D10	diff	t-stat	D1	D10	diff	t-stat	D1	D10	diff	t-stat
ROA	0.778	0.824	**0.046**	6.07	0.776	0.831	**0.057**	7.06	0.779	0.83	**0.052**	6.25	0.784	0.829	**0.047**	5.14
CFO	0.661	0.666	0.006	0.97	0.698	0.705	0.007	0.74	0.704	0.725	**0.021**	2.60	0.710	0.738	**0.028**	3.54
ΔNI	0.498	0.494	-0.004	-0.40	0.486	0.494	0.010	0.84	0.488	0.486	-0	-0.12	0.467	0.479	0.011	0.89
ACC	0.630	0.588	**-0.042**	-3.91	0.679	0.651	**-0.028**	-2.36	0.696	0.687	-0.009	-0.54	0.706	0.714	0.010	1.13
ΔLEVER	0.511	0.532	0.019	1.54	0.508	0.535	**0.026**	2.13	0.501	0.529	**0.027**	2.08	0.501	0.531	**0.030**	2.39
ΔLIQUID	0.523	0.498	**-0.023**	-1.93	0.525	0.526	-0.001	-0.04	0.529	0.532	0.004	0.30	0.518	0.522	0.004	0.45
ISS	0.279	0.261	-0.018	-1.43	0.241	0.221	**-0.018**	-1.73	0.217	0.192	**-0.025**	-2.39	0.200	0.175	**-0.025**	-2.33
ΔMARGIN	0.501	0.509	0.009	0.74	0.498	0.508	0.009	0.66	0.485	0.514	**0.031**	2.61	0.495	0.512	0.019	1.56
ΔTURN	0.504	0.478	**-0.026**	-1.84	0.491	0.479	-0.012	-0.99	0.474	0.471	-0.003	-0.20	0.455	0.466	0.009	0.69
FSCORE	5.032	4.950	-0.083	-1.41	5.044	5.054	0.010	0.18	4.977	5.063	**0.086**	1.69	4.951	5.076	**0.127**	2.23

Table 1.13. Non-cyclicality of horizon change premium

The table presents the non-cyclicality of horizon change premium. Decile portfolios are formed each month using equal weight. The sample period is from June 1982 to December 2016. Panel A reports results of the time series regression (equation (3)) of horizon change premium on state variable proxies in the last month, with t-stats Newey-West (1987) adjusted. h is the holding period (in terms of month) of the long-short horizon change portfolio.

	DY	DS	TS	RF	F-stat	R-squared
h = 0	-0.48**	0.00	0.00*	0.00**	1.61	2.24%
h = 1	0.02	0.00	0.00	0.00	0.32	0.46%
h = 3	-0.21	-0.01	0.00	0.00	1.29	2.92%

Table 2.1. Forecast error and Jump

This table presents the relative forecast error of the analysts who contribute to horizon jumps and the extent to which their forecasts are more accurate than the forecasts issued by the group of analysts who make new forecasts on the same day for the same firm, but do not contribute to the jump. Column (1) includes both the far-end earnings forecasts and other close-end forecasts, while column (2) includes only the close-end forecasts made by the analysts who affect a horizon jump.

	Jump		No jump	Difference	
	(1)	(2)	(3)	(1)-(3)	(2)-(3)
Day of jump	**-0.0788**	**-0.0793**	**-0.0689**	**-0.0099**	**-0.0104**
(t-stat)	**-29.99**	**-17.31**	**-20.35**	**-2.26**	**-1.87**
No. of Obs.	214,264	92,847	111,554		
Jump month end	**-0.0751**	**-0.0762**	**-0.0762**	0.0011	0.0000
(t-stat)	**-44.17**	**-26.29**	**-19.60**	0.30	0.00
No. of Obs.	214,264	92,847	111,554		
First month end	**-0.0130**	**-0.0145**	**-0.0056**	**-0.0074**	**-0.0089**
(t-stat)	**-11.00**	**-7.17**	**-4.24**	**-3.91**	**-3.82**
No. of Obs.	178,688	72,963	92,965		
Second month end	**-0.0065**	**-0.0095**	**-0.0044**	-0.0021	**-0.0051**
(t-stat)	**-5.57**	**-4.66**	**-3.47**	-1.15	**-2.23**
No. of Obs.	172,785	69,389	90,558		
Third month end	**-0.0090**	**-0.0147**	**-0.0151**	**0.0061**	0.0004
(t-stat)	**-7.65**	**-6.98**	**-11.65**	**3.25**	0.17
No. of Obs.	164,991	64,960	86,355		
Fourth month end	0.0007	**-0.0058**	**0.0032**	-0.0025	**0.0090**
(t-stat)	0.42	**-1.89**	**2.80**	-1.06	**-3.04**
No. of Obs.	151,599	56,650	75,588		

