What Drives the Dispersion Anomaly?

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Abstract

This paper shows that the anomalous negative relation between dispersion in analysts' earnings forecast and future stock returns is driven by the information content of dispersion about future firm profitability. Greater dispersion predicts lower future profitability, and the return predictive power of dispersion disappears after controlling for its information content on future profitability. We propose disclosure manipulation as a potential explanation for the relation between dispersion and future profitability. Consistent with our conjecture, disclosure quality is inversely related to analysts' earnings forecast dispersion. Moreover, the return predictive power of dispersion decreases monotonically in disclosure quality and is no longer statistically significant in the post-Sarbanes-Oxley period during which disclosure manipulation is attenuated. Finally, our results remain robust to considering the previously suggested explanations for the dispersion anomaly, including short-sale constraints, leverage, and credit risk.

JEL classification: G12; G14
Keywords: Dispersion anomaly; Profitability; Disclosure quality

1. Introduction

Diether, Malloy, and Scherbina (2002) show that firms with higher analysts' earnings forecast dispersion have lower future stock returns. In particular, they find that an equal-weighted portfolio of stocks in the highest quintile of dispersion underperforms the portfolio of stocks in the bottom quintile by 9.48% per year, and the results cannot be explained by the standard asset pricing models, including the capital asset pricing model (CAPM), the Fama and French (1993) model, and the Carhart (1997) model. If forecast dispersion proxies for future cash flow uncertainty, investors should demand higher, not lower, expected returns as a compensation for bearing higher uncertainty. As such, the negative relation between dispersion and stock returns is anomalous.

This paper shows that analysts' earnings forecast dispersion negatively predicts future firm profitability, and the return predictability of forecast dispersion is driven by its information content about future profitability. We begin our analysis by showing that analysts' forecast dispersion has a strong predictive power for future return on assets and return on equity, our proxies for firm profitability. Using Fama-MacBeth (1973) regressions of forecasting future profitability, we find that a one-standard-deviation increase in dispersion is associated with -0.66% (-1.26%) drop in one-quarter-ahead return on assets (return on equity).

Since cash flow (profitability) is an important determinant of expected returns (Fama and French, 2006, 2015) and analyst forecast dispersion has a strong correlation with future profitability, the return predictive power of analyst forecast dispersion can be induced by its information content about future profitability. We conduct three sets of tests to examine this prediction. First, when we control for future profitability, the predictive power of dispersion for stock returns flips sign to become positive and is statistically insignificant in Fama-MacBeth cross-sectional regressions. In contrast, the return predictive power of firm size, book-to-market equity ratio, momentum, and investment remains qualitatively unchanged when we control for future profitability. That is, future profitability subsumes an explanatory power of dispersion only, among the variables that are known to predict cross-sectional stock returns. Second, we perform sequential portfolio double sorts first by future profitability and then by dispersion. Consistent with the Fama-MacBeth cross-sectional regression results, we find that, in each future profitability quintile, stocks with higher analysts' earnings forecast dispersion have higher, not lower, future raw returns as well as Carhart (1997) four-factor alphas. This result suggests that, after controlling for future profitability, the negative relation between forecast dispersion and future stock returns disappears.

Third, we examine whether a profitability factor helps explain the dispersion anomaly. The *q*-factor model proposed by Hou, Xue, and Zhang (2015) predicts that firms with high expected profitability (i.e., low dispersion stocks) should earn higher expected returns than firms with low expected profitability (i.e., high dispersion stocks) for a given investment. Relatedly, Fama and French (2015) show that, *ceteris paribus* (e.g., holding constant firm investment and market-to-book equity ratio), expected future profitability is positively related to expected returns, using the dividend discount model in conjunction with clean surplus accounting. Therefore, if profitability indeed drives the dispersion effect, a profitability factor should substantially reduce the magnitude of the anomaly. Using the RMW factor (Fama and French, 2015), ROE factor (Hou, Xue and Zhang, 2015) or PMU factor (Novy-Marx, 2013), we consistently find that the profitability factor explains well the dispersion effect. For example, the low-minus-high dispersion quintile hedge portfolio earns the Carhart four-factor alpha of 0.61% per month (*t*-value = 4.48). Adding the ROE factor into the CAPM makes the low-minus-high dispersion hedge portfolio alpha insignificantly different from zero (only 0.07% per month). We further show that Hou, Xue, and Zhang's (2015) four-factor model and Novy-Marx's (2013) four-factor model both make the low-minus-high dispersion hedge portfolio alpha insignificantly different from zero.

Why does analysts' earnings forecast dispersion contain information about future profitability? We propose that this is due to the disclosure manipulation of corporate managers. The accounting literature documents that managers have substantial discretion in earnings disclosure and they have strong incentives to engage in disclosure manipulation due to career concerns and incentive compensation (e.g., see Armstrong, Guay and Weber 2010 for a review). Compared with corporate outsiders such as equity analysts, managers possess superior information about future profitability of the firm (e.g., they can directly observe customer orders). When future profitability is expected to be good, managers tend to timely release good news, often providing detailed supplementary information. By contrast, when future profitability is expected to be bad, managers tend to withhold bad news and disclose relatively vague information (e.g., Jin and Myers 2006; Kothari, Shu and Wysocki 2009). For example, Graham, Harvey and Rajgopal (2005) provide survey evidence that some CFOs often withhold bad news, hoping that they may not have to disclose such bad news if the firm's situation improves prior to the mandatory disclosure. Kothari, Shu and Wysocki (2009) present empirical evidence showing that managers tend to withhold bad news but immediately reveal good news to investors.

When managers expect low future profitability, they withhold the information or only disclose vague information. Such disclosure manipulation increases analyst earnings forecast dispersion because the source of analysts' forecast dispersion is mainly the difference in their private information (Lang and Lundholm, 1996; Dhaliwal, Li, Tsang and Yang, 2011). When there is a lack of accurate public information that can be used to forecast the firm's future earnings prospects, analysts place less weight on common public information and more weight on their heterogeneous private information, which leads to greater forecast dispersion. For example, Lang and Lundholm (1996) find that firms with lower levels of informative disclosure have greater analyst forecast dispersion. Rajopal and Venkatachalam (2011) document that financial reporting quality is inversely related to analyst forecast dispersion. Thus, there should be a negative relation between analyst earnings forecast dispersion and future profitability of the firm.

We verify that earnings disclosure quality is associated with dispersion, as well as future profitability in our sample. As proxies for disclosure quality, we use accrual-based measures of earnings quality (e.g., Francis, LaFond, Olsson, and Schipper, 2005). Consistent with the literature (e.g., Rajopal and Venkatachalam, 2011), we find strong evidence that earnings disclosure quality is inversely related to analyst forecast dispersion, and that lower disclosure quality predicts lower future profitability.

