The Frequency of Financial Analysts’ Forecast Revisions: Theory and Evidence about Determinants of Demand for Predisclosure Information

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Abstract: A fundamental property of a financial market is its degree of price informativeness. A major determinant of price informativeness is predisclosure information collected by financial analysts and then privately disseminated to clients, who make the recommended trades. We develop a dynamic model of the analyst’s optimal strategy of forecast revision frequency with endogenous analysts and endogenous traders. We then empirically test the model’s predictions. We find that forecast revision frequency is positively associated with earnings variability, trading volume, and earnings response coefficients, and negatively associated with skewness of trading volume. Thus, we find strong empirical support for our dynamic model.

Keywords: analysts’ forecast revisions, forecast revision frequency, predisclosure information

1. INTRODUCTION

In this paper, we theoretically and empirically examine a measure of predisclosure information: financial analysts’ frequency of forecast revisions. We first develop a dynamic model, with endogenous analysts and endogenous traders, and solve for the individual analyst’s optimal strategy of forecast revision frequency. We then empirically test the predictions of the model. Our results of those tests indicate that analysts’ forecast

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revision frequency increases with trading volume, earnings volatility, and earnings response coefficients, and decreases with informed trading as proxied by the skewness of trading volume, which strongly supports the model.

One of the most fundamental properties of a financial market is its degree of price informativeness – that is, the amount of private information impounded into the stock price. In the empirical literature, there are two widely-used measures of price informativeness. One measure is the probability of informed trading (PIN). Easley et al. (1996a, 1997a and 1997b) develop an asymmetric information model of market microstructure and directly estimate PIN from intraday stock market data. A second measure is price nonsynchronicity, which was proposed by Roll (1988) and developed by Morck et al. (2000), Durnev et al. (2003) and Durnev et al. (2004). Price nonsynchronicity estimates how much the stock price variation is driven by firm-specific, private information relative to total price variation.

But what determines the degree of price informativeness of a given financial market? One of the major factors is information collected by financial analysts and then privately disseminated to clients, who make the recommended trades. Our theoretical contribution is to develop a dynamic model of this process. We endogenize both the number of analysts and the number of traders. Our model is the first to solve for the individual analyst’s optimal dynamic strategy, which is the analyst’s optimal revision frequency. For a given stock, the analyst’s revision frequency leads to the traders’ frequency of private informed trading, which ultimately determines the price informativeness of that stock.

Specifically, we develop a multi-period model in which each analyst chooses the number of forecast revisions during the period to maximize his net compensation. Corresponding to real-world practice, we model the analyst’s compensation as a function of expected profit from sale of the forecast, net of the costs to gather and compile information. Within that framework, we use a multiple-trader extension of a one-period Kyle (1985) model to calculate the value of the information to the analyst, based on the expected profits the information can yield for informed traders, and derive the analyst’s optimal number of revisions. We find that optimal revision frequency is increasing in the variance of liquidity trading volume, earnings volatility, and the earnings-response coefficient, and decreasing in the number of informed traders and the cost of revision.

Our empirical contribution is to test the novel predictions of the model about the firm and market characteristics that are associated with forecast revision frequency.

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3 This ex-ante decision about the number of forecast revisions is a simplification of the process where each forecast is a separate decision, based on the arrival of new information. The decision corresponds more closely to the decision to revisit an existing forecast and actively pursue additional information about the next earnings release.
4 According to Adair (1996), analysts receive a large portion of their compensation in the form of bonuses. These bonuses are not allocated evenly, but are based on a complex system of subjective and objective evaluations of each analyst by brokers, clients, and the underwriting side of the firm. We assume that analysts who generate recommendations that are more valuable for clients will receive higher evaluations from clients and brokers, and thus will receive higher bonuses.
5 We view this single period model as an abstraction of a single interval from an infinite horizon setting.
We find that forecast revision frequency is positively associated with trading volume, earnings variability, and earnings response coefficients, and negatively associated with skewness of trading volume. For robustness, we test a narrower measure of forecast revision frequency to avoid forecasts that potentially arise from herding, and find even stronger results. Thus, we find strong empirical support for our dynamic model of analyst and trader activity, which helps explain the determinants of price informativeness.

The paper is organized as follows: Section 2 provides a discussion of related prior theoretical and empirical research. Section 3 describes the setting, derives the informed trader’s optimal trading strategy and the analyst’s optimal number of revisions. Section 4 analyzes the comparative statics. Section 5 extends the theory to allow for endogenous entry of traders and analysts, and determines the number of analysts and traders in equilibrium. Section 6 develops the empirical hypotheses. Section 7 describes data sources, variable measurements, and empirical tests. Section 8 presents the empirical results. Section 9 concludes. All proofs are in the Appendix.

2. RELATED LITERATURE

(i) Theoretical Research

The related prior theoretical research can be organized into three categories. The first is composed of static models with endogenous analysts, but no traders. In this group, Trueman (1990) approaches analysts’ revision incentives from the perspective of effects of revising on analyst reputation and finds that analysts may choose not to revise in response to newly acquired information for reputational reasons. Trueman (1994) examines circumstances that lead to the phenomenon of analyst herding, from the perspective of analysts of differing ability. Barron et al. (1998) demonstrate the relation between observable properties of analysts’ forecasts, such as dispersion and error in the mean forecast, and the information environment constructs of consensus and uncertainty.

The second category comprises static models with endogenous traders, but no analysts. In this group, Kim and Verrecchia (1994) model certain kinds of market participants as ‘information processors’ who take the public information released at the time of an earnings announcement and engage in costly additional processing to obtain private information that can be traded on at a profit. McNichols and Trueman (1994) demonstrate that public disclosure that occurs at regular and expected intervals, such as earnings announcements, also stimulates private information acquisition.

The third category is composed of dynamic models with endogenous traders, but no analysts. Abarbanell et al. (1995) model forecasts in relation to endogenously determined prices, volume, and private information acquisition.

Our incremental theoretical contribution is to develop a dynamic model with both endogenous analysts and endogenous traders. Our model includes endogenous entry to become an analyst or trader. We are the first to solve for the individual analyst’s dynamic revision strategy.

(ii) Empirical Research

Prior empirical research examining forecast activity has focused on activity during limited periods within quarters. Stickel (1989) documents increased forecast activity
in the two weeks following interim announcements of first-, second-, and third-quarter earnings as compared to the two weeks immediately preceding the announcement. Stuerke (2005) provides evidence that the relation between earnings surprises and forecast revision activity after interim and annual earnings announcements is influenced by the relation between earnings and stock returns. Barron and Stuerke (1998) demonstrate that residual uncertainty after earnings announcements is positively related to the number of revisions late in the quarter. In contrast to these three papers, we examine analyst activity throughout the quarter, and provide evidence about determinants of forecast revision activity throughout the quarter. We also note that all three of these studies control for the number of analysts following the firm. Hence their results suggest that revision activity is not fully explained by analyst following, and that revision activity captures elements of informational supply beyond analyst following.6

A related body of accounting literature investigates analyst following as a measure of informational supply, as a measure of private information transferred to traders, or as a measure of the informativeness of firms’ disclosure policies.7 However, the total number of analysts following a given firm includes analysts who actively update forecasts after acquiring information, analysts who update forecasts after observing the forecasts of other analysts, and analysts who rarely update their forecasts. The inclusion of all three types of analysts (active, herding, and inactive, respectively) in a measure of the level of private information acquisition and dissemination assumes either (1) that both the proportions and activity levels of the analysts following a firm are the same for all firms and all time-periods, or (2) that firms’ information environments are influenced similarly by the activities of all three types of analysts. Further, the total number of analysts following the firm includes both analysts who respond quickly to information released by the firm, and those who do not. Intuitively, analyst forecast revision frequency seems closer to the underlying construct of information acquisition and dissemination than does analyst following.8

3. THE THEORY

(i) The Setting

Consider a setting in which there are liquidity traders, \(A\) analysts, \(I\) traders per analyst who purchase information from a given analyst, and market makers, all of whom are risk neutral. The economy has one risky stock on a risky firm and a risk-free asset. Latent information is generated over time about the risky firm’s current fiscal period earnings. On a known date, the risky firm announces the realized earnings for a given fiscal period. In the overall period between successive earnings announcements, there are \(T\) discrete trading dates, which are indexed using the calendar dates \(t = 0, 1, 2, \ldots, T\). Hence, calendar date \(t = 0\) corresponds to the prior earnings announcement, date \(t = 1\) is the first trading date, and so on. Date \(t = T\) is the last trading date and date EA

6 Our data lends credence to this notion. For example, when we consider only firms with nine analysts who provide forecasts, the number of forecast revisions made during the quarter ranges from 0 to 16, with a median of 4 and mean of 4.7.
8 In recent research, revision activity has been used as a measure of firms’ information environments (e.g., Leung and Srinidhi, 2006).
Figure 1
Model Activity Timeline

![Timeline Diagram]

Activities at each date $t$

- Earnings process evolves
- Liquidity traders place trades
- Market makers:
  1) observe net order flow
  2) set price
- Trades take place

Additional activities if date $t$ is a forecast revision date $r_n$

- Analyst:
  1) acquires information
  2) revises forecast
  3) sells forecasts to informed investors
- Informed Traders:
  4) each trader submits a market order
  5) trades take place
- Information:
  6) post-trade, the information is revealed and the price adjusts

is the next earnings announcement (see Figure 1). For a cost of revision $C_R$, a particular analyst can collect and process the latent information to revise his forecast of current period earnings. Then the given analyst can sell his revised forecast to $I$ traders for a profit. Each analyst chooses the number of forecast revisions $N$ to make during the overall period between earnings announcements and chooses a specific set of revision dates $r_1, r_2, \ldots, r_N$ from the list of calendar dates 1, 2, \ldots, $T$ (see Figure 1). Define the $n^{th}$ revision interval as $\Delta t_n \equiv r_n - r_{n-1}$ and normalize the first revision interval as $\Delta t_1 \equiv r_1 - 0$. Thus, the set of revision dates $r_1, r_2, \ldots, r_N$ completely determines the set of revision intervals $\Delta t_1, \Delta t_2, \ldots, \Delta t_N$ and vice versa. Since all of the analysts have identical preferences and face the identical decision problem, they will all choose the same revision dates.