Table 2.2. Correlation table of analyst characteristics

This table presents the Pearson correlation among the independent variables in equation (4), both in the raw (upper triangle) and rank-adjusted (lower triangle) terms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
General experience (1)	1	0.395	0.472	0.107	0.083	0.009	0.057
Firm experience (2)	0.365	1	0.300	0.067	0.057	0.013	0.085
Broker tenure (3)	0.458	0.362	1	0.136	0.138	0.014	0.072
Workload (4)	0.292	0.193	0.315	1	-0.036	0.054	0.032
Broker reputation (5)	0.040	0.013	0.114	0.071	1	0.001	0.079
Accuracy (6)	-0.044	-0.067	-0.066	-0.081	0.025	1	-0.139
Boldness (7)	0.112	0.145	0.177	0.140	0.069	-0.106	1

Table 2.3. Horizon jump and analyst characteristics

This table presents the coefficient estimation results of the logit model in equation (4). The dependent variable, $Jump_{i,j,t}$ is an indicator variable that equals 1 if analyst *j* makes a jump for firm *i* in year *t*, and equals 0 otherwise. The analyst characteristics are rank-adjusted. All standard errors are clustered on analyst level.

General experience	-0.0106	**-0.0709**	-0.0087
(z-stat)	-0.30	-2.08	-0.26
Firm experience	**-0.3651**	**-0.3846**	**-0.3678**
(z-stat)	-15.20	-15.80	-15.33
Broker tenure	**-0.1615**	**-0.2205**	**-0.1460**
(z-stat)	-4.57	-6.51	-4.22
Workload	**0.0615**	0.0103	**0.0518**
(z-stat)	2.00	0.34	1.72
Broker reputation	**0.6804**	**0.1567**	**0.7258**
(z-stat)	17.25	5.08	18.92
Accuracy	**0.1184**	**0.1082**	**0.1210**
(z-stat)	5.82	5.37	5.93
Boldness	0.0114	0.0018	0.0186
(z-stat)	0.55	0.09	0.88
Industry FE	N	Y	Y
Year FE	Y	Y	Y
Broker FE	Y	N	Y
No. of Obs.	180,271	175,994	175,005
Pseudo R2	0.0982	0.0752	0.1066

Table 2.4. Career outcome and horizon jump

This table presents the coefficient estimation results of the logit model in equation (5). Career outcome are defined as an indicator variable that equals 1 in five ways: *favorable* outcome is defined as rising rank of the broker the analyst is associated with, in the next year than the current (here, I don't require the analyst to change to a different broker house in the next year.); *promotion* is defined as the analyst's new associated broker house reputation is one quintile higher than the current broker house in (1), and in (2) as the analyst's new associated broker house is 2 decile more reputed than the current one. *Unfavorable* is defined as the contrary moving direction among broker reputation ranks (again, no requirement for the analyst changing to a different broker house in the next year for the variable). *Demotion* happens when analyst's new broker is ranked one quintile lower than the current one. *Departure* is an indicator variable that equals 1 if the analyst disappears in the next year, and 0 otherwise. $Jump_{j,t}$ is an indicator variable that equals 1 if analyst *j* makes at least one jump in year *t*, and equals 0 otherwise. All standard errors are clustered on analyst level.

