Analysts’ Incentive and Dispersion Effect

Chuan-Yang Hwang

e-mail:cyhwang@ntu.edu.sg
Division of Banking and Finance
Nanyang Business School
Nanyang Technological University
Singapore 639798

Yuan Li

 e-mail:liyu0002@ntu.edu.sg
Division of Banking and Finance
Nanyang Business School
Nanyang Technological University
Singapore 639798

August 2008
Analysts’ Incentive and Dispersion Effect

Abstract
In this paper, we explain the negative relationship between analysts’ forecast dispersion and future stock return, commonly known as the dispersion effect, as a result of analysts’ incentive of not fully downward revising their earnings forecasts when they possess bad news about the firms they cover. Unlike previous literature, we argue that there is no causality between dispersion and future return; we instead argue that the negative relationship between them arises from the fact that they are both affected by analysts’ incentive. Consistent with this conjecture, we find (1) that analysts’ incentive simultaneously increases dispersion and induces an upward bias in reported consensus forecasts, (2) that the dispersion effect only exists among firms with bad future earnings, (3) that the dispersion effect disappears once we control for the incentive-induced upward bias in the reported consensus forecast, and (4) that the dispersion effect is stronger among firms with low information uncertainty. The last two findings offer support unique to our analysts’ incentive based explanation of the dispersion effect.

JEL Classification: G14

Keywords: Analysts’ incentive; Dispersion effect
1. INTRODUCTION
Diether, Malloy and Scherbina (2002) (henceforth DMS) document a negative cross-sectional relationship between dispersion in analysts’ earnings forecasts and future stock returns (henceforth dispersion effect) which cannot be explained by standard asset pricing models such as CAPM, or the Fama and French (1983) model. To explain the dispersion effect, DMS appealed to the idea by Miller (1977) that prices reflect a more optimistic valuation if pessimistic investors are kept out of the market due to short-sale constraints. Firms with more diverse investor opinions, such as those with high dispersion in analysts’ forecasts, are more likely to generate lower returns as there would be a larger upward bias in the stock prices when the opinions of the more pessimistic investors have been censored. DMS also interpret their results as a rejection of the notion that dispersion in forecasts can be viewed as a proxy for information risk. However, treating dispersion in forecasts as a proxy for unpriced information risk, Johnson (2004) shows that the dispersion effect can be consistent with a rational asset pricing model in which the expected return of stocks would decrease with idiosyncratic asset risk in the presence of leverage. Viewing dispersion as a proxy for both analyst disagreement and information asymmetry, Sadka and Scherbina (2007) suggest the following: that the dispersion effect is a result of pricing error, it is especially prominent among illiquid stocks, and that it can be persistent through time.

A common theme in these papers is that dispersion is exogeneous and can be viewed as a measure of information uncertainty [Johnson (2004), Sadka and Scherbin (2007)] or as a measure of difference of opinion [DMS, Sadka and Scherbina (2007)], and that high dispersion causes a low future return. In this paper, we offer an alternative explanation of the dispersion effect: there is no causality between dispersion and future return; instead they are linked through analysts’ incentive. This is because analysts’ incentive of not fully downward revising their forecasts when they possess bad news would simultaneously increase forecast dispersion and induce an upward bias in consensus forecasts and stock prices.

It has long been suggested that the incentive structure of analysts can distort their earnings forecasts. Analysts have incentives to issue optimistic views when they face pressure to help their brokerage firms procure investment banking business [Dugar et al. (1995) and Lin and McNichols (1998)], generate trading volume [Cowen et al. (2006)], or to obtain access to managers’ inside information [Lim (2001)]. These incentives are more pervasive across firms
that have bad yet publicly unknown information. While non-incentive-driven analysts revise their forecasts downward promptly to pursue accurate forecasts, incentive-driven analysts retain their previous forecasts as they do not wish to be the first runner to bring bad news to the public. This sluggish reaction of incentive-driven analysts results in a dispersion increase for firms with bad news. Another consequence of analysts’ incentive is that consensus forecasts would be upward-biased as they do not reflect the full extent of the bad news known to analysts. If investors utilize consensus forecasts to make their investment choices, the upward-biased consensus forecast would lead to stocks being overpriced as well as a lower future return. The main idea in our paper can be illustrated with a simple example. A firm covered by three analysts who have respectively made the following forecasts about the earning of next year: $2, $2.5 and $3 per share, is hit with a piece of bad news which would amount to a reduction of earning by $0.5 per share. If no analysts are affected by incentive upon learning this news, they will all downward revise their forecasts by $0.5 per share to $1.5, $2 and $2.5 respectively. In this case, the consensus forecast would be downward revised from $2.5 to $2 per share and the dispersion remains unchanged. On the other hand, if the analyst who has made the highest forecast (other things being constant, she is the one most likely to be affected by incentive) decides to maintain her previous forecast, the new forecasts would become $1.5, $2 and $3. In this case, dispersion increases and the consensus forecast is biased upward by $0.5/3, resulting in a negative relationship between dispersion and future return, now known as the dispersion effect. Note that even if the incentive-driven analyst downward revises her forecast, as long as the revision is less than the bad news entails, the dispersion effect ensues. This simple example brings out the essence of our thesis that there is no causality between dispersion and return, and that the negative relationship between the two arises from the fact that they are affected by a common source—analysts’ incentive.

Consistent with the testable hypotheses we develop from this thesis, we find (1) that the dispersion increases with analysts’ incentive, (2) that the dispersion effect exists only among firms facing future bad news, (3) that the dispersion effect disappears once we control for the upward bias in consensus forecast induced by analysts’ incentive, and (4) that stronger analysts’ incentive and stronger dispersion effect can be found among firms with lower information uncertainty. The last two findings are new in the literature and offer unique support to our thesis.
We are not alone in recognizing the effect that analysts’ incentive might have on stock
gains. Although DMS mainly relies on short sale constraints emphasized in the Miller (1977)
model to explain the dispersion effect, they also suggest that the incentive structure of analysts
can be viewed as an alternative mechanism to short-sale constraints in suppressing negative
information. Scherbina (2007) presents evidence showing that stock prices do not immediately
reflect the negative information embedded in reduced analyst coverage, which suggests that
when setting prices, investors do not, or cannot, take into account the upward bias in the
consensus forecast induced by analysts’ incentive to withhold unfavorable information. This
forms the basis of our, and DMS’s argument that analysts’ incentive can affect stock returns.
However, our paper differs from DMS and Scherbina (2007) in one important aspect. In our
hypothesis, incentive affects both dispersion and future returns, but there is no causality running
from dispersion to future return. In contrast, dispersion in DMS and Scherbina (2007) is thought
to be exogenous rather than affected by incentives, and is thought to be able to cause lower
future returns since it would enhance the upward bias in stock prices induced by incentives.

Neither are we alone in arguing that dispersion can be affected by incentives. In an
independent paper from ours, Erturk (2006) also proposes that analysts’ sluggishness to
downward revise their forecasts increases forecast dispersion. Erturk (2006) does not provide
direct evidence for his conjecture; he only shows that firms with bad news will have higher
forecast dispersion levels and greater dispersion change, which is also consistent with the
managerial incentive hypothesis proposed by Liu, Xu and Yao (2004). They argue that managers
of bad news firms have incentive to hide bad news by reducing disclosure or by purposely
making more opaque news announcements, which results in greater information uncertainty and
high dispersion in analysts’ forecasts. Our paper differs from Ertuck (2006) and Liu, Xu and Yao
(2004) in three aspects. First, we provide direct evidence showing that analysts’ incentive
heightens dispersion. Second, we estimate the upward bias induced by analysts’ incentive in
consensus forecasts. Third, we offer evidence of analysts’ incentive rather than managerial
incentive being more responsible for the dispersion effect by showing that the dispersion effect
vanishes once we control for the analysts’ incentive-induced bias we estimate.