In the first stage, the analysts acquire and compile information about the risky firm on each revision date. They use this information to forecast the end-of-period reported earnings and sell their forecasts to traders who then become informed. Each analyst maximizes expected profit by choosing his optimal number of forecast revisions and his optimal set of revision dates. For simplicity, we assume that analyst compensation is a direct function of trading profits of client traders. Further, we want both analysts and informed traders to have some degree of market power in a non-cooperative equilibrium. Hence, we assume that the price that analysts charge for their information allows them to capture a fraction $f$ of the available profits and informed traders retain the remaining fraction $1 - f$ of the profits. These profits are determined by the market-clearing price set by market makers who observe only the net order flow and, thus, cannot distinguish informed trades from liquidity trades.

9 Among the components of analyst compensation are bonus amounts that are allocated based on brokers’, institutional traders’, and individual traders’ satisfaction with the analyst (Adair, 1996). Analyst compensation is not merely a function of the analyst’s incentives to revise his forecast. For example, Adair (1996) models components of analyst compensation that impact the optimistic bias in analysts’ forecasts. However, for simplicity, this model addresses only the components of analyst compensation that affect the analyst’s decision to issue forecast revisions.
In the second stage, each informed trader uses the analyst’s forecast to determine the quantity of shares in the risky asset that will maximize his expected profit from the trade. He knows that the market maker cannot distinguish an informed trade from a liquidity trade. Each informed trader places an order for his optimal quantity with the market maker, who observes the total order flow. The market maker determines the price at which the market clears, and trading takes place. At this point, the analyst’s forecast is only partially reflected in the price of the risky asset. After the informed trader has earned his profits from the trade, the analyst publicly announces his forecast, and market makers adjust the price of the asset to fully impound the newly-announced information.

Let $y_t$ be the Bayesian update of current period earnings using all latent information up through calendar date $t$. Define $\Delta y_t = y_t - y_{t-1}$ as the change in the Bayesian update of current period earnings using the latent information that is generated on calendar date $t$. Assume that latent information on each calendar date $t$ generates an i.i.d. Bayesian update which is normally distributed as $\Delta y_t \sim N(0, \sigma_y^2)$, with a mean of 0 and a variance of $\sigma_y^2$. Thus, the cumulative variance of the Bayesian update over the $n^{th}$ revision interval is proportional to the number of days $\Delta t_n$ in the interval as given by:

$$
\sigma_y^2 (r_n - r_{n-1}) = \sigma_y^2 \Delta t_n.
$$

Let $v_t$ be the value of the risky asset on date $t$. For simplicity, assume that the value of the asset on date $t$ is proportional to the Bayesian update of earnings on date $t$, $v_t = R \cdot y_t$. In other words, $R$ is an assumed constant price-to-earnings ratio (or value-to-earnings ratio). This implies that $\Delta v_t$, the change in the asset value on calendar date $t$, is given by $\Delta v_t \equiv v_t - v_{t-1} = R \Delta y_t$. This equation shows that $R$ scales a given change in earnings to the corresponding change in value and thus can be interpreted as an earnings-response coefficient. It follows that the change in asset value is normally distributed $\Delta v_t \sim N(0, R^2 \sigma_y^2)$, where the variance $\sigma_v^2 = R^2 \sigma_y^2$. The cumulative variance of the change in asset value over the $n^{th}$ revision interval is $R^2 \sigma_y^2 (r_n - r_{n-1}) = R^2 \sigma_y^2 \Delta t_n$, which is also proportional to $\Delta t_n$.

Figure 2 summarizes the analysts’ revision activity. It depicts that, at the $n^{th}$ revision interval, all analysts collect the new information since the last earnings announcement or publicly announced forecast and compile it to arrive at a new forecast of earnings. They sell this information to speculative traders who are willing to pay a price (higher commissions) to become informed. Each speculative trader chooses his optimal quantity of shares and makes a single trade on the information. Since each speculative trader receives the same information from his analyst, the optimal quantity of shares will be the same for each informed trader. Therefore, the analysis of the trading profit focuses on the decision of a single trader. The market maker sets the trading price based upon the total order flow and the informed trader earns his profit. At this point, part of the new information is impounded in the price of the asset through this trade. After the trade is complete, the analyst announces the revised forecast, and the price of the risky asset adjusts to fully impound the new information.

10 Analysts’ forecasts or revisions are generally provided to brokers for release to preferred clients, and later released to the public (see Waymire, 1986).
(ii) The Trading Equilibrium

Now we analyze the second stage of our model and solve for the informed trader’s profit-maximizing trade that exploits the information obtained from his particular analyst. This stage is built on the well-known model of Kyle (1985) as extended by Admati and Pfleiderer (1988). In the following subsection, we work back to the first stage of our model and solve for the analyst’s optimal frequency of forecast revision.

We focus on the $n$th revision interval. Let $v(r_{n-1}) \equiv v_p$ be the prior value of the security from the previous revision date $r_{n-1}$. On date $r_n$, each of the $A$ analysts acquires identical information, revises his forecast, and sells his private information to his own $I$ traders. So, there are $AI$ informed traders on date $r_n$. Each of the $AI$ informed traders receives identical private information that the value of the risky asset is $v(r_n) \equiv v$ and then submits an optimal market order to exploit this information. For simplicity, we assume that the informed traders only have one trading opportunity to exploit their information. After their trades are cleared, the private information is revealed and the next period price is updated. Let $u$ be the number of shares traded by liquidity traders on date $r_n$ and assume that $u$ is normally distributed as $u \sim N(0, \sigma_u^2)$. Let $z$ be the net order flow observed by the market makers. The informed traders conjecture that the market makers will set a market-clearing price $p$ as a linear function of the net order flow:

$$p = \mu + \lambda z,$$

where $\mu$ and $\lambda$ are constants. The $i$th informed trader maximizes his expected profits by choosing his trade quantity $x$:

$$\max_x E[x(v - p)\mid v] = \max_x [x(v - \mu - \lambda (x + (AI - 1)\bar{x}))],$$

where $\bar{x}$ is the average trade quantity among all informed traders. If $x_i$ is the total number of shares bought by the $i$th informed trader, the total quantity bought is $x = \sum x_i$. Then, the expected profit is

$$\max_x E[x(v - p)\mid v] = \max_x [(v - p)(\sum x_i)\mid v] = \max_x [\sum x_i(v - \mu - \lambda (x + (AI - 1)\bar{x}))].$$

The time subscript is suppressed for the rest of this subsection.
where $\bar{x}$ is his conjecture about the average quantity traded by other informed traders and the net order flow is $z = x + (AI - 1) \bar{x} + u$. Solving for the first order condition yields:

$$\frac{\partial (\cdot)}{\partial x} = v - \mu - 2\lambda x^* - \lambda (AI - 1) \bar{x} = 0.$$  \hspace{1cm} (4)

Since all informed traders receive the same forecasts, the $i^{th}$ informed trader conjectures that all informed traders will optimally choose to trade the same number of shares, which implies that $x^* = \bar{x}$. Substituting $x^*$ in place of $\bar{x}$ in the first order condition and solving for $x^*$, we obtain:

$$x^* = \left( \frac{v - \mu}{\lambda (AI + 1)} \right) \equiv \beta (v - \mu), \hspace{1cm} \text{where} \hspace{1cm} \beta \equiv \frac{1}{\lambda (AI + 1)}. \hspace{1cm} (5)$$

There are many market makers who are competitive. In equilibrium, they set the trading price to clear the market at:

$$p(z) = E[v \mid z] = E[v \mid AI\beta (v - \mu) + u]. \hspace{1cm} (6)$$

Evaluating the conditional expectation and matching the resulting expression to the conjectured form, $\mu + \lambda z$, one obtains:

$$\mu = v_p \text{ and } \lambda = \left( \frac{\sigma_v \sqrt{AI}}{\sigma_u (AI + 1)} \right) \sqrt{\Delta t_n} = \left( \frac{R \sigma_y \sqrt{AI}}{\sigma_u (AI + 1)} \right) \sqrt{\Delta t_n}, \hspace{1cm} \text{where} \hspace{1cm} \sigma_v = R \sigma_y. \hspace{1cm} (7)$$

Depending on the relative market power of analysts and informed traders, the informed traders pay fraction $f$ of their profits for their analysts’ information and keep fraction $1 - f$ for themselves. Hence, the ex-ante expected profit of an individual informed trader from trading on the $n^{th}$ revision interval is:

$$E[\Pi_{Inf} (\Delta t_n)] = \frac{(1 - f) k \cdot \sqrt{\Delta t_n}}{AI}, \hspace{1cm} \text{where the constant} \hspace{1cm} k \equiv \frac{\sigma_y R \sigma_u \sqrt{AI}}{(AI + 1)}. \hspace{1cm} (8)$$

