"Information precision and its determinants"

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ARTICLE INFO	Donglin Li, Gang George Li and Ming Li (2012). Information precision and its determinants. *Insurance Markets and Companies*, *3*(1)
RELEASED ON	Tuesday, 20 November 2012
JOURNAL	"Insurance Markets and Companies"
FOUNDER	LLC "Consulting Publishing Company "Business Perspectives"

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
0	0	0

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Information precision and its determinants

Abstract

Investors commonly rely on information received from analyst forecast to optimize portfolios and control investment risk. This paper presents a stochastic model of earnings to study and estimate the precision of information in biased analyst earnings forecasts about the unobservable expected (or future) earnings growth rates of firms, and examines factors that may affect the information precision. Using data from I/B/E/S, this study finds that the precision of information about expected earnings growth rates varies from firm to firm and is associated with firm-specific characteristics such as earnings growth volatility and the number of analysts studying a firm. The precision of information is also found associated with analyst characteristics such as analysts' ability, skills and accessible resources in acquiring non-public firm information about expected earnings growth rates. The empirical results in this study suggest a possible explanation of Stickel's (1992 and 1995) finding that investors tend to respond more to the recommendations of large broker analysts. In addition, the results have implications for how investors utilize information from financial analyst to manage firm-specific risk.

Keywords: information precision, analyst forecast, analyst characteristics.

Introduction

In risk management literature, how investors utilize information from financial analysts to manage their exposures to idiosyncratic investment risk is an important research question. Analyst earnings forecasts provide an important source of information about the unobservable expected (or future) earnings growth rates of firms. Despite the extensive study of analyst earnings forecasts, several interesting research questions still remain unaddressed about the precision of information that investors receive from analyst earnings forecasts. First, how do we measure the precision of information that investors receive from biased analyst earnings forecasts?[1] Second, in the financial market, do analyst earnings forecasts provide investors with relatively precise or noisy information about the unobservable expected earnings growth rates of firms? Third, if the precision of information that investors receive from biased analyst earnings forecasts varies from firm to firm, what variables of interest affect the precision of information? For example, do firm characteristics such as earnings growth volatility and the number of analysts studying a firm affect the precision of information? On the other hand, do analyst characteristics such as analysts' ability, skill and assessable resources also contribute to the precision of information?

These issues have become more relevant in light of the recent financial crisis in the U.S. Although financial analysts' earnings forecasts are a key determinant of stock prices, the effect of them on asset prices are murky at best. For example, several financial analysts, including the famous George Soros and Meredith Whitney, warned unsustainable bubbles in housing markets back in 2004 and 2005. Apparently few investors heeded this message seriously until 2008. What was the reason that the market ignored these warning signs? One would postulate that these warnings were just like a typical noise that overwhelmed the market. They were just too noisy to pay attention to. We have seen too many missed forecasts by financial analysts. But this is not the reason to discredit all financial analysts, as many investors would hold this thought. The main issue is "we don't have a ready tool to measure the informativeness of analyst research. Or we don't know how precise the warnings are".

In this paper, we address the research questions discussed above as well as pragmatic applications. We first present a model of earnings with a time-varying expected growth rate and then discuss how to use the model and the I/B/E/S data set to estimate the precision of information that investors receive from analyst earnings forecasts. In addition, we examine how firm and analyst characteristics affect the precision of information.

We use biased earnings forecasts to construct unbiased earnings forecasts, which are used to estimate the precision of information. This approach is based on the idea that unbiased earnings forecasts are analysts' expectations of future earnings conditional on analysts' information about unobservable expected earnings growth rates. Thus, unbiased earnings forecasts incorporate analysts' information about expected earnings growth rates. By using unbiased forecasts, investors can extract this information. Thus, our approach is consistent with the practice in accounting and finance that unbiased forecasts are used as investors' expectation of future earnings (see, for example, Brown, Foster and Noreen, 1985; Hughes and Ricks, 1987; McNichols, 1989; Landsman and Maydew, 2002; Frankel et al., 2006). Our estimation shows that the precision of informa-

[1] Earnings forecasts have been found to be biased by many empirical studies, for example, Abarbanell (1991), Brown, Foster and Nereen (1985), and Stickel (1990).

tion that investors receive from analyst earnings forecasts varies from firm to firm. For some firms, analyst earnings forecasts provide relatively precise information to investors; for some firms, information provided to investors by analyst forecasts is relatively noisy.