If the dispersion anomaly is driven by managerial disclosure manipulation in anticipation of low future firm profitability, we expect the return predictive power of dispersion to be stronger in firms with lower earnings disclosure quality. When we double sort stocks into quintile portfolios first by disclosure quality and then by dispersion, we find that the Carhart four-factor alphas of the low-minus-high dispersion hedge portfolios increase monotonically as disclosure quality weakens. Similarly, the interaction term between disclosure quality and dispersion drives out dispersion itself in Fama-MacBeth cross-sectional regressions of predicting future stock returns.

The Sarbanes-Oxley Act (SOX) enacted in 2002 provides a quasi-natural experiment for us to further verify the proposed disclosure manipulation explanation to the dispersion anomaly. As the most important disclosure reform in the U.S. corporate history, SOX significantly reduces earnings disclosure manipulation and increases disclosure quality for publicly listed firms (e.g., Lobo and Zhou, 2006; Cohen, Dey and Lys, 2008). We expect the dispersion anomaly to be substantially weakened in the post-SOX era due to the significantly tightened disclosure requirements. Consistent with this prediction, we find that in the post-2003 period, the relation between analyst earnings forecast dispersion and future stock returns is no longer statistically significant.

Several explanations for the dispersion anomaly have been proposed in the literature. Diether, Malloy and Scherbina (2002) suggest that analyst earnings forecast dispersion is a measure of divergence of investor opinions and interpret their findings as evidence in favor of Miller's (1977) prediction that asset prices will be overvalued if pessimistic investors are kept out of the market by short-sale constraints. Higher divergence of opinions as proxied by greater forecast dispersion causes stocks to be overpriced initially and hence leads to lower future returns as the overpricing is corrected over time. This explanation is silent on the relation between dispersion and future firm profitability. Johnson (2004) provides an alternative explanation that dispersion is a proxy for idiosyncratic risk when asset values are unobservable. Since the equity claim of a levered firm can be viewed as a call option on the firm's assets, firms with higher dispersion are likely to have higher current equity value and hence lower expected stock returns. Similarly, this explanation only relates dispersion to future stock returns but not future firm profitability. Finally, Avramov, Chordia, Jostova and Philipov (2009) argue that the dispersion-return relation can be explained by financial distress as proxied by credit rating downgrades. They show that the profitability of dispersion-based trading strategies is mainly driven by a small number of the worst-rated firms and is significant only during periods of deteriorating credit conditions.

Since we propose and show that the return predictive power of analysts' earnings forecast dispersion is driven by the fact that dispersion contains information about future firm profitability due to disclosure manipulation, we need to further distinguish this explanation from the aforementioned explanations in the literature. We partition our full sample into subsamples based on short-sale constraints, leverage and credit risk, respectively. In all subsamples, we consistently find that the return predictive power of dispersion disappears completely or flips sign when we control for future profitability, suggesting that future profitability is the driving force behind the dispersion anomaly.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 documents the empirical evidence on dispersion, future profitability, and future stock returns. Section 4 provides the evidence on the dispersion anomaly and disclosure manipulation. Section 5 presents the evidence that help distinguish our proposed explanation from the alternative explanations in the literature. Section 6 concludes. All variables are defined in Table A1 in the Appendix.

2. Data

Monthly analyst annual earnings forecast data are obtained from the Institutional Brokers' Estimate System (I/B/E/S). We use the unadjusted file in I/B/E/S, since Diether, Malloy and Scherbina (2002) emphasize that the adjusted file is subject to the rounding error issue. Since the I/B/E/S data is available from January 1976, our sample period is from 1976 to 2014. We obtain month returns for all common stocks (CRSP share code 10 or 11) listed on NYSE, AMEX and NASDAQ from the Center for Research in Security Prices (CRSP). Following Jegadeesh and Titman (1993, 2001) and Diether, Malloy and Scherbina (2002), we exclude stocks with a closing price below \$5 at the end of each month to mitigate market microstructure-related issues. Compustat provides accounting data such as net income, total assets and book value of equity. Firms with negative book value of equity are excluded (Fama and French 1993). Following Diether, Malloy and Scherbina (2002) and others, we compute dispersion as the standard deviation of analyst earnings forecasts in a month divided by the absolute value of the mean forecast in that month. Our final sample consists of 8,495 unique firms with 751,176 firm-month observations spanning the January 1976 to December 2014 period.

Table 1 provides descriptive statistics of the number of firms, forecast dispersion, and market capitalization during various subperiods from 1976 to 2014. All statistics in Table 1 are computed cross-sectionally in each month and then averaged over time. To mitigate the influence of outliers, forecast dispersion and all accounting ratios are winsorized at the 1 and 99 percentiles of the sample. Table A1 in the Appendix provides the variable definitions. Similar to other studies, the average of market capitalization of stocks increases over time. In contrast, the averages of forecast dispersion and number of forecasts are relatively stable. Consistent with prior studies (e.g., Gu and Wu, 2003; Verardo, 2009), forecast dispersion is highly skewed; the mean is substantially greater than the median.

At the end of month *t*, we sort all stocks into equally-weighted quintile portfolios based on their analyst earnings forecast dispersion in month *t*. The quintile portfolios are then held for the next month. Table 2 reports the average monthly portfolio returns of the dispersion quintiles. Consistent with the findings in Diether, Malloy and Scherbina (2002) and other studies, we find an inverse relation between dispersion and future stock returns. The average portfolio returns decrease monotonically as we move from the lowest dispersion portfolio (Quintile 1) to the highest dispersion portfolio (Quintile 5). As such, the low-minus-high dispersion hedge portfolio (Quintile 1 – Quintile 5) earns an average return of 0.44% per month with the (Newey and West (1987) corrected) *t*-value being 2.40.

Table 2 also reports the averages of various firm characteristics such as firm size (SIZE), book-to-market equity ratio (BM), and six-month past returns (MOM) for the dispersion portfolios. It shows that dispersion is negatively related to firm size and past returns but positively related to book-to-market equity ratio. That is, high dispersion stocks tend to be smaller in firm size and have higher book-to-market equity ratios and lower past returns. Since these firm characteristics are known to predict the cross-section of future stock returns, we control for their effects by estimating alphas using the Carhart (1997) four-factor model, consisting of the market factor (MKT), size factor (SMB), book-to-market factor (HML), and momentum factor (UMD). The results, reported in Table 2, show that the inverse relation between dispersion and future stock returns cannot be attributable to exposures to these factors. Alphas of the dispersion quintile portfolios decline monotonically from 0.23% for Quintile 1 to – 0.38% for Quintile 5. The four-factor alpha of the low-minus-high dispersion hedge portfolio (Quintile 1 – Quintile 5) remains positive at 0.61% per month and highly significant (*t*-value = 4.48). Thus, consistent with the literature, controlling for the exposures to the four factors does not weaken (in fact further increases) the dispersion effect.