(iii) Frequency of Analyst Revisions

We now turn to the first stage of our model. Each individual analyst seeks to maximize his compensation over $T$ periods by choosing the optimal number of forecast revisions $N^*$ and the optimal set of revision intervals $\Delta t_1, \Delta t_2, \ldots, \Delta t_N$. In any period, each analyst can incur the cost of forecast revision $C_R$ and collect the cumulative information about the amount of the earnings release. We assume that information about future earnings evolves and becomes available to the analysts continuously over the period. Each analyst then forecasts earnings, which translates into changes in firm value. Since earnings changes are normally distributed, the change to earnings is given by $\Delta y = y_t - y_{t-1}$, the volatility of earnings is $\sigma^2 \Delta t$, and the volatility of earnings maps into the cumulative variance of firm value as $\sigma^2 \Delta t = R^2 \sigma^2 \Delta t$, as described above. From these assumptions about the earnings process, it follows that the optimal revision strategy of each identical analyst spans the entire period and revision intervals are as nearly equal as is possible.
For \( N \) forecast revisions, define the floor interval \( \Delta t^- \) and ceiling interval \( \Delta t^+ \) as:

\[
\begin{align*}
\Delta t^- &\equiv \text{Floor} \left( \frac{T}{N} \right) = \text{Quotient} \left( \frac{T}{N} \right), \\
\Delta t^+ &\equiv \text{Ceiling} \left( \frac{T}{N} \right) = \text{Quotient} \left( \frac{T}{N} \right) + 1.
\end{align*}
\]

For example, suppose the number of trading days between successive earnings announcements is 91 days (\( T = 91 \)) and the analyst is planning three forecast revisions (\( N = 3 \)). Then we have \( \frac{T}{N} = 30.3333 \ldots \) days, \( \Delta t^- = 30 \) days, and \( \Delta t^+ = 31 \) days. The following lemma proves that, for \( N \) forecast revisions, each analyst’s optimal revision strategy is a combination of floor and ceiling intervals, which spans all of the calendar dates from 0 to \( T \).

**Lemma 1:** For \( N \) forecast revisions, an optimal set of revision intervals \( \Delta t_1, \Delta t_2, \ldots, \Delta t_N \) includes \( \text{Mod} \left( \frac{T}{N} \right) \) number of ceiling intervals \( \Delta t^+ \) and \( N - \text{Mod} \left( \frac{T}{N} \right) \) number of floor intervals \( \Delta t^- \), where \( \text{Mod} \left( \frac{T}{N} \right) \) is the residual (or modulus) from dividing \( T \) by \( N \).

Continuing with the example of \( T = 91 \) and \( N = 3 \), Lemma 1 says that optimal set of revision intervals includes \( \text{Mod} \left( 91, 30 \right) = \text{one} \) ceiling interval of 31 days and \( 3 - \text{Mod} \left( 91, 30 \right) = \text{two} \) floor intervals of 30 days.

The intuition for Lemma 1 is that it is optimal to have the revision intervals as nearly equal as possible, rather than to have a mix of large revision intervals and small revision intervals. Since profit is a concave function of the revision interval, the marginal rate of increase in profit declines over longer intervals. Thus, it maximizes overall profit to equate the marginal profit from each revision interval as nearly as possible. That is, set the marginal profit of \( \Delta t_1 \) as close as possible to the marginal profit of \( \Delta t_2 \) as close as possible \ldots as close as possible to the marginal profit of \( \Delta t_N \). Marginal profit is equated as nearly as possible by choosing all revision intervals to be either \( \Delta t^+ \) or \( \Delta t^- \). Further, Lemma 1 says that it is optimal to span all calendar dates from 0 to \( T \), rather than stop at \( T - 1 \) (or leave some other gap). The intuition is that stopping early would leave the latent information \( \Delta y_T = y_T - y_{T-1} \) (or some other latent information) unexploited and thus leave money on the table. Spanning all calendar dates is the reason an optimal strategy involves a specific number of \( \Delta t^+ \) intervals and a specific number of \( \Delta t^- \) intervals.\(^{13}\)

Next, we compute the individual analyst’s expected profit from \( N \) forecast revisions \( E \left[ \prod_{\text{Anal}} (N) \right] \). Starting with equation (8), we take the summation over the optimal set of revision intervals \( \Delta t_1, \Delta t_2, \ldots, \Delta t_N \) for \( N \) revisions, multiply by \( AI \) informed traders, substitute the analysts’ fraction \( f \) in place of the informed trader fraction \( 1 - f \), divide by \( A \) analysts, and then subtract \( N \) instances of the analyst’s cost of forecast revision \( C_R \)

\(^{13}\) This result is consistent with observed forecasts late in the quarter, and particularly with the revisions of revisions made earlier in the quarter that comprise 18% of the forecasts in our sample. Further, as analysts are compensated as a function of forecasts provided to informed traders rather than announced forecasts, it is also consistent with situations where analysts provide information to clients late in the quarter, and allow announced earnings to provide the publicly announced information. See Bagnoli et al. (1999) for research providing evidence about whisper forecasts at the end of fiscal quarters.
to get:

\[
E \left[ \Pi_{\text{Anal}} (N) \right] = \frac{\sum_{n=1}^{N} k \sqrt{\Delta t_n}}{A} - NC_R = \frac{f k S_N}{A} - NC_R,
\]

where \( S_N = \text{Mod}(T, N) \sqrt{\Delta t^+} + [N - \text{Mod}(T, N)] \sqrt{\Delta t^-} \). The optimal number of revisions \( N^* \) is the number of revisions which maximizes this profit function.

**Proposition 1:** The optimal number of revisions \( N^* \) is determined by a set of critical values \( c_n \) for \( n = 0, 1, 2, 3, \ldots, T-1 \) of the analyst’s cost of forecast revision \( C_R \). The critical value \( c_n \) is defined as the point where the analyst’s expected profit is the same for \( n \) and \( n+1 \) revisions. Therefore, the optimal number of revisions \( N^* \) is:

\[
N^* = \begin{cases} 
0 & \text{when } C_R > c_0 \\
 n \in 1, 2, \ldots, T-1 & \text{when } c_n > C_R > c_{n+1} \\
T & \text{when } c_{T-1} > C_R 
\end{cases}
\]

where the critical values \( c_0, c_1, \ldots, c_{T-1} \) are given by \( c_n = \left( \frac{f k}{A} \right) (S_{n+1} - S_n) \) for \( n \geq 1 \), and \( c_0 = \frac{f k S_1}{A} \).

To develop the intuition for the optimal strategy, consider what would happen if the cost of revising a forecast \( C_R \) was extremely high. Then the optimal number of revisions would be zero \( (N^* = 0) \). If the cost \( C_R \) was extremely low, then it would be optimal to revise at every time \( (N^* = T) \). For intermediate values of the cost \( C_R \), we get the appealing result that a lower cost leads to more revisions.

4. COMPARATIVE STATICS

Analyzing the comparative statics of the optimal strategy in Proposition 1 generates a number of predictions about the individual analyst’s optimal number of revisions, as expressed in Proposition 2.

**Proposition 2:** The individual analyst’s optimal number of revisions \( N^* \) is:

1. weakly increasing in earnings volatility \( \sigma_y \),
2. weakly increasing in the earnings-response coefficient \( R \),
3. weakly increasing in the standard deviation of liquidity trading \( \sigma_u \),
4. weakly decreasing in the number of informed traders \( I \), and
5. weakly decreasing in the cost of forecast revision \( C_R \).

Proposition 2 makes a number of interesting empirical predictions about the determinants of individual analyst’s revision frequency. After controlling for other influences, the cross-section of each individual analyst’s revision frequency is predicted...
Figure 3
Optimal Number of Revisions ($N^*$) by the Cost of Revision and by: (1) Earnings Volatility, (2) Earnings-Response Coefficient, or (3) Standard Deviation of Uninformed Trade

Note:
c0–c10 are critical values. The critical value $c_n$ ($n = 0, 1, 2, 3, \ldots, 10$) is where the analyst’s profit for $n$ revisions is exactly equal to the analyst’s profit for $n + 1$ revisions.

to be increasing in the standard deviation of earnings, the earnings-response coefficient, and the standard deviation of liquidity trading, and decreasing in the number of informed traders and the cost of forecast revision.

These relationships can be seen visually with the graphs provided in Figures 3 and 4. For illustration purposes, we set $T = 90$ days, $f = 0.5$, $\sigma_y = 1$, $R = 7$, $\sigma_u = 1$, $A = 4$, $I = 7$. Figure 3 shows the optimal number of revisions $N^*$ in a two-dimensional space with earnings volatility $\sigma_y$ on the x-axis and the cost of revision $C_R$ on the y-axis. There is a region where it is optimal to make 0 revisions, another region where it is optimal to make 1 revision, a third region where it is optimal to make 2 revisions, etc. The boundaries between these regions are a series of critical value lines. For example, the boundary between the 0-revision and 1-revision regions is a solid line labeled $c_0$. This line is all of the points in this two-dimensional space where the critical value equation, $c_0 = \left( \frac{fK}{A} \right)$, holds. Similarly, the boundary between the 1-revision and 2-revision regions is a dashed line labeled $c_1$, based on all of the points where the critical value equation, $c_1 = \left( \frac{fK}{1} \right) (S_2 - S_1)$, holds.

To see the first prediction, that $N^*$ is increasing in earnings volatility, $\sigma_y$, fix the cost of revision $C_R$ on the y-axis (say, at 2.0) and examine the change as earnings volatility increases (moving horizontally from left to right). The optimal number of revisions increases from 0 to 1 to 2 . . . to more than 10. Thus, we see that greater earnings volatility, $\sigma_y$ makes each revision more valuable and thus leads to more revisions, $N^*$. Conversely, fix the earnings volatility $\sigma_y$ on the x-axis (say, at 1) and examine the effect of increasing the cost of revision, $C_R$, (moving vertically from bottom to top).
The optimal number of revisions decreases from more than 10 to 10 to 9 to \ldots to 0. Thus, we see the fifth prediction that a larger cost of revision, $C_R$, leads to fewer revisions $N^*$. 