Recently, Avramov et al. (2008) postulated that the dispersion effect is a result of
financial distress, signified by credit rating downgrades. Focusing on firms rated by S&P, they
find that the dispersion effect concentrates on the worst rated stocks and only exists during
periods of deteriorating credit conditions in which the lowest rated stocks experience a large price drop and a large increase in forecast dispersion. Avaramov et al. (2008) did not offer a specific explanation for these results other than that they are related to financial distress. However, their results are consistent with our hypothesis since deteriorating credit conditions or financial distress can be considered extremely bad news, and that analysts’ incentive, and therefore the dispersion effect, would be strongest in such firms and periods.

In addition to providing an alternative explanation of the dispersion effect that does not view dispersion as an exogenous proxy for difference of opinion or information uncertainty, our paper also contributes to the literature in two other aspects. First, we show that dispersion is affected by analysts’ incentive. This validates the concern raised by Johnson (2004) that dispersion in analysts’ forecast may not be a good proxy for measuring difference of opinion or information uncertainty [cf. DMS, Sadka and Scherbina (2007)] since it is contaminated by analysts’ incentive. Second, we uncover a surprising new finding that the dispersion effect is stronger among firms with lower information uncertainty – contrary to implications from the most prominent explanations of the dispersion effect – which can serve as a useful stylized fact for future works in this area.

The layout of the paper is as follows. In the next section, we develop four testable hypotheses. Section 3 describes our data and sample characteristics. Section 4 tests the hypotheses. Section 5 contains the robustness check of our results. Section 6 summarizes and concludes.

2. HYPOTHESES DEVELOPMENT

Analysts interpret public information and collect new information. They spend enormous amounts of time and money analyzing firms’ financial statements and searching for private information. It is reasonable to assume that an analyst’s opinion of a firm’s value is more correct and timely than those of general investors, especially than those of individual investors. Therefore investors will rely on analysts’ issued forecasts to make their investments. However, are forecasts observed by investors always the analysts’ true beliefs about a given firm? Because of their compensation structure, analysts have incentives to issue relatively optimistic opinions. Accounting literature offers a large amount of empirical evidence supporting the existence of
analysts’ incentives. For example, Dugar et al. (1995) document that the forecasts and recommendations of investment banking analysts are optimistic relative to non-investment banking analysts; Lin and McNichols (1998) provide evidence that affiliated analysts’ recommendations are more favorable than those of unaffiliated analysts; Lin and McNichols (2005) offer further evidence that affiliated analysts are more reluctant to downgrade their recommendations; Lim (2001) proposes that analysts trade off forecast bias to get access to managers’ inside information; Cowen, Groysberg and Healy (2006) find that the incentive to generate trading volume causes retail brokerage analysts to issue optimistic forecasts.

One manifestation of analysts’ incentive when they receive publicly unknown bad information is their reluctance to downward revise their forecasts, since they do not want to be the first to bring bad news to the public. Incentive-free analysts release all bad information by fully downward adjusting their forecasts, while incentive-driven analysts either do not, or only partially downward revise their forecasts. Furthermore, incentive-driven analysts are also more likely to have previously made relatively favorable forecasts. Consequently, two things happen: (1) bad information known by analysts is not fully reflected in their forecasts and (2) forecast dispersion increases as our simple example demonstrated earlier.

The intensity of analysts’ incentive and its influence vary across firms. Analysts of firms whose managers are the main source of information may have stronger incentives to refrain from downward revising forecasts in order to cultivate their relationship with the management [Lim (2001)]. Similarly, analysts of firms intending to conduct security issuance or M&A in the near future have stronger incentives to retain their forecasts in order to win the underwriting business from these firms, even if they know that the prospects of the firms they cover are poor [Dugar et al. (1995)]. If analysts’ incentive indeed increases dispersion as we postulate, then the cross-sectional difference in analysts’ incentive would lead to a cross-sectional difference in the change in dispersion, which would in turn lead to a higher level of dispersion in general. This implies that among bad news firms, those with high levels of dispersion are likely to be the ones that experience strong analysts’ incentive and a large increase in dispersion. Furthermore, since greater analysts’ incentive of withholding bad information results in a greater upward bias in the consensus forecast, we also expect the upward bias in the consensus forecast to increase with level of dispersion.
Note that the same logic does not apply to firms with good news. When analysts receive publicly unknown good information, they revise their forecasts upward promptly; thus, high dispersion firms with good news are not expected to have lower future returns. This asymmetry of incentives between good news and bad news firms forms the basis of the following two hypotheses.

**Hypothesis 1:** The dispersion effect exists only among bad news firms.

**Hypothesis 2:** Analysts’ incentive, change in dispersion, and upward bias in consensus forecasts would increase with level of dispersion among bad news firms.

As previously emphasized, what distinguishes our thesis from other explanations of the dispersion effect is that there is no causality between dispersion and future return. The negative relationship between dispersion and future return arises from the fact that analysts’ incentive causes high dispersion and low return at the same time. Since the direct cause of low future return is the incentive-induced bias in consensus forecasts, if we control for this bias, the indirect negative relationship between future return and dispersion should be subsumed (or greatly reduced) by its direct negative relationship with the upward bias in the consensus forecast. Thus, we have the following testable hypothesis that can offer unique support to our analysts’ incentive based explanation of the dispersion effect.

**Hypothesis 3:** After controlling for incentive-induced upward bias embedded in consensus earnings forecasts, the dispersion effect should greatly diminish if not vanish.

Previous literature often used forecast dispersion as a proxy of information uncertainty since analysts would have relatively more divergent beliefs when a firm’s information environment is more uncertain-- in such an environment, information is harder to get and is less precise. Indeed, DMS shows that forecast dispersion is strongly positively related to earnings variability and standard deviation of past stock returns, both of which are thought to be good measures of information uncertainty [Zhang (2006), Jiang et al. (2005) and Subrahmanyam et al.](#)
Since both information uncertainty and analysts’ incentive can contribute to high dispersion, high dispersion firms with low information uncertainty are more likely to be covered by incentive-driven analysts and thus exhibit a stronger dispersion effect. On the other hand, the high dispersion of firms with high information uncertainty less likely originates from analysts’ incentive, and dispersion effect should be less significant. This argument leads to the following hypothesis.

**Hypothesis 4:** Firms with low information uncertainty exhibit stronger dispersion effects as high forecast dispersion is more likely to be generated by analysts’ incentive.

### 3. DATA AND SAMPLE CHARACTERISTICS

Our main sample comes from three sources. Returns are drawn from the CRSP Monthly Stocks Combined File. Financial data are drawn from COMPUSTAT. Analyst forecast data are from IBES. The sample period is from Jan 1983 to Dec 2006.

We construct our sample as follows. We retrieve earnings forecasts with forecast period one and forecast period two (FPI=1 or FPI=2) from IBES Adjusted Detail History File. Earnings forecasts in this file appear on a split adjusted basis so that historical data can be compared with current data on the same basis. Forecasts are rounded to 4 decimals, therefore eliminating rounding issues arisen from using adjusted detail file (cf. DMS). Following DMS, we extend each forecast until its revision date. If a revision date precedes the actual forecast date, the forecast will be assumed valid only for the month in which it was made. If in any give month, there is more than one forecast for the same analyst and the same fiscal year, we use the latest forecast. To ensure that all forecasts are comparable with respect to the timeline, we require our sample firms to have December fiscal year ends.

We keep forecasts prevailing at the end of each quarter to implement our empirical tests. Since we restrict our sample to firms with December fiscal year ends, we keep the annual forecasts for fiscal year \( yr \) earnings prevailing in December of year \( yr - 1 \) and in March, June and September of year \( yr \). In order to study how analysts revise their forecasts each quarter \( t \), we
require that forecasts by the same analysts for the same fiscal year earnings are available in both quarter $t$ and quarter $t-1$. In other words, we require an analyst to have two non-missing successive forecasts. Furthermore, we also require firms to have at least three analysts each quarter whose forecasts satisfy the above requirements.