3. Dispersion, Future Profitability, and Future Stock Returns

In this section, we examine whether dispersion predicts future profitability of the firm and whether the return predictive power of dispersion is driven by its information content about future profitability.

3.1. Dispersion and Future Profitability

To verify our conjecture of a negative relation between analyst forecast dispersion and future profitability of the firm, we run Fama and MacBeth (1973) cross-sectional regressions of future firm profitability on analyst forecast dispersion (DISP). Throughout our analysis, we use Newey and West (1987) corrected standard errors to account for potential autocorrelation and heteroskedasticity in regression residuals. Future profitability is measured as one-quarter-ahead return on assets (ROA) or return on equity (ROE).[1] Table 3 presents the results. In the univariate regressions (columns 1 and 4), the coefficient of DISP is negative and highly significant. When future ROA (ROE) is used as the dependent variable, the coefficient of DISP is –2.299 (–4.390) with the t-value being –28.39 (–35.10). A one-standard-deviation increase in DISP is related to -0.66% (-1.26%) drop in one-quarter-ahead ROA (ROE).

[1] Our results do not change in any qualitative manner if we use one-year-ahead ROA and ROE instead.

Results do not change when we include other firm characteristics, i.e., size, book-to-market, momentum, and investment, in the multivariate regressions (columns 2 and 5). The predictive power of dispersion on future profitability remains strong. Results for the other firm characteristics are intuitive and consistent with the prior studies. For example, consistent with Fama and French (1995), size and momentum predicts future profitability positively, while book-to-market ratio predicts future profitability negatively. We further document that investment is negatively related to future profitability in the cross-section, which is consistent with the time-series evidence of Kothari, Lewellen and Warner (2015). To control for the persistency in firm profitability, we include the most recent ROA or ROE as an additional control variable and find qualitatively similar results (columns 3 and 6).

To summarize, consistent with our conjecture, we document a strong inverse relation between analyst forecast dispersion and future profitability of the firm. Thus, higher dispersion implies lower expected future profitability, which should imply lower future stock returns according to investment-based asset pricing theory.

3.2. The Dispersion Effect after Controlling for Future Profitability

In this section, we examine the prediction that the return predictive power of analyst earnings forecast dispersion derives from its information content about future profitability of the firm. We conduct three sets of tests to examine this prediction.

First, we run Fama-Macbeth cross-sectional regressions of future stock returns in month t on dispersion measured in month t-1, controlling for future profitability. The results are reported in Table 4. Column 1 of Table 4 shows that, in univariate regression specification, dispersion has strong negative predictive power of future stock returns, consistent with the portfolio results in Table 2. In column 2, the coefficient of dispersion remains negative and significant at the 1% level after we control for firm size, book-to-market equity ratio, momentum and investment. A one-standard-deviation increase in DISP is related to -0.17% drop in one-month-ahead stock return. This economic magnitude is also comparable with the portfolio results in Table 2. We next further control for future ROA in column 3 (future ROE in column 4). Consistent with the prediction that the dispersion effect mainly reflects its information content on future profitability, the coefficient of dispersion flips sign to become positive and is statistically insignificant. Also consistent with our expectation, the coefficient of future ROA in column 4 (future ROE in column 5) is positive and highly significant. Thus, the Fama-MacBeth cross-sectional regression results in Table 4 strongly support the conjecture that the return predictability of dispersion reflects its information content on future profitability.

Next, we examine the return predictability of dispersion conditional on future profitability in a portfolio setting. At the end of each month *t*, we first sort stocks equally into quintile portfolios based on future profitability. In each future profitability quintile, we then sort stocks equally into quintile portfolios based on analyst forecast dispersion in month *t*. The 25 portfolios are rebalanced each month, and we calculate their one-month-ahead equal-weighted portfolio returns and Carhart four-factor alphas. The results are reported in Table 5. Panel A of Table 5 shows that, after controlling for future ROA, there is no longer a negative relation between dispersion and one-month-ahead Carhart four-factor alphas. In fact, across all future ROA quintiles, the dispersion Quintile 1 – Quintile 5 hedge portfolio alphas are all negative and are statistically significant at the 1% level in four out of five future ROA quintiles. When we average across the future ROA quintiles, the average alpha of dispersion Quintile 1 is significantly lower than that of dispersion Quintile 5 by 0.62% per month and the difference is significant at the 1% level. Panel A further shows that results are qualitatively the same when we perform sequential portfolio double sort based on future ROE and dispersion. Panel B shows qualitatively similar results for portfolio raw returns instead of four-factor alphas. Therefore, the portfolio results clearly show that the dispersion effect flips sign after controlling for future profitability – lower dispersion stocks have lower, not higher, future Carhart four-factor alphas.

Third, we examine whether the low-minus-high dispersion hedge portfolio alpha documented in Table 2 attenuates when we control for a profitability factor. According to the investment-based asset pricing theory, *ceteris paribus* (e.g., holding investment and market-to-book equity ratio constant), firms with higher expected future profitability (i.e., lower dispersion) should earn higher future stock returns. Therefore, adding a profitability factor should substantially reduce the magnitude of the low-minus-high dispersion hedge portfolio alpha if the anomaly mainly reflects the information content of dispersion on future profitability. We augment the CAPM with a profitability factor and then examine the ability of this model to explain the dispersion anomaly. We consider three different profitability factors proposed by three studies, namely, the RMW factor by Fama and French (2015), the ROE factor by Hou, Xue and Zhang (2015) and the PMU factor by Novy-Marx (2013).[2] The results are reported in Table 6.

Panel A of Table 6 shows that the RMW factor substantially explains the dispersion anomaly. The factor loading of RMW is highly significant for all the dispersion quintile portfolios and decreases monotonically from 0.16 for the lowest dispersion quintile (Quintile 1) to –0.74 for the highest dispersion portfolio (Quintile 5). This suggests that a firm's exposure to the RMW factor varies systematically according to its analyst forecast dispersion. Moreover, augmenting CAPM with the RMW factor substantially attenuate the low-minus-high dispersion alpha, which is only 0.28% (*t*-value = 2.18). In contrast, the Carhart four-factor model yields a low-minus-high dispersion alpha of 0.61% (*t*-value = 4.48) in Table 2. Panel B (Panel C) shows that the ROE factor (the PMU factor) is even more effective in explaining the dispersion anomaly. The ROE factor (the PMU factor) loadings

[2] Following Novy-Marx (2013), we use the industry-adjusted PMU (gross profitability) factor. Novy-Marx (2013) shows that industry-adjusted PMU factor has greater power than straight PMU factor in explaining the cross section of expected stock returns.

decrease monotonically with dispersion from 0.15 (0.42) for Quintile 1 to -0.76 (-1.10) for Quintile 5. Adding the ROE factor (the PMU factor) in the CAPM almost eliminates the low-minus-high dispersion alpha – the alpha is only 0.07% (0.09%) per month with the *t*-value being 0.51 (0.50).[3]