	Favorable	Promotion (1)	Promotion (2)	Unfavorable	Demotion	Departure
jump	**0.0487**	**0.1089**	**0.1218**	**-0.0525**	-0.0365	**0.0840**
(z-stat)	2.68	3.62	4.11	-2.89	-0.84	4.01
General experience	**-0.0158**	**-0.0422**	**-0.0437**	**0.0152**	**0.0242**	**-0.0233**
(z-stat)	-6.16	-10.59	-11.29	5.93	4.33	-6.16
Broker tenure	**0.0071**	**0.0348**	**0.0387**	**-0.0074**	-0.0143	**0.0178**
(z-stat)	1.81	5.24	5.91	-1.90	-1.48	4.03
Workload	**-0.0166**	**-0.0408**	**-0.0504**	**0.0175**	**0.0146**	**-0.0676**
(z-stat)	-9.18	-8.46	-10.47	9.64	4.41	-18.05
Broker reputation	**-0.0265**	**-1.3004**	**-0.5291**	**0.0264**	**0.9368**	**0.0019**
(z-stat)	-24.36	-15.41	-9.16	24.49	9.12	2.18
Accuracy	**-0.18**	**-0.2069**	**-0.2716**	**0.16**	-0.0341	**-0.40**
(z-stat)	-3.35	-2.57	-3.48	3.10	-0.29	-7.50
Boldness	**0.29**	**0.4545**	**0.4382**	**-0.28**	-0.1477	**0.56**
(z-stat)	5.63	5.86	5.81	-5.50	-1.30	10.93
Year FE	Y	Y	Y	Y	Y	Y
Broker FE	Y	Y	Y	Y	Y	Y
No. of Obs.	80,191	14,056	13,413	80,166	13,409	79,380
Pseudo R2	0.5664	0.1614	0.135	0.567	0.0936	0.086

Figure 1.1. Horizon Jump timing

This figure presents the frequency of horizon jumps taking place in different trading days relative to the quarterly earnings announcements (QEAs). The percent of jumps are reported on the left axis while the corresponding number of jumps are reported on the right axis.

