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Disagreement, Underreaction, and Stock Returns

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Disagreement, Underreaction, and Stock Returns

Abstract

We explore analysts' earnings forecast data to improve upon one popular disagreement measure—the analyst forecast dispersion measure—proposed by Diether, Malloy, and Scherbina (2002). Our analysis suggests that changes in the standard deviations of forecasted earnings can work as a complementary disagreement measure that is comparable across stocks and immune from other return-predictive information contained in the normalization scalars of analyst forecast dispersion measures. We also document evidence that the change-based disagreement measure predicts future cross-sectional returns significantly only when changes in the mean forecasts are negative. This finding suggests that the interaction between disagreement and underreaction to earnings news affects asset prices.

JEL Classification: G02, G12, G14

Keywords: Disagreement, short-sale constraints, underreaction, cross-section of stock returns.

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1. Introduction

Investors' disagreement on public information affects asset prices. Miller (1977) suggests that, when investors hold diverse opinions, negative information held by pessimistic investors will not be fully reflected in stock prices under short-sale constraints and, therefore, stocks are likely to be overpriced.[1] Any attempt to test the pricing impact of disagreement would certainly require a reasonable measure for differences of opinion. The analyst forecast dispersion measure proposed by Diether, Malloy, and Scherbina (DMS hereafter) (2002) is one of the most popular measures for disagreement.[2] The DMS measure is computed as the standard deviation of analysts' earnings

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[1] Chen, Hong, and Stein (2002) and Hong and Stein (2003) extend Miller's (1977) model to study the breadth-return relation and stock market crashes, respectively. Harrison and Kreps (1978), Harris and Raviv (1993), Scheinkman and Xiong (2003), and Cen, Lu, and Yang (2013) develop dynamic models that build on heterogeneous beliefs and short-sale constraints and arrive at the same conclusions. Banerjee (2011) incorporates disagreement in a rational expectations framework and studies how investors use prices to update their valuations.

[2] More than 30 papers in top-tier finance and accounting journals employ this measure of disagreement. The DMS paper has been cited more than 1200 times according to Google Scholar as of writing.

forecasts (denoted by *STD*, the numerator) scaled by the absolute mean of analysts' earnings forecasts (denoted by $|Mean|$, the scalar) for each stock at the end of each month. Consistent with Miller's prediction, DMS (2002) show that disagreement—as proxied by analyst forecast dispersion—indeed has a significant predictive power for future returns in the cross-section, especially for small-cap stocks where short-sale constraints are most likely to be binding.

We replicate the results in DMS (2002) in an extended sample period from 1983 to 2009 based on analyst forecast dispersion measures with three normalization scalars, including the absolute mean of forecasted earnings ($|Mean|$, the original scalar in DMS (2002)), the book value of equity per share (*BEPS*), and the book value of assets per share (*BAPS*).[3] We find that the results in DMS (2002) are robust to the choice of scalars and to whether recent or lagged scalars are used. These results appear to be consistent with the popular interpretation regarding the return predictability of the analyst forecast dispersion measure. In other words, the numerator in the DMS measure (i.e., *STD*) captures the disagreement among analysts (and also investors), while the denominator (i.e., $|Mean|$) is simply normalization scalar to remove the common factor of the number of shares outstanding so that the DMS measure is comparable across stocks.

However, we document two findings that are at odds with the above popular interpretation. First, consistent with Cheong and Thomas (2011) and Ball (2011), we find that *STD* (the numerator) and all three normalization scalars (the denominators) are weakly correlated. In our full sample, none of the correlation coefficients between *STD* and these scalars is higher than 0.24.[4] More importantly, for the stocks of small firms and the stocks with low scalar values (where the analyst forecast dispersion measures have the strongest predictive power for future returns), the correlation

[3] We exclude price per share since it is a scalar that may be biased against the finding in DMS (2002). Specifically, when disagreement leads to an asset overvaluation under short-sale constraints, using inflated price as a scalar may mechanically reduce the spread in the analyst forecast dispersion measure. We thank the editor for pointing this out to us.

[4] As a benchmark for comparison, the correlation between the numerator and the scalar of the book-to-market ratio is 0.54 in our sample.

coefficients between *STD* and all normalization scalars are close to zero and, in some cases, negative. While Cheong and Thomas (2011) and Ball (2011) have provided a few useful explanations for the scale-invariance of *STD*,[5] such low correlations between *STD* and its scalars cast doubt on the economic motivation for constructing analyst forecast dispersion measures using these scalars as a normalization device.

Second, we find that the scalars of analyst forecast dispersion measures can predict future stock returns independently, particularly among small-cap stocks, and the return predictability varies across scalars. For example, when we control for the variation in *STD* in a 3×3×3 sequential sort (i.e., by firm size, *STD*, and then the scalar), variation in $|Mean|$ generates an average return spread of 79.7 basis points (bps) per month among small-cap stocks.[6] This return spread is larger than the one generated by the variation in *STD*, which is 55.1 bps after controlling for the variations in $|Mean|$. Further, our results suggest that, for stocks of mid-sized firms, *STD*, *BEPS*, and *BAPS* do not predict future returns and the return predictability of the original DMS measure for these firms is almost entirely contributed by $|Mean|$. Given that the correlations between *STD* and normalization scalars are low, this finding suggests that the dispersion measures used in the literature may capture not only disagreement but also other return-predictive information contained in the scalars.

Our two findings above call for a cleaner and more meaningful disagreement measure that improves upon the analyst forecast dispersion measure in DMS (2002) along two dimensions. First, the improved measure must be able to purge the firm fixed effects that are artificially driven by variables like the number of shares outstanding or the size of the firm to ensure that cross-sectional

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[5] In particular, Ball (2011) suggests that the scale-invariance of *STD* might be driven by the fact that all forecasted earnings are reported to the nearest cent irrespective of the level of scalars. This is consistent with our finding that the correlations between *STD* and alternative scalars are even lower when the scalar values are lower.

[6] The corresponding average return spreads generated by the variations in *BEPS* and *BAPS* for small-cap stocks are 55.9 bps and 47.8 bps, respectively, after controlling for the variation in *STD*.

comparisons are economically meaningful. Second, the improved measure must be immune from "contamination" by other return-predictive information contained in the scalars while still capturing disagreement among investors.

The first contribution of our paper is to suggest such an improved disagreement measure. Specifically, in the same spirit of the decomposition of the book-to-market ratio by Daniel and Titman (2006) and Fama and French (2008), we dynamically decompose the DMS (2002) dispersion measure and propose the change in *STD* (in logarithm) as a disagreement measure that is complementary to the original DMS measure. By construction, this change-based disagreement measure does not require a scalar and because it represents the growth rate of *STD*, it is comparable across stocks. We verify that our change-based disagreement measure predicts stock returns negatively and its predictive power is strong among small firms, which is consistent with the prediction of Miller's disagreement theory. For instance, for stocks in the smallest size quintile, the variation in the change-based disagreement measure generates an average monthly return spread of 64 bps, which is statistically significant at the 1% level.

As an application of our disagreement measure, we use it and find a novel interaction between disagreement and underreaction to earnings news in predicting stock returns in the cross section. Specifically, the decomposition of the DMS measure yields another component—the change in mean forecasts (which is essentially the revision of consensus forecasts)—originating from the scalar in the original DMS measure. We examine the return predictability of this component and particularly its interaction with disagreement in predicting future returns both theoretically and empirically. As the first step, we follow the post-forecast revision drift literature (e.g., Givoly and Lakonishok, 1980; Stickel, 1991; Chan, Jegadeesh, and Lakonishok, 1996; Gleason and Lee, 2003; and Zhang, 2006) and verify that the change in mean positively predicts future returns. The literature has interpreted this return predictability as "underreaction to earnings news": when investors and analysts react insufficiently to good (bad) earnings news, the stock price goes up (down) too slowly and as a result subsequent returns will continue to be high (low) on average until the fundamentals are fully reflected in prices. While this underreaction idea is well known in the literature, our analysis goes one step further to examine the interaction between disagreement and underreaction for the first time. We find that changes in *STD* (as a disagreement measure) predict future returns significantly only when changes in mean (as an underreaction measure) are negative. This interaction analysis constitutes the second contribution of our paper, by pointing out new economic insights using our disagreement measure.

To understand this interaction result, we argue that short-sale constraints are more likely to be binding in a down market for three reasons. First, the stock price drops too little in a down market due to underreaction to bad news, so that the stock is substantially overpriced and investors are likely to (short) sell it. In Appendix I, we formalize this notion in a parsimonious framework which incorporates underreaction to news in a disagreement model and we build our empirical analysis based on the model-derived predictions. Second, as the stock price continues to drop, the short selling is likely to be restricted by the short-sale rules (e.g., the "tick-test rule") before 2007. Third, even if the short selling is possible, its costs can be much higher in down markets when the demand for short selling increases significantly. Therefore, our change-based disagreement measure should have a stronger (negative) return predictability when the changes in mean forecasts are negative.

Our paper is broadly related to two strands of literature: the literature on disagreement and the literature on underreaction. In a huge number of empirical studies on disagreement, the literature has extensively relied on the DMS (2002) measure to proxy for disagreement.[7] While the DMS

[7] Hong and Stein (2007) provide an excellent review of earlier studies in the disagreement literature. Among more recent studies that test Miller's (1977) theory, Scherbina (2004, 2008) suggests that disagreement leads to upward bias in analyst forecasts and inefficient information processing in equity market. Sadka and Scherbina (2007) analyze the interactive effect of disagreement and liquidity on asset mispricing. Moeller, Schlingemann, and Stulz (2007) and Chatterjee, John, and Yan (2012) show that disagreement affects acquirer returns, total takeover premiums, and pre-announcement target

measure can capture the effect of disagreement to a large extent, our change-based measure can additionally purge the contamination effect of return-predictive information contained in the scalars. At a broad level, our paper makes a methodological contribution to the construction of scaled ratios that are used to predict cross-sectional stock returns in the literature. That is, researchers should verify that the numerator and the scalar are reasonably correlated in order to justify the economic meaningfulness of using scalars. In addition, researchers should avoid using earnings-related scalars, such as $|Mean|$, which is known to have a strong return predictability.

Among a large number of studies on underreaction to earnings news, our paper is most relevant to the ones on the post-forecast revision drift. Within this literature, the closest study to ours is Zhang (2006) who argues that news volatility predicts returns differently in good news versus in bad news. Our paper differs from and complements Zhang (2006) in two important ways. First, the standard deviation of analysts' earnings forecasts is a measure for disagreement in our paper but a proxy for information uncertainty in Zhang (2006). His story is that information uncertainty amplifies the effect of psychological biases, which are the behavioral source of underreaction. Second, the return predictions are different in the two papers. We expect that the standard deviation of analysts' earnings forecasts negatively predicts future returns among those stocks with bad news, while its return predictability is insignificant among those stocks with good news. In contrast, Zhang (2006) argues that the standard deviation of analysts' earnings forecasts amplifies the positive (negative) prediction of stock returns for those stocks experiencing good (bad) news.

2. Sample Characteristics

2.1. Sample Selection

stock price run-ups in mergers and acquisitions. Carlin, Longstaff, and Matoba (2014) provide a comprehensive literature review of recent development in the disagreement literature.