We further examine the ability of the recently developed asset pricing models, including the Fama and French (2015) five-factor model, the Hou, Xue and Zhang (2015) four-factor model, and the Novy-Marx (2013) four-factor model, in explaining returns across the dispersion portfolios. The results, also reported in Table 6, are qualitatively similar to those of the above simple two-factor models.[4] For example, the alpha of the low-minus-high dispersion portfolio in the Fama-French five factor model is 0.43% (t-value = 3.80), the alpha in the Hou-Xue-Zhang four-factor model is 0.16% (*t*-value = 1.36), and the alpha in Novy-Marx four-factor model is -0.08 (*t*-value = -0.41). Moreover, the loading of the profitability factor continues to monotonically decrease from dispersion Quintile 1 to Quintile 5 with a large loading spread (ranging from 0.73 to 1.48) across all the three asset pricing models, suggesting that the profitability factor well explains the dispersion effect. The other factors do not help explain the dispersion anomaly.

In summary, the empirical results from the three sets of tests conducted in this section all strongly support the prediction that the return predictive power of dispersion reflects mainly its information content about future profitability of the firm.

4. Dispersion, Disclosure Quality, and Future Stock Returns

In this section, we examine whether the information content of dispersion on future firm profitability, and hence the return predictive power of dispersion, arise due to disclosure

[3] It is worth noting that the loading of the market factor is monotonically increasing from dispersion Quintile 1 to Quintile 5. Thus, the market factor does not help explain the dispersion anomaly at all.
[4] Note that none of Fama and French (2015), Hou, Xue and Zhang (2015) and Novy-Marx (2013) examine whether their models explain the dispersion anomaly.

manipulation—that is, when corporate managers expect future profitability to be low, they withhold the information or only disclose vague information, which, in turn, leads to high analyst earnings forecast dispersion. We conduct three sets of tests for this conjecture.

4.1. Dispersion and Earnings Disclosure Quality

First, we examine whether there is an inverse relation between dispersion and earnings disclosure quality in our sample using Fama-Macbeth regressions of dispersion on the proxies of earnings disclosure quality. The literature suggests that the main source of analysts' earnings forecast dispersion is the heterogeneity in their private information due to a lack of accurate public information that can be used to forecast the firm's future earnings (Lang and Lundholm 1996; Dhaliwal, Li, Tsang and Yang 2011; Rajopal and Venkatachalam 2011). Following the recent studies (e.g., Francis, LaFond, Olsson, and Schipper 2005; Rajgopal and Venkatachalam 2011; Chaney, Faccio, and Parsley 2011; Bhattacharya, Desai, and Venkatachalam 2013; Guo and Qiu 2016), we construct two *inverse* proxies of earnings disclosure quality, DA_Quality and Abs_DA, both of which measure the level of managerial manipulation in discretionary accruals. DA_Quality (Abs_DA) is the standard deviation (the median absolute value) of discretionary accruals in the past five fiscal years. Larger values of DA_Quality or Abs_DA imply lower earnings disclosure quality and hence noisier earnings disclosure.

To calculate discretionary accruals for each firm-year, we use the model suggested by Dechow, Sloan, and Sweeney (1995), which is a modified version of the Jones' (1991) model, to decompose total accruals into a non-discretionary component and a discretionary component. Following Kothari, Leone and Wasley (2005), we further add return on assets, i.e., earnings before extraordinary items (Compustat item: IB) scaled by lagged total assets, as a regressor to the model to account for the effect of firm profitability on the non-discretionary component of accruals.

Specifically, we estimate the following cross-sectional regression model within each of the Fama-French 48 industries with at least 8 firms in the full Compustat universe during a year:

$$\frac{TA_{i,t}}{Assets_{i,t-1}} = b_1 \frac{1}{Assets_{i,t-1}} + b_2 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + b_3 \frac{PPE_{i,t}}{Assets_{i,t-1}} + b_4 \frac{IB_{i,t}}{Assets_{i,t-1}} + \varepsilon_{i,t}. \quad (1)$$

In equation (1), TA is total accruals calculated as TA=ΔAR+ΔINV+ΔOCA-ΔAP-ΔOCL-DP, where ΔAR is the change in total receivables (Compustat item: RECT); ΔINV is the change in total inventories (Compustat item: INVT); ΔOCA is the change in total other current assets (Compustat item: ACO); ΔAP is the change in (trade) accounts payable (Compustat item: AP); ΔOCL is the change in total other current liabilities (Compustat item: LCO); DP is depreciation and amortization (Compustat item: DP). For each year, equation (1) is estimated for each firm excluding the firm itself from the estimation. Sales is net sales (Compustat item: SALE); Assets is total assets (Compustat item: TA); PPE is property, plant and equipment (Compustat item: PPEGT); IB is earnings before extraordinary items. The estimated coefficients b_1, b_2, b_3 and b_4 are then used to estimate the non-discretionary component of total accruals (NDA) as following:

$$NDA_{i,t} = b_1 \frac{1}{Assets_{i,t-1}} + b_2 \frac{\Delta Sales_{i,t} - \Delta AR_{i,t}}{Assets_{i,t-1}} + b_3 \frac{PPE_{i,t}}{Assets_{i,t-1}} + b_4 \frac{IB_{i,t}}{Assets_{i,t-1}}. \quad (2)$$

Discretionary accruals (DA) are then defined as

$$DA_{i,t} = \frac{TA_{i,t}}{Assets_{i,t-1}} - NDA_{i,t}. \quad (3)$$

Because Diamond and Verrecchia (1991) and many others suggest that small firms tend to have worse disclosure quality, we further use market capitalization (Size) as an alternative simple proxy of disclosure quality. The Fama-Macbeth regression results are reported in Table 7. In each month, the dependent variable, DISP, is matched with the most recently available DA_Quality or Abs_DA, inverse proxy for earnings disclosure quality (we require at least a 4-month reporting lag to ensure that the accounting data are publically available). Industry fixed effects are included in all regressions of the table to account for potential cross-industry heterogeneity in dispersion (we use Fama-French 48-industry classification).

As we can see, consistent with the findings in the literature (e.g., Rajopal and Venkatachalam 2011), DA_Quality and Abs_DA are both strongly and positively related to dispersion with the Newey-West adjusted *t*-value being 5.70 and 8.28 in columns 1 and 3, respectively. The results do not change qualitatively when we add Size into the regressions (columns 2 and 4). A one-standard-deviation increase in DA_Quality (Abs_DA) on average related to a 2.06% (1.11%) increase in dispersion. As expected, Size is strongly and negatively related to dispersion at the 1% level as well.