Return on assets ($Roa$) in this paper is measured as the quarterly earnings before extraordinary items (data 8) divided by total asset (data 44) at the end of the last quarter, obtained from COMPUSTAT Industrial Quarterly database. Assuming investors form expectations of $Roa$ of a particular quarter based on the $Roa$ of the same quarter of the previous year, then change in $Roa$ ($\Delta Roa$) of quarter $t$ from year $yr - 1$ to year $yr$ can be interpreted as the unexpected $Roa$ of quarter $t$ in year $yr$ which we use to proxy for the news or information possessed by analysts at quarter $t-1$ in year $yr$. Note that analysts’ forecasts at the end of the fourth quarter of year $yr$ should not be influenced by the firms’ earnings information of one quarter ahead, which is part of year $yr +1$ earnings. Therefore we only match analysts’ forecast dispersion change during first, second and third quarter to the earnings information of second, third and fourth quarter respectively.

We further scale $\Delta Roa$ by its standard deviation calculated with the data within the last eight years (with a minimum of four years of non-missing data). We define analysts as possessing good (bad) news when the scaled $\Delta Roa$ of the firms covered are above (below) the median in a particular quarter. To ensure that our results are not affected by microstructure-related issues, we exclude firms with prices below 5 dollars at the end of a portfolio-formation quarter. Our final sample has 58,122 firm-quarter observations.

Table 1 presents summary statistics of analysts’ forecasts. Dispersion is the standard deviation of forecasts scaled by the absolute value of the mean forecast. The dispersion change of quarter $t$ ($\Delta disp_t$) is calculated as the difference between the standard deviation of forecasts at the end of quarter $t$ and the standard deviation of forecasts at the end of quarter $t-1$, scaled by the absolute value of the mean forecast at the end of quarter $t-1$. All variables except for coverage are winsorized at the 1st and 99th percentiles. In our later tests, measures related to analyst forecasts are all winsorized at the 1st and 99th percentiles as well. We use two information uncertainty proxies: one from financial market, and one based on accounting variables. The first information uncertainty proxy is stock return volatility ($Rvol$), which is
calculated as the standard deviation of monthly stock returns over the past five years, ending at
the portfolio formation date (with a minimum of 24 non-missing return observations). The other
information uncertainty proxy is earnings volatility (Evol), which is measured as the standard
deviation of annual earnings over the past five years (with a minimum of 3 years’ non-missing
observations). To ensure that the information is known by investors at the time of portfolio
formation, we follow Fama and French (1992) by matching earnings information of fiscal year
\( t - 1 \) to the period between July of calendar year \( t \) and June of calendar year \( t + 1 \). Annual
earnings are measured as earnings before extraordinary item (data 18) divided by total asset (data
6) at the beginning of the fiscal year, which are drawn from COMPUSTAT Industrial Annual.
Panel B reports the correlation coefficients between these two information uncertainty proxies
and the forecast dispersion, which are all positively significant (p<0.0001). However, the
magnitude of the correlation between forecast dispersion and these two information uncertainty
proxies (0.240 and 0.186 respectively) is not as high as the correlation between these two
information uncertainty proxies themselves (0.546), which is consistent with our conjecture that
forecast dispersion may capture something more than information uncertainty – such as analysts’
incentives.

4. Hypotheses Testing

4.1 Asymmetry of the Dispersion Effect between Good News and Bad News Firms

Hypothesis 1 predicts that dispersion effect exists only in bad news firms, since analysts
have incentives to withhold bad news, but not good news. Table 2 reports the testing results of
this hypothesis.

Each quarter, we independently assign firms into five groups based on their forecast
dispersions at the end of quarter \( t \) and two groups based on scaled \( \Delta Roa \) of quarter \( t + 1 \). D1
(D5) contains firms in the lowest (highest) dispersion quintile; good (bad) news firms are those
firms whose scaled \( \Delta Roa \) values are above (below) the median.

Column 2 verifies the existence of the dispersion effect in our sample: high dispersion
firms have lower returns than those of low dispersion firms. The raw return differential between
D5 and D1 is -0.76% per month (\( t = -2.78 \)), which is similar to the magnitude reported in DMS
even though we have used a more restricted sample due to the aforementioned data requirements.
that we use only forecasts from analysts who have non-missing forecasts between two successive quarters. Column 3 and Column 4 report results supporting Hypothesis 1 that the dispersion effect only exists in bad news firms. Among bad news firms, the average raw return of D5 is lower than that of D1 by 0.98% per month, which is highly significant ($t=-3.41$), while among good news firms, the returns of D5 firms are not significantly different from those of D1 firms ($t=-1.29$). The pattern is the same if returns are risk adjusted by Fama-French three factors (MKT, SMB and HML) or four factors (MKT, SMB, HML and MOM).

4.2 Analyst' Incentive, Change in Dispersion and Upward Bias in Consensus Forecast

4.2.1 Estimating incentive and incentive-free forecasts

Analysts’ incentive of not fully downward revising their forecasts when they possess bad news is the key variable of our thesis. Without data describing how analysts benefit from their access to managers, and how their employers benefit from business dealings with firms they cover, we would not have a direct measure of it. Thus, we can only estimate analysts’ incentive based on data of how analysts revise their forecasts when they possess bad news. To facilitate our discussion, we first define the following variables.

\[ adj \_value, \] incentive-free individual analyst forecast at quarter $t$

\[ value, \] observed individual analyst forecast at quarter $t$

\[ truemean, \] incentive-free consensus forecast at quarter $t$

\[ adj \_mean, \] the average of incentive-free individual forecasts, and is by definition the same as \[ truemean, \]

\[ mean, \] observed consensus forecast at quarter $t$

We assume that other things being constant, analysts affected by incentives will issue more favorable forecasts; therefore, at quarter $t$ we identify a pool of analysts as potentially incentive-driven if their forecasts at quarter $t - 1$ rank among the top fourth of all forecasts. Within this pool, we identify analysts as incentive-driven if their downward revisions in the face of bad news are less than those of the incentive-free consensus at the quarter forecast. Stated formally, a
particular analyst is incentive-driven if and only if his value_{t-1} is among the top fourth of quarter \( t-1 \) forecasts, and \( \text{value}_t - \text{value}_{t-1} > \text{true mean}_{t} - \text{mean}_{t-1} \) in the face of bad news. The incentive-free forecast (\( \text{adj \_ value}_t \)) of this analyst can be obtained by adding the amount of under-revision (\( \text{true mean}_t - \text{mean}_{t-1} - (\text{value}_t - \text{value}_{t-1}) \)) onto her \( \text{value}_t \). In other words, \( \text{adj \_ value}_t = \text{value}_t + (\text{true mean}_t - \text{mean}_{t-1} - (\text{value}_t - \text{value}_{t-1})) \) for incentive-driven analysts and \( \text{adj \_ value}_t = \text{value}_t \) for incentive-free analysts.

As \( \text{adj \_ value}_t \) depends on \( \text{true mean}_t \), which in turn is the average of \( \text{adj \_ value}_t \), \( \text{true mean}_t \) can only be estimated iteratively via

\[
\text{adj \_ value}_{t} = \text{value}_t + (\text{true mean}_t - \text{mean}_{t-1} - (\text{value}_t - \text{value}_{t-1}))
\]

(1)

where \( \text{adj \_ value}_{t} \) is the estimated value of \( \text{adj \_ value}_t \), and \( \text{true mean}_t \) is the estimated value of \( \text{true mean}_t \).

In this iterative procedure, we use \( \text{mean}_t \) as the initial value of \( \text{true mean}_t \), to get the initial value of \( \text{adj \_ value}_{t} \) from equation (1). Then by taking the cross-sectional average of these initial values of \( \text{adj \_ value}_t \), we derive the initial value of \( \text{adj \_ mean}_t \), which is the estimated value of \( \text{adj \_ mean}_t \). Since \( \text{true mean}_t \) is the same as \( \text{adj \_ mean}_t \), a good estimate of an incentive-free forecast requires \( \text{true mean}_t \) to be very close to \( \text{adj \_ mean}_t \). Thus, if the initial value of \( \text{true mean}_t \), \( \text{adj \_ mean}_t > 0.001 \), we reduce \( \text{true mean}_t \) by 0.001 and repeat the above process (identifying incentive-driven forecasts, estimating the incentive-free individual forecasts.