Our basic sample consists of all NYSE-, AMEX-, and Nasdaq-listed common stocks in the intersection of: (a) the Center for Research in Security Prices (CRSP) stock file, (b) the merged Compustat annual industrial file, and (c) the unadjusted summary historical file of the Institutional Brokers' Estimate System (I/B/E/S) for the period from January 1983 to December 2009.[8] To be included in the sample for a given month (i.e., month *t*), a stock must satisfy the following five criteria. First, the mean and standard deviation of analyst forecasts of the one-year-ahead (*FY*1) earnings per share of the stock in the current and previous five months (i.e., from month *t*-5 to month *t*) must be available from the I/B/E/S unadjusted summary historical file. Second, the prices, returns, and total market capitalizations of the stock for the period from month *t*-6 to month *t*+1 must be available from CRSP. Third, there must be sufficient data from CRSP and Compustat to compute the Fama and French (1992, 1993) book-to-market ratio of the stock as of December of the previous year. Fourth, the stock must be priced above five dollars at the end of the current month (i.e., month *t*) and the book value of stockholders' equity at the end of the last fiscal year before month *t* must be positive in the Compustat records. Finally, as in Fama and French (1992, 1993), the stock must not be a certificate, an American depositary receipt (ADR), shares of beneficial interest (SBIs), a unit trust, a closed-end fund, a real estate investment trust (REIT), or a financial firm. This screening process yields 852,387 stock-month observations from June 1983 to December 2009 or an average of 2,630 stocks per month.[9]

2.2. Summary Statistics

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[8] Although I/B/E/S provides data starting from 1976, our sample period begins from January 1983 for two reasons. First, before January 1983, I/B/E/S provided a limited coverage of stocks, which would reduce the power of our tests. Second, the data sample of DMS (2002) also starts from 1983; adopting the same starting year would enable us to compare our analysis with theirs.

[9] Following previous studies (e.g., Jegadeesh and Titman (1993)), we exclude stocks priced below five dollars. Such stocks not only have small analyst followings, they also incur large transaction costs due to their poor market liquidity (thin trading and large bid-ask spreads), which could distort the feasibility of any trading strategies discussed in this paper. We also exclude stocks with a negative book value of stockholders' equity simply to ensure that financially distressed firms do not drive our results and the book value of equity per share can be a meaningful scalar in our analysis.

Table 1 provides summary statistics describing our sample. All independent variables are either lagged by one month or computed based on public information that was already available to investors at the end of month *t*. Panel A of Table 1 reports the time-series averages of the cross-sectional means, medians, standard deviations, and other summary statistics. The mean and median of firm size are \$2.05 billion and \$0.51 billion, respectively, which are much larger than the corresponding values for all CRSP stocks. This is not surprising considering that our final sample excludes all small stocks in the CRSP sample that are priced below five dollars and/or stocks followed by fewer than two analysts.

[Insert Table 1 Here]

3. Analyst Forecast Dispersion Measures with Alternative Scalars

3.1. The Return Predictability of DMS Measures with Alternative Scalars

We start our analysis by replicating DMS's (2002) results for the extended sample period from 1983 to 2009 with analyst forecast dispersion measures that make use of various scalars—the absolute mean of forecasted earnings ($|Mean|$), book value of equity per share (*BEPS*), and book value of total assets per share (*BAPS*). $|Mean|$ is the original denominator in DMS (2002), *BEPS* is an alternative scalar suggested in their Section II, and *BAPS* is an additional popular scalar we are adding for robustness checks.[10] We exclude price per share since it is a scalar that may be biased against the finding in DMS (2002).[11]

Our replication results are reported in Table 2. We find that the return predictability of analyst forecast dispersion measures with alternative scalars is robust in the extended sample period. The

[10] We scale the book value of equity (total assets) reported at the end of the last fiscal year by the number of shares outstanding at the end of month *t* to obtain *BEPS* (*BAPS*), which ensures that the number of shares outstanding implied in the numerator and denominator of analyst forecast dispersion measures is the same. Our results do not change if we use the number of shares outstanding at the end of the last fiscal year to compute *BEPS* and *BAPS*.

[11] As mentioned in Footnote 3, since stock prices will be relatively high in the presence of the high divergence of opinion, scaling the standard deviation of forecasted earnings by price will mechanically reduce the spread in the disagreement measures and lead to weakened return predictability.

return patterns based on all three measures are identical to those reported in DMS (2002). Specifically, all three measures generate positive and statistically significant hedging portfolio returns by simultaneously longing stocks in the lowest dispersion quintile and shorting stocks in the highest dispersion quintile. Further, the hedging portfolio returns in size quintiles are monotonically decreasing as firm size increases.[12]

[Insert Table 2 Here]

3.2. Two Interesting Observations

While the main results in DMS (2002) hold true in our extended sample irrespective of the choice of scalars and of whether we use the most recent or lagged scalars, we observe two interesting patterns pertaining to the DMS measures with various scalars. First, consistent with Cheong and Thomas (2011) and Ball (2011), we find that the correlation coefficients between *STD* (the numerator of all analyst forecast dispersion measures) and all three normalization scalars are quite low. According to our calculations in Table 2, the time-series average of correlation coefficients between *STD* and $|Mean|$ is only 0.24 and the correlations between *STD* and the other two scalars are even lower (i.e., 0.22 with *BEPS* and 0.20 with *BAPS*). These correlations are much lower than those between the numerators and denominators of other common ratios. For example, as mentioned in Footnote 4, the time-series average of the correlation coefficients between the numerator and denominator of the book-to-market ratio is 0.54 in our sample. Further, the correlation coefficients between the numerator and all three scalars are the lowest for stocks in the smallest size quintile where the analyst forecast dispersion measures have the strongest predictive powers for future returns.

In Table 3, we sort all stocks into deciles at the beginning of each month based on scalars (i.e., $|Mean|$, *BEPS* and *BAPS*) and report the time series average for the mean, median and standard

[12] In Table A1 of our Online Appendix, we show that the replicated results above are also robust to the use of scalars that are lagged for one year.

deviation of the standard deviation of forecasted earnings within each decile group.[13] Consistent with results in Table 1 of Cheong and Thomas (2011), we find that the standard deviation of forecasted earnings do not increase with its common scalars, particularly when the level of scalars are low (e.g., from group 1 to group 4). The low correlations, also known as the scale-invariance in Cheong and Thomas (2011) and Ball (2011), give rise to a concern about whether using these scalars as a normalization device is economically meaningful.

[Insert Table 3 Here]

Second, we find that scalars can predict future returns independently, especially for stocks of small firms. We support this claim by performing standard portfolio sorts based on size and all components of alternative analyst forecast dispersion measures. In Panel A of Table 4, we first double sort stocks based on firm size and then *STD* (the numerator). We find that *STD* without scaling has a strong predictive power for future returns in the two smallest size quintiles.

[Insert Table 4 Here]

In Panels B to D of Table 4, we double sort stocks based on firm size and each of our normalization scalars. We find that $|Mean|$, the original scalar in DMS (2002), has a very strong predictive power for future stock returns across all size quintiles except for the largest one.[14] The monthly return spread generated by the hedging strategy based on $|Mean|$ (i.e., longing stocks with high $|Mean|$ and shorting stocks with low $|Mean|$ simultaneously) in the full sample is 61.6 bps, which is even larger than that generated by the DMS analyst forecast dispersion measure. The return predictabilities of *BEPS* and *BAPS* are much weaker than that of $|Mean|$.[15] However, both scalars are able to generate large return spreads in the two smallest size quintiles, where the analyst forecast

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[13] There are, on average, 263 stocks per month in each decile group.

[14] Cen, Hillary, and Wei (2013) also find that analysts' forecast earnings per share (*FEPS*) can predict future stock returns and attribute its return predictability to analysts and investors' cross-sectional anchoring bias to the industry median.

[15] The result indicates that the dispersion measures using *BEPS* and *BAPS* as the scalar might be better than the DMS (2002) disagreement measure using $|Mean|$ as the scalar since the former two measures have a lower return predictability than the latter one.

dispersion measures display strong return predictability. For example, the hedging portfolio based on *BEPS* generates an average monthly return spread of 51.1 bps in the smallest size quintile, which is statistically significant at the 5% level. A similar strategy based on *BAPS* can generate a monthly spread of 44.9 bps in the smallest size quintile. Although its statistical significance is marginal (i.e., near the 13% level), its magnitude is approximately half of that generated by the dispersion measure (with *BAPS* as the scalar) in the smallest size quintile. Overall, all three scalars can generate larger hedging portfolio returns in the full sample than that based on *STD*—the numerator that captures the economic meaning of disagreement.

3.3. A Static Decomposition Analysis of Analyst Forecast Dispersion Measures

Our second observation in Section 3.2 indicates that both the numerator *STD* and the scalars contain return-predictive information. Given that the numerator and the scalars are not highly correlated, it is possible to decompose the return predictability of analyst forecast dispersion measures with various scalars and to identify the portion coming solely from the disagreement component in the numerator. The following equation illustrates a static decomposition of analyst forecast dispersion measures:[16]

$$\log(Disp_t) \equiv \log(STD_t) - \log(Scalar_t). \tag{1}$$

We conduct sequential sorts based on the two components of the static decomposition, i.e., *Log*(*STD*) and *Log*(*Scalar*),[17] where the first sort is based on *STD*. By controlling the variation in *STD* within each *STD* group, we are able to examine the return spread driven by the variation in the

[16] To understand the contribution of each component to the variation in *DISP*, we decompose $Var[\log(Disp)]$ as follows: $Var[\log(Disp)] \equiv Cov[\log(Disp), \log(STD)] - Cov[\log(Disp), \log(Scalar)]$. Dividing both sides by $Var[\log(Disp)]$ yields $1 \equiv Beta\,(STD) - Beta(Scalar)$. We find that on average, *STD* is responsible for 56.2% of the total variation in *DISP* and $|Mean|$ for the remaining 43.8%, indicating that both components are almost equally important in explaining the variation in the DMS dispersion measure.

[17] Since portfolio sorts only rely on the rank of variables and the natural logarithm is simply a monotonic transformation, we sort stocks based on *STD* and various scalars directly.

scalars. Similarly, one can reverse the order of sorting variables and examine the return spreads driven by the variation in *STD* after controlling for the variations in scalars.