We next examine the information content of DA_Quality and Abs_DA on future firm profitability by regressing quarterly ROA or ROE on past DA_Quality or Abs_DA (with at least a 4-month reporting lag). The Fama-Macbeth regressions results in Table 8 show that, similar to dispersion, both DA_Quality and Abs_DA negatively predict future ROA at the 1% level (columns 1 and 2). The predictive power of DA_Quality and Abs_DA for future ROE is qualitatively similar to, but weaker than, that for future ROA (columns 3 and 4). The coefficients of the other variables in Table 8 show similar signs as those in Table 3. In particular, Size positively predicts future profitability at the 1% level.

To summarize, consistent with the disclosure manipulation explanation, we find a strong inverse relation between dispersion and earnings disclosure quality. Furthermore, earnings disclosure quality also contains information about future profitability of the firm.

4.2. The Dispersion Effect Conditional on Earnings Disclosure Quality

Second, if the dispersion anomaly is driven by managerial disclosure manipulation in anticipation of low future firm profitability, we expect the return predictive power of dispersion to be stronger in firms with lower earnings disclosure quality. We examine this conjecture in Table 9.

Column 1 of Table 9 is the baseline model from column 2 of Table 4, which shows dispersion has significantly negative predictive power for future stock returns at the 1% level even after controlling for other common cross-sectional stock return predictors. Next, we include a disclosure quality proxy (i.e., DA_Quality, Abs_DA or Size) and its interaction term with dispersion in columns 2-4, respectively. Column 2 (column 3) shows that the interaction term, DISP*DA_Quality (DISP*Abs_DA), has significantly negative coefficient at the 5% level while the coefficient of dispersion itself becomes statistically insignificant. Similarly, column 4 shows that the interaction term, DISP*Size, has positive albeit insignificant coefficient while the coefficient of dispersion itself is also statistically insignificant. These results show that the return predictive power of dispersion is stronger in firms with lower earnings disclosure quality.

For robustness, we further perform portfolio double sorts. In each month, we sort stocks first on the most recent earnings disclosure quality and then on dispersion into 25 quintiles. That is, we examine the return predictive power of dispersion conditional on earnings disclosure quality. The results are reported in Table 10. Panel A shows that the Carhart four-factor alpha of the Quintile 1 – Quintile 5 dispersion hedge portfolio is monotonically increasing from the lowest DA_Quality quintile to the highest DA_Quality quintile, confirming a stronger return predictive power of dispersion in firms with lower earnings disclosure quality (recall that DA_Quality is an inverse proxy for earnings disclosure quality). Panel B shows qualitatively similar results when we examine the return predictive power of dispersion conditional on Abs_DA. Results are also qualitatively similar when we use Size as an alternative simple proxy for disclosure quality. Consistent with the finding in Diether, Malloy and Scherbina (2002), the return predictive power of dispersion is stronger for smaller firms, which tend to have worse disclosure quality.

4.3. SOX and the Dispersion Effect

Third, we use the 2002 Sarbanes-Oxley Act as a quasi-natural experiment. As the most important disclosure reform in the U.S. corporate history that tightens corporate governance and internal controls and imposes substantial penalties to managers who are caught of manipulating information disclosure, SOX significantly reduces earnings disclosure manipulation and increases disclosure quality for publicly listed firms (e.g., Lobo and Zhou 2006; Cohen, Dey and Lys 2008). If the dispersion anomaly is driven by disclosure manipulation, we expect the dispersion anomaly to be weakened substantially after the enactment of SOX. We split our full sample into a pre-SOX subsample and a post-SOX subsample and re-run the Fama-Macbeth cross-sectional return predictive regressions in Table 4 for each subsample. The results are reported in Table 11.

Panel A shows that, consistent with the full-sample results in Table 4, dispersion has strong and negative return predictive power in the pre-SOX subsample, and its regression coefficient becomes positive and insignificant once we control for future firm profitability. By contrast, Panel B shows that dispersion has no return predictive power in the post-SOX subsample even without controlling for future profitability. Thus, consistent with the disclosure manipulation explanation, the return predictive power of dispersion is no longer statistically significant in the post-SOX period.

To summarize, the empirical results in this section lend strong support to the disclosure manipulation explanation of the disclosure anomaly.

5. Alternative Explanations

As discussed in the introduction, Diether, Malloy and Scherbina (2002) suggest that analyst earnings forecast dispersion is a measure of divergence of investor opinions which, in combination with short-sale constraints, causes stocks to be overpriced initially and have lower returns subsequently. This explanation conjectures that the dispersion anomaly should concentrate in stocks with binding short-sale constraints; but, it is silent on the relation between dispersion and future firm profitability. Johnson (2004) suggests that the equity claim of a levered firm can be viewed as a call option on the firm's assets, and firms with higher dispersion are likely to have higher current equity value and hence lower expected stock return. This explanation predicts that the dispersion anomaly should be more pronounced for firms with higher leverage; the explanation does not relate dispersion to future profitability either. Finally, Avramov, Chordia, Jostova and Philipov (2009) argue that the dispersion anomaly can be explained by financial distress as proxied by credit rating downgrades. They show that the profitability of dispersion-based trading strategies is driven by a small number of the worst-rated firms and is significant only during periods of deteriorating credit conditions.

Since we propose and show that the dispersion anomaly is driven by the information content of dispersion on expected future profitability due to disclosure manipulation, we need to distinguish this explanation from the aforementioned explanations in the literature. Therefore, we partition our full sample into subsamples based on short-sale constraints and firm leverage, respectively, and examine the dispersion anomaly in different samples. The Fama-Macbeth regression results are reported in Table 12.

The literature suggests that low institutional ownership is a good proxy for binding short-sale constraints (e.g., Chen, Hong, and Stein, 2002; D'Avolio, 2002; Asquith, Pathak, and Ritter, 2005; Nagel 2005; Saffi and Sturgess, 2009; Guo and Qiu, 2014); moreover, it is known that put options trading alleviates short-sale constraints (e.g., Danielsen and Sorescu, 2001; Guo and Qiu, 2014). Thus, in each month we split our full sample into subsamples according to the median institutional ownership (Panel A) and whether a stock has put options trading (Panel B). We further partition our full sample into subsamples according to the median market leverage ratio (Panel C). Finally, in Panel D, we partition the full sample into subsamples of stocks with high credit risk (non-investment grade), stocks with low credit risk (investment grade) and unrated stocks, according to the S&P Long-Term Domestic Issuer Credit Rating from Compustat.