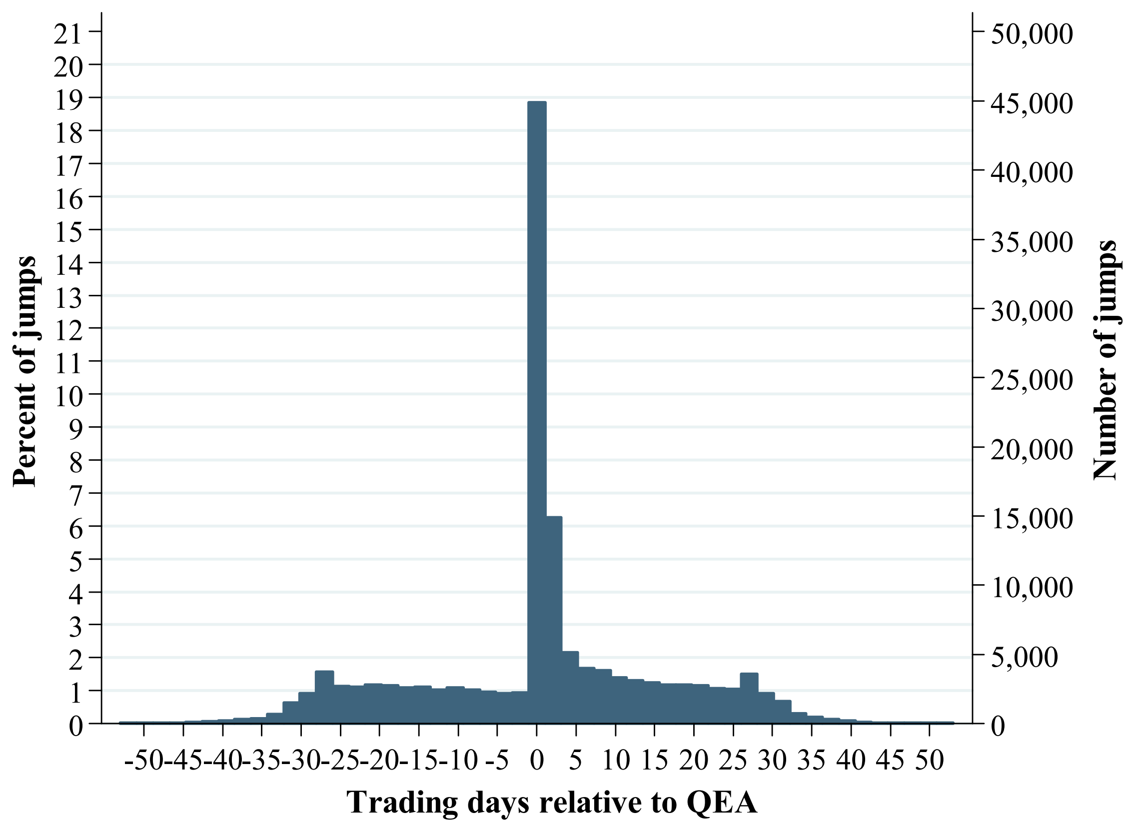
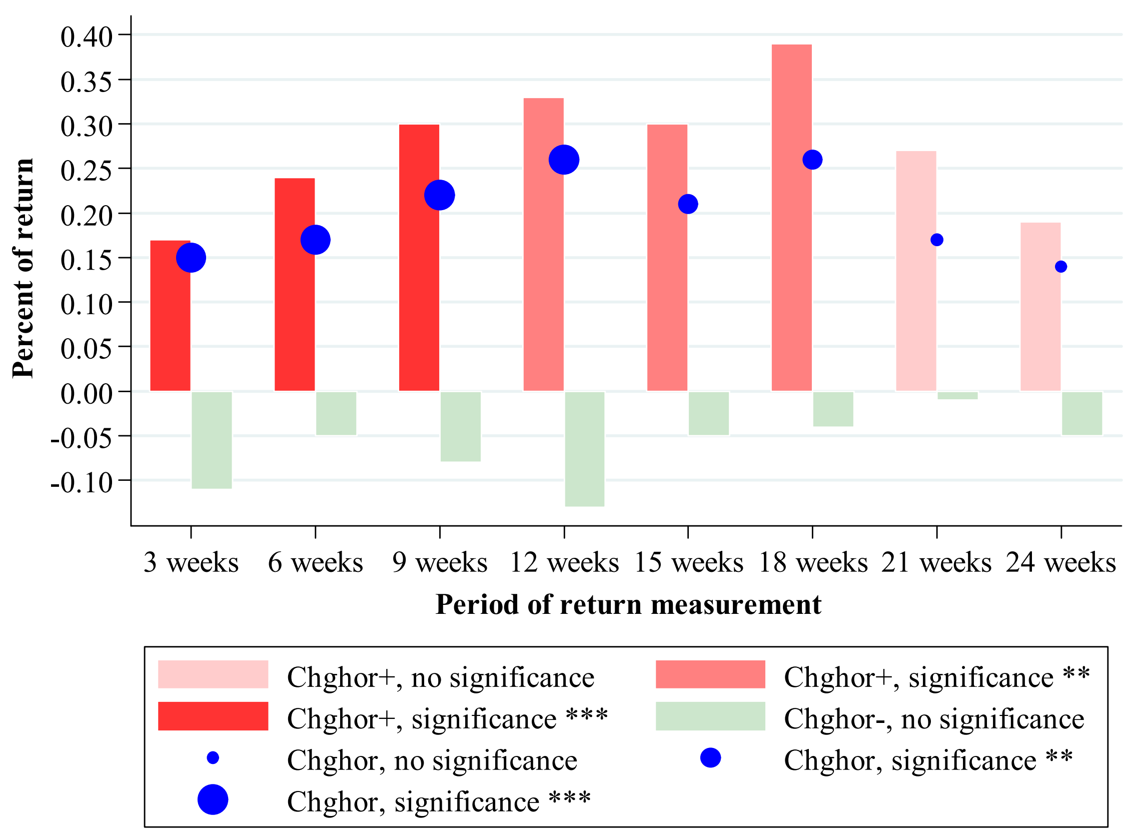


Figure 1.2. CARs over time

The figure presents the time variation of the average abnormal cumulative return in a 45-trading-day window following the horizon jump (in green solid line), in comparison with the average cumulative abnormal return of all other stocks that do not experience horizon jumps on the event days (in red dashed line). The 95% confidence interval bands around the average returns are shaded gray.

Figure 1.3. Return predictability by weeks

This figure presents the coefficients and significance levels of the Chghor variable in panel estimations of equation (1) for returns 3, 6, ... , 24 weeks ahead on the independent variables. All standard errors are clustered on the industry x month level. The bar intensity and dot size express the level of significance. (The coefficients are presented in the percentage form without % sign.)