It is important to point out that the static decomposition does not work for most common ratios where the numerator and the denominator are highly correlated, because in this case the sort based on the numerator is essentially the same as that based on the scalar. However, in our study, the low correlations between *STD* and its scalars as we discussed in Section 3.2 guarantee the mathematical validity of sequential sorts. We therefore perform the sequential sorts based on *STD* (the numerator) and various scalars within each size group. Since we are carrying out triple sorts, we divide stocks into three groups in each layer to ensure that each portfolio under a 3×3×3 sort contains a sufficient number of stocks for a good property of diversification. The results of sequential sorts based on *Size*, *STD* and |*Mean*| are reported in Panels A to C of Table 5.[18]

[Insert Table 5 Here]

The results of the static decomposition based on sequential sorts have two important implications. First, they allow us to observe the decomposed return predictability of analyst forecast dispersion measures that are attributable to the numerator and the scalar. For small-cap firms, after controlling for the variations in |*Mean*|, the variation in *STD* generates an average return spread of 55.1 bps per month;[19] after controlling for the variation in *STD*, the variation in |*Mean*| generates an average return spread of 79.7 bps per month,[20] which is much higher than that driven by the variations in the numerator (*STD*). For medium-sized firms, this pattern is even more obvious. After controlling for the variations in |*Mean*|, the variations in *STD* generate hedging portfolio returns between 8.1 bps and 15.5 bps in different |*Mean*| groups and none of them is statistically significant

[18] Results of sequential sorts based on *Size*, *STD* and one of the other two scalars (i.e., *BEPS* or *BAPS*) are provided in Table A2 in the Online Appendix.
[19] This is calculated as (0.490+0.718+0.445)÷3=0.551 (Panel B of Table 5).
[20] This is calculated as (0.800+0.803+0.788)÷3=0.797 (Panel A of Table 5).

at the 10% level. However, the variation in $|Mean|$ still generates a significant average return spread of 49.8 bps per month after controlling for the variation in *STD*.[21]

Second, the results of static decomposition further cast doubt on the economic meaningfulness of using scalars in constructing the analyst forecast dispersion measures. While results in Tables 2 and 3 suggest that the correlation coefficients between the numerator and various scalars are low (especially for stocks of small firms), the results in Panel C of Table 5 suggest that these correlations can be close to zero and, in some cases, negative when the level of scalar is low. This observation is consistent with Ball's (2011) explanation that the scale-invariance of *STD* might be driven by the fact that all forecasted earnings are reported to the nearest cent irrespective of the level of the scalars. Although the low correlation between *STD* and various scalars can be explained, it still challenges the economic meaningfulness of using scalars as a normalization device.

4. A Dynamic Decomposition Analysis of the DMS Measure

Although *STD* may improve upon the original DMS measure and provide a cleaner disagreement measure, this variable per se is not economically comparable across stocks. That is, in addition to disagreement, there exist other latent factors that can *artificially* drive variations in *STD*. For instance, if a firm splits its shares and analysts adjust their forecasts accordingly, its *STD* will artificially drop. However, this change in *STD* has nothing to do with disagreement. A better and cleaner disagreement measure requires us to control for these latent factors. In doing so, we need to find a scalar that can largely absorb the effect of these latent factors, and at the same time, this scalar does not predict future returns. Otherwise it will contaminate the return predictability of the constructed disagreement measure. As we argue below, the lagged *STD* can serve this purpose, which motivates our dynamic decomposition approach in this section.

[21] This is calculated as (0.452+0.551+0.492)÷3=0.498.

4.1 The Decomposition Approach

To find an improved and comparable measure of disagreement across stocks, we perform a dynamic decomposition of the DMS analyst forecast dispersion measure in a similar way to the decomposition of the book-to-market ratio by Daniel and Titman (2006) and Fama and French (2008). Doing so allows us to find an improved disagreement measure that is comparable across stocks, and more importantly, discover and verify its economic properties under Miller's (1977) theoretical framework.

The decomposition is formally shown as follows:

$$
\begin{aligned}
\log(Disp_t) \equiv \log\left(\frac{STD_t}{|Mean_t|}\right) \\
&= \log\left(\frac{STD_{t-k}}{|Mean_{t-k}|}\right) + \log\left(\frac{STD_t/adj_t}{STD_{t-k}/adj_{t-k}}\right) - \log\left(\frac{|Mean_t|/adj_t}{|Mean_{t-k}|/adj_{t-k}}\right) \\
&= \log(Disp_{t-k}) + [\log(adj.STD_t) - \log(adj.STD_{t-k})] \\
&- [\log(adj.|Mean_t|) - \log(adj.|Mean_{t-k}|)] \\
&= \log(Disp_{t-k}) + Chg\_Std(t-k,t) - Chg\_Mean(t-k,t). \qquad (2)
\end{aligned}
$$

In Equation (2), $Disp_t$, STD_t, and $|Mean_t|$ represent the DMS analyst forecast dispersion measure, standard deviation, and absolute mean of analysts' earnings forecasts at month t, respectively. adj_t is the cumulative adjustment factor for stock splits and dividend distributions in month t. This variable makes the standard deviation and mean of analysts' earnings forecasts comparable over time. $Chg\_Std(t\text{-}k,t)$ and $Chg\_Mean(t\text{-}k,t)$ are the change in standard deviation and change in absolute mean (both in logarithm) of analysts' earnings forecasts from month $t\text{-}k$ to month t: $Chg\_Std(t\text{-}k,t) \equiv log(adj.Std_t) - log(adj.Std_{t\text{-}k})$ and $Chg\_Mean(t\text{-}k,t) \equiv log(adj.|Mean_t|) - log(adj.|Mean_{t\text{-}k}|)$.[22] One can easily see that the analyst forecast dispersion measure at month t

[22] Under this specification, $Chg\_Mean(t\text{-}k,t)$ may be meaningless if the mean of earnings forecasts at time t or $t\text{-}k$ is negative. However, less than 5% of the observations in our sample have negative forecasted earnings. Therefore, the

comprises three components: the lagged analyst forecast dispersion measure at month *t-k* (i.e., $log(Disp_{t-k})$), change in standard deviations of analysts' earnings forecasts from month *t-k* to month *t* (i.e., *Chg_Std*(*t-k,t*)), and change in the consensus forecasts from month *t-k* to month *t* (i.e., *Chg_Mean*(*t-k,t*)). As discussed above, such decomposition allows us to isolate a disagreement measure that is comparable across stocks.

In Equation (2), *Chg_Std*(*t-k,t*) is essentially constructed as the growth rate of standard deviation from month *t-k* to month *t*, which is economically comparable in the cross section. One can also interpret this disagreement measure as using lagged *STD* as a scalar in the spirit of Chen, Hong, and Stein (2002, p. 181), who use the *change* in ownership breadth to purge artificial firm fixed effects on the level of ownership breadth.

In our empirical analysis, we gradually increase *k* until $log(Disp_{t-k})$ loses its return predictability. The results are shown in Table A3 in our Online Appendix and suggest that the predictive power of $log(Disp_{t-k})$ for future stock returns indeed declines as *k* increases. When *k* is equal to or larger than 5, $log(Disp_{t-k})$ loses its return predictability in all size quintiles.[23] Therefore, we decompose $log(Disp_t)$ into $log(Disp_{t-5})$, *Chg_Std*(*t*-5,*t*), and *Chg_Mean*(*t*-5,*t*) in our paper. Clearly, in this decomposition, the predictive power of $log(Disp_t)$ for future returns must come mainly from *Chg_Std*(*t*-5,*t*) and *Chg_Mean*(*t*-5,*t*). Under this decomposition, $log(Disp_{t-5})$ needs not be included in our analysis, and thus we can focus solely on the dynamics between *Chg_Std*(*t*-5,*t*) and *Chg_Mean*(*t*-5,*t*) in our empirical tests below.[24]

4.2 Return Predictability of the Change-Based Disagreement Measure

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difference between $Mean_t$ and $|Mean_t|$ is almost negligible in the full sample. We conduct a robustness check based on a subsample that excludes all firms with negative earnings. Our results remain qualitatively and quantitatively unchanged.

[23] DMS (2002) also find that the return predictability of $Disp_{t-k}$ decreases when *k* increases and completely disappears six months after portfolio formation.

[24] To ensure that the decomposition in Equation (2) would not mechanically attribute all of log(*Disp*)'s predictive power to $\Delta\log(|Mean|)$ since $\Delta\log(Std) = 0$, we follow footnote 16 to carry out the variance decomposition of Equation (2). We find that the change in *STD* and change in $|Mean|$ contribute to 24.5% and 10.9% of the total variation in contemporaneous *DISP*, respectively, suggesting that the change in *STD* contributes to more variations in *DISP* than the change in $|Mean|$.

We first run a standard portfolio sort test, to examine the return predictability of the changed-based disagreement measure. Specifically, we double sort stocks into 5×5 groups according to size and the change in standard deviations to examine the independent return predictability power of our change-based disagreement measure after controlling for firm size only. The average one-month-ahead portfolio returns are reported in Table 6.

[Insert Table 6 Here]

Similar to the DMS dispersion measure, the change-based disagreement measure predicts stock returns negatively. In addition, the return predictability declines as firm size increases. After removing the return-predictive information contained in the scalar (i.e., $|Mean|$), the change-based disagreement measure generates smaller return spreads than the DMS measure in all size groups. Further, the hedging portfolio returns based on the change-based disagreement measure are only statistically significant in the two smallest size quintiles. This finding is consistent with our previous finding that the return predictability of the DMS measure in the medium size group is almost entirely driven by the information contained in the scalar (i.e., $|Mean|$).

Our results are robust to the adjustment of portfolio raw returns based on the Fama-French (1993) and Carhart (1997) four-factor model. The portfolio alphas suggest that the return spreads generated by the change-based disagreement measure among the two smallest quintiles are primarily driven by the overvaluation of stocks on the short side (i.e., stocks with a high level of disagreement). This is consistent with Miller (1977) that, under short-sale constraints (which is most likely to be true for small stocks than for large stocks), stocks with a high level of disagreement are overvalued as pessimistic views are not reflected in the stock prices; however, stocks with a low level of disagreement are not necessarily undervalued. As an application of our proposed change-based disagreement measure, in the next sub-section, we derive and find a novel interaction between disagreement and under-reaction to earnings news in predicting future returns.

4.3. The Interaction between Disagreement and Underreaction: A Model-Derived Hypothesis

Based on the decomposition approach discussed in Section 4.1, the change in standard deviation *Chg_Std*(*t*-5,*t*) in Equation (2) proxies for investor disagreement, while the change in mean *Chg_Mean*(*t*-5,*t*) captures investors' underreaction to earnings news in the finance and accounting literature. In Appendix I, we provide a theoretical framework to analyze their return predictabilities. We expect that the change in standard deviation predicts future returns negatively following the disagreement literature and the change in mean forecasts predicts future returns positively following the post-forecast revision drift literature (see Proposition A1). More importantly, our theoretical framework and the improved disagreement measure allow us to generate new testable predictions on the interaction between disagreement and underreaction (see Proposition A2) as summarized in the following hypothesis.

Hypothesis: The predictive power of *Chg_Std*(*t*-5,*t*) for future returns depends on the sign of *Chg_Mean*(*t*-5,*t*): *Chg_Std*(*t*-5,*t*) negatively predicts future stock returns only when *Chg_Mean*(*t*-5,*t*) is negative. In contrast, the predictive power of *Chg_Mean*(*t*-5,*t*) for future returns does not depend on the sign of *Chg_Std*(*t*-5,*t*): *Chg_Mean*(*t*-5,*t*) always positively predicts future returns irrespective of whether the standard deviation of analysts' earnings forecasts is increasing or decreasing.

4.4. Portfolio Sorts Based on the Dynamic Decomposition

At the beginning of each month, we sort stocks into three equal groups based on firm size (*MV*) at the end of the previous month.[25] Stocks in each size group are then sorted into three subgroups based on the change in mean forecasts, *Chg_Mean*(-5,0). Stocks in each subgroup are further sorted into three groups based on the change in the standard deviation of earnings forecasts,

[25] Our results are robust when we first sort stocks based on the residual institutional ownership following Nagel (2005). This robustness check is provided in Table A3 of our Online Appendix.

Chg_Std(-5,0). Panel A of Table 7 reports the time-series averages of one-month-ahead stock returns of equal-weighted portfolios based on the 3×3×3 subgroups.