Consistent with the divergence-of-opinions explanation, columns 1, 2, 5 and 6 of Panel A shows that the dispersion anomaly is stronger in the low institutional ownership subsample than in the high institutional ownership subsample; columns 1, 2, 5 and 6 of Panel B show that the dispersion anomaly only concentrates on stocks with no put options trading. Moreover, columns 3, 4, 7 and 8 of both panels show that the return predictive power of dispersion disappears completely or flips sign to become positive when we control for future ROA or ROE. Panel C shows that, consistent with Johnson's (2004) explanation, the dispersion anomaly appears to be statistically more significant (with larger absolute *t*-value) in the high leverage subsample than in the low leverage subsample. When we control for future firm profitability, the coefficient of dispersion flips sign and becomes statistically insignificant. Finally, Panel D shows that, consistent with the findings in Avramov, Chordia, Jostova and Philipov (2009), the dispersion anomaly mainly concentrates in unrated firms and firms with high credit risk. Again, across all credit-risk subsamples, the return predictive power of dispersion disappears completely or flips sign to become positive when we control for future profitability.

To summarize, across all subsamples sorted based on short-sale constraints, leverage and credit risk, we consistently find that the return predictive power of dispersion disappears completely or flips sign when we control for future profitability, suggesting that future profitability is the driving force behind the dispersion anomaly.

6. Conclusion

In this paper, we propose and show that the dispersion anomaly, i.e., the cross-sectional stock return predictive power of analysts' earnings forecast dispersion documented in the literature, is driven by the information content of dispersion on expected future profitability of the firm due to disclosure manipulation. We find that greater dispersion strongly predicts lower future profitability of the firm. The investment-based asset pricing theory predicts that, *ceteris paribus*, firms with lower expected future profitability should earn lower future stock returns. Consistent with this prediction, we find that the dispersion anomaly derives entirely from the information content of dispersion about future profitability. When we control for future profitability in Fama-Macbeth regressions and double-sorted portfolios, the dispersion anomaly disappears entirely or even flips sign to become positive. Moreover, we find that adding a profitability factor into the CAPM well explains the dispersion effect as the profitability factor substantially diminishes the alpha of the low-minus-high dispersion hedge portfolio or even makes the hedge portfolio alpha insignificantly different from zero.

The literature suggests that, when future profitability is expected to be bad, insider managers tend to withhold bad news and disclose relatively vague information to outsiders (e.g., Graham, Harvey and Rajgopal 2005; Jin and Myers 2006; Kothari, Shu and Wysocki 2009). Such disclosure manipulation in turn increases analysts' earnings forecast dispersion because the source of analysts' forecast dispersion is mainly the difference in their private information. When there is a lack of accurate public information, analysts place less weight on common public information and rely more on their heterogeneous private information to forecast future earnings of the firm, which leads to greater forecast dispersion (e.g., Lang and Lundholm 1996; Dhaliwal, Li, Tsang and Yang 2011; Rajopal and Venkatachalam 2011).

Consistent with the proposed disclosure manipulation explanation of the dispersion anomaly, we document that earnings disclosure quality proxied by accruals quality is inversely related to analyst forecast dispersion; moreover, lower disclosure quality predicts lower future firm profitability. When we double sort stocks into quintile portfolios first by disclosure quality and then by dispersion, we find that the return predictive power of dispersion decreases monotonically in disclosure quality. Similarly, the interaction term between disclosure quality and dispersion drives out dispersion itself in the Fama-Macbeth regressions of predicting future stock returns. The 2002 Sarbanes-Oxley Act

(SOX) provides a quasi-natural experiment to further verify the proposed disclosure manipulation explanation to the dispersion anomaly. SOX is the most important reform in U.S. corporate history, which significantly reduces disclosure manipulation and increases disclosure quality. The proposed explanation predicts that the dispersion anomaly should attenuate substantially in the post-SOX era. Consistent with this prediction, we find that the relation between analyst earnings forecast dispersion and future stock returns is no longer statistically significant in the post-SOX period.

Finally, to distinguish between the proposed explanation and other alternative explanations suggested in the literature, we examine the dispersion anomaly in different subsamples sorted based on short-sale constraints, firm leverage or credit risk. Across all subsamples, we consistently find that the return predictive power of dispersion disappears completely or flips sign to become positive when we control for future firm profitability, suggesting that future profitability is the driving force behind the dispersion anomaly.

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Table 1. Summary Statistics of Dispersion and Other Firm Characteristics

The table reports summary statistics of characteristics of sample stocks during subperiods from 1976 to 2014. DISP is the standard deviation of analysts' earnings forecasts in a month divided by the absolute value of the mean forecast in that month. We require common stocks (codes 10 and 11) with closing prices being no less than $5. We exclude firms with negative book value of equity as well as firms whose DISP is non-existent.

Merged I/B/E/S, CRSP, and COMPUSTAT					
Period	Average # of Firms	Average Market Value(in millions)	Average # of Forecasts	Mean of DISP	Median of DISP
1976-1980	894	753	7.50	0.08	0.04
1981-1985	1387	815	9.32	0.16	0.06
1986-1990	1531	1315	10.38	0.17	0.06
1991-1995	1805	1762	9.32	0.14	0.05
1996-2000	2251	3217	8.07	0.13	0.04
2001-2005	1733	4680	8.57	0.12	0.03
2006-2010	1717	5618	9.03	0.13	0.04
2011-2014	1503	7959	10.84	0.12	0.03

Table 2. Dispersion Portfolios

This table reports the averages of various firm characteristics for the dispersion quintile portfolios. At the end of each month all stocks are sorted into quintile portfolios based on DISP, the standard deviation of analysts' earnings forecasts divided by the absolute value of the mean forecast. The firm characteristics are firm size (SIZE), book-to-market equity ratio (BM), and six-month past returns (MOM). The Carhart (1997) four-factor alphas are reported, which are obtained from the regression of excess returns of dispersion portfolio on a constant, the market factor (MKT), size factor (SMB), book-to-market factor (HML), and momentum factor (UMD). Excess returns are calculated as the difference between monthly stock returns and the one month Treasury bill rate from Kenneth French's Website. DISP and BM have been winsorized at 1% and 99% of the sample. Newey and West (1987) *t*–statistics adjusted for autocorrelation and heteroscedasticity are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

DISP Quintile	DISP	Return	SIZE	BM	MOM	Carhart Alphas	(*t*-value)
D1	0.01	1.33	13.61	0.55	0.12	0.23***	(2.75)
D2	0.03	1.25	13.59	0.61	0.11	0.15*	(1.95)
D3	0.05	1.18	13.33	0.66	0.11	0.06	(1.02)
D4	0.09	1.13	13.05	0.72	0.10	-0.05	(-0.77)
D5	0.48	0.89	12.63	0.80	0.07	-0.38***	(-4.04)
D1-D5	-0.47***	0.44**	0.98	-0.28***	0.05***	0.61***	(4.48)
(*t*-value)	(-26.21)	(2.40)	(21.08)	(-17.89)	(3.13)		

Table 3. Dispersion and Future Profitability

The tables reports the results of the Fama and MacBeth (1973) cross-sectional regressions of future firm profitability on analyst forecast dispersion (DISP). The regression model is specified as follows:

$$ROE_{t+1}(\text{or } ROA_{t+1}) = a + b * DISP_t + c * Control_t + \varepsilon_{t+1}$$