APPENDIX B

Variable definitions

Panel A: Analyst forecast variables		
Variable	Definition	Data source
$Horizon_{i,j,t}$	The largest number of months ahead of the fiscal period end of all annual earnings forecasts made by analyst j for firm i in the past year before month t. $Horizon_{i,t}$ is the arithmetic average of $Horizon_{i,j,t}$ over all outstanding forecasts.	I/B/E/S
$Chghor_{i,t}$	The change in analyst average horizon over the past month t-1 for firm i.	I/B/E/S
$RChghor_{i,t}$	$Chghor_{i,t}$ relative to $Horizon_{i,t}$.	
$Chghor+_{i,t}$	The lengthening part of the change in horizon $Chghor+_{i,t}$ is defined as $\max(0,chghor_{i,t})$ for firm i in month t.	I/B/E/S
$Chghor-_{i,t}$	The prolonged silence part of the change in horizon $Chghor-_{i,t}$ is defined as $-\min(0,chghor_{i,t})$.	I/B/E/S
$Jump_{i,j,t}$	An indicator variable that equals 1 if an analyst j is identified as contributing to the average horizon jump of firm i in month t, and 0 otherwise. Horizon jump occurs when the change in horizon of the stock i is in the top decile in month t. $Jump_{j,t}$ is an indicator variable that equals 1 if analyst j makes at least one jump in year t, and 0 otherwise.	I/B/E/S
$FREV_{i,t}$	Rolling sum of monthly consensus forecast revision for the current fiscal year over the past half year, scaled by price of the stock i in the prior month.	I/B/E/S, CRSP
$Revlev_{i,t}$	The consensus level of stock i buy/sell recommendation in month t. Re-code 1 as the strong sell and 5 as the strong buy.	I/B/E/S
$RecRev_{i,t}$	The revision of consensus recommendation over the past quarter for firm i.	I/B/E/S
$LTGlev_{i,t}$	The level of consensus LTG forecast for firm i in month t.	I/B/E/S
$LTGrev_{i,t}$	The revision of the consensus LTG forecast for firm i over the past quarter.	I/B/E/S
$Dispersion_{i,t}$	Measures the differences of opinion and is defined as the standard deviation of analysts' current annual earnings forecasts scaled by the absolute value of consensus annual forecast for the same fiscal year	I/B/E/S

Panel B: Firm characteristic variables		
$SUE_{i,t}$	The standardized unexpected earnings, is defined as the difference between the actual earnings of the past quarter and the earnings of the same quarter in the last fiscal year, scaled by the standard deviation of the quarterly earnings over the past 2 years.	Compustat
$IO_{i,t}$	The institutional ownership, or the level of short-sale constraints and is constructed as the fraction of common shares owned by institutional investors.	Institutional Holdings (13f) file, CRSP
$Turnover_{i,t}$	The share volume divided by the number of shares outstanding.	CRSP
$Beta_{i,t}$	The market factor loading in the Fama-French factor model that involves the time serial regression involving the returns over the past 60 months for firm i.	
$Size_{i,t}$	The natural log of the market capitalization in millions of firm i in month t.	CRSP
$B/M_{i,t}$	The ratio of common equity over the market capitalization.	Compustat, CRSP
$RETP_{i,t}$	The raw return over the past year, with one month lag.	CRSP
$RETP1_{i,t}$	The raw return over the past half year, with one month lag.	CRSP
$RETP2_{i,t}$	The raw return from last year to 6 months ago.	CRSP
$Idiovol_{i,t}$	Idiosyncratic volatility, which is constructed in 3-steps: (1) regress the monthly return over the past 60 months on the three Fama-French factors and remember the loadings (2) use the loadings for the daily returns of the current month to get the daily excess return (3) find the standard deviation of the excess return in the current month.	CRSP
$EP_{i,t}$	Earning to price ratio, which divides the earnings over the past year by the price in the current month t.	Compustat, CRSP
$SG_{i,t}$	Sales growth, which divides the rolling sum of sales over the past year by the rolling sum of sales in the year before the past year.	Compustat
$TA_{i,t}$	Total accruals to total assets.	