We use a cross-sectional analysis to examine how firm and analyst characteristics affect the precision of information. We find that the precision of information about the expected earnings growth rate of a firm is associated with firm characteristics such as the number of the analysts studying the firm and earnings growth volatility. The number of the analysts following a firm surrogates the amount of effort taken by analysts to obtain private information about the expected earnings growth rate of the firm. Earnings growth volatility of a firm denotes how volatile the earnings growth process is and thus indicates how difficult it is to obtain precise information about the expected earnings growth rate of the firm.

In addition, we find that the precision of information is also related to analyst characteristics such as the size of a brokerage firm in which analysts work. Specifically, the more analysts coming from large brokerage firms, the more precise information is. There are two possible explanations for this empirical finding. First, brokerage firm size may denote the resources available for analysts to gain private information about expected earnings growth rates of firms. As pointed out by Clement (1999), a large brokerage firm is expected to provide better resources such as better databases and administrative support for analysts to obtain precise information. Thus, the more analysts coming from large brokerage firms, the more precise information is supposed to be. Second, brokerage firm size may also denote analysts' ability and skill, since larger brokerage firms tend to have better financial resources to compensate for their analysts, and thus can hire analysts with a better ability and skill. Regardless of what explanation is more likely, this empirical result provides a possible explanation of Stickel's (1992 and 1995) finding that investors tend to respond more to the recommendations of the analysts from large brokerage firms. Investors may respond more to the recommendations of these analysts, because large broker analysts have more accurate non-public firm information about expected earnings growth rates.

We don't find significant evidence that analyst working experience is associated with the precision of information. Analyst working experience may not be correlated with information precision, since long working experience does not automatically imply a better skill and a higher ability to obtain more precise

information. On the other hand, as discussed above, the size of a brokerage firm where analysts work may better surrogate analysts' ability and skill.

Our work is related to prior studies that use analyst forecasts to infer analysts' information characteristics. A partial list of works in this area includes Barry and Jenning (1992), Abarbanell, Lanen and Verrecchia (1995), and Barron, Kim, Lim and Stevens (1998), Hong and Kubik (2003), Frankel et al. (2006). Despite similarity, our work differs from their works in the following three aspects. First, we present a stochastic model of earnings with an unobservable time-varying expected growth rate, which must be estimated by using both historical earnings data and non-public firm information. Thus our model captures the notion that analysts use more than historical earnings data to make forecasts. Second, our paper addresses how to estimate the precision of information that investors receive from biased analyst earnings forecasts. Third, this paper documents some empirical evidences about how information precision is affected by firm and analyst characteristics.

The rest of the paper is organized as follows. Section 1 presents a model to discuss how to estimate the precision of information about the expected earnings growth rate of a firm. Section 2 discusses several variables of interest that may affect the precision of information. Section 3 discusses the data used in this study. The empirical results and discussion are presented in section 4. The final section concludes the paper.

1. The model

In this section, we present a simple continuous-time model of earnings to discuss how to use biased analyst forecasts to estimate the precision of information that investors receive from analyst earnings forecasts in the financial market. While a similar discrete-time model can be used to achieve the same purpose, the continuous-time model makes exposition much easier.

Consider an earnings process $X(t)$, which is as follows:

$$dX = \mu dt + \sigma_X dW_X, \qquad (1)$$

where $u(t)$ is the expected earnings growth rate at time t and is unobservable, σ_X is the volatility of the earnings growth rate and assumed to be a constant, and $W_X(t)$ is a standard Brownian motion. Moreover, the expected earnings growth rate $\mu(t)$ is time-varying and evolves as follows:

$$d\mu = \kappa(\overline{\mu} - \mu)dt + \sigma_\mu dW_\mu, \qquad (2)$$

where σ_μ is the volatility of the expected earnings growth rate and assumed to be a constant, κ is the

mean-reverting speed parameter, $\bar{\mu}$ is the long-run mean of the expected growth rate, and $W_\mu(t)$ is a standard Brownian motion, correlated with $W_X(t)$.

The consideration of a mean-reverting expected earnings growth rate in equation (2) captures the notion that in the real world, the expected earnings growth rate of a firm is not a constant but time-varying and related to business cycles (see Kandel and Stambaugh, 1990). Previous authors such as Wang (1993) and Veronesi (2000) also model the expected growth rate of dividends as a mean-reverting process, as we do here.

While analysts cannot observe $\mu(t)$, they are assumed to have a private signal as follows:

$$dI = \mu dt + \sigma_I dW_I, \tag{3}$$

where σ_I is the volatility of this signal and assumed to be a constant, and $W_I(t)$ is a standard Brownian motion, which, for simplicity, is assumed to be independent of other Brownian motions. While a general correlation structure among Brownian motions can be considered, it will introduce more parameters to be estimated but yield similar results.