Size, book-to-market, momentum, investment, and current profitability are used as control variables. All variables are winsorized at 1 and 99 percentiles of the sample. Newey and West (1987) *t*-statistics adjusted for autocorrelation and heteroscedasticity are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ROE as a profitability measure			ROA as a profitability measure		
	(1)	(2)	(3)	(4)	(5)	(6)
Dispersion	-4.390***	-3.137***	-1.474***	-2.299***	-1.632***	-0.591***
	(-35.10)	(-19.88)	(-15.53)	(-28.39)	(-19.41)	(-14.28)
Size		0.468***	0.223***		0.203***	0.082***
		(8.64)	(10.10)		(7.57)	(8.64)
BM		-2.084***	-1.117***		-1.134***	-0.516***
		(-14.02)	(-11.13)		(-13.23)	(-9.60)
Mom		2.718***	1.819***		1.342***	0.785***
		(12.96)	(12.47)		(12.97)	(13.22)
Investment		-0.326**	-0.217***		-0.227***	-0.159***
		(-2.09)	(-2.75)		(-3.05)	(-6.28)
Profitability			0.482***			0.578***
			(21.98)			(-36.71)
Adj. R^2	0.072	0.180	0.375	0.072	0.189	0.459

Table 4. The Dispersion Effect after Controlling for Future Profitability

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of future stock returns in month *t*+1 on dispersion measured in month *t*, controlling for future profitability. The regression model is specified as follows:

$$r_{t+1} = a + b * DISP_t + c * ROE_{t+1}(\text{or } ROA_{t+1}) + d * Control_t + \varepsilon_{t+1}$$

Size, book-to-market, momentum, and investment are used as control variables. All variables are winsorized at 1 and 99 percentiles of the sample. Newey and West (1987) *t*-statistics adjusted for autocorrelation and heteroscedasticity are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Return	(1)	(2)	(3)	(4)
DISP	-0.541***	-0.589***	0.113	0.131
	(-3.31)	(-3.60)	(0.78)	(0.89)
Size		-0.090**	-0.156***	-0.170***
		(-2.22)	(-3.92)	(-4.29)
BM		0.066	0.640***	0.598***
		(0.38)	(3.48)	(3.31)
Mom		0.912***	0.248	0.175
		(3.65)	(0.95)	(0.67)
Investment		-0.501***	-0.380***	-0.440***
		(-4.09)	(-3.37)	(-4.25)
Future ROA			42.331***	
			(13.55)	
Future ROE				22.892***
				(13.13)
Adj.R^2	0.004	0.042	0.055	0.055

Table 5. Sequential Double Sorts on Future Profitability and Dispersion

The table reports the results of sequential portfolio double sorts on future profitability and dispersion. At the end of each month *t*, we first sort stocks equally into quintile portfolios based on future profitability. In each future profitability quintile, we then sort stocks equally into quintile portfolios based on analyst forecast dispersion in month *t*. The 25 portfolios are rebalanced each month, and we calculate their Carhart four-factor alphas (Panel A) and one-month-ahead equal-weighted portfolio returns (Panel B). Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Carhart four-factor alpha								
		DISP						
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
ROE quintile	1 (L)	-1.58	-1.65	-1.70	-1.47	-1.54	-0.04	(-0.22)
	2	-0.71	-0.66	-0.48	-0.45	0.21	-0.92***	(-4.97)
	3	-0.01	0.10	0.12	0.34	0.69	-0.71***	(-4.96)
	4	0.58	0.49	0.44	0.56	1.15	-0.58***	(-3.82)
	5 (H)	0.99	0.88	0.99	1.36	1.84	-0.86***	(-4.71)
Controlling for ROE		-0.15	-0.17	-0.13	0.07	0.47	-0.62***	(-4.47)
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
ROA quintile	1 (L)	-1.51	-1.53	-1.69	-1.52	-1.58	0.06	(0.33)
	2	-0.47	-0.48	-0.51	-0.43	0.25	-0.72***	(-4.04)
	3	0.06	0.09	0.00	0.33	0.80	-0.74***	(-5.27)
	4	0.46	0.33	0.47	0.59	1.11	-0.65***	(-4.57)
	5 (H)	0.90	0.90	0.89	1.17	1.84	-0.94***	(-5.31)
Controlling for ROA		-0.11	-0.14	-0.17	0.03	0.48	-0.60***	(-4.40)

Panel B: Raw return								
		DISP						
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
ROE quintile	1 (L)	-0.93	-0.92	-0.96	-0.68	-0.71	-0.22	(-1.34)
	2	-0.02	0.02	0.22	0.29	1.07	-1.08***	(-5.51)
	3	0.70	0.77	0.83	1.11	1.54	-0.84***	(-5.44)
	4	1.26	1.20	1.18	1.32	2.02	-0.76***	(-4.77)
	5 (H)	1.69	1.58	1.75	2.18	2.85	-1.16***	(-5.84)
Controlling for ROE		0.54	0.53	0.61	0.84	1.35	-0.81***	(-5.52)
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
ROA quintile	1 (L)	-0.87	-0.80	-0.97	-0.70	-0.75	-0.12	(-0.69)
	2	0.23	0.22	0.26	0.31	1.14	-0.91***	(-5.10)
	3	0.79	0.80	0.75	1.11	1.66	-0.88***	(-5.28)
	4	1.17	1.02	1.24	1.34	1.99	-0.83***	(-5.05)
	5 (H)	1.57	1.56	1.61	1.94	2.72	-1.15***	(-5.87)
Controlling for ROA		0.58	0.56	0.58	0.80	1.35	-0.78***	(-5.20)

Table 6. Factor Regressions of Dispersion Portfolio Returns on a Profitability Factor