[Insert Table 7 Here]

Consistent with the disagreement literature, *Chg_Std*(-5,0) predicts future stock returns negatively, and consistent with the post-forecast revision drift literature, *Chg_Mean*(-5,0) predicts future stock returns positively. The return predictability of *Chg_Std*(-5,0) diminishes as firm size increases. These results suggest that the basic properties of the DMS disagreement measure are maintained by the change-based disagreement measure. This is consistent with the prediction of Miller's (1977) disagreement theory in that short-sale constraints are most likely to be binding for small firms.

The most striking observation in Table 7 is that, while the predictive power of *Chg_Mean*(-5,0) does not depend on the sign of *Chg_Std*(-5,0), the predictive power of *Chg_Std*(-5,0) is only statistically significant for firms in the low *Chg_Mean*(-5,0) groups except for large firms. For example, the hedging portfolio based on *Chg_Std*(-5,0) within the low *Chg_Mean*(-5,0) group for small firms generates an average monthly return of 56.4 bps, which is statistically significant at the 1% level. In contrast, the hedging portfolio returns based on *Chg_Std*(-5,0) within the medium and high *Chg_Mean*(-5,0) groups are both much lower and neither one is statistically significant at the 10% level. To further investigate the characteristics of stocks within the low *Chg_Mean*(-5,0) group, we report the average values of *Chg_Mean*(-5,0) and *Chg_Std*(-5,0) for each of the 27 (3×3×3) subgroups in Panels B and C of Table 5, respectively. We find that the average values of *Chg_Mean*(-5,0) for the stocks within the low *Chg_Mean*(-5,0) group are all negative. This provides a useful hint for further testing our hypothesis to see if *Chg_Std*(-5,0) exhibits strong return predictability only when the stock price is likely to fall so that the short-sale constraints are more likely to be binding (because of more overvaluation resulting from underreaction to bad news).

To ensure that our results are not driven by common risk and firm characteristic factors, we consider portfolio alphas instead of portfolio raw returns in Table A4 of our Online Appendix. Our results are not affected after controlling for common risk and firm characteristic factors. In another robustness check reported in Table A5 of our Online Appendix, we replace firm size by residual institutional ownership (Nagel, 2005) in portfolio sorts. Consistent with our prediction, our results are particularly strong among stocks of low institutional ownership, where stocks have a high level of short-sale constraints.

4.5 Fama and MacBeth Regressions

In this section, we perform the Fama and MacBeth (1973) regression tests at the individual stock level to test our hypothesis for the change-based disagreement measure, as outlined in Section 4.3. In Fama-MacBeth regressions, the dependent variable is measured in the unit of raw returns because all controls of firm characteristics can be addressed by including relevant explanatory variables in the regressions. For each cross-section, we run a regression with the following specification:

$$\begin{aligned} Ret_i &= \alpha + \beta_1 Chg\_Std(-5,0) + \beta_2 Chg\_Std(-5,0) \times NegChg\_Mean\ Dummy \\ &+ \beta_3 Chg\_Mean(-5,0) + \beta_4 Chg\_Mean(-5,0) \times NegChg\_Std\ Dummy \\ &+ \sum_{j=5}^{n} \beta_j Other\ Controls_j + \varepsilon_i. \end{aligned} \quad (3)$$

In this specification, *NegChg_Std*(-5,0) *Dummy* is a dummy variable that equals 1 if *Chg_Std*(-5,0) is negative and 0 otherwise. Similarly, *NegChg_Mean*(-5,0) *Dummy* is a dummy variable that equals 1 if *Chg_Mean*(-5,0) is negative. The correlation matrix in Table 1 suggests that multicollinearity is not a major concern when we include *Chg_Std*(-5,0) and *Chg_Mean*(-5,0) with other independent variables given that the correlations of these variables with other control variables are quite low.

We include several control variables in this specification. *log*(*MV*) is the natural logarithm of market capitalization. *log*(*BM*) is the natural logarithm of the book-to-market ratio. *Ret*(-1,0) is the past one-month stock return before time *t*, and *Ret*(-7,-1) is the past-six-month stock return lagged by a month. *Accrual* is the total accounting accruals defined by Sloan (1996), and E/P is the earnings-to-price ratio. These control variables are included because previous studies have shown that they possess return predictability (e.g., Fama and French 1992; Jegadeesh, 1990; Jegadeesh and Titman, 1993, 2001). We extract only the information that is publicly available before the end of month *t* in constructing these variables. To mitigate the impact from extreme values, all control variables except for *Ret(-7, -1)* and *Ret(-1,0)* are censored at the 1% and 99% level. Detailed definitions of these variables are provided in Appendix II.

Results from the Fama and MacBeth regressions are presented in Table 8. We start with a replication of the Fama-MacBeth regression presented in DMS (2002) in Column (1) of Table 8. We find that the analyst forecast dispersion measure (*Disp*) has a negative and significant predictive power for future returns. The economic significance and statistical significance of *Disp* are reduced significantly when we include *Chg_Mean*(-5,0) in the regression. Specifically, the absolute magnitude of the coefficient on *Disp* is reduced from 0.251 in Column (1) to 0.189 in Column (2). This result is consistent with our earlier claim that information contained in the scalar contributes significantly to the overall return predictability of the DMS analyst forecast dispersion measure. Consistent with the disagreement literature and the post-earnings revision drift literature, the results in Column (3) suggest that *Chg_Std*(-5,0) predicts future stock returns negatively, and *Chg_Mean*(-5,0) predicts future stock returns positively. The corresponding *t*-statistics suggest that the return predictability of *Chg_Mean*(-5,0) is statistically significant at the 1% level and the return predictability of *Chg_Std*(-5,0) is statistically insignificant in the full sample, both of which are consistent with our earlier findings in Table 7.

[Insert Table 8 Here]

In Column (4) of Table 8, we introduce an interaction term between *Chg_Std*(-5,0) and *NegChg_Mean*(-5,0) *Dummy*. Our result suggests that the predictive power of *Chg_Std*(-5,0) for future stock returns is statistically significant at the 1% level only when *Chg_Mean*(-5,0) is negative. Specifically, when *Chg_Mean*(-5,0) is negative, a one-standard-deviation increase in *Chg_Std*(-5,0) is associated with a decrease of 9.4 bps (= 0.113×0.832 from Table 1) in one-month-ahead stock returns, which is nine times higher than that observed for the unconditional case of 0.92 bps (= 0.011×0.832 from Table 1). After we incorporate the interaction term, the coefficient on *Chg_Std*(-5,0) remains statistically insignificant, suggesting that the change in standard deviations of analysts' earnings forecasts cannot predict future stock returns when the mean of earnings forecasts is revised upward and the stock price is likely to increase. In Column (5) of Table 8, we add another interaction term between *Chg_Mean*(-5,0) and *NegChg_Std*(-5,0) *Dummy* to test whether the predictive power of *Chg_Mean*(-5,0) for future stock returns also depends on the sign of *Chg_Std*(-5,0). Our result suggests that the predictive power of *Chg_Mean*(-5,0) for future stock returns does not depend on the sign of *Chg_Std*(-5,0).

Our results are robust in other settings. In Tables A6 and A7 of our Online Appendix, we compute the mean of *Chg_Mean*(-5,0) for each month *t* and partition the time series into two groups depending on whether the monthly average *Chg_Mean*(-5,0) is positive or negative. We find that the return spreads from the trading strategy based on *Chg_Std*(-5,0), both in portfolio returns and portfolio alphas, are much higher when the monthly average *Chg_Mean*(-5,0) is negative. In Table A8, we run a Fama-MacBeth regression similar to Equation (3) around earnings announcements. Consistent with our results in Table 8, we find that the changes in the standard deviation of forecast earnings, which are triggered by earnings announcements in this setting, have a much stronger predictive power for post earnings announcement drift (i.e., PEAD) when the changes in mean forecasts are negative.

5. Conclusion

Diether, Malloy, and Scherbina (2002) find that stocks with greater dispersion of analysts' earnings forecasts (*Disp*)—as measured by the standard deviation of analysts' earnings forecasts scaled by the absolute mean of earnings forecasts—subsequently earn significantly lower risk-adjusted returns. They interpret their results as being consistent with Miller's (1977) prediction that under short-sale constraints, stock prices do not fully reflect the view of pessimistic investors and, therefore, stocks with high *Disp* tend to be overpriced.[26] Our study replicates the results in DMS (2002) in an extended sample period and demonstrates that the results are robust to the choice of scalars. However, we also make two interesting observations that potentially challenge the way we currently interpret the return predictabilities of analyst forecast dispersion measures with alternative scalars. First, we observe that the correlations between the standard deviation of forecasted earnings (*STD*, the numerator) and various normalization scalars are low, particularly for stocks of small firms and stocks with a low level of scalars. Second, we observe that quite a number of common scalars can predict future returns independently while the original scalar in DMS (2002), the absolute mean of forecasted earnings (i.e., $|Mean|$), has a particularly strong predictive power for future returns. The first observation challenges the economic meaningfulness of using scalars as a normalization device, while the second observation raises the question of whether the return

[26] Using individual investors' trading accounts to construct an investor-based measure of dispersion of opinion, Goetzmann and Massa (2005) also find that the higher the dispersion for a stock, the lower the future stock returns. However, in a recent paper, Jiang and Sun (2014) use the standard deviation of active holdings across all active mutual funds to measure fund managers' dispersion of beliefs for a stock and find that the dispersion is positively associated with the stock's future returns. Jiang and Sun (2014) argue that their results are also consistent with investors' divergent beliefs in the presence of short-sale constraints. The reason for the different results is that Miller (1977) and others study divergent information instead of difference of opinion regarding stock prices.

predictability of analyst forecast dispersion measures is solely attributable to the disagreement component in the numerator.

To address these two issues, we propose a new disagreement measure—the change in standard deviation of forecasted earnings—based on a dynamic decomposition of the DMS analyst forecast dispersion measure. The change-based disagreement measure is constructed as the growth rate of *STD* and, therefore, is comparable across stocks and unaffected by other return predictive information contained in scalars. We verify that the change-based disagreement measure maintains the empirical properties as predicted by Miller (1977). Further, the dynamic decomposition allows us to reveal the interactive effect between disagreement and underreaction to earnings news on future returns. We argue that the short-sale constraints are more likely to be binding when investors underreact to bad news and the stock price is likely to fall. Therefore, our change-based disagreement measure should have a stronger (negative) return predictability when the change in mean forecasts is negative. We formalize this notion in a parsimonious theoretical model, test the model-derived prediction with empirical data, and find supportive evidence.

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Appendix I: A Theoretical Framework

In this appendix, we formulate a parsimonious model of return predictability of analyst forecasts to formalize our idea developed in the main text. The economy lasts for one period and has two tradable assets: one bond with a (net) risk-free rate of zero, and one stock that pays a dividend of $\tilde{v}$ at the end of the period. We assume that

$$\tilde{v} = \bar{v} + \tilde{\theta} + \tilde{\varepsilon}, \tag{A1}$$

where parameter $\bar{v} > 0$ is a constant representing the unconditional mean of the firm's cash flow, the random variable $\tilde{\theta} \sim N(0, \sigma_\theta^2)$ (with $\sigma_\theta > 0$) represents the component that analysts can forecast, and the random variable $\tilde{\varepsilon} \sim N(0,1)$ is the residual uncertainty of the firm's cash flow.[27] The stock has a total supply of one unit and its price is denoted by $\tilde{p}$.