1 Ideally, we would like to use \( \text{adj \_ std dev}_t = \text{value}_t + (\text{true mean}_t - \text{true mean}_{t-1} - (\text{value}_t - \text{adj \_ value}_{t-1})) \) to calculate incentive free forecast since \( \text{mean est}_{t-1} \) and \( \text{value}_{t-1} \) may also be upward biased. However, this specification requires an analyst to have valid forecast for a firm every quarter throughout the year, which reduces our firm-quarter-analyst observations from 379,880 to 195,575. Furthermore, the analysts dropped out tend to be more optimistic than the remaining analysts: controlling firm quarter, mean forecast of dropped out analysts is significantly higher than that of the remaining analysts by 0.023 (\( t = 20.56 \)). The potential reason is that as the annual earnings announcements are approaching, incentive-driven analysts tend to drop out, and the above specification eliminates forecasts of these incentive-driven analysts in the early period of the year. Therefore, though this alternative specification is more precise, it will introduce new bias into the measure. In fact, other things equal, upward consensus bias (appearing in section 4.2.2) should be larger using this specification than the original one in the main text. However, because of the dropout of incentive-driven analysts, the upward consensus bias calculated from the specification is actually lower than the one calculated from our original specification.
from equation (1), taking cross-sectional average of these estimates and comparing it with $truemean_t$, until the absolute value of the difference between $truemean_t$ and $adj\_mean_t$ is less than 0.001. At this point, $adj\_value_t$ and $adj\_mean_t$ respectively become the estimates of the incentive-free individual forecast and the incentive-free consensus forecast that we will use in the subsequent analyses.

4.2.2 Results

We have argued that analysts of bad news firms have incentive to withhold information which would result in an increase in dispersion. This implies that we are more likely to find firms that have experienced greater incentive and dispersion increases in the high dispersion and bad news group. In particular, Hypothesis 2 predicts that both analysts’ incentive and dispersion change would increase with the level of dispersion. An early hint supporting this prediction can be found in Table 2, in which we present the average number of firms in each dispersion quintile for the bad news group and the good news group separately. In the low dispersion quintiles, there are more firms in the good news group than in the bad news group. In sharp contrast, we find more bad news firms in the high dispersion quintiles.

In Table 3, we test Hypothesis 2 more directly by examining how analysts’ incentive and dispersion change across dispersion quintiles. Although Hypothesis 2 applies to bad news firms only, good news firms serve as a benchmark for how dispersion changes across different dispersion levels in the absence of incentive, since analysts have no incentive to withhold good information. Column 2 in Table 3 reports analysts’ incentive for bad news firms ($incentive$); this is measured as the ratio of the number of incentive-inflicted analysts (as defined above) to the total number of analysts whose previous quarter forecasts are among top fourth. We see that $incentive$ monotonically increases with forecast dispersion, and that the average differential between the highest- and lowest- dispersion groups is 18.8%, which is highly statistically significant ($t=26.37$).

In quarter $t$, we measure bias in consensus forecast ($bias_t$) as the difference between incentive-free mean forecast ($adj\_mean_t$) and observed mean forecast ($mean_t$) scaled by the absolute value of $mean_t$. Column 3 of Table 3 shows that the magnitude of upward bias in the consensus forecast is also increasing in dispersion. Specifically, there is almost no consensus
forecast bias in the lowest dispersion firms; however, in the highest dispersion quintile, $bias_i$ is a very significant 1.7%. The bias differential between D5 and D1 is also statistically significant ($t=-26.52$). Forecast dispersion change of quarter $t$ ($\Delta disp_i$) is measured as the difference between the standard deviations of forecasts at the ends of quarter $t$ ($stdev_{t_i}$) and quarter $t-1$ ($stdev_{t-1_i}$), scaled by the absolute value of the mean forecast at the end of quarter $t-1$ ($mean_{t-1_i}$); that is: $\Delta disp_i=(stdev_{t_i}-stdev_{t-1_i})/abs(mean_{t-1_i})$. We choose to scale the difference by the mean forecast of the previous quarter in order to ensure that the dispersion change is not driven by the mean forecast change. Column 4 shows that in all dispersion quintiles, forecast dispersion decreases. However, relative to other dispersion quintiles, the magnitude of dispersion decrease in D5 is smaller. The $\Delta disp_i$ differential between D5 and D1 is positive, which is marginally significant ($t=1.76$). However, the effect of incentives on dispersion is best measured as the abnormal dispersion change ($ab\_\Delta disp_i$) against the benchmark dispersion change ($ben\_\Delta disp_i$) when analysts incentives are absent, for which we have argued that the $\Delta disp_i$ of good news firms is a good proxy. Column 5 of Table 3 shows that $ben\_\Delta disp_i$ is negative for all quintiles, and that the absolute value of $ben\_\Delta disp_i$ increases with dispersion. This indicates that as time goes by, some uncertainty is resolved and this is especially true for firms with greater uncertainty (proxied by higher dispersion.) Column 6 presents the abnormal dispersion change ($ab\_\Delta disp_i$) of bad news firms, which is measured as the difference between $\Delta disp_i$ and $ben\_\Delta disp_i$. $ab\_\Delta disp_i$ is not significant in low dispersion quintiles (D1-D3), but is positive and highly significant in the two highest dispersion quintiles (D4 and D5), which suggests that analysts’ incentive increases dispersion significantly for bad news firms. This is why these firms end up in the high dispersion quintile, in addition to the fact that some of these firms may inherently have a greater information uncertainty. In summary, Hypothesis 2 is strongly supported by the results reported in Table 3.

The last two columns of Table 3 offer additional evidences that firms in high dispersion quintiles experience greater increase in dispersion because of analysts’ incentive. $adj\_\Delta disp_i$ and $ab\_adj\_\Delta disp_i$ represent the dispersion increase and the abnormal dispersion increase respectively, based on incentive-free analysts’ forecast. In particular, $adj\_\Delta disp_i$ is measured as
the standard deviation of incentive-free forecasts at the end of quarter $t$ in excess of the standard deviation of observed forecasts at the end of quarter $t-1$, scaled by the absolute value of observed consensus forecast at the end of quarter $t-1$. We can see that abnormal dispersion increase in each quintile is no longer significantly different from each other. These results are reassuring as it speaks to the efficacy of our mechanism in estimating analysts’ incentive and incentive-free forecast.

4.3 Dispersion Effect after Controlling for Bias in Consensus Forecast

We have shown in Table 2 that the dispersion effect exists only in bad new firms. In this section, we test Hypothesis 3 to see if the dispersion effect among bad news firms diminishes after we control for the incentive-induced embedded in the consensus forecast. Table 4 reports results from Fama-MacBeth regressions that regress monthly returns of bad news firms in quarter $t$ on a combination of dispersion, analysts’ incentive and incentive-induced upward bias in the consensus forecast measured in quarter $t-1$, in addition to some control variables commonly known to impact stock returns, such as book to market, market capitalization and momentum. The significantly negative coefficient of dispersion in Column 2 verifies the dispersion effect in bad news firms in a regression setting. The significantly negative coefficient of incentive and significantly positive coefficient of bias in Column 3 and Column 4 respectively suggest that our estimates of incentive-free forecasts, analysts’ incentive, as well as incentive-induced bias in consensus forecasts are quite effective. They further suggest that that analysts’ incentive of withholding bad information and the resultant bias in consensus forecasts affect stock returns. Column 5 indicates that including analysts’ incentive in the regression diminishes the dispersion effect, but that dispersion remains significant. Note that Hypothesis 3 is built upon the argument that incentive-induced upward biases in consensus forecasts are the ultimate cause of low return in high dispersion firms; thus, the indirect negative relationship between dispersion and return, linked through incentive, should be dominated or subsumed by this bias. Column 6 shows that dispersion is indeed completely subsumed by this bias. This result is consistent with the prediction from Hypothesis 3 and is convincing evidence that the dispersion effect observed in literature can be explained by analysts’ incentive to withhold bad information.
4.4 Dispersion Effect and Information Uncertainty