The volatility σ_I determines the precision of information or the signal. When σ_I is large, information is relatively noisy; when σ_I is small, information is relatively precise. At one extreme, when $\sigma_I = 0$, investors have perfect information about expected earnings growth rates. At the other extreme, when $\sigma_I \to \infty$, the signal conveys no information and analysts use just historical earnings data to learn about expected earnings growth rates.

In this paper, the signal about the expected earnings growth rate is equal to the fundamentals plus a noisy term. Thus, this modeling approach is similar to that in Veronesi (2000) and Wang (1994).

Since analysts cannot observe the expected earnings growth rate, to forecast future earnings, they have to estimate the value of $\mu(t)$ from information $I(t)$, and the observation of $X(t)$. As shown in Liptser and Shiryayev (1978), the conditional distribution of $\mu(t)$ based on analysts's information $F_t = \{X(s); I(s); s \le t\}$ at time t is also normal, and the mean $m(t)$ of this conditional distribution evolves according to the following distribusion process, which is derived in the Appendix. The result is summarized in the following lemma.

Lemma 1. Let $m(t) = E[\mu(t)/F_t]$ be the estimate of the expected earnings growth rate. Then $m(t)$ satisfies the following stochastic differential equation:

$$dm(t) = \kappa(\bar{m} - m)dt + a_1 d\tilde{W}_I + a_2 d\tilde{W}_X, \tag{4}$$

$$d\tilde{W}_X = \frac{1}{\sigma_X}[dX(t) - mdt], \quad d\tilde{W}_I = \frac{1}{\sigma_I}[dI - mdt],$$

where a_1 and a_2 are constants, defined in the Appendix. The innovation processes $\tilde{w}_I$ and $\tilde{w}_X$ are standard Brownian motions with respect to $F_t \equiv z^{X,I}(t)$. In fact, the information structure generated by $F^{\bar{W}}(t)$ is equivalent to that generated by $F^{X,I}(t)$, where $\tilde{W} = [\tilde{W}_I, \ \tilde{W}_X]^T$.

In equation (4), the estimate of the expected earnings growth rate follows a mean-reverting two-dimension process with a constant volatility. Two uncorrelated Brownian motions, $d\tilde{W}_X$ and $d\tilde{W}_I$, are, respectively, the normalized innovation processes of the earnings and signal realizations. These two stochastic components convey new information about surprises in earnings and signals. For example, when there is an unexpected high signal $d\tilde{W}_I > 0$, the analyst increases the expectation of $\mu(t)$.

When the estimate of the expected earnings growth rate at time t is $m(t)$, the earnings are evolving as follows:

$$dX = mdt + \sigma_X d\tilde{W}_X. \tag{5}$$

Also, equation (4) can be simplified as:

$$dm(t) = \kappa(\bar{\mu} - m)dt + \sigma_m d\tilde{W}_m, \tag{6}$$

where $\sigma_m = \sqrt{a_1^2 + a_2^2}$, $\bar{\mu} = \bar{m}$ and $\tilde{W}_m(t)$ is a standard Brownian motion.

Now analysts can use the estimate of $m(t)$ at time t to forecast future earnings $X(s)$, $s > t$. Let $UFS(s) = E[X(s) \mid F_t]$, $s > t$, the unbiased earnings forecast at time t. Then the following lemma summarizes the relationship between the unbiased analyst forecast of future earnings $X(s)$, $UFS(s)$, $s > t$, and the estimate of the expected earnings growth rate, $m(t)$.

Lemma 2. Let $UFS(s) = E[X(s) \mid Ft]$ be the unbiased forecast of earnings $D(s)$, $s > t$. Then, we have

$$UFS(s) = X(t) + \bar{\mu}(s-t) + \frac{(m(t) - \bar{\mu})}{\kappa}(1 - e^{-\kappa(s-t)}),$$

where $\bar{\mu}$ is the long-run mean of the expected earnings growth rate.

Clearly, analysts use more than historical earnings data to forecast future earnings, since $m(t)$ in $UFS(s)$ is the estimation of the unobservable expected growth rate of earnings conditional on the analysts' information set, which includes historical earnings data and non-public firm information. This helps understand why analyst earnings forecasts are more accurate than the earnings forecasts that are based only on past earnings data (see, for example, Brown, Foster and Noreen, 1985).