We employ analyst forecasts to generate heterogeneous beliefs among investors whose trading, in turn, affects prices. In this way, analyst forecasts are reflected in prices and generate their return predictability in our economy. Specifically, we assume that there are two analysts—an optimistic analyst (U) and a pessimist analyst (D)—whose forecast reports give signals about $\tilde{\theta}$. The optimistic analyst reports an upward-biased signal

$$\tilde{s}_U = \tilde{\theta} + \tilde{\delta}, \tag{A2}$$

while the pessimist analyst reports a downward-biased signal

$$\tilde{s}_D = \tilde{\theta} - \tilde{\delta}, \tag{A3}$$

where $\tilde{\delta}$ captures disagreement among analysts. On average, the signals of analysts give true information $\tilde{\theta}$. We assume that $\tilde{\delta}$ is uniformly distributed over [0,1]; that is, $\tilde{\delta} \sim U[0,1]$. In addition, we assume that all the underlying random variables—i.e., $\tilde{\theta}$ (the mean of analyst forecasts), $\tilde{\delta}$ (the analyst disagreement), and $\tilde{\varepsilon}$ (the residual cash flow uncertainty)—are mutually independent. We

[27] The assumption that $\tilde{\theta}$ and $\tilde{\varepsilon}$ have a non-zero mean is without loss of generality, since their means can be absorbed by the constant $\bar{v}$. Also, the assumption that $\tilde{\varepsilon}$ has a unit variance does not affect our results.

deliberately assume that $\tilde{\theta}$ and $\tilde{\delta}$are independent of each other to ensure that the interdependence between their return predictability is *endogenously* generated by the market equilibrium. Variable $\tilde{\theta}$ corresponds to *Chg_Mean* in our empirical analysis in the main text, while variable $\tilde{\delta}$ corresponds to *Chg_Std*.

There is a continuum [0,1] of traders who have constant-absolute-risk-aversion (CARA) utility with a risk tolerance normalized to 1. These traders are further categorized into three classes according to their beliefs and investment constraints. The first class of traders is buyers of mass $\mu_B > 0$. They face short-sale constraints and each of them is a dogmatic believer of one or the other analyst. Thus, buyers as a group inherit the disagreement $\tilde{\delta}$ in analyst forecasts. Their trading will generate the return predictability of the disagreement $\tilde{\delta}$. We can think of buyers as mutual funds. If buyer *i* believes in analyst $a \in \{U, D\}$, the CARA-normal structure implies that his/her demand is

$$Max\{0, \bar{v} + \tilde{s}_a - \tilde{p}\}. \qquad (A4)$$

We assume that half of the buyers believe in $\tilde{s}_U$, while the other half believe in $\tilde{s}_D$. Thus, the aggregate demand of buyers is

$$D_B(\tilde{p}; \tilde{s}_U, \tilde{s}_D) = 0.5\mu_B Max\{0, \bar{v} + \tilde{s}_U - \tilde{p}\} + 0.5\mu_B Max\{0, \bar{v} + \tilde{s}_D - \tilde{p}\}. \qquad (A5)$$

The second class of traders are underreactors of mass $\mu_C > 0$. They completely ignore analyst forecasts, underreact to information $\tilde{\theta}$, and are not subject to short-sale constraints. Thus, their total demand is

$$D_C(\tilde{p}) = \lambda_C(\bar{v} - \tilde{p}) \ with \ \lambda_C = \frac{\mu_C}{\sigma_\theta^2 + 1}. \qquad (A6)$$

Parameter λ_C can be understood as the "effective" mass of underreactors. The behavior of underreactors could be motivated by their limited ability to process information in the market (e.g., Hirshleifer and Teoh, 2003; DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009, 2011). In line with the findings in Cohen, Gompers, and Vuolteenaho (2002) that individual investors are more likely to underreact to cash-flow news, we can think of underreactors in our model as individual investors.

The third class of traders are arbitrageurs of mass $\mu_A = 1 - \mu_B - \mu_C > 0$. These traders correctly aggregate all analyst signals and do not face short-sale constraints. We can think of them as hedge funds. The total demand of arbitrageurs is

$$D_A(\tilde{p}; \tilde{s}_U, \tilde{s}_D) = \mu_A(\bar{v} + \tilde{\theta} - \tilde{p}). \tag{A7}$$

The first two classes of traders are essential for our results. We incorporate arbitrageurs simply to demonstrate the robustness of our results.

In equilibrium, the market clears. That is,

$$D_A(\tilde{p}; \tilde{s}_U, \tilde{s}_D) + D_B(\tilde{p}; \tilde{s}_U, \tilde{s}_D) + D_C(\tilde{p}) = 1, \tag{A8}$$

which states that the total stock demand from the three classes of traders is equal to the total unit supply.

We can use the demand functions and the market clearing condition to compute the equilibrium price as follows:

$$\tilde{p} = \begin{cases} \bar{v} + \dfrac{\mu_A \tilde{\theta} - 1}{\mu_A + \lambda_C}, & if\ \lambda_C \tilde{\theta} \le -(\mu_A + \lambda_C)\tilde{\delta} - 1, \\ \bar{v} + \dfrac{(\mu_A + 0.5\mu_B)\tilde{\theta} + 0.5\mu_B \tilde{\delta} - 1}{\mu_A + 0.5\mu_B + \lambda_C}, & if\ -(\mu_A + \lambda_C)\tilde{\delta} - 1 < \lambda_C \tilde{\theta} < (\mu_A + \mu_B + \lambda_C)\tilde{\delta} - 1, \\ \bar{v} + \dfrac{(\mu_A + \mu_B)\tilde{\theta} - 1}{\mu_A + \mu_B + \lambda_C}, & if\ \lambda_C \tilde{\theta} \ge (\mu_A + \mu_B + \lambda_C)\tilde{\delta} - 1. \end{cases} \tag{A9}$$

The price is equal to the expected dividend $\bar{v}$ adjusted by a term representing the equity premium. The three different regions of $(\tilde{\theta}, \tilde{\delta})$ reflect the tightness of buyers' short-sale constraints.

By Equation (A9), the price reacts positively to information $\tilde{\theta}$, but not to the full extent in the sense that $\frac{\partial \tilde{p}}{\partial \tilde{\theta}} < 1$. The reason is that underreactors do not respond to information $\tilde{\theta}$ fully, which generates the positive return predictability of $\tilde{\theta}$ (i.e., the mean of analyst forecasts).[28] The price also positively reacts to disagreement $\tilde{\delta}$ in the middle region where short-sale constraints are binding for some buyers but not for others. Because the dividend $\tilde{v}$ is independent of $\tilde{\delta}$, this sensitivity of prices to $\tilde{\delta}$ generates a negative *return* predictability of $\tilde{\delta}$ (i.e., the standard deviation of analysts' earnings forecasts). This mechanism is effectively Miller's (1977) hypothesis.

The realized stock return per share is defined as

$$\tilde{R} = \tilde{v} - \tilde{p}. \tag{A10}$$

Then, the regression coefficients of $\tilde{\theta}$ and $\tilde{\delta}$ used to forecast return $\tilde{R}$ are, respectively,

$$\beta_{\tilde{\theta}} \equiv \frac{Cov(\tilde{R},\tilde{\theta})}{Var(\tilde{\theta})} \ and \ \beta_{\tilde{\delta}} \equiv \frac{Cov(\tilde{R},\tilde{\delta})}{Var(\tilde{\delta})}. \tag{A11}$$

We label the above two β's as the "earnings news" beta and the "disagreement" beta, respectively. We can show that $\beta_{\tilde{\delta}} < 0$ and $\beta_{\tilde{\theta}} > 0$. The following proposition summarizes our discussion above.

Proposition A1. *The standard deviation $\tilde{\delta}$ of analysts' earnings forecasts negatively predicts future returns, while the mean $\tilde{\theta}$ of earnings forecasts positively predicts future returns. That is, $\beta_{\tilde{\delta}} < 0$ and $\beta_{\tilde{\theta}} > 0$.*

Proof. Using the total covariance formula, we have

$$Cov(\tilde{R},\tilde{\theta}) = E\left[Cov(\tilde{R},\tilde{\theta}|\tilde{\delta})\right] + Cov\left(E(\tilde{R}|\tilde{\delta}), E(\tilde{\theta}|\tilde{\delta})\right) = E\left[Cov(\tilde{R},\tilde{\theta}|\tilde{\delta})\right].$$

Equation (A9) shows that conditional on $\tilde{\delta}$, $\tilde{R}$ and $\tilde{\theta}$ are positively correlated because of the underreaction. That is, $Cov(\tilde{R},\tilde{\theta}|\tilde{\delta}) > 0$ as long as $\lambda_C > 0$, and as a result, $Cov(\tilde{R},\tilde{\theta}) > 0$ and hence $\beta_{\tilde{\theta}} > 0$. Similarly, we have $Cov(\tilde{R},\tilde{\delta}) = E\left[Cov(\tilde{R},\tilde{\delta}|\tilde{\theta})\right]$. By Equation (A9), given any realization of $\tilde{\theta}$, for the second branch of the price function, we have $Cov(\tilde{R},\tilde{\delta}|\tilde{\theta}) < 0$ as long as $\mu_B > 0$ (because of Miller's hypothesis), while for the first and the third branches of the price

[28] Note that in the absence of underreactors (i.e., when $\mu_C = 0$ and hence $\lambda_C = 0$), $\frac{\partial \tilde{p}}{\partial \tilde{\theta}} = 1$. In this case, the regression coefficient of $\tilde{\theta}$ used to forecast returns will degenerate to 0 in Equation (A11).

function, we have $Cov(\tilde{R}, \tilde{\delta}|\tilde{\theta}) = 0$. Thus, the unconditional covariance $Cov(\tilde{R}, \tilde{\delta})$ is negative, and hence $\beta_{\tilde{\delta}} < 0$. QED.

We next examine how the mean and standard deviation of analysts' earnings forecasts interact to predict future stock returns. We define *conditional* disagreement betas as

$$\beta_{\tilde{\delta}}^{+} \equiv \frac{Cov(\tilde{R}, \tilde{\delta}|\tilde{\theta} > 0)}{Var(\tilde{\delta}|\tilde{\theta} > 0)} \ \ and \ \ \beta_{\tilde{\delta}}^{-} \equiv \frac{Cov(\tilde{R}, \tilde{\delta}|\tilde{\theta} < 0)}{Var(\tilde{\delta}|\tilde{\theta} < 0)}, \qquad (A12)$$

where $\beta_{\tilde{\delta}}^{+}$ and $\beta_{\tilde{\delta}}^{-}$ are the regression coefficients of $\tilde{\delta}$ used to forecast returns when information $\tilde{\theta}$ is surprisingly high (i.e., above its unconditional mean) and low (i.e., below its unconditional mean), respectively. Note that Miller's hypothesis works through the combination of disagreement and short-sale constraints. When the market is on the rise (i.e., when $\tilde{\theta}$ is higher than the conditional mean), stock prices rise too little because of underreaction. Consequently, buyers are likely to purchase the stock, and so the short-sale constraints are likely to be irrelevant. As a result, the analyst disagreement $\tilde{\delta}$ is unable to predict future returns (i.e., $\beta_{\tilde{\delta}}^{+} \approx 0$). When the market is on the decline, underreaction to bad news causes the price to drop too little. Consequently, buyers are likely to short the stock, and so the short-sale constraints are likely to be binding. Hence, the analyst disagreement $\tilde{\delta}$ will predict future returns in a down market (i.e., $\beta_{\tilde{\delta}}^{-} < 0$).