In this section, we examine the interaction between the dispersion effect and information uncertainty. Hypothesis 4 predicts a stronger dispersion effect when information uncertainty is lower. We use stock return volatility (Rvol) and earnings volatility (Evol) as proxies of information uncertainty. Firms with uncertainty that ranks among the top 1/3 of the sample are classified as high uncertainty firms; firms with uncertainty that ranks among the bottom 2/3 are classified as low uncertainty firms. We use the 1/3 cutoff to ensure that firms in D5 are roughly evenly distributed between low and high information uncertainty groups, because forecast dispersion is positively related to information uncertainty. As firms with high information uncertainty are likely to be riskier than firms with low information uncertainty, we report the dispersion effect in terms of the Fama-French four-factor risk adjusted return (Alpha) of D5-D1 in Table 5. Panel A first uses Rvol as the proxy of uncertainty. It shows that the Alpha of the low uncertainty group is -0.54% per month (t=-2.87), while that of the high uncertainty group is -0.12% per month (t=-0.41). Furthermore, the difference in magnitude of the dispersions between high and low uncertainty groups mainly comes from firms with future bad news. To be more specific, within bad news firms, Alpha is significantly negative when uncertainty is low (t=-2.87), but is not statistically different from zero when uncertainty is high (t=0.90). In contrast, within the good news group, Alpha is not significantly different from zero for both low and high information uncertainty groups. We also use Evol as the proxy of information uncertainty and find similar and somewhat stronger results that support Hypothesis 4: that the dispersion effect is stronger within firms with low information uncertainty.

Note the underlying premise behind Hypothesis 4: that among firms of high dispersion, those with low information uncertainty must have been comparatively more impacted by analysts’ incentive. This is because both information uncertainty and analysts’ incentive contribute positively to forecast dispersion; high dispersion firms with little contribution from information uncertainty must find greater contribution from analysts’ incentive. We consequently expect that in high dispersion firms, analysts’ incentive and the bias they generate are larger in those firms with low information uncertainty. We provide tests for this premise in Panels B. We still use Rvol and Evol as information uncertainty proxies, and report the median value of incentive related variables of high dispersion firms that have bad future news. We
choose to report median values since the distribution of bias is skewed. As shown in both panels, analysts’ incentive and upward bias of D5 firms (the top dispersion quintile) are indeed significantly larger in firms with lower information uncertainty. This is despite the fact that the dispersion level is lower in the low information uncertainty group, and should have augured for a smaller incentive and bias as demonstrated in Table 3. Consequently, these results provide a strong support for the premise behind our formulation of Hypothesis 4, and reinforce the support for the hypothesis itself.

As with the results in Section 4.3, the results in this section also provide unique support to our incentive-based explanation of the dispersion effect. Though previous literature provides several mechanisms for the generation of the dispersion effect, there is one common feature among them: they all use forecast dispersion as a proxy of information uncertainty, regard the dispersion effect as stemming from information uncertainty, and predict that the dispersion effect increases with information uncertainty. For example, in DMS, greater information uncertainty leads to more heterogeneous opinions, which in turn generates a larger stock overpricing in the presence of short sale constraints, leading to a stronger dispersion effect. Sadka and Scherbina (2007) argue that the higher the information uncertainty, the higher the information advantage of potentially better-informed investors. Market makers will set a higher spread or provide a smaller depth in order to protect themselves; therefore, trading cost increases with dispersion, explaining the persistence of the dispersion effect through time. In Johnson (2004), stock price is viewed as the option value of a levered firm. Information uncertainty results in parameter risk; the higher the parameter risk, the higher the stock price, and the lower the future return. This also leads to a stronger dispersion effect among firms with high information uncertainty, as these firms also have high dispersion in general. Therefore the affirmative testing results of Hypothesis 4 in this section that the dispersion effect decreases with information uncertainty provides a strong support to our incentive-based explanation of the dispersion effect since all other models/explanations have predicted the opposite.

5. Robustness

5.1 The asymmetry of the dispersion effect in a less restrictive sample
In testing the asymmetry of the dispersion effect in section 4.1, we require that an analyst also has valid forecast in the previous quarter. One concern with this requirement is that dispersion calculated from these analysts’ forecasts may not represent dispersion using all valid analysts’ forecasts. We address this concern by using forecast dispersion retrieved from IBES unadjusted summary file, which is defined as standard deviation of forecasts scaled by absolute value of mean forecast (‘STDEV’ and ‘MEANEST’ in IBES respectively).

In table 6, we independently assign stocks into 5 groups based on their forecast dispersions at the end of month $t$ and two groups based on scaled Roa of month $t+1$. Stocks are held for one month. The results are similar to that of table 2. Specifically, dispersion effect only exists in the group with bad news. Moreover, among high dispersion quintiles, there are more firms in the bad news group than in the good news group; while among low dispersion quintiles, that reverse is true. This ensures that our previous results are not due to the way we calculated forecast dispersion.

### 5.2 Dispersion effect and information uncertainty in a less restrictive sample

In Section 4.4, we documented supportive evidence for Hypothesis 4 using the same sample used to test Hypotheses 1 to 3, which requires sample firms to have information on their future operating performance, and requires each analyst covering the firms also to have non-missing forecasts in the previous quarter. Since the future operating performance of firms and individual analysts’ forecasts are not needed to test Hypothesis 4, we redo the test with a more comprehensive sample that does not require such information and that is close to those used in other studies. This not only serves as a robustness check for the test of Hypothesis 4, but also documents a negative relationship between the dispersion effect and information uncertainty from a more general sample. That such a relationship exists in a general sample is a more useful stylized fact for future studies.

The dispersion quintiles and the high and low information uncertainty groups are formed in the same way as in Section 4.4, but the standard deviation and the mean of forecasts are obtained directly from IBES Unadjusted Summary History File rather than calculated from IBES Adjusted Detail History File. Panel A in Table 6 reports the time series means of descriptive
characteristics for each portfolio when Rvol is used as the proxy of information uncertainty. The second column shows that the number of highest dispersion firms is similar between the low information uncertainty group and the high information uncertainty group (173 and 218 respectively). Column 3 to Column 6 show that book to market value, size and the past 12-month returns are systematically related to dispersion and information uncertainty. Firms with low information uncertainty tend to be larger, have lower book-to-market values and lower returns in the past 12 months. Also, for both information uncertainty portfolios, high dispersion firms tend to be losers and have higher book-to-market values. These observations suggest that we should focus on risk-adjusted returns when we compare portfolio returns across dispersion and information uncertainty.

Panel B reports time series mean returns of different holding periods (one month, 3 months, 6 months and 12 months.) Similar to Jegadeesh and Titman (1993), the portfolio return in month t with K months holding period is constructed as

$$R_{p_{t}} = \frac{1}{K} \sum_{j=2}^{K+1} R_{t-j}$$

where \(R_{t-j}\) is the equally-weighted portfolio return in month t for portfolios formed in month t-j.