What happens if one replaces earnings volatility with the earnings-response coefficient, $R$, on the x-axis of Figure 3 in place of earnings volatility, $\sigma_y$? This change produces the identical graph! This is less surprising when we note that both $R$ and $\sigma_y$ enter the expected profit constant $k \equiv \frac{\sigma_y R \sqrt{AI}}{\sigma_u S_N}$ in a linear manner and $k$ enters the critical value equations $c_u = \left( \frac{f_k A}{A} \right) (S_{n+1} - S_n)$ and $c_0 = \frac{f_k S_1}{A}$ in a linear manner as well. Hence, Figure 3 simultaneously illustrates that a greater earnings-response coefficient, $R$, makes each revision more valuable and thus leads to more revisions, $N^*$. The standard deviation of liquidity trading, $\sigma_u$, also enters the expected profit constant $k$ in a linear manner. So, substituting $\sigma_u$ on the x-axis of Figure 3 also produces the identical graph, which illustrates the third prediction. So Figure 3 is identical in $(C_R, \sigma_y)$ space, in $(C_R, R)$ space, and in $(C_R, \sigma_u)$ space; it simultaneously illustrates the first three and the fifth predictions of Proposition 2.

Figure 4 shows the optimal number of revisions $N^*$ in a two-dimensional space with the number of informed traders $I$ on the x-axis and the cost of revision $C_R$ on the y-axis. To visualize the fourth prediction, fix the cost of revision, $C_R$, on the y-axis (say, at 0.5) and examine the result of increasing the number of informed traders (moving horizontally from left to right). The optimal number of revisions decreases from more than 10 to 10 to 9 to \ldots to 1. Hence, Figure 4 illustrates that more informed traders, $I$, have the net effect of competing away some of the revision profits and thus, an increase in $I$ leads to fewer revisions, $N^*$.

## 5. ENDOGENOUS ENTRY OF ANALYSTS AND TRADERS

In our analysis to this point, the number of analysts and informed traders has been exogenous. In this section, we allow endogenous entry of analysts and traders, and determine the number of analysts and informed traders in equilibrium.

From the individual informed trader’s profit function (equation (8)), it is clear that increasing the number of informed traders decreases the profit of each individual informed trader. Additional people will choose to become informed traders until the individual’s marginal profit drops to the marginal cost of becoming an informed trader. Let $C_I$ be the cost of becoming an informed trader. This cost would include the time and effort involved in establishing a brokerage account at an investment bank that shares analyst forecasts and recommendations with preferred clients. In equilibrium, the marginal benefit is equal to the marginal cost:

$$\frac{(1 - f) \sigma_y R \sigma_u S_{N^*}}{\sqrt{AI} \ (AI + 1)} = C_I.$$  

Similarly, from the individual analyst profit function (equation (9)), it is clear that increasing the number of analysts decreases the profit of each individual analyst. Additional people will choose to become analysts until the individual analyst’s marginal profit drops to the marginal cost of becoming an analyst. Let $C_A$ be the cost to become an analyst. This cost is primarily human capital, including extensive financial and accounting knowledge. In equilibrium, the marginal benefit is equal to the marginal
Figure 4
Optimal Number of Revisions \((N^\ast)\) by the Cost of Revision and by the Number of Informed Traders

Note:
\(c_0\text{--}c_{10}\) are critical values. The critical value \(c_n\) \((n = 0, 1, 2, 3, \ldots 10)\) is where the analyst’s profit for \(n\) revisions is exactly equal to the analyst’s profit for \(n + 1\) revisions.

\[
\frac{f\sigma_y R\sigma_u \sqrt{T} S_{N^\ast}}{\sqrt{A} (AI + 1)} - N^\ast c_R = C_A. \tag{12}
\]

Equations (11) and (12) provide two simultaneous equations for two unknowns. Solving them together yields the equilibrium number of informed traders and analysts.

**Proposition 3:** With endogenous entry, the equilibrium number of informed traders is:

\[
I^\ast = \text{floor} \left[ \frac{(1 - f) (C_A + N^\ast C_R)}{f C_I} \right] \tag{13}
\]

and the equilibrium number of analysts is the floor of the unique real root of the cubic equation:

\[
A^\ast (A^\ast I^\ast + 1)^2 = \frac{I^\ast [f \sigma_y R\sigma_u S_{N^\ast}]^2}{(C_A + N^\ast C_R)^2}. \tag{14}
\]

The equilibrium number of informed traders is driven by the fraction of profits retained by the informed traders \(1 - f\) versus the fraction of profits gained by the analysts \(f\) and by the cost to become an informed trader \(C_I\) versus the various...
analyst costs \( C_A + N^* C_R \). The equilibrium number of analysts\(^{15} \) is driven by the relative profitability of revision activity \( f \sigma_y R \sigma_u S_N \) and by the various analyst costs \( C_A + N^* C_R \).

6. HYPOTHESIS DEVELOPMENT

In this section, we specify the hypotheses and variables that will be used to test the empirical predictions of the model and the variables that will be used to control for other known relationships. The empirical predictions of Proposition 2 are the basis for our hypotheses. Specifically, Proposition 2 predicts that an analyst’s revision frequency increases with earnings volatility, earnings response coefficients, and the standard deviation of liquidity trading, and decreases with informed trading and the cost of a forecast revision. Of these, the first four are firm-specific, and hence should have the same influence on all analysts’ decisions for a given firm-quarter. The cost of a revision, however, is primarily analyst effort, which is neither firm-specific nor observable. Therefore, we focus our analysis on the first four relations predicted by our model, and employ a measure of individual revision frequency based on an average analyst.

Our model predicts that individual analyst revision frequency is increasing in the volatility of the earnings process. The volatility of earnings can be viewed as the unpredictable component of earnings, as the rate at which new information about earnings becomes available, or as the variability of earnings. One measure of the variability of earnings for a period is the residual from estimating a regression of the firm’s earnings process (Barefield and Comisky 1975 and 1979). Hypothesis 1 is:

\[ H_1: \text{The frequency of analysts’ forecast revisions for a firm is positively associated with the variability of that firm’s earnings process.} \]

Our model predicts that individual analyst revision frequency is increasing in the earnings response coefficients (ERCs), or the stock price response to earnings. Hypothesis 2 is:

\[ H_2: \text{The frequency of analysts’ forecast revisions for a firm is positively associated with the firm’s earnings response coefficient.} \]

Our model predicts that individual analyst revision frequency is increasing in the variance of the net order flow from liquidity trading. While liquidity trading cannot be directly observed, trading volume is readily observable. When average trading volume is high, the average number of liquidity shares traded is also expected to be high, and the level of average trading volume may disguise informed trades (Bhushan, 1989a). Thus, Hypothesis 3 is:

\[ H_3: \text{The frequency of analysts’ forecast revisions for a firm is positively associated with the firm’s prior average trading volume.} \]

---

\(^{15}\) In the proof, it is shown that the discriminant of equation (14) is positive. Therefore, the cubic equation has one real root and two complex conjugate roots. The real root is the economically-meaningful solution and adding the floor function simply rounds it down to the nearest integer.
Our model predicts that individual analyst revision frequency is decreasing in the total number of informed traders following the risky firm. Bamber et al. (1999) find that differential interpretations are associated with trading volume when trading volume is unusually high. On days when private information is generated, there should be relatively more shares traded. On days when no private information is generated, there should be relatively fewer shares traded. The difference between information days and non-information days should generate skewness of daily trading volume. Hence, we employ the skewness of prior daily trading volume as a proxy for the number of informed traders. This leads to Hypothesis 4:

**H4:** The frequency of analysts’ forecast revisions for a firm is negatively associated with prior skewness of trading volume.

In summary, the following relations are predicted:

\[
\text{Revision Frequency} = f(\text{volatility}, \text{ERC}, \text{average volume}, \text{skewness of volume}).
\]

Two control variables, firm size and average stock price movement, are included in the tests. Prior literature has documented associations between (1) firm size and analyst following (e.g., Bhushan, 1989b; Dempsey, 1989; Brennan and Hughes, 1991; Cheon et al., 2001; and Ryan, 2004) and (2) firm size and transfer of information (e.g., Atiase, 1985 and 1987; Collins et al., 1987; and Christensen et al., 2004). If more information is either supplied to analysts or demanded by traders for larger firms, then firm size should be positively associated with revision frequency, holding analyst following constant. Conversely, if large firms are more visible, and therefore traders rely less on analysts for information, firm size should be negatively associated with revision frequency, holding analyst following constant. In either case, omission of firm size from our regression estimation would potentially bias coefficients of other variables in the estimation, and we therefore include firm size as a control variable.

Stock price movement may occur because many informed trades have been placed and part or all of the information implicit in those trades has been inferred by all other market participants. In that case, daily stock price movement will capture the extent of informed trading, and will be positively correlated with the skewness of trading volume and negatively related to frequency of forecast revisions. In contrast, daily stock price movement may reflect the sensitivity of stock price to new information. If daily price movement captures price sensitivity to new information, it will be positively correlated with earnings response coefficients, and positively related to forecast revision frequency. In either case, omission of average daily stock price movement from the regression estimation would potentially bias coefficients of other variables in the estimation, and we therefore include it as a control variable.