Recall that the unconditional mean of $\tilde{\delta}$ is 0.5. We can similarly define *conditional* earnings news betas as

$$\beta_{\tilde{\theta}}^{+} \equiv \frac{Cov(\tilde{R}, \tilde{\theta}|\tilde{\delta} > 0.5)}{Var(\tilde{\theta}|\tilde{\delta} > 0.5)} \ \ and \ \ \beta_{\tilde{\theta}}^{-} \equiv \frac{Cov(\tilde{R}, \tilde{\theta}|\tilde{\delta} < 0.5)}{Var(\tilde{\theta}|\tilde{\delta} < 0.5)}, \qquad (A13)$$

which are the regression coefficients of $\tilde{\theta}$ used to forecast returns when disagreement $\tilde{\delta}$ is surprisingly high and low (i.e., the realized $\tilde{\delta}$ is above and below its unconditional mean of 0.5), respectively. However, the return predictability of $\tilde{\theta}$ is mainly driven by the underreaction of the second group of investors (i.e., by a positive λ_C), and hence, the value of $\tilde{\delta}$ does not affect the power of $\tilde{\theta}$ in predicting future returns, and as a result, $\beta_{\tilde{\theta}}^{+} > 0$ and $\beta_{\tilde{\theta}}^{-} > 0$. We formally prove the following proposition.

Proposition A2. *When the mean $\tilde{\theta}$ of analyst earnings forecasts is positive, the standard deviation $\tilde{\delta}$ of analysts' earnings forecasts does not predict future returns. But when the mean $\tilde{\theta}$ of analysts' earnings forecasts is negative, the standard deviation $\tilde{\delta}$ of analysts' earnings forecasts negatively predicts future returns. That is, $\beta_{\tilde{\delta}}^{+} = 0$ and $\beta_{\tilde{\delta}}^{-} < 0$. Independent of the standard deviation $\tilde{\delta}$ of analysts' earnings forecasts, the mean $\tilde{\theta}$ of analysts' earnings forecasts always positively predicts future returns. That is, $\beta_{\tilde{\theta}}^{+} > 0$ and $\beta_{\tilde{\theta}}^{-} > 0$.*

Proof. When $\tilde{\theta} > 0$, only the third branch of the price function is relevant; that is, $\tilde{p} = \bar{v} + \frac{(\mu_A+\mu_B)\tilde{\theta}-1}{\mu_A+\mu_B+\lambda_C}$. To see this, note that because $\tilde{\delta}$ has a support of [0,1], we have $(\mu_A + \mu_B + \lambda_C)\tilde{\delta} - 1 < (\mu_A + \mu_B + \lambda_C) - 1$. By the definition of $\lambda_C = \frac{\mu_C}{\sigma_{\tilde{\theta}}^2+1}$ and the fact that $(\mu_A + \mu_B + \mu_C) = 1$, we have $(\mu_A + \mu_B + \lambda_C)\tilde{\delta} - 1 < 0$. Therefore, for any $\tilde{\theta} > 0$, we have $\lambda_C\tilde{\theta} > 0 > (\mu_A + \mu_B + \lambda_C)\tilde{\delta} - 1$ and hence $\tilde{p} = \bar{v} + \frac{(\mu_A+\mu_B)\tilde{\theta}-1}{\mu_A+\mu_B+\lambda_C}$, which means that $Cov\left(\tilde{R}, \tilde{\delta} | \tilde{\theta} > 0\right) = 0$ and hence $\beta_{\tilde{\delta}}^{+} = 0$. In contrast, when $\tilde{\theta} < 0$, both the first and second branches of the price function are relevant, in which case $Cov\left(\tilde{R}, \tilde{\delta} | \tilde{\theta}\right) \leq 0$ (and the inequality holds with a positive probability). Thus, $Cov\left(\tilde{R}, \tilde{\delta} | \tilde{\theta} < 0\right) < 0$ and $\beta_{\tilde{\delta}}^{-} < 0$. For the conditional earnings news betas, note that for all three branches, as long as $\lambda_C > 0$, we have $Cov\left(\tilde{R}, \tilde{\theta} | \tilde{\delta}\right) > 0$, and hence $\beta_{\tilde{\theta}}^{+} > 0$ and $\beta_{\tilde{\theta}}^{-} > 0$. QED.

Appendix II: Definition of Data Items

Data Item	Definition
Accrual	Total accruals scaled by average total assets = [(ΔCA - ΔCash) - (ΔCL - ΔSTD - ΔTP) - Dep]/TA, as defined by Sloan (1996), where ΔCA = change in current assets, ΔCash = change in cash and cash equivalents, ΔCL = change in current liabilities, ΔSTD = change in debt included in current liabilities, ΔTP = change in income taxes payable, Dep = depreciation and amortization expense, and TA is the average of the beginning-of-year and end-of-year book values of total assets. The accounting information is extracted from the most recent accounting statements announced before the end of month *t*. (Data source: Compustat)
Chg_Mean(-5,0)	The change in absolute mean of analyst forecasts from the end of month *t*-5 to the end of month *t* = log (**the absolute mean of analyst forecasts for month t-5/CRSP cumulative share adjustment factor for month *t*-5) – log [(the absolute mean of analyst forecasts for month *t*/CRSP cumulative share adjustment factor for month *t*)**]. (Data Source: I/B/E/S)
Chg_Std(-5,0)	The change in standard deviation from the end of month *t*-5 to the end of month *t* = **log (the standard deviation of analysts' earnings forecasts for month *t*-5/CRSP cumulative share adjustment factor for month *t*-5) – log [(the standard deviation of analysts' earnings forecasts for month *t*/CRSP cumulative share adjustment factor for month *t*)**]. (Data Source: I/B/E/S)
Disp	The analyst forecast dispersion measure of Diether, Malloy, and Scherbina (2002). Disp for month t = the standard deviation of analysts' earnings forecasts in month *t* (Std)/the absolute value of forecast mean in month *t* (|Mean|). (Data source: I/B/E/S)
STD	The standard deviation of forecasted earnings (i.e., the numerator of *Disp*). (Data source: I/B/E/S)
|*Mean*|	The absolute mean of forecasted earnings (i.e., the denominator of *Disp*). (Data source: I/B/E/S)
BEPS	Book value of equity per share = Total book value of equity reported at the end of the last fiscal year/Number of shares reported at the end of month *t*. (Data source: Compustat and CRSP)
BAPS	Book value of total assets per share = Total book value of total assets reported at the end of the last fiscal year/Number of shares reported at the end of month *t*. (Data source: Compustat and CRSP)
E/P	The historical earnings-to-price ratio is calculated as follows: First, the net income before extraordinary items for the most recently announced fiscal year-end (I/B/E/S item *FY0EDATS*) is divided by the number of shares outstanding to obtain the historical earnings per share (*E*) for the end of month *t*–1. *E* is then divided by the stock price (*P*) on the same day to obtain *E/P*. (Data sources: Compustat, CRSP, and I/B/E/S)
log(BM)	The natural logarithm of Fama and French's (1992) book-to-market (BM) ratio, where the value for July of year *y* to June of year *y*+1 is computed using the book value of equity for the fiscal year-end in calendar year *y*-1 from Compustat and the market value of equity at the end of December of year *y*-1 from CRSP. (Data sources: CRSP and Compustat)
log(MV)	The natural logarithm of market capitalization of a firm at time *t*. (Data Source: CRSP)
Ret(0,1)	The monthly cumulative raw return of a stock for month *t*+1. (Data Source: CRSP)
Ret(-1,0)	The monthly cumulative raw return of a stock for month *t*. (Data Source: CRSP)
Ret(-7,-1)	The cumulative raw return of a stock for the period from the end of month *t*-7 to the end of month *t*-1. (Data Source: CRSP)

Table 1 Summary statistics and correlation matrix

This table reports descriptive statistics for the final sample during the period from January 1983 to December 2009. The sample includes all stocks listed on the NYSE, AMEX, and Nasdaq, excluding stocks priced below $5 at the end of the previous month and stocks with negative book value of equity. *MV* is market capitalization in million dollars; *Ret*(*s,t*) is the cumulative stock returns from month s to month t; *E/P* is the earnings-to-price ratio; *BM* is book-to-market ratio of equity; *DISP* is the DMS analyst forecast dispersion measure; *STD* is the standard deviation of forecasted earnings; |*Mean*| is the absolute mean of forecasted earnings; *BEPS* is the book value of equity per share; *BAPS* is the book value of total assets per share; *Chg_Std*(-5,0) is the log change in standard deviation of forecasted earnings per share (FEPS) from month -5 to month 0; and *Chg_Mean*(-5,0) is the log change in the mean absolute value of FEPS from month -5 to month 0. Only stocks for which sufficient data are available in the CRSP, Compustat, and I/B/E/S databases to compute the firm characteristics defined in Appendix II are included in the sample. In Panel A, the time-series averages of common statistics for the major dependent and independent variables are reported. The time-series averages of correlation coefficients between each pair of variables are reported in Panel B.

Panel A: Summary statistics

Variable	MV	Ret(0,1)	E/P	BM	Accrual	DISP	STD	|Mean|	BEPS	BAPS	Chg_Std(-5,0)	Chg_Mean(-5,0)	Ret(-1,0)	Ret(-7,-1)
Mean	2051.24	0.010	0.106	0.563	-0.027	0.191	0.157	2.275	21.290	86.56	0.036	0.022	0.015	0.097
Median	514.91	0.006	0.100	0.510	-0.034	0.046	0.071	1.434	10.405	24.61	0.037	0.034	0.008	0.059
STD	4700.40	0.116	0.094	0.322	0.074	1.156	1.454	24.820	66.001	264.46	0.832	0.370	0.119	0.328
Skewnes	4.61	0.538	0.339	0.956	0.597	22.494	24.950	25.913	8.332	7.59	0.091	-0.475	1.090	2.044
Q1	200.42	-0.053	0.056	0.318	-0.069	0.022	0.034	0.786	5.770	11.12	-0.490	-0.071	-0.050	-0.087
Q3	1574.53	0.067	0.152	0.741	0.008	0.111	0.146	2.384	17.961	60.82	0.548	0.141	0.071	0.225

Panel B: Correlation coefficients

Variables	MV	Ret(0,1)	E/P	BM	Accrual	DISP	STD	|Mean|	BEPS	BAPS	Chg_Std(-5,0)	Chg_Mean(-5,0)	Ret(-1,0)
Ret(0,1)	0.002												
E/P	0.061	0.029											
BM	-0.103	0.019	0.337										
Accrual	-0.077	-0.023	0.031	-0.101									
DISP	-0.089	-0.019	-0.191	0.117	-0.071								
STD	0.074	-0.005	0.044	0.202	-0.123	0.399							
|Mean|	0.362	0.021	0.331	0.062	-0.060	-0.280	0.240						
BEPS	0.075	0.012	0.112	0.172	-0.077	0.002	0.220	0.259					
BAPS	0.057	0.006	0.162	0.181	-0.067	-0.001	0.199	0.261	0.723				
Chg_Std(-5,0)	-0.005	-0.005	0.009	-0.021	0.025	0.161	0.282	0.015	0.000	0.002			
Chg_Mean(-5,0)	0.022	0.019	-0.046	-0.057	-0.019	-0.256	-0.036	0.130	-0.005	-0.007	0.066		
Ret(-1,0)	0.011	-0.015	0.006	0.027	-0.026	0.000	-0.006	0.000	0.002	-0.001	-0.011	0.029	
Ret(-7,-1)	0.026	0.028	0.006	0.011	-0.056	-0.077	-0.047	0.045	-0.003	-0.004	-0.039	0.228	-0.006