Note that we have skipped a month between the portfolio formation period and the holding period to avoid impacts from market microstructure. Risk-adjusted return (FF-4 alpha) is obtained as the intercept of a time-series regression where \(R_{p_{t}}\) is regressed on Fama-French three factors and Carhart’s momentum factors (MKT, SMB, HML and MOM.) We first examine a one-month holding period return in Panel B. Without distinguishing between low and high information uncertainties (Rvol), D5 (high dispersion quintile) firms have lower returns than do D1 (low dispersion quintile) firms by 0.43% per month. This confirms the dispersion effect in our sample, although the magnitude of the effect is somewhat smaller than that documented by DMS (2002). This difference may reflect the fact that we have required sample firms to have at least 24 months of return data for the calculation of Rvol, and that we have skipped the first month in measuring portfolio returns. Our focus, though, is on comparing the dispersion effect between high and low information uncertainty groups. Continuing with the one-month holding period, D5-D1’s raw return in the low information uncertainty group is -0.40%, which is significantly negative \((t = -2.42)\). On the other hand, the raw return of D5-D1 in the high uncertainty group is -0.27%, which is not statistically significant \((t = -0.32)\). As noted earlier,
because firms’ characteristics are systematically related to dispersion and information uncertainty, we should draw our conclusions based on risk-adjusted return. Risk adjustment does seem to make the dispersion effect stronger and the difference more significant between high and low information uncertainty groups. Alpha of D5-D1 in the low uncertainty group is a very significant \(-0.56\% (t = -4.18)\), while it is an insignificant \(0.21\% (t = -1.06)\) in the high uncertainty group. This result reconfirms support for Hypothesis 4, that the dispersion effect is stronger among firms with lower information uncertainty, even in a more general sample. The results in the longer holding periods (3 month, 6 months and 12 months) are essentially the same as those in the one month holding period.

We next repeat the test by using earnings volatility (Evol) as the proxy of information uncertainty. The descriptive characteristics of the resultant portfolios are similar to those reported in Panel A and are thus not reported. Panel C is the counterpart of Panel B, where Evol replaces Rvol as the proxy of information uncertainty. Although the dispersion effect measured in the raw returns does not seem to be different in longer holding periods, the dispersion effect measured in the risk-adjusted return is consistently larger among firms with low information uncertainty for all holding periods, just as we have seen in Panel B. In summary, the evidence from this less restricted sample offers support for our incentive-based explanation over other prominent explanations of dispersion effect.

6. Summary and Conclusion

In this paper, we propose and test an incentive-based explanation of the dispersion effect. We argue that there is no causality between high dispersion in analysts’ forecasts and low stock returns. Rather, the negative relationship between dispersion and return is spurious and is a result of the fact that analysts’ incentive causes both high dispersion and low return in firms with bad news. This incentive-based explanation necessarily predicts that the dispersion effect only exists in firms with bad news, as analysts are not influenced by incentives when they possess good news. It also predicts a stronger dispersion effect in firms with low information uncertainty. This particular prediction is inconsistent with other prominent explanations of the dispersion effect. Thus, the finding in this paper that the dispersion effect is indeed stronger in firms with low information uncertainty constitutes a very strong support for our incentive-based explanation.
We also derive an algorithm to measure the unobservable analysts’ incentive and the bias it creates in consensus forecast. We further find that the dispersion effect disappears after we control for this incentive-induced bias. This result not only speaks to the efficacy of our algorithm in measuring analysts’ incentive, but also provides another strong support for our explanation.

Analysts’ forecast and the dispersion within their forecasts have been widely used to proxy the level and the divergence in analysts’ or investors’ true opinions [Klein (1990), Doukas et al. (2002), Easton et al. (2002) and Bamber et al. (1999)] Our findings have demonstrated that analysts’ incentive can create systematic bias in consensus forecast and forecast dispersion, and further suggest that care should be given in interpreting empirical results which involve such forecast statistics.

One implicit assumption in our hypotheses-- and one that seems to be borne out by the data-- is that investors trust and rely on analysts’ forecasts to price stocks. In other words, investors seem to suffer from some undefined behavior bias that makes them fail to recognize, or properly address, the incentive-induced bias in analyst forecasts. Understanding the nature of this behavior bias should be an interesting topic of future research.
REFERENCES


Table 1 Summary Statistics

Panel A presents the forecast statistics of our main sample. Meanest is mean earnings forecast at the end of quarter t. Medest is the medium earnings forecast at the end of quarter t. Coverage is the number of analysts whose earnings forecasts are valid at the end of quarter of t. Forecast dispersion (Disp) is the standard deviation of earnings forecasts, scaled by the absolute value of the mean forecast at the end of quarter t. Observations with a mean forecast of zero have been deleted. Dispersion change (Δdisp) is the difference between the standard deviation of earnings forecasts at the end of quarters t and that of quarter t-1, scaled by the absolute value of the mean forecast at the end of quarter t-1. These forecast statistics are calculated using individual analyst earnings forecasts, which are drawn from IBES Adjusted Detail History File. Except for coverage, all variables are winsorized at the 99th and 1st percentiles. Panel B presents the Pearson correlation coefficient between the dispersion and two information uncertainty proxies: Rvol and Evol. Return volatility (Rvol) is calculated as standard deviation of monthly returns in the previous 5 years, with a minimum of 24 non-missing return observations. Earnings volatility (Evol) is measured as standard deviation of annual earnings in the past 5 years (with a minimum of 3 years), where earnings are defined as the earnings before extraordinary item (data 18) divided by total asset (data 6). Stocks with price below five dollars are excluded. The sample period is from Jan 1983 to Dec 2006.

<table>
<thead>
<tr>
<th>Panel A: Forecast Statistics</th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>25th</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meanest</td>
<td>1.46</td>
<td>1.23</td>
<td>1.38</td>
<td>0.61</td>
<td>2.03</td>
</tr>
<tr>
<td>Medest</td>
<td>1.45</td>
<td>1.23</td>
<td>1.38</td>
<td>0.61</td>
<td>2.05</td>
</tr>
<tr>
<td>Coverage</td>
<td>9.68</td>
<td>8.00</td>
<td>6.53</td>
<td>4.00</td>
<td>13.00</td>
</tr>
<tr>
<td>Disp</td>
<td>0.14</td>
<td>0.04</td>
<td>0.35</td>
<td>0.02</td>
<td>0.11</td>
</tr>
<tr>
<td>Δdisp</td>
<td>-0.01</td>
<td>-0.00</td>
<td>0.10</td>
<td>-0.02</td>
<td>0.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Correlation Coefficient</th>
<th>Rvol</th>
<th>Evol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disp</td>
<td>0.240</td>
<td>0.186</td>
</tr>
<tr>
<td>(p&lt;0.0001)</td>
<td></td>
<td>(p&lt;0.0001)</td>
</tr>
<tr>
<td>Rvol</td>
<td></td>
<td>0.546</td>
</tr>
<tr>
<td>(p&lt;0.0001)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 2 Return by Forecast dispersion and Unexpected News

Each quarter, stocks are independently sorted into five groups based on analyst forecast dispersion at the end of quarter t (dispersion), and into two groups based on scaled ΔRoa in quarter t+1. Firms with scaled ΔRoa above median are defined as good news firms, while firms with scaled ΔRoa below median are defined as bad news firms. Stocks are held for the next quarter (3 months). Return is the time series average of monthly return for each portfolio. Number is the average number of firms in each portfolio. Stocks with prices below five dollars are excluded. T statistics are in parentheses. The sample period is from Jan 1983 to Dec 2006.