7. **EMPIRICAL TESTS**

(i) **Data Sources and Variable Measurement**

In empirical tests, we use analyst annual and quarterly forecast and actual quarterly earnings data from the 1976–1996 Institutional Brokers Estimate System (I/B/E/S)
Detail data. Annual forecasts are used in the measure of analyst revision activity; one-quarter-ahead forecasts are used as a proxy for earnings expectations in our estimations of firm-specific ERCs. Earnings announcement dates and quarterly earnings per share (EPS) are from the 1996 Compustat Quarterly P-S-T and Full Coverage data and annual EPS is from the Compustat Annual P-S-T data. Share prices, returns, and trading volume are from the Center for Research in Security Prices (CRSP). Data is organized by firm-quarter. To be included in the sample, a firm must have at least 20 quarters\(^{16}\) with (1) analysts’ forecasts of quarterly EPS available in the I/B/E/S detail data, (2) actual quarterly EPS in either the I/B/E/S data or Compustat data, and (3) returns data from CRSP for at least 50 of the 200 trading days prior to the earnings announcement and for a three-day window at the announcement. Firm-quarters missing any of the above data are eliminated from the sample. The resulting sample includes 727 firms, and 21,594 firm-quarter observations, over the years from 1986 to 1995.

Firm-specific ERCs are estimated as \(\gamma_1\) from the regression:

\[
\text{CAR}_{it} = \gamma_0 + \gamma_1 \left( \frac{\text{UE}_{it}}{P_{i(t-2)}} \right) + \epsilon_{it},
\]

where \(\text{CAR}_{it}\) is the cumulative abnormal return from day \(-1\) to day \(+1\) around the quarterly earnings announcement date, estimated using a market model,\(^{17}\) \(\text{UE}_{it}\) is unexpected earnings in the quarter’s earnings announcement, \(P_{i(t-2)}\) is the closing stock price two days before the earnings announcement, \(\gamma_0\) and \(\gamma_1\) are firm-specific regression parameters, and \(\epsilon_{it}\) is the error term.\(^{18}\) Unexpected earnings is measured as the difference between forecasted quarterly EPS and actual quarterly EPS from the I/B/E/S data if actual EPS is reported in that data,\(^{19}\) and otherwise actual quarterly EPS is primary EPS before extraordinary items from the quarterly Compustat data. Forecasted EPS is the mean of new one-quarter-ahead forecasts reported by I/B/E/S in the most recent month prior to the earnings announcement date in which at least one new forecast is reported.\(^{20}\) For hypothesis tests, we use the natural logarithm of these estimates of firm-specific ERCs (LnERC).

---

16 The requirement of 20 quarters of data for each firm allows for reliable estimates of firm-specific ERCs.

17 The market model is estimated over trading days \(-200\) to \(-2\), where the announcement date is day 0, using the CRSP value-weighted index.

18 Firms with extreme values for \(\gamma_1\) were investigated for influential observations and re-estimated after excluding highly influential observations.

19 Philbrick and Ricks (1991) point out the importance of using a measure of EPS that includes and excludes the same items as the forecasts. Analysts’ forecasts and actual earnings in the I/B/E/S data are stated on the same basis, and actual earnings are adjusted to reflect the items included in analysts forecasts (which are not necessarily the same as earnings per share before extraordinary items). Use of this EPS number reduces measurement error in unexpected earnings. Among the items included in net income that are often excluded from analysts’ forecasts are non-operating items and the effect of one-time events.

20 Because this estimation of each firm’s ERC is a noisy measure of firms’ price responses to new information, any ERC that is not significantly different from zero is set to zero. The natural log of 0.0001 plus the ERC is used in hypothesis tests. Alternate tests were conducted using an indicator variable that was set equal to 1 if the firm-specific ERC was greater than 1.57 (above the median) and 0 otherwise. Results of these tests were similar to those presented in Tables 3 and 4. However, the coefficient on the indicator variable was significantly positive at \(p < 0.01\) for all quarters and both measures of the dependent variable, unlike results using LnERC. This may be due to the inherent noise of the estimated ERCs.
Average volume is calculated as the mean of the average daily shares traded, from CRSP, and is measured over the prior year, ending at day \( t - 2 \), as:

\[
\overline{Volume} = \frac{1}{T} \sum_{t=1}^{T} Volume_t,
\]

where \( T \) equals the number of trading days where volume is available in the data. The natural logarithm of average daily volume (denoted \( \ln Volume \)) is used in hypothesis tests to mitigate heteroskedasticity arising from skewness of the untransformed variable. Skewness of trading volume is also measured over the prior year, and is calculated as:

\[
\text{Skew}(Volume) = \frac{\sum_{i=1}^{n} (Volume_n - \overline{Volume})^3}{\sigma^3},
\]

where \( \sigma \) is the standard deviation of \( \overline{Volume} \).\(^{21}\) Firm size, also from CRSP, is the market value of equity two days before the earnings announcement for the quarter during which analyst activity is measured, and is also log-transformed (\( \ln Size \)).

The average daily price movement is calculated by using the high, low, and closing stock prices for each day from the CRSP daily data for the prior fiscal year as:

\[
|\text{Price Change}| = \frac{1}{T} \sum_{t=1}^{T} \left( \frac{\text{High} - \text{Low}}{\text{Price}} \right).
\]

Days where no trading occurred were excluded from the calculation.

Our measure of earnings volatility (\( \ln Volatility \)) employs the residual \( \varepsilon_t \) from the time-series regression of each company’s current-year earnings on its prior-year earnings:

\[
\text{NI}_t = \alpha + \beta \text{NI}_{t-1} + \varepsilon_t,
\]

where NI denotes Net Income Before Extraordinary Items from the Compustat annual data. To obtain earnings volatility, we square the residual \( \varepsilon_t \), divide by the absolute value of net income \( |\text{NI}_t| \) and take the log as follows:

\[
\ln Volatility = \ln \left( \frac{\sum_{i=1}^{T} \varepsilon_i^2}{T \sum_{i=1}^{T} |\text{NI}_i|} \right).
\]

Our results are robust to alternative specifications of volatility.\(^{22}\)

Our measure of revision frequency employs annual forecasted earnings per share. The dependent variable used to capture analyst revision frequency in this study is the number of revisions of forecasted annual earnings per share between quarterly earnings

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\(^{21}\) The variable is divided by 10,000 for purposes of hypothesis tests.

\(^{22}\) Alternative tests were conducted using the absolute difference between actual quarterly EPS and forecasted quarterly EPS in the first month of the fiscal period as a measure of earnings predictability. The results were qualitatively similar to the results presented in Tables 3 and 4, and lead to identical inferences.
announcements,23 divided by analyst following at the earnings announcement date.24 For a forecast to be included in our count of forecast revisions, it must be a revision of an annual earnings forecast for the current fiscal year in the I/B/E/S detail data, released between the day after an earnings announcement and the day before the subsequent quarterly announcement. Individual analyst revision frequency (denoted IndivFrequency) is accumulated over all analysts who could have revised forecasts during the period (e.g., analysts who have at least one forecast of annual earnings per share for the firm in the I/B/E/S detail data before the announcement of the previous quarter’s earnings). As an alternative, active individual analyst revision frequency (denoted IndivFrequency2) is computed based on analysts who issue a revised forecast within 20 trading days after the earnings announcement.25 Use of this alternative measure is intended to reduce the influence of herding analysts on the dependent variable.26

Table 1, Panel A contains descriptive statistics for all variables. The mean (median) IndivFrequency per firm-quarter is 0.69 (0.67) for all revisions, and 0.44 (0.40) for IndivFrequency2. Revision frequency differs significantly across fiscal quarters,27 but the other variables do not differ significantly by quarter. Therefore, hypothesis tests are conducted and results are presented by fiscal quarter. Table 1, Panel B contains descriptive statistics for the individual analyst revision frequency separated into fiscal quarters. IndivFrequency is lowest following the announcement of fourth quarter earnings (i.e., during the first quarter), and increases throughout the year.

(ii) Description of Regression Models

Since the data includes multiple firm-quarter observations for firms, there is dependency in the data, which biases the standard errors for regression coefficients upward. To mitigate this problem, indicator variables for years 1987–1995 are used in the regressions. The following regression model is used to test the hypotheses presented above:

\[
\text{IndivFrequency} = \beta_0 + \sum_{Y=87}^{95} \beta_Y I_Y + \beta_1 \ln \text{ERC} + \beta_2 \ln \text{Volatility} \\
+ \beta_3 \ln \text{Volume} + \beta_4 \text{Skew(Volume)} + \beta_5 \ln \text{Size} + \varepsilon, \tag{15}
\]

23 This use of annual forecasts as a revision measure and the quarter between releases of quarterly earnings per share as the period examined is consistent with prior literature (Stickel, 1989; Barron and Stuerke, 1998; and Stuerke, 2005).

24 In additional tests, we estimated our regressions with analyst following as an independent variable rather than the denominator of the dependent variable. Collinearity diagnostics of those estimations indicated extreme collinearity between analyst following and each of our variables of interest. The results of those tests demonstrate a strong effect of analyst following on the number of forecast revisions. In those estimations, the \(r^2\) statistics were considerably higher (0.58 – 0.66), as were condition indices. Beyond that, however, the results of those tests were qualitatively similar to the results presented in Tables 3 and 4.

25 This variable is similar to that used in Barron and Stuerke (1998). However, Barron and Stuerke focus on revisions of revisions after the announcement, and only count the second revision during the quarter. In our study, IndivFrequency2 is based on the number of all revisions by analysts who issue a revision within the first 20 trading days of the quarter.

26 Other analysts’ forecasts are a low-cost source of information for analysts and may also reflect analysts’ opportunities for revising based on other analysts’ forecasts. Revisions by all analysts may include revisions that arise from observing other analysts’ forecasts, so that scaling by analyst following may not fully control for herding. While these revisions represent one type of information acquisition and dissemination activity, it is not the type of activity addressed by the theory.