In Lemma 2, to forecast future earnings, analysts have to use their information to learn about the value of the current expected earnings growth rate. To use discrete-time data of analyst earnings forecasts to estimate the precision of information, we first derive the discrete-time versions of equations (5) and (6) as follows:

$$X(t) = X(t-1) + a_1 + \phi_1 m(t-1) + \varepsilon_X(t) \ , \qquad (7)$$

$$m(t) = \alpha_2 + \phi_2 m(t-1) + \varepsilon_m(t), \qquad (8)$$

where

$$\alpha_1 = \mu\left(1 - \frac{1-e^{-\kappa}}{k}\right), \quad \alpha_2 = \overline{\mu}(1 - e^{-\kappa}),$$

$$\sigma_1^2 = Var[\varepsilon_X(t)] = \sigma_X^2 + \frac{\sigma_m^2}{\kappa^2}[1 - 2\beta(1) + \beta(2)] + \frac{2\sigma_{mX}}{\kappa}[1 - \beta(1)], \qquad (9)$$

$$\sigma_2^2 = Var[\varepsilon_X(t)] = \sigma_m^2 \beta(2), \qquad (10)$$

$$\sigma_{12} = Cov[\varepsilon_X(t), \ \varepsilon_m(t)] = \beta(1)\sigma_{mX} + \frac{\sigma_m^2}{\kappa}[\beta(1) - \beta(2)]. \qquad (11)$$

Lemma 4. Let v be the estimation error in the steady state, as defined in the Appendix. Then we have:

$$\sigma_{mX} = \sigma_{\mu X} + v, \qquad (12)$$

$$\sigma_m^2 = \frac{v^2}{\sigma_I^2} + \frac{(v + \sigma_{\mu|X})^2}{\sigma_X^2}, \qquad (13)$$

where estimation error v is a function of σ_X, σ_μ, κ, $\rho_{X\mu}$ and σ_I.

Let ρ_{12} be the correlation between $\varepsilon_X(t)$ and $\varepsilon_m(t)$. Using equations (9) to (13), we can have σ_1, σ_2 and

$$\Lambda = \left(\frac{X(t) - \overline{X}(t)}{\sigma_1}\right) - 2\rho_{12}\frac{X(t) - \overline{X}(t)}{\sigma_1}\frac{m(t) - \overline{m}(t)}{\sigma_2} + \left(\frac{m(t) - \overline{m}(t)}{\sigma_1}\right)^2,$$

$$\overline{X}(t) = X(t-1) + \alpha_1 + \varphi_1 m(t-1),$$

and

$$\overline{m}(t) = \alpha_2 + \varphi_2 m(t-1).$$

Thus, if we have time-series data about $X(t)$ and $m(t)$ for a firm, we can maximize the natural log of the likelihood function defined in (14) to estimate σ_X, σ_μ, κ, $\rho_{X\mu}$, $\overline{\mu}$ and σ_I. In section 4, we discuss how to use analyst forecast data from I/B/E/S to calculate $X(t)$ and $m(t)$.

Next we examine several variables of interest that may affect the precision of information.

2. What determines the precision of information?

In this section, we briefly discuss several variables of interest that may affect the precision of information

$$\varphi_1 = \frac{1-e^{-\kappa}}{k}, \quad \varphi_2 = e^{-\kappa},$$

$$\varepsilon_X(t) = \int_{t-1}^{t} \sigma_X d\tilde{W}_X(\tau) + \frac{\sigma_m}{\kappa}\int_{t-1}^{t}(1 - e^{-\kappa(t-\tau)})d\tilde{W}_m(\tau),$$

$$\varepsilon_X(t) = \sigma_m \int_{t-1}^{t}(e^{-\kappa(t-\tau)})d\tilde{W}_m(\tau).$$

Lemma 3. Let $\varepsilon_X(t)$ and $\varepsilon_m(t)$ be defined as above. Let σ_1 and σ_2 be the standard deviations of $\varepsilon_X(t)$ and $\varepsilon_m(t)$, respectively. *Let* $\sigma_{12} = \rho_{12}\sigma_1\sigma_2$ be the covariance of these two random variables. Define $\beta(i) = (1 - e^{-i\kappa}) / (i\kappa)$. Then $\varepsilon_X(t)$ and $\varepsilon_m(t)$ are both normal, with the following moments:

$$E[\varepsilon m(t)] = E[\varepsilon_X(t)] = 0,$$

σ_{12} expressed them as functions of σ_X, σ_μ, κ, $\rho_{X\mu}$, $\overline{\mu}$ and σ_I. Then, using equations (7) and (8), we have the likelihood function as follows:

$$L(\sigma_X, \sigma_\mu, \kappa, \rho_{X\mu}, \overline{\mu}, \sigma_I) = \prod_{t=1}^{n} f(\sigma_1, \sigma_2, \rho_{12})\exp(Q(t)), \quad (14)$$

$$f(\sigma_1, \sigma_2, \rho_{12}) = (2\pi\sigma_1\sigma_2\sqrt{1 - \rho_{12}^2})^{-1},$$

$$Q(t) = -\frac{1}{2(1-\rho_{12}^2)}\Lambda,$$

where

that investors receive from analyst forecasts. Subsection 2.1 discusses the variables that are related to firm characteristics and subsection 2.2 studies the variables that are linked to analyst characteristics.

2.1. Firm characteristics. *2.1.1 The number of analysts studying a firm.* The precision of information is expected to be positively associated with how much effort taken by analysts to obtain precise information. In the financial market, the number of analysts, as suggested by Hong and Stein (1999), Bhushan (1989) and Collins, Kothari and Rayburn (1987), measures the amount of effort taken by analysts to acquire precise information about the expected earnings growth rate of a firm. Thus, when a firm has more analysts to follow it, information about the expected earnings growth rate tends to be more precise.

2.1.2. Earnings growth volatility. The precision of information is also expected to be related to how risky a firm's earnings growth is. The more risky earnings growth, the more difficult to obtain precise information about the expected earnings growth rate. So, in this paper, we use earnings growth volatility to capture this idea and test whether this variable is empirically associated with the precision of information.

2.2. Analyst characteristics. *2.2.1. Analysts' ability and skill.* While we cannot observe analysts' ability and skill, we may use some indicators of analysts' ability and skill to investigate whether the precision of information is correlated with analysts' ability and skill. We use two kinds of indicators to surrogate analysts' ability and skill. The first indicator is analysts' working experience. Since the analyst labor market can be considered a tournament in which strong analysts remain and the weak are forced out of the profession, it is expected that an analyst with a long working experience may have a better ability and skill to obtain more precise information about the expected earnings growth rate of a firm. The second indicator of analysts' ability and skill is the size of a brokerage firm in which analysts work. Since large brokerage firms have better financial resources to compensate for their analysts, they can hire analysts with a better ability and skill. Thus, it is expected that the more analysts coming from large brokerage firms, the more precise the information is. We use the number of the analysts employed by a brokerage firm to denote the size of the brokerage firm.

2.2.2. Resources available for analysts. Analysts working in large brokerage firms may obtain more precise information about the expected earnings growth rate, since they have access to better databases and superior resources to gain managers' private information about future earnings growth rates (Clement, 1999). We also use the number of the analysts employed by a brokerage firm to denote the resources available for analysts.

3. Data and sample selection

In this section, we discuss how to use actual quarterly earnings and analyst forecasts of quarterly earnings reported in I/B/E/S to calculate $X(t)$ and $m(t)$, which are defined in equations (7) and (8), respectively.

Previous studies have shown that analyst earnings forecasts are biased. Following Das, Levine and Sivaramakrishnan (1998), we estimate the bias in analyst earnings forecasts for a firm as follows:

$$Bias = \frac{\sum_{t=1}^{T}(FST(t)-ESP(t))}{T}, \tag{15}$$

where $FST(t)$ is the forecast of the earnings at quarter t, $ESP(t)$ is the actual earnings at quarter t, and T is the total number of quarters in the historical earnings data.

From equation (15), the unbiased forecast of the earnings at quarter t, $UFS(t)$, is $FST(t) - Bias$.

According to equation (7), $X(t)$ is the actual quarterly earnings at quarter t. That is,

$$X(t) = ESP(t).$$

The estimate of the expected quarterly earnings growth rate, $m(t)$ at quarter t, according to Lemma 2, is:

$$m(t) = (UFS(t+1) - ESP(t) - \overline{\mu})\left(\frac{\kappa}{1-e^{-\kappa}}\right) + \overline{\mu},$$

where $ESP(t)$ is the actual earnings at quarter t, $UFS(t+1)$ is the unbiased forecast of the earnings per share at quarter $(t + 1)$, $\overline{\mu}$ and κ are two of the six parameters to be estimated.

We use the I/B/E/S summary file to obtain the consensus forecasts of quarterly earnings and the number of analysts studying a firm at each quarter. Specifically, in the summary file, in each month of a quarter, there is a concensus forecast of the earnings in that quarter. In this paper, $FST(t)$ in equation (15) is the mean of the three monthly forecasts of the earnings at quarter t. Actual quarterly earnings data are extracted from I/B/E/S actual files. The sample starts from the last quarter of 1985 and ends in the last quarter of 2008.