$ACC+_{i,t}$	The positive part of $TA_{i,t}$.	Compustat
$ACC-_{i,t}$	The negative part of $TA_{i,t}$.	Compustat
$CAPEX_{i,t}$	Capital expenditure to total assets, which is the rolling sum of the four quarters of capital expenditure divided by the average of total assets in the current and 4-quarters ahead.	Compustat
$NegBV_{i,t}$	An indicator variable that equals 1 if the book equity of stock i in month t is negative, and is 0 otherwise.	Compustat
$NegEarn_{i,t}$	An indicator variable that equals 1 if the earnings of stock i over the past 4 quarters is negative, and is 0 otherwise.	Compustat
$Leverage_{i,t}$	Sum of long-term and short-term debt divided by common equity.	Compustat
$Earnvol_{i,t}$	The standard deviation of the quarterly income before extraordinary items over the preceding five years.	Compustat
$Assetgrowth_{i,t}$	The percent growth of current total assets on the total assets of the previous quarter.	Compustat
$Dividend_{i,t}$	Total dividends, which is dividends per share times common shares outstanding.	Compustat
$Shareprice_{i,t}$	The absolute value of stock price for firm i in month t.	CRSP
$ROA_{i,t}$	Income before extraordinary items, scaled by the total assets of the previous quarter.	Compustat
$CFO_{i,t}$	Cash flow from operation, scaled by the total assets of the previous quarter.	Compustat
$ISS_{i,t}$	Issuance of common equity in the current quarter.	Compustat
$\Delta NI_{i,t}$	Change in net income, the difference between ROA of the current and the previous quarter.	Compustat
$\Delta LEVER_{i,t}$	Change in long-term debt ratio over the past quarter, which is measured as long-term debt scaled by total assets.	Compustat
$\Delta LIQUID_{i,t}$	Change in current ratio over the past quarter.	Compustat
$\Delta MARGIN_{i,t}$	Change in gross margin ratio over the past quarter.	Compustat
$\Delta TURN_{i,t}$	Change in asset turnover ratio over the past quarter.	Compustat

Panel C: Analyst characteristic and career outcome variables		
General experience$_{j,t}$	Number of years since an analyst j's first appearance in I/B/E/S detail file to current year t. The rank-adjusted form is constructed as her rank in year t minus one and divided by the total number of analysts covering firm i minus 1.	I/B/E/S
Firm experience$_{i,j,t}$	Number of years since an analyst j's first coverage of firm i to current year t. The rank-adjusted form is constructed as her rank in year t minus one and divided by the total number of analysts covering firm i minus 1.	I/B/E/S
Broker tenure$_{j,t}$	Number of years since an analyst j's first appearance in a broker house to current year t. The rank-adjusted form is constructed as her rank in year t minus one and divided by the total number of analysts covering firm i minus 1.	I/B/E/S
Workload$_{j,t}$	Number of firms analyst j covers in year t. The rank-adjusted form is constructed as her rank in year t minus one and divided by the total number of analysts covering firm i minus 1.	I/B/E/S
Broker reputation$_{j,t}$	Number of analysts employed by a broker house that analyst j works for in year t. The rank-adjusted form is constructed as her rank in year t minus one and divided by the total number of analysts covering firm i minus 1.	I/B/E/S
Accuracy$_{j,t}$	The ranking of average first forecast error for analyst j over all firms she covers at the beginning of a fiscal year for a firm. Forecast error is the absolute distance between her forecast and the actual earning, scaled by actual earnings.	I/B/E/S
Boldness$_{j,t}$	The ranking of average first forecast boldness for analyst j over all firms she covers at the beginning of a fiscal year for a firm. Forecast boldness is the absolute distance between her forecast and the consensus earnings forecast, scaled by actual earnings.	I/B/E/S
Favorable$_{j,t+1}$	An indicator variable that equals 1 when the rank of the broker the analyst is associated with in year t+1 higher than the broker the analyst works for in year t. (No requirement of movement to a new broker.)	I/B/E/S

$Promotion_{j,t+1}$	Promotion (1): An indicator variable that equals 1 when the analyst's new associated broker house reputation is one quintile higher than the current broker house she works with. Promotion (2): An indicator variable that equals 1 when the analyst's new associated broker house is 2 decile more reputed than the current one.	I/B/E/S
$Unfavorable_{j,t+1}$	An indicator variable that equals 1 when the rank of the broker the analyst is associated with in year t+1 lower than the broker the analyst works for in year t. The analyst is not required to move to a different broker house in year t+1, for this definition.	I/B/E/S
$Demotion_{j,t+1}$	An indicator variable that equals 1 when analyst's associated broker in year t+1 is ranked one quintile lower than the broker in year t.	I/B/E/S
$Departure_{j,t+1}$	An indicator variable that equals 1 if the analyst disappears from the I/B/E/S sample in the next year, and is 0 otherwise.	I/B/E/S

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