27 Tests for a difference of means were significant at \(\alpha < 0.01\) for all pairs of quarters.
Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Descriptive Statistics ((n = 21,594))</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IndivFrequency</td>
<td>0.69</td>
<td>0.35</td>
<td>0</td>
<td>0.67</td>
<td>3</td>
</tr>
<tr>
<td>IndivFrequency2</td>
<td>0.44</td>
<td>0.29</td>
<td>0</td>
<td>0.40</td>
<td>3</td>
</tr>
<tr>
<td>Size</td>
<td>3,505,171</td>
<td>7,769,393</td>
<td>10,031</td>
<td>1,149,062</td>
<td>119,220,000</td>
</tr>
<tr>
<td>Average Volume</td>
<td>71,375</td>
<td>114,906</td>
<td>834</td>
<td>35,592</td>
<td>2,371,521</td>
</tr>
<tr>
<td></td>
<td>Price Change</td>
<td>0.70</td>
<td>0.39</td>
<td>0.07</td>
<td>0.62</td>
</tr>
<tr>
<td>Volatility</td>
<td>190.26</td>
<td>3,256.54</td>
<td>0</td>
<td>3.23</td>
<td>212,983</td>
</tr>
<tr>
<td>Skew(Volume)</td>
<td>54,723</td>
<td>71,601</td>
<td>79</td>
<td>32,722</td>
<td>743,444</td>
</tr>
</tbody>
</table>

| **Panel B: Descriptive Statistics of Individual Revision Frequency by Quarter** |         |         |         |        |         |
| First Quarter, \(n = 5,282\) |         |         |         |        |         |
| IndivFrequency            | 0.679  | 0.367   | 0       | 0.636  | 3       |
| IndivFrequency2           | 0.428  | 0.296   | 0       | 0.389  | 3       |
| Second Quarter, \(n = 5,813\) |         |         |         |        |         |
| IndivFrequency            | 0.692  | 0.363   | 0       | 0.655  | 3       |
| IndivFrequency2           | 0.417  | 0.295   | 0       | 0.375  | 2.5     |
| Third Quarter, \(n = 5,586\) |         |         |         |        |         |
| IndivFrequency            | 0.699  | 0.357   | 0       | 0.667  | 2.5     |
| IndivFrequency2           | 0.443  | 0.288   | 0       | 0.400  | 2       |
| Fourth Quarter, \(n = 5,561\) |         |         |         |        |         |
| IndivFrequency            | 0.706  | 0.338   | 0       | 0.667  | 2.5     |
| IndivFrequency2           | 0.462  | 0.283   | 0       | 0.429  | 2       |

Notes:
- \(\text{IndivFrequency}\) = The average number of revisions of an individual analyst, measured as the total number of revisions of existing forecasts made between earnings announcements, divided by analyst following
- \(\text{IndivFrequency2}\) = The average number of revisions of an active individual analyst, measured as the total number of revisions of existing forecasts made between earnings announcements by analysts who provide a forecast in the 20 trading days following an earnings announcement, divided by analyst following
- \(\text{Size}\) = Market value of equity at the beginning of the fiscal year
- \(\text{AverageVolume}\) = Average daily trading volume over the year prior to the quarter’s earnings announcement.
- \(\text{|Price Change|}\) = The magnitude of the average daily stock price movement over the year prior to the earnings announcement, measured as the difference between the daily high and low stock prices, scaled by the closing price
- \(\text{Volatility}\) = Squared residuals from the estimation of net income before extraordinary items as a random walk with trend, scaled by the absolute value of net income before extraordinary items
- \(\text{Skew(Volume)}\) = Skewness of daily trading volume of the year prior to the quarter’s earnings announcement.

where the variables are measured as defined above, \(I_Y\) is an indicator variable for year \(Y\), and \(\beta_Y\) is the corresponding coefficient. An alternative model including average daily stock price changes as a control variable is also estimated:

\[
\text{IndivFrequency} = \beta_0 + \sum_{Y=87}^{95} \beta_Y I_Y + \beta_1 \text{LnERC} + \beta_2 \text{LnVolatility} + \beta_3 \text{LnVolume} + \beta_4 \text{Skew(Volume)} + \beta_5 \text{LnSize} + \beta_6 \text{|Price Change|} + \epsilon. \tag{16}
\]

The coefficients \(\beta_1, \beta_2\) and \(\beta_3\) are all predicted to be positive. The coefficient \(\beta_4\) is predicted to be negative. No predictions are made about sign or significance for \(\beta_0\).

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for any specific year, or for $\beta_5$ or $\beta_6$, in part because of the effect of analyst following in the denominator of $IndivFrequency$.

8. EMPIRICAL RESULTS

(i) Univariate Evidence

Pearson pairwise correlations for the entire sample are presented in Table 2. Examination of the correlation table indicates that several pairs of the variables are highly correlated. $\ln Volume$, $\ln Size$ and $\ln Volatility$ are all correlated at greater than 0.30, suggesting the presence of collinearity in the regressions. The correlation between $\ln ERC$ and the magnitude of $Price Change$ is 0.066, the correlation between $Skew(\text{Volume})$ and $Price Change$ is $-0.154$, and the magnitude of $Price Change$ is positively correlated with both measures of $IndivFrequency$, consistent with average daily price movement capturing stock price sensitivity to new information rather than the incidence of informed trading. The two measures of the dependent variable, $IndivFrequency$ and $IndivFrequency^2$, are correlated at 0.916. Further, all of the independent variables are significantly correlated with both measures of the dependent variable, in the predicted directions, except for $\ln ERC$, which is significantly correlated only with the measure of revisions by active analysts.

(ii) Results of Multivariate Tests

Results from the estimations of equations (15) and (16) using active individual analysts revision frequency are presented in Table 3. There are two advantages to the use of a measure based on active analysts over a measure based on all analysts. First, the theory assumes an analyst who actively acquires and disseminates information, so there is greater construct validity when the dependent variable is based on active analysts. Second, this measure of the dependent variable is less likely to include revisions that arise from herding. Revisions that arise from herding are likely to introduce noise, and possibly bias, into the measure of the dependent variable.

Table 3 reports results for regression estimations where the dependent variable is active individual analysts’ revision frequency, $IndivFrequency^2$. Estimates of the coefficient on $\ln ERC$ are positive and significant at $p < 0.01$ in all quarters except the second quarter, providing support for the hypothesized relation between analyst revision frequency and ERCs. The coefficient estimates of $\ln Volatility$ are significantly positive at $p < 0.01$ in all four quarters, whether the regression is estimated with or without the additional control variable. These results provide support for the hypothesized relation between individual analyst revision frequency and earnings predictability, and suggest that forecast revisions are more likely when earnings are less predictable. The coefficient estimates on $\ln Volume$ are positive and significant at $p < 0.01$ ($p < 0.05$) in three (four) quarters when $|Price Change|$ is not included in the regression, and are significant at $p < 0.01$ in all quarters when $|Price Change|$ is included. This provides support for the hypothesized positive relation between individual analyst

28 White’s (1980) test indicated heteroskedasticity for all regression estimations. Therefore $t$-statistics reported in the tables are calculated using White’s asymptotically consistent covariance matrix.
Table 2
Pearson Pairwise Correlations (n = 21,594)

|                  | LnVolume | LnVolatility | LnSize | |Price Change| LnERC | Skew(Volume) | IndivFrequency |
|------------------|----------|--------------|--------|-----------------|--------|---------------|----------------|
| LnVolatility     | 0.438∗   |              |        |                 |        |               |                |
| LnSize           | 0.738∗   | 0.335∗       |        |                 |        |               |                |
| |Price Change| | 0.363∗ | 0.208∗ | 0.575∗ | 0.566∗ | 0.015 | 0.015 | 0.013 | −0.103∗ | 0.916∗ |
| LnERC            | −0.015   | −0.074∗      | 0.026∗ |                 |        |               |                |
| Skew(Volume)     | −0.015   | 0.015        | 0.097∗ | −0.154∗         | −0.117∗|                |                |
| IndivFrequency   | 0.090∗   | 0.372∗       | 0.018∗ | 0.117∗          | 0.013  | −0.103∗       |                |
| IndivFrequency2  | 0.092∗   | 0.155∗       | 0.012  | 0.113∗          | 0.038∗ | 0.103∗        | 0.916∗         |

Notes:

<p>| | |</p>
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>IndivFrequency</td>
<td>The average number of revisions of an individual analyst, measured as the total number of revisions of existing forecasts made between earnings announcements, divided by analyst following</td>
</tr>
<tr>
<td>IndivFrequency2</td>
<td>The average number of revisions of an active individual analyst, measured as the total number of revisions of existing forecasts made between earnings announcements by analysts who provide a forecast in the 20 trading days following an earnings announcement, divided by analyst following</td>
</tr>
<tr>
<td>LnSize</td>
<td>The natural log of the market value of equity at the beginning of the fiscal year</td>
</tr>
<tr>
<td>LnVolume</td>
<td>The natural log of the average daily trading volume over the year prior to the earnings announcement</td>
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<td>Price Change</td>
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<tr>
<td>LnERC</td>
<td>The natural log of the firm-specific earnings response coefficient</td>
</tr>
<tr>
<td>LnVolatility</td>
<td>The natural log of the squared residuals from the estimation of net income before extraordinary items as a random walk with trend, scaled by the absolute value of net income before extraordinary items</td>
</tr>
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<td>Skew(Volume)</td>
<td>The skewness of average daily trading volume.</td>
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* Significant at $p < 0.01$. 