Table 2 One-month-ahead portfolio returns sorted by size and the analyst forecast dispersion measures with alternative scalars

At the beginning of each month, stocks are first sorted into quintiles (SZ1–SZ5) based on market capitalization at the end of the previous month. Stocks in each size quintile are further sorted into five groups based on analyst forecast dispersion measures with alternative scalars. The numerator of all dispersion measures is the standard deviation of analysts' forecasted earnings. All denominators, including the absolute value of mean forecasts (Panel A), book value of equity per share (Panel B) and book value of total assets per share (Panel C), reflect the most recent information before portfolio formation. Any tied values of sorting variables at the margin between two groups are assigned to the group with a lower rank. Equal-weighted portfolios are constructed for each subgroup and are held for one month. In addition to the time-series average of portfolio returns of each subgroup, we also report the time-series average of hedging portfolio returns (e.g., DISP1–DISP5), which is the average return for the hedging portfolio that longs stocks in the lowest dispersion quintile (DIPS1) and shorts stocks in the highest dispersion quintile (DISP5). In each size quintile, we also report the time-series average of correlation coefficients (i.e., *Corr*(*N,D*)) between the numerator and denominator of analyst forecast dispersion measures. The sample period is from January 1983 to December 2009. All stocks in the sample are covered by at least two analysts in the previous month and are priced above $5 per share. The *t*-statistics adjusted by the Newey-West (1987) method are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Ret(0,1)	Size group					
	SZ1	SZ2	SZ3	SZ4	SZ5	All
Panel A: DISP=STD of analysts' earnings forecasts/|Forecasted earnings per share for the next fiscal year| (i.e., |Mean|)						
DISP1 (L)	1.375	1.271	1.184	1.176	1.090	1.219
DISP2	1.298	1.241	1.107	1.071	0.947	1.133
DISP3	0.919	0.942	1.111	0.928	1.050	0.990
DISP4	0.718	0.862	1.047	1.083	0.980	0.938
DISP5 (H)	0.146	0.606	0.731	0.866	0.916	0.653
DISP (L-H)	1.229***	0.665***	0.452**	0.310	0.174	0.566***
t-stat	(6.70)	(3.18)	(1.96)	(1.32)	(0.74)	(2.92)
Corr(*STD,* |*Mean*|)	0.208	0.215	0.226	0.222	0.258	0.240
Panel B: DISP=STD of analysts' earnings forecasts /Book value of equity per share (i.e., BEPS)						
DISP1 (L)	1.124	1.092	1.184	1.191	1.023	1.123
DISP2	1.275	1.278	1.161	1.012	1.017	1.148
DISP3	1.096	1.046	1.013	0.983	1.020	1.032
DISP4	0.801	0.909	1.076	1.023	0.997	0.961
DISP5 (H)	0.161	0.596	0.747	0.916	0.927	0.669
DISP (L-H)	0.963***	0.496*	0.436*	0.274	0.097	0.453**
t-stat	(4.59)	(1.68)	(1.71)	(1.15)	(0.41)	(2.02)
Corr(*STD, BEPS*)	0.173	0.176	0.229	0.264	0.370	0.220
Panel C: DISP=STD of analysts' earnings forecasts /Book value of total asset per share (i.e., BAPS)						
DISP1 (L)	1.175	1.182	1.212	1.192	1.121	1.176
DISP2	1.182	1.181	1.140	1.194	1.042	1.148
DISP3	1.023	1.196	1.063	1.028	0.925	1.047
DISP4	0.794	0.868	1.049	0.857	0.868	0.887
DISP5 (H)	0.282	0.493	0.718	0.854	1.028	0.675
DISP (L-H)	0.893***	0.689**	0.493	0.338	0.093	0.501*
t-stat	(3.73)	(2.15)	(1.52)	(1.11)	(0.30)	(1.82)
Corr(*STD, BAPS*)	0.158	0.165	0.190	0.210	0.316	0.199

Table 3 Variation in STD within decile groups based on scalars

At the beginning of each month, stocks are first sorted into ten groups based on a common scalar of analyst forecast dispersion measures (i.e., $|Mean|$ in Panel A, *BEPS* in Panel B, and *BAPS* in Panel C). Then we compute the mean, median and standard deviation of standard deviation of forecasted earnings within each decile group. The table reports the time-series average of these variables for the sample period from January 1983 to December 2009.

Panel A: |Mean| Group		1	2	3	4	5	6	7	8	9	10
STD	Mean	0.123	0.095	0.094	0.098	0.102	0.110	0.118	0.133	0.158	0.536
	Median	0.068	0.050	0.050	0.052	0.057	0.062	0.071	0.081	0.097	0.163
	STD	0.176	0.145	0.139	0.149	0.148	0.161	0.158	0.177	0.210	4.400
Panel B: BEPS Group		1	2	3	4	5	6	7	8	9	10
STD	Mean	0.086	0.077	0.081	0.090	0.100	0.111	0.123	0.147	0.185	0.565
	Median	0.042	0.042	0.047	0.052	0.060	0.068	0.079	0.095	0.118	0.198
	STD	0.165	0.122	0.118	0.132	0.142	0.153	0.157	0.183	0.220	4.393
Panel C: BAPS Group		1	2	3	4	5	6	7	8	9	10
STD	Mean	0.069	0.069	0.077	0.089	0.105	0.124	0.145	0.180	0.214	0.494
	Median	0.037	0.040	0.047	0.054	0.065	0.079	0.093	0.110	0.124	0.132
	STD	0.102	0.093	0.104	0.129	0.136	0.159	0.181	0.240	0.294	4.367

Table 4 One-month-ahead portfolio returns sorted by size and the components of alternative analyst forecast dispersion measures

At the beginning of each month, stocks are first sorted into quintiles (SZ1–SZ5) based on market capitalization at the end of the previous month. Stocks in each size quintile are further sorted into five groups based on components of alternative analyst forecast dispersion measures, including the standard deviation of forecasted earnings (the numerator), absolute mean of forecasted earnings (Scalar A), book value of equity per share (Scalar B), and book value of total assets per share (Scalar C). Equal-weighted portfolios are constructed for each subgroup and are held for one month. In addition to the time-series average of portfolio returns of each subgroup, we also report the time-series average of hedging portfolio returns based on these components. The sample period is from January 1983 to December 2009. All stocks in the sample are covered by at least two analysts in the previous month and are priced above $5 per share. The *t*-statistics adjusted by the Newey-West (1987) method are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Ret(0,1)	Size group					
	SZ1	SZ2	SZ3	SZ4	SZ5	All
Panel A: Portfolio returns sorted by the standard deviation of analysts' earnings forecasts (i.e., Numerator=STD)						
STD1(L)	1.182	1.056	1.024	0.940	0.964	1.033
STD2	1.127	1.102	1.201	1.063	1.006	1.100
STD3	0.867	0.879	1.048	0.993	0.972	0.952
STD4	0.757	1.113	1.023	1.098	1.024	1.003
STD5(H)	0.434	0.755	0.941	1.096	1.061	0.857
STD(L-H)	0.747***	0.301**	0.084	-0.156	-0.097	0.176
t-stat	(4.97)	(2.01)	(0.51)	(-1.04)	(-0.60)	(1.37)
Panel B: Portfolio returns sorted by the absolute mean of analysts' earnings forecasts (i.e., Scalar A=|Mean|)						
MEAN1(L)	0.367	0.559	0.779	0.739	0.819	0.652
MEAN2	0.728	0.889	0.874	1.053	0.919	0.893
MEAN3	0.921	0.950	1.066	0.988	1.011	0.987
MEAN4	1.107	1.189	1.187	1.092	1.124	1.140
MEAN5(H)	1.352	1.344	1.281	1.253	1.113	1.268
MEAN(H-L)	0.984***	0.785***	0.502*	0.514*	0.295	0.616***
t-stat	(4.80)	(3.24)	(1.82)	(1.84)	(1.08)	(2.68)
Panel C: Portfolio returns sorted by the book value of equity per share (i.e., Scalar B=BEPS)						
BEPS1(L)	0.564	0.751	0.826	0.770	0.928	0.768
BEPS2	0.782	0.822	0.975	1.013	0.900	0.898
BEPS3	0.955	1.059	1.027	1.012	1.010	1.012
BEPS4	1.080	1.070	1.161	1.102	1.048	1.092
BEPS5(H)	1.075	1.218	1.193	1.227	1.098	1.162
BEPS(H-L)	0.511**	0.467	0.367	0.457	0.170	0.394
t-stat	(2.06)	(1.45)	(1.18)	(1.61)	(0.68)	(1.51)
Panel D: Portfolio returns sorted by the book value of asset per share (i.e., Scalar C=BAPS)						
BAPS1(L)	0.570	0.563	0.712	0.718	0.897	0.692
BAPS2	0.921	0.951	1.031	1.010	0.953	0.973
BAPS3	0.892	1.082	1.139	1.080	0.966	1.032
BAPS4	1.052	1.182	1.131	1.142	1.085	1.118
BAPS5(H)	1.020	1.141	1.169	1.173	1.084	1.117
BAPS(H-L)	0.449	0.578	0.457	0.454	0.188	0.425
t-stat	(1.51)	(1.48)	(1.20)	(1.27)	(0.58)	(1.30)

Table 5 Sequential triple sorts based on Size, STD, and |Mean|

At the beginning of each month, stocks are first sorted into three groups (Small, Medium, and Large) based on market capitalization (*Size*) at the end of month *t*. In Panel A, stocks in each size group are then sorted into three subgroups based on the standard deviation of forecasted earnings (*STD*), and stocks in each *STD* subgroup are further sorted into three groups based on the absolute mean of forecasted earnings (|*Mean*|). In Panel B, we reverse the order of the latter two sorting variables, i.e., after the sort based on firm size, we sort stocks based on |*Mean*| first and then *STD*. In addition to the time-series averages of portfolio returns of 3×3 subgroups, we also report the time-series average of hedging portfolio returns based on the latter two sorting variables. In Panel C, we report the time-series average of correlation coefficients between STD and |Mean| in all size groups. The sample period is from January 1983 to December 2009. All stocks in the sample are covered by at least two analysts in the previous month and are priced above $5 per share. The *t*-statistics adjusted by the Newey-West (1987) method are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Sequential Sort by Size, STD and |Mean|