4. Empirical results

4.1. Descriptive univariate statistics. To estimate the volatility of the signal, σ_I, we maximize the natural logarithm of the likelihood function defined in equation (14). Since there is no closed-form solution, we use Nelder and Mead's (1965) optimization approach to estimate σ_I, whose initial value is set at 15% for each firm. The estimation exercise shows that the mean and standard deviation of $\hat{\sigma}_I$ are about 16% and 20%, respectively. The relatively noisy signal for the expected earnings growth rate can has a volatility of more than 300%, but the relatively precise signal about the expected earnings growth rate of a firm has a volatility of less than 1%. Thus the precision of information about unobservable expected earnings growth rates varies from firm to firm.

$\hat{\sigma}_I$ is the estimate of the precision of information about the expected earnings growth rate of each share. Since the level of earnings may be related to the precision of information, to control for the impact of the level of earnings, we define a variable $SVOL =$

$\ln(\hat{\sigma}_I/EPS)$, where Ln indicates the natural logarithm and *EPS* is the average earnings per share. Thus, *SVOL* measures the precision of information about the expected growth rate of each dollar of earnings. Panel A of Table 1 reports the statistics for all the variables of interest in our model.

Panel B of Table 1 shows the Pearson correlation coefficients of the regression variables. Note that a large value of *SVOL* means a low precision of information. As shown there, the precision of information is negatively correlated with earnings growth volatility. This variable denotes how difficult it is to obtain precise information about the expected earnings growth rate of a firm. As expected, the precision of information is positively correlated with the number of the analysts studying a firm and the size of the brokerage firm. The former surrogates the amount of effort taken by analysts to obtain precise information about expected earnings growth rates; the latter represents analysts' skill, ability and accessible resources to obtain information. While the precision of information is positively correlated with analysts' experience, this correlation is not significant. Working experience may not be related to the precision of information, since it does not automatically imply a better ability and skill of analysts to acquire precise information.

Panel A in Table 1 also shows the distribution of the regression variables. Since the means of these variables are different from the medians, they are generally skewed.

The univariate statistics in Table 1 provide us with a basic picture about the relation between information precision and each individual variable of interest. In the following, we consider all the variables of interest in the following regression to test how the precision of information is affected by these variables.

4.2. Results from regression analysis. Table 2 reports the regression results on how firm and analyst characteristic variables affect the precision of information about the expected earnings growth rate of a firm.

The regression equation is as follows:

$$SVOL = \beta_0 + \beta_1 EVOL + \beta_2 ACS + \beta_4 EXP + \beta_5 NUM + \varepsilon,$$

where all the variables are defined in Table 2 and the firm index is suppressed.

As expected, the coefficient for earnings growth volatility, denoted by *EVOL*, is positive and significant. This empirical finding confirms our intuition that it is difficult for analysts to obtain very precise information about the expected earnings growth rate of a firm if the firm's earnings growth process is very volatile. The coefficient for the number of analysts following a firm is negative and significant. This empirical result is expected, since the number of analysts following a firm approximates the amount of effort taken by analysts to obtain precise information about the expected earnings growth rate. The more effort taken by analysts, the more precise the information is.

The coefficient for the brokerage firm size variable, denoted by ACS, is negative and also significant at the 1% level. This empirical finding has two implications. First, if brokerage firm size is a good surrogate of the resources available for analysts to obtain precise information, the empirical finding implies that the more resources are available for analysts, the more precise information they are likely to obtain. Since large brokerage firms provide analysts with more resources to access managers' private information about future earnings growth rates, the analysts from large brokerage firms are more likely to obtain precise information. Second, if brokerage firm size represents analysts' ability and skill to obtain precise information, the finding implies that the analysts who have a better skill or a higher ability are likely to obtain more precise information about expected earnings growth rates for the firms they follow. Since large brokerage firms have better financial resources to compensate for their analysts and thus can hire analysts with better skills and higher ability than small brokerage firms, the analysts from large brokerage firms are more likely to provide very precise information to investors. Regardless of what implication is more likely, this empirical result provides a possible explanation of Stickel's (1992 and 1995) finding that investors tend to respond more to the recommendations of large broker analysts. Investors may respond more to the recommendations of these analysts, because large broker analysts have more precise information about expected earnings growth rates of the firms they follow.