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Table 3
Determinants of Active Individual Analyst Revision Frequency Regression Estimation of
\[ \text{IndivFrequency} = \beta_0 + \sum_{t=87}^{95} \beta_t I_t + \beta_1 \text{LnERC} + \beta_2 \text{LnVolatility} + \beta_3 \text{LnVolume} + \beta_4 \text{Skew(Volume)} + \beta_5 \text{LnSize} + \beta_6 \frac{|\text{PriceChange}|}{\varepsilon} \]

| Year | Intercept | Year Indicators | LnERC | LnVolatility | LnVolume | Skew(Volume) | LnSize | |Price Change| | #N | Adj.R2 |
|------|-----------|----------------|-------|--------------|----------|--------------|--------|-----------------|---------------|-------|--------|
| 1st Quarter | 0.308 | 0.043-0.046 | 0.004 | 0.011 | 0.017 | -0.004 | -0.009 | 5,249 | 0.05 |
| | (3.18)** | (6.95)** | (3.43)** | (8.91)** | (-2.22)* |
| | 0.430 | 0.028-0.161 | 0.003 | 0.010 | 0.022 | -0.003 | -0.028 | 0.104 | 5,249 | 0.06 |
| | (2.86)** | (6.49)** | (4.35)** | (6.13)** | (-5.72)** | (7.66)** |
| 2nd Quarter | 0.351 | 0.131-0.211 | 0.001 | 0.017 | 0.016 | -0.005 | -0.019 | 5,386 | 0.09 |
| | (0.74) | (12.62)** | (3.05)** | (-9.78)** | (-4.37)** |
| | 0.557 | 0.107-0.205 | 0.0004 | 0.017 | 0.023 | -0.003 | -0.047 | 0.154 | 5,386 | 0.11 |
| | (0.35) | (12.19)** | (4.43)** | (-6.49)** | (-9.25)** | (11.67)** |
| 3rd Quarter | 0.496 | 0.036-0.132 | 0.004 | 0.018 | 0.010 | -0.005 | -0.016 | 5,465 | 0.07 |
| | (3.87)** | (13.35)** | (1.96)* | (-11.71)** | (-4.10)** |
| | 0.658 | 0.024-0.134 | 0.004 | 0.017 | 0.016 | -0.004 | -0.039 | 0.126 | 5,465 | 0.09 |
| | (3.55)** | (12.93)** | (3.12)** | (-6.93)** | (-8.41)** | (9.57)** |
| 4th Quarter | 0.472 | 0.046-0.137 | 0.003 | 0.013 | 0.017 | -0.005 | -0.018 | 5,494 | 0.06 |
| | (2.90)** | (9.61)** | (3.52)** | (-11.35)** | (-4.75)** |
| | 0.612 | 0.035-0.149 | 0.003 | 0.012 | 0.022 | -0.004 | -0.039 | 0.115 | 5,494 | 0.07 |
| | (2.59)** | (9.16)** | (4.52)** | (-8.24)** | (-8.43)** | (8.79)** |

Notes:
IndivFrequency = The average number of revisions of an active individual analyst, measured as the total number of revisions of existing forecasts made between earnings announcements by analysts who provide a forecast in the 20 trading days following an earnings announcement, divided by analyst following
LnERC = The natural log of the firm-specific earnings response coefficient
LnVolatility = The natural log of the squared residuals from the estimation of net income before extraordinary items as a random walk with trend, scaled by the absolute value of net income before extraordinary items
LnVolume = The natural log of the average daily trading volume over the year prior to the earnings announcement
Skew(Volume) = The skewness of average daily trading volume
LnSize = The natural log of the market value of equity at the beginning of the fiscal year
|PriceChange| = The magnitude of the average daily stock price movement over the year prior to the earnings announcement, measured as the difference between the daily high and low stock prices, scaled by the closing price.

White's t-statistics in parentheses. ** Significant at p < 0.01; * Significant at 0.01 < p < 0.05.
revision frequency and prior trading volume. Estimates of the coefficient of \( \text{Skew(Volume)} \) are negative and significant at \( p < 0.01 \) in all quarters, for both specifications of the regression, supporting the hypothesized negative relation between individual analyst revision frequency and skewness of daily trading volume. The negative and significant coefficient estimates for \( \ln \text{Size} \) may indicate that analysts revise forecasts less often for large firms. Finally, coefficient estimates for \( |\text{Price Change}| \) are positive and significant at \( p < 0.01 \).

Table 4 presents results from the estimations of equations (15) and (16) using individual analysts’ revision frequency, \( \text{IndivFrequency} \), as the dependent variable. These results do not provide evidence of an association between individual analyst revision frequency and ERCs. Estimates of the coefficient on \( \ln \text{ERC} \) are not significantly different from zero when the dependent variable is based on revisions by all analysts, except in the third quarter. However, coefficient estimates of all other variables are similar to those presented in Table 3 and discussed above.

While the coefficient estimates of these regressions are statistically significant, the \( r^2 \) statistics are modest, though consistent with those found in prior published papers about analyst revision activity. Several factors, however, may contribute to this situation. First, our variables are proxies for the constructs in our model, and as such, contain noise. Next, the values used for \( \ln \text{ERC} \) have the same value for all observations of the same firm, rather than taking a new value with each firm-quarter. Finally, our model does not include variables used in prior literature that are likely to reflect either new information or changes in informational demand, such as the magnitude of earnings surprises or dispersion in prior forecasts. Those variables are associated with revisions at specific times in the quarter, rather than throughout the quarter. All three of these factors may be related to the relatively low \( r^2 \) statistics we observe.

The results presented in these tables provide support for the hypothesized associations. All coefficient estimates except \( \ln \text{ERC} \) are consistently significant in the predicted direction, whether the dependent variable is based on active analysts or all analysts. The mixed results regarding \( \ln \text{ERC} \) may arise because (1) ERCs are associated with revision frequency by active analysts, but not by analysts who are herding, (2) the ERC is the appropriate measure of price sensitivity to new information only for earnings

29 Tests were also conducted using the average daily percent change in price as an alternate measure of this variable. The results of those tests were consistent with the results presented and discussed above, but also resulted in higher collinearity condition indices and higher variance inflation factors.

30 Regression diagnostics indicate the strong presence of multi-collinearity among the variables. This appears to arise in part from the correlation between firm size and average daily trading volume. However, omission of firm size from the regression would bias the coefficient of volume. Further, use of the natural log of multiple variables appears to induce additional collinearity.

31 The \( r^2 \) statistics reported in Stickel (1989) range from 0.0275 to 0.0475, those in Barron and Stuerke (1998) range from 0.07 to 0.12, and those in Stuerke (2005) range from 0.03 to 0.06.

32 The dependent variables in Table 3 are statistically significant, but are they economically significant? This can be assessed by using the estimated regression equations in Table 3 to forecast (i.e., backcast) revision frequency by active analysts. For example, evaluating the first estimated regression in Table 3 at the means of the independent variables forecasts 0.348 revisions by active analysts in the first quarter. If the regression coefficient on \( \ln \text{Volume} \) is set to zero, the forecasted ratio of revisions to active analysts drops to 0.172. This represents a \( -50.7\% \) change, which is clearly economically significant. Performing similar experiments based on the other independent variables, \( \ln \text{Volatility}, \ln \text{ERC}, \) and \( \text{Skew(Volume)} \), result in forecast changes of \( -3.5\%, 0.5\% \) and 6.1\% respectively. These changes are more humble, but still economically meaningful.

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Table 4
Determinants of Individual Analyst Revision Frequency Regression Estimation of 
IndivFrequency = 
\[ \beta_0 + \sum_{t=87}^{95} \beta_Y I_t + \beta_1 \text{LnERC} + \beta_2 \text{LnVolatility} + \beta_3 \text{LnVolume} + \beta_4 \text{Skew(} \text{Volume} \text{)} + \beta_5 \text{LnSize} + \beta_6 |\text{PriceChange}| + \varepsilon \]

| Intercept | Year Indicators | LnERC | LnVolatility | LnVolume | Skew(Volume) | LnSize | | PriceChange | #N | Adj.R^2 |
|-----------|----------------|-------|--------------|----------|--------------|--------|-----------|-----|---------|
| 1st Quarter | 0.340 | 0.032-0.165 | 0.002 | 0.017 | 0.028 | −0.003 | −0.002 | 5,249 | 0.06 |
|            | (1.19) | (8.70)** | (4.67)** | (−5.50)** | (−0.34) |
| 0.471 | 0.037-0.179 | 0.001 | 0.016 | 0.033 | −0.002 | −0.022 | 0.112 | 5,249 | 0.06 |
|            | (0.92) | (8.32)** | (5.47)** | (−3.25)** | (−3.73)** | (6.75)** |
| 2nd Quarter | 0.823 | 0.023-0.135 | 0.0004 | 0.025 | 0.13 | −0.005 | −0.024 | 5,386 | 0.07 |
|            | (0.31) | (14.27)** | (2.01)** | (−8.03)** | (−4.62)** |
| 1.058 | 0.025-0.122 | −0.0001 | 0.024 | 0.021 | −0.003 | −0.056 | 0.175 | 5,86 | 0.09 |
|            | (−0.07) | (13.92)** | (3.30)** | (−5.14)** | (−9.06)** | (10.08)** |
| 3rd Quarter | 0.803 | 0.006-0.104 | 0.003 | 0.024 | 0.017 | −0.006 | −0.023 | 5,465 | 0.07 |
|            | (2.52)** | (14.33)** | (2.78)** | (−9.68)** | (−4.87)** |
| 0.983 | 0.003-0.115 | 0.003 | 0.024 | 0.023 | −0.004 | −0.049 | 0.141 | 5,465 | 0.08 |
|            | (2.22)* | (13.93)** | (3.81)** | (−6.72)** | (−8.45)** | (8.30)** |
| 4th Quarter | 0.823 | 0.008-0.075 | 0.001 | 0.016 | 0.020 | −0.005 | −0.025 | 5,494 | 0.04 |
|            | (1.06) | (9.58)** | (3.41)** | (−8.91)** | (−5.25)** |
| 0.981 | 0.004-0.089 | 0.001 | 0.015 | 0.025 | −0.004 | −0.048 | 0.130 | 5,494 | 0.06 |
|            | (0.75) | (9.17)** | (4.33)** | (−6.22)** | (−8.46)** | (8.12)** |