<table>
<thead>
<tr>
<th></th>
<th>Return</th>
<th>Dispersion</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Bad</td>
<td>good</td>
</tr>
<tr>
<td>D1</td>
<td>1.28</td>
<td>0.65</td>
<td>1.83</td>
</tr>
<tr>
<td>D2</td>
<td>1.1</td>
<td>0.35</td>
<td>1.84</td>
</tr>
<tr>
<td>D3</td>
<td>1.12</td>
<td>0.32</td>
<td>1.91</td>
</tr>
<tr>
<td>D4</td>
<td>0.88</td>
<td>0.1</td>
<td>1.67</td>
</tr>
<tr>
<td>D5</td>
<td>0.52</td>
<td>-0.34</td>
<td>1.47</td>
</tr>
<tr>
<td>D5-D1</td>
<td>-0.76</td>
<td>-0.98</td>
<td>-0.36</td>
</tr>
<tr>
<td></td>
<td>(-2.78)</td>
<td>(-3.41)</td>
<td>(-1.29)</td>
</tr>
<tr>
<td>FF-4 Alpha</td>
<td>-0.53</td>
<td>-0.67</td>
<td>-0.24</td>
</tr>
<tr>
<td></td>
<td>(-2.75)</td>
<td>(-3.16)</td>
<td>(-1.13)</td>
</tr>
</tbody>
</table>

Table 3 Analysts’ Incentive within Bad News Firms

At the end of each quarter t, we assign firms to five portfolios based on their forecast dispersion. This table focuses on firms with future bad news, whose scaled ΔRoa of quarter t+1 are below medium value. incentive at the end of quarter t is measured as the ratio of number of incentive-inflicted analysts at the end of quarter t to the total number of analyst whose forecasts at the end of quarter t-1 are among top 1/4. bias of quarter t is the difference between the adjusted mean forecast and the observed mean forecast of quarter t scaled by the absolute value of observed mean forecast of quarter t. Dispersion change (Δdisp) at the end of quarter t is the difference between the standard deviation of earnings forecasts of quarter t and that of quarter t-1, divided by the absolute value of the mean forecast of quarter t-1. Benchmark dispersion change (ben Disp) is the dispersion change in good news firms (scaled ΔRoa above median), which is measured in the same way as firms with future bad news. Abnormal dispersion change (ab disp) is the difference between Δdisp and ben disp. Adjusted dispersion change (adj disp) at the end of quarter t is the difference between the standard deviation of incentive-free earnings forecasts at the end of quarter t and the standard deviation of observed earnings forecasts the end of quarter t-1, divided by the absolute value of the mean forecast at the end of quarter t-1. Abnormal adjusted dispersion change (ab adj disp) is the difference between adj disp and ben disp. T statistics are in parentheses. Stocks with prices below five dollars are excluded. The sample period is from Jan 1983 to Dec 2006.

<table>
<thead>
<tr>
<th></th>
<th>incentive</th>
<th>bias</th>
<th>Δdisp</th>
<th>ben _Δdisp</th>
<th>ab _Δdisp</th>
<th>adj _Δdisp</th>
<th>ab _adj _Δdisp</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1(Low)</td>
<td>0.142</td>
<td>-0.000</td>
<td>-0.010</td>
<td>-0.010</td>
<td>0.000(-0.86)</td>
<td>-0.010</td>
<td>-0.001(-1.65)</td>
</tr>
<tr>
<td>D2</td>
<td>0.210</td>
<td>-0.001</td>
<td>-0.009</td>
<td>-0.009</td>
<td>0.000(0.42)</td>
<td>-0.010</td>
<td>-0.001(-1.26)</td>
</tr>
<tr>
<td>D3</td>
<td>0.238</td>
<td>-0.001</td>
<td>-0.011</td>
<td>-0.012</td>
<td>0.001(1.26)</td>
<td>-0.013</td>
<td>-0.001(-1.14)</td>
</tr>
<tr>
<td>D4</td>
<td>0.274</td>
<td>-0.004</td>
<td>-0.011</td>
<td>-0.016</td>
<td>0.005(3.30)</td>
<td>-0.017</td>
<td>-0.001(-0.35)</td>
</tr>
<tr>
<td>D5(High)</td>
<td>0.330</td>
<td>-0.017</td>
<td>-0.003</td>
<td>-0.029</td>
<td>0.026(6.30)</td>
<td>-0.031</td>
<td>-0.002(-0.50)</td>
</tr>
<tr>
<td>D5-D1</td>
<td>0.188</td>
<td>-0.017</td>
<td>0.007</td>
<td>-0.019</td>
<td>0.026</td>
<td>-0.020</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(-26.37)</td>
<td>(-26.52)</td>
<td>(1.76)</td>
<td>(-5.16)</td>
<td>(6.34)</td>
<td>(-5.32)</td>
<td>(-0.32)</td>
</tr>
</tbody>
</table>
Table 4 Analysts’ Incentive and Stock Return

This table presents the Fama-Machbeth regression results for firms with future bad news. The dependent variable is the monthly return of quarter t+1. Independent variables are three analysts’ incentive related variables, as defined in Table 3, and control variables at the end of quarter t. *beta* is portfolio beta, which is calculated following Fama (1992). *ln me* is the log transformation of firm’s size; *ln btm* is the log transformation of book to market value; *mom* is the compounded stock return over the previous 12 months.

<table>
<thead>
<tr>
<th></th>
<th>-0.51</th>
<th>-0.45</th>
<th>-0.30</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>dispersion</strong></td>
<td>(-2.93)</td>
<td>(-2.42)</td>
<td>(-1.57)</td>
</tr>
<tr>
<td><strong>incentive</strong></td>
<td>-0.33</td>
<td>-0.28</td>
<td></td>
</tr>
<tr>
<td><strong>bias</strong></td>
<td>13.46</td>
<td>9.67</td>
<td></td>
</tr>
<tr>
<td><strong>beta</strong></td>
<td>-0.49</td>
<td>-0.53</td>
<td>-0.53</td>
</tr>
<tr>
<td><strong>ln me</strong></td>
<td>0.22</td>
<td>0.25</td>
<td>0.23</td>
</tr>
<tr>
<td><strong>ln btm</strong></td>
<td>0.18</td>
<td>0.15</td>
<td>0.16</td>
</tr>
<tr>
<td><strong>mom</strong></td>
<td>0.03</td>
<td>0.00</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(1.63)</td>
<td>(1.36)</td>
<td>(1.46)</td>
</tr>
<tr>
<td></td>
<td>(1.63)</td>
<td>(1.56)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.02)</td>
<td>(0.13)</td>
</tr>
<tr>
<td></td>
<td>(-0.17)</td>
<td>(0.03)</td>
<td></td>
</tr>
</tbody>
</table>
Table 5 Forecast Dispersion and Information Uncertainty

Panel A reports the Fama-French four factor alpha of D5-D1 for low and high information uncertainty groups separately. Return volatility (Rvol) and earnings volatility (Evol) are used as information uncertainty proxies. The high information uncertainty group (High) includes firms with uncertainty values among the top 1/3, while the low information uncertainty group (Low) includes firms with uncertainty values among bottom 2/3 each quarter. Firms with above medium scaled ΔRoa are defined as ‘good news’, while firms with below medium scaled ΔRoa are defined as ‘bad news’. Panel B reports the median values of disp, incentive and bias for the highest dispersion firms which have future bad news. Stocks with prices below five dollars are excluded. T statistics are in parentheses. The sample period is from Jan 1983 to Dec 2006.

### Panel A: FF-4 factors alpha of D5-D1

<table>
<thead>
<tr>
<th>Information Uncertainty</th>
<th>Groups Based on Rvol</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td>-0.54(-2.87)</td>
<td>-0.12(-0.41)</td>
</tr>
<tr>
<td></td>
<td>Good News</td>
<td>-0.31(-1.43)</td>
<td>-0.43(-1.24)</td>
</tr>
<tr>
<td></td>
<td>Bad News</td>
<td>-0.61(-2.87)</td>
<td>0.33(0.90)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Information Uncertainty</th>
<th>Groups Based on Evol</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td>-0.61(-3.28)</td>
<td>-0.36(-1.35)</td>
</tr>
<tr>
<td></td>
<td>Good News</td>
<td>-0.28(-1.33)</td>
<td>-0.45(-1.36)</td>
</tr>
<tr>
<td></td>
<td>Bad News</td>
<td>-0.78(-3.55)</td>
<td>-0.10(-0.30)</td>
</tr>
</tbody>
</table>