However, the coefficient for the analyst working experience variable (EXP), as expected, is negative, but not significant. This result indicates that the number of working years as an analyst is not significantly correlated with information precision. This may be true, because long working experience does not automatically imply a better skill and higher ability of analysts for acquiring precise information. Rather, the size of a brokerage firm where analysts work can be a better indicator of analysts' skill and ability, as shown above.

Conclusions

In this paper, we present a stochastic model of earnings to study and estimate the precision of information that investors receive from analysts earnings forecasts. In addition, we examine whether firm and analyst characteristics, such as earnings growth volatility, the number of analysts following a firm and analysts's experience, ability, skills and accessible resources for obtaining information, affect information precision. The firm and analyst characteristics variables are jointly analyzed since they are likely to be correlated. We use a cross-sectional analysis since our objective is to find out the cross-sectional differences in information precision.

Information precision is found to decrease with earnings growth volatility and increase with the number of the analysts following a firm, analysts' ability, skill and assessable resources used in obtaining precise information. One important implication of our empirical results is that analysts from large brokerage firms tend to provide investors with more precise information about future earnings growth rates. Thus, our study provides a possible explanation of the finding in the financial market that investors tend to respond more to the recommendations of large broker analysts.

While the paper has examined how to measure the precision of noisy information that investors receive from analysts forecasts, it has not addressed the important question of whether the precision of information has a significant impact on asset prices empirically. So the future research in this direction is to empirically examine the impact of information quality on asset prices.

Table 1. Discriptive statistics and Pearson correlation coefficients

Panel A: Descriptive statistics for dependent and independent variables (sample size: 319)					
	SVOL	EVOL	ACS	EXP	NUM
Mean	-0.34	-1.90	5.60	1.56	2.04
Median	-0.43	-1.87	6.01	1.58	1.98
SD	0.80	1.02	0.92	0.20	0.48
Minimum	-3.34	-5.26	2.77	0.91	0.30
Maximum	5.60	0.70	6.48	2.15	3.01
Panel B: Pearson correlation coefficients among variables (sample size: 319)					
	SVOL	EVOL	ACS	EXP	NUM
SVOL	1.000				
EVOL	0.158**	1.000			
ACS	-0.143**	0.187**	1.000		
EXP	-0.030	0.053	-0.036	1.000	
NUM	-0.116*	-0.097*	0.013	0.194**	1.000

Notes: $SVOL$ = Ln (growth signal volatility for each dollar of earnings), Ln means the natural logarithm. $EVOL$ = Ln (standard deviation of the earnings growth rate). EXP = Ln (the average number of working years for the analysts reporting the firm). NUM = Ln (the number of the analysts reporting the firm). ACS = Ln (the average number of the analysts employed by brokerage firms). Significance: ** < 0.01; * < 0.05.

Table 2. Information precision and firm and analyst characteristics (sample size: 319)

$$SVOL = \beta_0 + \beta_1 EVOL + \beta_3 ACS + \beta_4 EXP + \beta_5 NUM + \varepsilon$$

	EVOL	ACS	EXP	NUM	Adj.R^2
Predicted signs	+	–	–	–	–
Estimated coefficient	0.144	-0.154	-0.120	-0.145	6%
t-value	3.41**	-3.30**	-0.58	-1.65*	

Notes: $SVOL$ = Ln (growth signal volatility for each dollar of earnings), Ln means the natural logarithm. $EVOL$ = Ln (standard deviation of the earnings growth rate). EXP = Ln (the average number of working years for the analysts reporting the firm). NUM = Ln (the number of the analysts reporting the firm). ACS = Ln (the average number of the analysts employed by brokerage firms). Significance: ** < 0.01, * < 0.05.

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Appendix. Proofs of the results in the paper

Proof of lemma 1. We use Theorem 12.1 in Liptser and Shiryayev (1977) to show Lemma 1. Under the similar notation, we rewrite our problem as follows:

$$ds = \begin{pmatrix} dI \\ dX \end{pmatrix} = [a_{s0} + a_{s1}\mu]dt + \begin{pmatrix} \sigma_I & 0 \\ 0 & \sigma_X \end{pmatrix}\begin{pmatrix} dW_I \\ dW_X \end{pmatrix},$$

$$d\mu = [a_{\mu0} + a_{\mu1}\mu]dt + \sigma_\mu dW_\mu,$$

where ds is a 2×1 vector signal, which is used by investors to estimate $\mu(t)$, the state variable. Other parameters are as follows:

$$a_{s0} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad a_{s1} = \begin{bmatrix} 1 \\ 1 \end{bmatrix},$$