Notes:
IndivFrequency = The average number of revisions of an individual analyst, measured as the total number of revisions of existing forecasts made between earnings announcements, divided by analyst following
LnERC = The natural log of the firm-specific earnings response coefficient
LnVolatility = The natural log of the squared residuals from the estimation of net income before extraordinary items as a random walk with trend, scaled by the absolute value of net income before extraordinary items
LnVolume = The natural log of the average daily trading volume over the year prior to the earnings announcement
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|PriceChange| = The magnitude of the average daily stock price movement over the year prior to the earnings announcement, measured as the difference between the daily high and low stock prices, scaled by the closing price.
White’s t-statistics in parentheses. ** Significant at p < 0.01; * Significant at 0.01 < p < 0.05.
surprises, or (3) the estimated ERC is inherently noisy and the coefficient will therefore be biased toward zero.33

Thus, we find strong empirical support for our dynamic model of analyst and trader activity. Our model helps explain factors that influence analysts’ decisions to provide clients with revised forecasts. These forecasts are the basis of private informed trading, which ultimately determines the price informativeness of a stock.

9. CONCLUSION

One of the most fundamental properties of a financial market is its degree of price informativeness – that is, the amount of private information impounded into the stock price. But what determines the degree of price informativeness of a given financial market? One of the major factors is information collected by financial analysts and then privately disseminated to clients, who make the recommended trades. Our theoretical contribution is to develop a dynamic model of this process with endogenous analysts and endogenous traders. Our model is the first to solve for the individual analyst’s optimal dynamic strategy, which is the analyst’s optimal revision frequency. For a given stock, the analyst’s revision frequency leads to the traders’ frequency of private informed trading, which ultimately determines the price informativeness of that stock. We find that optimal revision frequency is increasing in the variance of liquidity trading volume, earnings volatility, and the earnings-response coefficient and decreasing in the number of informed traders and the cost of revision. Our empirical contribution is to test the novel predictions of the model using analyst, market, and accounting data. We find that revision frequency is positively associated with trading volume, earnings variability, and earnings response coefficients, and negatively associated with skewness of trading volume. For robustness, we test a narrower measure of forecast revision frequency to avoid forecasts that potentially arise from herding and find even stronger results. Thus, we find strong empirical support of our dynamic model of analyst and trader activity that helps explain the determinants of price informativeness.

APPENDIX

Proof of Lemma 1: Begin with any arbitrary initial assignment for $N$ revision intervals $\Delta t_1, \Delta t_2, \ldots, \Delta t_N$. If the revision intervals sum to less than $T$, then increase the last revision interval so that they do sum to $T$. This change will strictly increase the $E[\Pi_{Anal}(N)]$ function because revision intervals enter via the square root function $\sqrt{\Delta t_n}$, which is strictly increasing for longer intervals.

Now sort the (modified) revision intervals into four categories:

- Greater Than Set = All revision intervals $\Delta t_n$, such that $\Delta t_n > \Delta t^+$
- $\Delta t^+$ Set = All revision intervals $\Delta t_n$, such that $\Delta t_n = \Delta t^+$
- $\Delta t^-$ Set = All revision intervals $\Delta t_n$, such that $\Delta t_n = \Delta t^-$
- Less Than Set = All revision intervals $\Delta t_n$, such that $\Delta t_n < \Delta t^-$.  

33 The results may also be affected by dependency in the data, as the sample includes multiple observations for the 727 firms included, and the use of year indicators will not completely control for this dependency.

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Now take any member of the Greater Than Set and reduce it by one period and increase by one period any member of the Less Than Set or the $\Delta t^-$ Set. This change will strictly increase the $E[\Pi_N]$ function because of the concavity of the square root function $\sqrt{\Delta t_n}$. In other words, one period changes in revision intervals $\sqrt{n+1} - \sqrt{n}$, have declining marginal impact:

$$\sqrt{1} - \sqrt{0} > \sqrt{2} - \sqrt{1} > \sqrt{3} - \sqrt{2} > \ldots > \sqrt{T - 1} - \sqrt{T - 2} > \sqrt{T} - \sqrt{T - 1}.$$ 

Hence, the increase in the $E[\Pi_{Anal}(N)]$ function caused by a unit increase in the Less Than Set or in the $\Delta t^-$ Set is greater than the reduction caused by a unit decrease in the Greater Than Set. Continue doing this until all members of the Greater Than Set are eliminated.

Now take each remaining member of the Less Than Set and increase it by one and decrease by one period any member of the $\Delta t^+$ Set. By the same argument as above, this change will strictly increase the $E[\Pi_{Anal}(N)]$ function. Continue doing this until all members of the Less Than Set are eliminated. As a result of this process, all remaining revision intervals are members of the $\Delta t^+$ Set or the $\Delta t^-$ Set. Further, since the revision intervals sum to $T$, there must be $\text{Mod}(T, N)$ number of $\Delta t^+$ intervals and $N - \text{Mod}(T, N)$ number of $\Delta t^-$ intervals. Q.E.D.

**Proof of Proposition 1:** Define a set of critical values $c_n$ for $n = 0, 1, 2, 3, \ldots, T - 1$ where the individual analyst’s expected profit is the same for $n$ and $n + 1$ revisions, $E[\Pi_{Anal}(n)] = E[\Pi_{Anal}(n + 1)]$. For $n \geq 1$, use equation (9) to obtain:

$$\frac{f k S_{n+1}}{A} - n c_n = \frac{f k S_n}{A} - (n + 1) c_n.$$ 

Solving for $c_n$, we get:

$$c_n = \left(\frac{f}{A}\right)(S_{n+1} - S_n).$$

For $n = 0$, the analyst is indifferent between 0 and 1 revisions, $E[\Pi_{Anal}(n + 1)] = 0$. Use equation (9) to obtain $\frac{f k S_n}{A} - c_0 = 0$. Solving for $c_0$, we get $c_0 = \frac{f k S_1}{A}$. Q.E.D.

**Proof of Proposition 2:** By definition of the critical values $c_n$ for $n = 0, 1, 2, 3, \ldots, T - 1$, the optimal number of revisions $N^*$ is weakly increasing in these critical values. In turn, the critical values have the following relationships to the exogenous parameters:

1. \(\frac{\partial c_n}{\partial \sigma_y} = \left(\frac{f R \sigma_u \sqrt{T}}{\sqrt{A} (AI + 1)}\right)(S_{n+1} - S_n) > 0\) and \(\frac{\partial c_0}{\partial \sigma_y} = \left(\frac{f R \sigma_u \sqrt{T}}{\sqrt{A} (AI + 1)}\right)S_1 > 0\),

2. \(\frac{\partial c_n}{\partial R} = \left(\frac{f \sigma_y \sigma_u \sqrt{T}}{\sqrt{A} (AI + 1)}\right)(S_{n+1} - S_n) > 0\) and \(\frac{\partial c_0}{\partial R} = \left(\frac{f \sigma_y \sigma_u \sqrt{T}}{\sqrt{A} (AI + 1)}\right)S_1 > 0\),

3. \(\frac{\partial c_n}{\partial \sigma_u} = \left(\frac{f \sigma_y R \sqrt{T}}{\sqrt{A} (AI + 1)}\right)(S_{n+1} - S_n) > 0\) and \(\frac{\partial c_0}{\partial \sigma_u} = \left(\frac{f \sigma_y R \sqrt{T}}{\sqrt{A} (AI + 1)}\right)S_1 > 0\),
4. \[ \frac{\partial c_n}{\partial I} = \left( -\frac{f\sigma_{yR}\sigma_u(AI-1)}{2\sqrt{AI}(AI+1)^2} \right) (S_{n+1} - S_n) < 0 \text{ and} \]
\[ \frac{\partial c_0}{\partial M} = \left( -\frac{f\sigma_{yR}\sigma_u(AI-1)}{2\sqrt{AI}(AI+1)^2} \right) S_I < 0. \]

5. Holding the critical values fixed, an increase the cost of forecast revision \( G_R \) weakly moves the analyst into a lower number of revisions. Q.E.D.

**Proof of Proposition 3:** Equations (11) and (12) can be rewritten as:

\[ \sqrt{AI} \frac{(AI+1)}{(AI+1)} = AIC_I \]
\[ \sqrt{AI} \frac{(AI+1)}{(AI+1)} = A(C_A + N^c C_R) \]

respectively. Equating the right-hand side of these two equations and solving for \( I \) yields the equilibrium number of informed traders on the real number line. Adding the floor function rounds this value down to an integer value to obtain \( I^* \) in equation (13). Substituting \( I^* \) for \( I \) in equation (12) and rearranging it yields equation (14). The discriminant of equation (14) is \( 27e^2/(I^*)^4 + 4e/(I^*)^5 \), where \( e \) is the right-hand side of equation (14). Since the discriminant is positive, the cubic equation has one real root and two complex conjugate roots. The real root is the economically-meaningful solution and adding the floor function rounds it down to the nearest integer. Q.E.D.

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