Ret(0,1)	Small				Medium				Large			
	STD1(L)	STD2	STD3(H)	STD(L-H)	STD1(L)	STD2	STD3(H)	STD(L-H)	STD1(L)	STD2	STD3(H)	STD(L-H)
Mean1(L)	0.695	0.540	0.290	0.405***	0.809	0.783	0.806	0.003	0.735	0.957	0.887	-0.152
				(2.82)				(0.02)				(-0.76)
Mean2	1.241	0.928	0.601	0.640***	0.990	1.135	1.009	-0.019	0.985	0.966	1.047	-0.061
				(4.11)				(-0.14)				(-0.46)
Mean3(H)	1.495	1.342	1.078	0.417***	1.261	1.334	1.297	-0.037	1.148	1.075	1.189	-0.041
				(2.90)				(-0.26)				(-0.31)
Mean(H-L)	0.800***	0.803***	0.788***		0.452	0.551**	0.492**		0.414	0.118	0.302*	
	(3.86)	(3.80)	(4.84)		(1.53)	(2.22)	(2.53)		(1.39)	(0.46)	(1.66)	

Panel B: Sequential Sort by Size, |Mean| and STD

Ret(0,1)	Small				Medium				Large			
	Mean1(L)	Mean2	Mean3(H)	Mean(H-L)	Mean1(L)	Mean2	Mean3(H)	Mean(H-L)	Mean1(L)	Mean2	Mean3(H)	Mean(H-L)
STD1(L)	0.755	1.245	1.462	0.706***	0.856	1.097	1.389	0.532*	0.783	1.097	1.114	0.331
				(3.41)				(1.86)				(1.23)
STD2	0.562	0.997	1.347	0.785***	0.784	1.117	1.229	0.446*	0.943	0.873	1.140	0.197
				(3.67)				(1.84)				(0.76)
STD3(H)	0.266	0.527	1.017	0.752***	0.775	0.942	1.263	0.488**	0.903	0.954	1.155	0.251
				(4.63)				(2.52)				(1.32)
STD(L-H)	0.490***	0.718***	0.445***		0.081	0.155	0.125		-0.120	0.144	-0.041	
	(3.45)	(4.66)	(2.88)		(0.43)	(1.22)	(0.84)		(-0.67)	(0.96)	(-0.28)	

Panel C: Correlation Coefficient between |Mean| and STD

Corr(STD, |Mean|)	Small	Medium	Large
Mean1(L)	-0.090	-0.096	-0.114
Mean2	0.037	0.040	0.061
Mean3(H)	0.343	0.364	0.687

Table 6 One-month-ahead portfolio returns sorted by size and the change in standard deviation of forecasted earnings

At the beginning of each month, stocks are first sorted into quintiles (SZ1–SZ5) based on market capitalization at the end of the previous month. Stocks in each size quintile are further sorted into five groups based on the change in the standard deviation of forecasted earnings (i.e., *Chg_Std*(-5,0)). Equal-weighted portfolios are constructed for each subgroup and are held for one month. We report the time-series average returns of the hedging portfolio (i.e., the portfolio that longs the stocks in CS1 and shorts the stocks in CS5) based on *Chg_Std*(-5,0) for each size quintile. In Panel B, we also report alphas for the portfolios in the long and short positions. Alpha is the intercept from a time-series regression of returns based on the Fama and French (1993) three-factor model, plus the Carhart (1997) momentum factor. The sample period is from January 1983 to December 2009. All stocks in the sample are covered by at least two analysts in the previous month and are priced above $5 per share. The *t*-statistics adjusted by the Newey-West (1987) method are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Ret(0,1)	Size group					
	SZ1	SZ2	SZ3	SZ4	SZ5	All
Panel A: Portfolio return						
CS1(L)	1.039	1.043	1.003	0.999	0.907	0.998
CS2	0.937	1.088	1.044	1.076	1.042	1.037
CS3	0.882	1.020	1.065	1.060	1.013	1.008
CS4	0.954	1.013	1.075	1.057	0.935	1.007
CS5(H)	0.403	0.712	1.055	0.958	1.094	0.844
CS (L-H)	0.637***	0.331**	-0.052	0.041	-0.187*	0.154
t-stat	(5.03)	(2.57)	(-0.40)	(0.43)	(-1.65)	(1.19)
Panel B: Portfolio alpha						
CS1(L)	0.084	0.058	-0.063	-0.033	-0.070	-0.005
	(0.66)	(0.59)	(-0.73)	(-0.39)	(-1.02)	(-0.14)
CS5(H)	-0.547***	-0.273**	0.070	-0.008	0.129	-0.126
	(-4.18)	(-2.44)	(0.70)	(-0.09)	(1.39)	(-1.37)
CS (L-H)	0.631***	0.331***	-0.133	-0.025	-0.199	0.121
t-stat	(5.73)	(2.85)	(-0.09)	(-0.74)	(-1.55)	(1.35)

Table 7 One-month-ahead portfolio returns sorted by size, the change in mean forecasts, and the change in standard deviations of earnings forecasts

At the beginning of each month, stocks are first sorted into three groups (Small, Medium, and Large) based on market capitalization at the end of the previous month. Stocks in each size group are then sorted into three subgroups (CM1–CM3) based on *Chg_Mean* (-5, 0), and stocks in each subgroup are further sorted into three groups (CS1–CS3) based on *Chg_Std*(-5, 0). Panel A reports the time-series averages of one-month-ahead returns of equal-weighted portfolios for stocks in each subgroup. We also report the time-series averages of hedging portfolio returns for CM3-CM1 (i.e., the portfolio that longs stocks with the largest *Chg_Mean*(-5, 0) and shorts stocks with the smallest *Chg_Mean*(-5, 0)) and CS1-CS3 (i.e., the portfolio that longs stocks with the smallest *Chg_Std*(-5, 0) and shorts stocks with the largest *Chg_Std*(-5, 0)). In Panels B and C, we report the time-series averages of *Chg_Mean*(-5, 0) and *Chg_Std*(-5, 0) for each subgroup. The sample period is from January 1983 to December 2009. All stocks in the sample are covered by at least two analysts in the previous month and are priced above \$5 per share. The *t*-statistics adjusted by the Newey-West (1987) method are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equal-weighted Ret (0,1)

	Small				Medium				Large			
	CM1(L)	CM2	CM3(H)	CM(H-L)	CM1(L)	CM2	CM3(H)	CM(H-L)	CM1(L)	CM2	CM3(H)	CM(H-L)
CS1 (L)	0.474	1.166	1.362	0.888***	0.881	1.088	1.205	0.324*	0.930	1.093	0.966	0.035
				(5.39)				(1.74)				(0.19)
CS2	0.562	1.049	1.379	0.817***	0.792	1.222	1.271	0.479***	1.051	1.055	0.923	-0.128
				(4.94)				(2.86)				(-0.72)
CS3 (H)	-0.090	0.917	1.091	1.181***	0.620	1.079	1.345	0.725***	0.846	1.021	1.154	0.308*
				(7.73)				(4.45)				(1.70)
CS(L-H)	0.564***	0.249	0.271		0.261*	0.009	-0.140		0.084	0.072	-0.189*	
	(4.76)	(1.51)	(1.57)		(1.88)	(0.09)	(-1.04)		(0.74)	(0.97)	(-1.79)	

Panel B: Chg_Mean(-5,0)

	Small			Medium			Large		
	CM1(L)	CM2	CM3(H)	CM1(L)	CM2	CM3(H)	CM1(L)	CM2	CM3(H)
CS1 (L)	-0.556	0.011	0.506	-0.343	0.035	0.400	-0.218	0.039	0.290
CS2	-0.509	0.015	0.462	-0.318	0.038	0.387	-0.193	0.041	0.279
CS3 (H)	-0.580	0.017	0.499	-0.386	0.041	0.419	-0.259	0.042	0.336

Panel C: Chg_Std (-5,0)

	Small			Medium			Large		
	CM1(L)	CM2	CM3(H)	CM1(L)	CM2	CM3(H)	CM1(L)	CM2	CM3(H)
CS1 (L)	-1.241	-0.988	-1.028	-1.073	-0.882	-0.818	-0.884	-0.691	-0.622
CS2	0.009	-0.030	0.158	-0.068	-0.035	0.194	-0.088	-0.044	0.183
CS3 (H)	1.275	0.939	1.332	0.997	0.800	1.208	0.779	0.587	1.025

Table 8 Fama-MacBeth regressions of one-month-ahead returns on changes in standard deviations and means of analysts' earnings forecasts

This table reports the results from the Fama-MacBeth regressions to test the roles of *Chg_Mean*(-5,0) and *Chg_Std*(-5,0) in explaining the cross-section of stock returns. The dependent variable is the one-month-ahead raw return *Ret*(0,1) in the current month *t*. The explanatory variables include a constant (not reported), the change in forecast means (i.e., *Chg_Mean*(-5,0)), change in forecast standard deviations (i.e., *Chg_Std*(-5,0)), DMS analyst forecast dispersion measure (*Disp*), size (i.e., *log*(*MV*), book-to-market ratio (i.e., *log*(*BM*)), past returns (i.e., *Ret*(-1,0) and *Ret*(-7,-1)), accounting accruals (i.e., *Accrual*), and E/P ratio (i.e., *E/P*). *NegChg_Std Dummy* is a dummy variable that equals 1 if *Chg_Std*(-5,0) is negative and 0 otherwise. Similarly, *NegChg_Mean Dummy* is a dummy variable that equals 1 if *Chg_Mean*(-5,0) is negative and 0 otherwise. Detailed definitions are provided in Appendix II. The sample period is from January 1983 to December 2009. All stocks in the sample are covered by at least two analysts in the previous month and are priced above \$5 per share. The *t*-statistics adjusted by the Newey-West (1987) method are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable = *Ret*(0,1)	Model 1	Model 2	Model 3	Model 4	Model 5
Chg_Std(-5,0)			-0.011	0.008	0.002
			(-0.25)	(0.28)	(0.06)
Chg_Std(-5,0)×*NegChg_Mean Dummy*				-0.113***	-0.101**
				(-2.66)	(-2.14)
Chg_Mean(-5,0)		0.258***	0.322***	0.321***	0.352***
		(3.52)	(4.39)	(4.43)	(3.82)
Chg_Mean(-5,0)×*NegChg_Std Dummy*					-0.054
					(-0.52)
Disp	-0.251***	-0.189***			
	(-4.42)	(-3.35)			
log(*MV*)	-0.014	-0.013	-0.011	-0.011	-0.012
	(-0.32)	(-0.30)	(-0.25)	(-0.26)	(-0.27)
log(*BM*)	0.175*	0.172*	0.158	0.161	0.162
	(1.74)	(1.71)	(1.58)	(1.61)	(1.62)
Ret(-1,0)	-0.026***	-0.026***	-0.027***	-0.027***	-0.027***
	(-5.14)	(-5.21)	(-5.31)	(-5.31)	(-3.31)
Ret(-7,-1)	0.007**	0.006**	0.006**	0.006**	0.006**
	(2.30)	(2.09)	(2.02)	(2.02)	(2.01)
Accruals	-3.352***	-3.329***	-3.354***	-3.363***	-3.361***
	(-7.87)	(-7.75)	(-7.99)	(-8.01)	(-8.01)
E/P	2.124***	2.274***	2.535***	2.523***	2.498***
	(2.88)	(3.09)	(3.42)	(3.41)	(3.38)
Average no. of obs. per month (months)	1,761 (324)	1,761 (324)	1,761(324)	1,761(324)	1,761(324)
Average adjusted R-squared	0.049	0.050	0.050	0.050	0.050