$$a_{\mu0} = \kappa\bar{\mu}, \quad a_{\mu1} = -\kappa,$$

$$q_{ss} = \begin{bmatrix} \sigma_X^2 & 0 \\ 0 & \sigma_I^2 \end{bmatrix}, \quad q_{\mu\mu} = \sigma_\mu^2, \quad q_{\mu s} = [0 \quad \sigma_{\mu X}],$$

where $\sigma_{\mu X}$ denotes the covariance between $\mu(t)$ and $X(t)$. Let $F_t = \{s(\tau) : \tau \le t\}$ be the information set with respect to the observable process $s(t)$. Suppose that the prior is $\mu(0) \sim N(m(0); v(0))$. Then, according to Liptser and Shiryayev (1977), the posterior mean of $\mu(t)$; $m(t) = E[\mu \mid F_t]$; and the posterior variance of $\mu(t)$; $v(t) \equiv E[(m - \mu)(m - \mu)^T \mid F_t]$, are given, respectively, by the following stochastic differential equations:

$$dm(t) = (a_{\mu0} + a_{\mu1}m(t))dt + (v(t)a_{s1}^T + q_{\mu s})q_{ss}^{-1}d\tilde{W}_s, \tag{A1}$$

$$\frac{dv(t)}{dt} = -2\kappa v(t) + \sigma_\mu^2 - (v(t)a_{s1}^T + q_{\mu s})q_{ss}^{-1}(v(t)a_{s1}^T + q_{\mu s})^T. \tag{A2}$$

The earnings process then becomes

$$dX(t) = m(t)dt + \sigma_X d\tilde{W}_X.$$

The innovation process, $\tilde{W}_s(t) = [\tilde{W}_X, \tilde{W}_I]^T$, defined by $d\tilde{W}_s(t) = ds(t) - [a_{s0} + a_{s1m}]dt$ is a vector of Brownian motions.

The solution to the Ricatti equation in (A2) is given by:

$$v(t) = \frac{v_2 - v_1 \dfrac{v(0) - v_2}{v(0) - v_1} e^{-\bar{\omega}t}}{1 - \dfrac{v(0) - v_2}{v(0) - v_1} e^{-\bar{\omega}t}},$$

where $\overline{\omega} = \sqrt{b_2^2 - 4b_1 b_3}$, $\quad v_1 = \dfrac{-b_2 + \overline{\omega}}{2b_1}$ and $v_2 = \dfrac{-b_2 - \overline{\omega}}{2b_1}$,

$b = \sigma_I^2 \sigma_X^2$, $\quad b_1 = -(\sigma_X^2 + \sigma_I^2)/b$, and

$b_2 = -2\kappa - 2\sigma_{\mu X}\sigma_I^2/b$, $\quad b_3 = \sigma_\mu^2 - \sigma_{\mu X}\sigma_I^2/b$.

In this paper, we are interested only in the steady-state solution, where estimation errors do not change over time. We can assume that the economy starts at $-\infty$, and the convergence of learning to the steady state is guaranteed for any finite t, since $\overline{\omega} \geq 0$. When learning reaches the steady state, $dv(t)/dt = 0$. Let v be the solution to the Ricatti equation in the steady state. Then $v = v_2$.

In the steady state, we have

$$dm = \kappa(\overline{\mu} - m)dt + a_1 d\tilde{W}_I + a_2 d\tilde{W}_X, \tag{A3}$$

where

$$a_1 = \frac{v}{\sigma_I}, \quad a_2 = \frac{v + \sigma_{\mu X}}{\sigma_X}.$$

Equation (A3) can be simplified as:

$$dm = \kappa(\overline{\mu} - m)dt + \sigma_m d\tilde{W}_m, \tag{A4}$$

where $\tilde{W}_m$ is a standard Brownian motion and

$$\sigma_m = \sqrt{a_1^2 + a_2^2}.$$

Proof of Lemma 2. From equation (A4), we have:

$$m(s) = \overline{\mu} + e^{-\kappa(s-t)}(m(t) - \overline{\mu}) + \int_t^s e^{-\kappa(s-\tau)}\sigma_m d\tilde{W}_m(\tau), \text{ where } s > t.$$

Also, $X(s) = X(t) + \int_t^s m(\tau)d\tau + \int_t^s \sigma_X d\tilde{W}_X(\tau)$.

Then straight calculation leads to the result.

Proof of Lemma 3. According to the normal property of a Brownian motion, straight calculations lead to the result.

Proof of Lemma 4. $\sigma_{mX} = cov(dm; dX) = a_2 \sigma_X = \sigma_{\mu X} + v$.