### Panel B: Median of Analyst Incentive and Bias

<table>
<thead>
<tr>
<th>Information Uncertainty</th>
<th>Groups Based on Rvol</th>
<th>Low</th>
<th>High</th>
<th>Low-High</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>disp</td>
<td>0.264</td>
<td>0.327</td>
<td>-0.062(-8.37)</td>
</tr>
<tr>
<td></td>
<td>incentive</td>
<td>0.247</td>
<td>0.124</td>
<td>0.124(5.20)</td>
</tr>
<tr>
<td></td>
<td>bias</td>
<td>-0.005</td>
<td>-0.002</td>
<td>-0.003(-3.33)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Information Uncertainty</th>
<th>Groups Based on Evol</th>
<th>Low</th>
<th>High</th>
<th>Low-High</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>disp</td>
<td>0.264</td>
<td>0.327</td>
<td>-0.062(-8.37)</td>
</tr>
<tr>
<td></td>
<td>incentive</td>
<td>0.223</td>
<td>0.140</td>
<td>0.083(3.52)</td>
</tr>
<tr>
<td></td>
<td>bias</td>
<td>-0.005</td>
<td>-0.002</td>
<td>-0.003(3.42)</td>
</tr>
</tbody>
</table>
Table 6 Return by Forecast dispersion and Unexpected News

At the end of each month $t$, we sort stocks into five groups based on forecast dispersion, which is the ratio of standard deviation of earnings forecasts to absolute value of mean forecast, as reported in IBES Unadjusted Summary History file. Firms with above medium scaled $\Delta Roa$ of month $t+1$ are defined as ‘good news’, while firms with below medium scaled $\Delta Roa$ of month $t+1$ are defined as ‘bad news’. Scaled $\Delta Roa$ of month $t+1$ is the scaled $\Delta Roa$ of the quarter where month $t+1$ falls in. Stocks are held for one month. Return is time series average of monthly return for each portfolio. Number is the average number of firms in each portfolio. Stocks with a price below five dollars are excluded. T statistics are in parentheses. The sample period is from Jan 1983 to Dec 2006.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Bad News</th>
<th>Good News</th>
<th>Bad News</th>
<th>Good News</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1</td>
<td>1.4</td>
<td>0.65</td>
<td>2.1</td>
<td>150</td>
<td>158</td>
</tr>
<tr>
<td>D2</td>
<td>1.32</td>
<td>0.61</td>
<td>2.02</td>
<td>152</td>
<td>156</td>
</tr>
<tr>
<td>D3</td>
<td>1.19</td>
<td>0.3</td>
<td>2.08</td>
<td>154</td>
<td>154</td>
</tr>
<tr>
<td>D4</td>
<td>1.22</td>
<td>0.34</td>
<td>2.1</td>
<td>156</td>
<td>152</td>
</tr>
<tr>
<td>D5</td>
<td>0.97</td>
<td>0.06</td>
<td>1.95</td>
<td>158</td>
<td>150</td>
</tr>
<tr>
<td>D5-D1</td>
<td>-0.42</td>
<td>-0.59</td>
<td>-0.15</td>
<td>(-1.95)</td>
<td>(-2.59)</td>
</tr>
<tr>
<td>FF-4 Alpha</td>
<td>-0.46</td>
<td>-0.62</td>
<td>-0.18</td>
<td>(-3.12)</td>
<td>(-3.80)</td>
</tr>
</tbody>
</table>

($-0.66$) ($-1.15$)
Table 7 Portfolio Return by Forecast Dispersion and Information Uncertainty

At the end of each month, we sort stocks into five groups based on their forecast dispersion (Disp), which is the ratio of the standard deviation of earnings forecasts to the absolute value of the mean forecast, as reported in IBES Unadjusted Summary History file. \( \text{Rvol} \) and \( \text{Evol} \) are information uncertainty proxies, as defined in Table 1. The low information uncertainty group (Low) includes firms with uncertainty values among the bottom 1/3, while the high information uncertainty group (High) includes firms with uncertainty values among the top 2/3. Panel A presents the characteristics of each portfolio. Firm size (\( Me \)) is the market capitalization (in millions of dollars) at the end of month \( t \). Book-to-market (\( Btm \)) is the book value of equity divided by its market value at the end of month \( t \). Return Momentum (\( Mom \)) is accumulated returns from month \( t-11 \) to \( t \). In panel B, stocks are held for various months (1 month, 3 months, 6 months and 12 months). One month is skipped between portfolio formation period and holding period. Portfolio returns are equally weighted. We report the average return for each portfolio. Stocks with prices below five dollars are excluded. T statistics are in parentheses. The sample period is from Jan 1983 to Dec 2006.

### Panel A: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Me</th>
<th>Btm</th>
<th>Mom</th>
<th>Disp</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low High</td>
<td>Low High</td>
<td>Low High</td>
<td>Low High</td>
<td>Low High</td>
</tr>
<tr>
<td>D1</td>
<td>317</td>
<td>75</td>
<td>5.33</td>
<td>0.66</td>
<td>0.44</td>
</tr>
<tr>
<td>D2</td>
<td>314</td>
<td>88</td>
<td>4.24</td>
<td>1.00</td>
<td>0.49</td>
</tr>
<tr>
<td>D3</td>
<td>279</td>
<td>120</td>
<td>3.34</td>
<td>1.12</td>
<td>0.57</td>
</tr>
<tr>
<td>D4</td>
<td>237</td>
<td>159</td>
<td>2.88</td>
<td>0.85</td>
<td>0.67</td>
</tr>
<tr>
<td>D5</td>
<td>173</td>
<td>218</td>
<td>1.73</td>
<td>0.52</td>
<td>0.87</td>
</tr>
</tbody>
</table>

### Panel B: Return Volatility as Information Uncertainty Proxy

<table>
<thead>
<tr>
<th></th>
<th>One Month</th>
<th>Three Months</th>
<th>Six Months</th>
<th>Twelve Months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>D1</td>
<td>1.43</td>
<td>1.47</td>
<td>1.23</td>
<td>1.43</td>
</tr>
<tr>
<td>D2</td>
<td>1.32</td>
<td>1.39</td>
<td>1.09</td>
<td>1.34</td>
</tr>
<tr>
<td>D3</td>
<td>1.23</td>
<td>1.29</td>
<td>1.08</td>
<td>1.28</td>
</tr>
<tr>
<td>D4</td>
<td>1.23</td>
<td>1.29</td>
<td>1.14</td>
<td>1.24</td>
</tr>
<tr>
<td>D5</td>
<td>1.00</td>
<td>1.07</td>
<td>0.95</td>
<td>0.99</td>
</tr>
<tr>
<td>D5-D1</td>
<td>-0.43</td>
<td>-0.40</td>
<td>-0.27</td>
<td>-0.44</td>
</tr>
<tr>
<td></td>
<td>(-1.87)</td>
<td>(-2.42)</td>
<td>(-1.32)</td>
<td>(-2.83)</td>
</tr>
<tr>
<td>FF-4 alpha</td>
<td>(-2.77)</td>
<td>(-4.18)</td>
<td>(-1.06)</td>
<td>(-4.61)</td>
</tr>
</tbody>
</table>

### Panel C: Earnings Volatility as Information Uncertainty Proxy

<table>
<thead>
<tr>
<th></th>
<th>One Month</th>
<th>Three Months</th>
<th>Six Months</th>
<th>Twelve Months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>D1</td>
<td>1.42</td>
<td>1.47</td>
<td>1.20</td>
<td>1.43</td>
</tr>
<tr>
<td>D2</td>
<td>1.32</td>
<td>1.34</td>
<td>1.23</td>
<td>1.31</td>
</tr>
<tr>
<td>D3</td>
<td>1.20</td>
<td>1.29</td>
<td>1.02</td>
<td>1.27</td>
</tr>
<tr>
<td>D4</td>
<td>1.23</td>
<td>1.28</td>
<td>1.18</td>
<td>1.23</td>
</tr>
<tr>
<td>D5</td>
<td>1.00</td>
<td>1.10</td>
<td>0.93</td>
<td>1.09</td>
</tr>
<tr>
<td>D5-D1</td>
<td>-0.42</td>
<td>-0.37</td>
<td>-0.27</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(-1.82)</td>
<td>(-2.02)</td>
<td>(-1.20)</td>
<td>(-1.95)</td>
</tr>
<tr>
<td>FF-4 alpha</td>
<td>(-2.62)</td>
<td>(-3.39)</td>
<td>(-1.29)</td>
<td>(-3.64)</td>
</tr>
</tbody>
</table>