The table reports the results of factor regressions of the dispersion quintile portfolios on a profitability factor. In each panel, the upper tables show factor regression results for the augmented CAPM models with a profitability factor. We consider three different profitability factors proposed by three studies. Panel A uses the RMW factor proposed by Fama and French (2015), Panel B uses the ROE factor proposed by Hou, Xue and Zhang (2015), and Panel C uses the PMU factor proposed by Novy-Marx (2013). In each panel, the lower tables show factor regression results for the recently developed asset pricing models. The models are Fama and French (2015) five-factor model, the Hou, Xue and Zhang (2015) four-factor model, and the Novy-Marx (2013) four-factor model. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fama and French (2015) Profitability Factor (RMW)						
	D1	D2	D3	D4	D5	D1 - D5
	A two-factor model with RMW					
Alpha	0.26**	0.20*	0.17*	0.15	-0.03	0.28**
MKT	1.01***	1.05***	1.10***	1.16***	1.24***	-0.23***
RMW	0.16***	-0.01	-0.18***	-0.39***	-0.74***	0.89***
t (Alpha)	(2.54)	(1.95)	(1.69)	(1.23)	(-0.16)	(2.18)
t (MKT)	(39.68)	(40.78)	(42.87)	(35.74)	(28.48)	(-6.36)
t (RMW)	(3.31)	(-0.22)	(-3.44)	(-5.43)	(-7.66)	(10.85)
Adj.R^2 (%)	85.80	87.27	87.22	85.72	83.10	58.48
	The Fama and French five-factor model					
Alpha	0.05	0.00	-0.03	-0.11	-0.38***	0.43***
MKT	0.98***	1.01***	1.05***	1.11***	1.19***	-0.21***
SMB	0.50***	0.54***	0.60***	0.69***	0.87***	-0.37***
HML	0.01	0.07*	0.06	0.07	0.07	-0.06
RMW	0.39***	0.23***	0.08	-0.08	-0.34***	0.73***
CMA	0.03	-0.07	-0.10*	-0.04	0.00	0.02
t (Alpha)	(0.75)	(0.05)	(-0.55)	(-1.59)	(-4.32)	(3.80)
t (MKT)	(43.71)	(50.23)	(52.02)	(51.72)	(45.54)	(-7.08)
t (SMB)	(12.27)	(15.29)	(15.36)	(15.60)	(17.52)	(-8.95)
t (HML)	(0.20)	(1.69)	(1.28)	(1.33)	(1.33)	(-0.93)
t (RMW)	(6.00)	(4.58)	(1.50)	(-1.16)	(-5.56)	(12.43)
t (CMA)	(0.50)	(-1.51)	(-1.70)	(-0.58)	(0.05)	(0.26)
Adj.R^2 (%)	93.36	95.06	95.55	94.89	94.16	66.08

Table 6. Factor Regressions of Dispersion Portfolio Returns on a Profitability Factor (Continued)

Panel B: Hou, Xue, and Zhang Profitability Factor (ROE)						
	D1	D2	D3	D4	D5	D1 - D5
	A two-factor model with ROE					
Alpha	0.24**	0.23**	0.23**	0.24**	0.17	0.07
MKT	1.00***	1.05***	1.11***	1.18***	1.27***	-0.28***
ROE	0.15***	-0.03	-0.18***	-0.37***	-0.76***	0.92***
t (Alpha)	(2.11)	(2.16)	(2.20)	(2.05)	(1.11)	(0.51)
t (MKT)	(37.10)	(42.28)	(46.78)	(37.59)	(31.59)	(-8.81)
t (ROE)	(3.15)	(-0.74)	(-3.76)	(-6.44)	(-8.75)	(9.25)
Adj.R^2 (%)	85.53	87.43	87.77	86.70	85.67	67.35
	The Hou, Xue, and Zhang four-factor model					
Alpha	0.03	0.05	0.04	0.01	-0.13*	0.16
MKT	0.95***	0.99***	1.03***	1.09***	1.17***	-0.22***
ME	0.43***	0.46***	0.53***	0.62***	0.78***	-0.35***
I/A	0.06	-0.01	-0.06	-0.05	-0.05	0.11*
ROE	0.27***	0.09*	-0.04	-0.20***	-0.55***	0.82***
t (Alpha)	(0.36)	(0.56)	(0.55)	(0.14)	(-1.77)	(1.36)
t (MKT)	(35.99)	(48.51)	(50.00)	(53.93)	(47.84)	(-7.17)
t (ME)	(5.15)	(7.35)	(8.39)	(10.71)	(15.54)	(-7.31)
t (I/A)	(0.96)	(-0.08)	(-0.90)	(-0.75)	(-0.79)	(1.77)
t (ROE)	(4.94)	(1.77)	(-0.75)	(-3.90)	(-12.13)	(12.33)
Adj.R^2 (%)	91.95	94.04	95.35	95.43	96.02	75.74

Table 6. Factor Regressions of Dispersion Portfolio Returns on a Profitability Factor (Continued)

Panel C: Novy-Marx Profitability Factor (PMU)						
	D1	D2	D3	D4	D5	D1 - D5
	A two-factor model with PMU					
Alpha	0.18	0.18	0.19	0.21	0.09	0.09
MKT	1.02	1.06	1.11	1.17^{***}	1.26^{***}	-0.25^{***}
PMU*	0.42^{***}	0.07	-0.23^{*}	-0.56^{***}	-1.10^{***}	1.52^{***}
t (Alpha)	(1.62)	(1.53)	(1.57)	(1.45)	(0.42)	(0.50)
t (MKT)	(34.12)	(37.00)	(40.69)	(34.32)	(27.23)	(-6.25)
t (PMU*)	(4.65)	(0.67)	(-1.91)	(-3.59)	(-4.39)	(6.80)
Adj.R^2 (%)	86.07	87.31	86.84	84.64	80.22	47.45
	The Novy-Marx four-factor model					
Alpha	0.12	0.20^{*}	0.26^{**}	0.30^{**}	0.20	-0.08
MKT	1.03^{***}	1.06^{***}	1.10^{***}	1.16^{***}	1.25^{***}	-0.22^{***}
HML*	0.12	0.03	-0.06	-0.06	-0.08	0.20^{**}
UMD*	-0.02	-0.10^{**}	-0.11	-0.14^{*}	-0.17	0.15
PMU*	0.48^{***}	0.15	-0.17	-0.48^{**}	-1.00^{***}	1.48^{***}
t (Alpha)	(1.11)	(1.78)	(2.22)	(2.00)	(0.96)	(-0.41)
t (MKT)	(36.33)	(37.01)	(39.71)	(32.40)	(24.33)	(-5.63)
t (HML*)	(1.26)	(0.28)	(-0.55)	(-0.56)	(-0.59)	(1.97)
t (UMD*)	(-0.52)	(-2.24)	(-1.62)	(-1.78)	(-1.26)	(1.01)
t (PMU*)	(5.34)	(1.15)	(-1.09)	(-2.18)	(-2.70)	(4.24)
Adj.R^2 (%)	86.21	87.62	87.11	85.02	80.64	48.95

Table 7. Dispersion and Earnings Disclosure Quality

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of analyst forecast dispersion (DISP) on the proxies of earnings disclosure quality (EDQ). The regression model is specified as follows:

$$DISP_{t+1} = a + b * EDQ_t + c * Industry\ Indicators + \varepsilon_t$$

We use DA_Quality, Abs_DA and Size as proxies of earnings disclosure quality (EDQ). DA_Quality (Abs_DA) is the standard deviation (the median absolute value) of discretionary accruals in the past five fiscal years. Size is logarithm of market cap. We include industry indicator variables to control for industry fixed effects in all regressions to account for potential cross-industry heterogeneity in dispersion. We use the Fama-French 48-industry classification scheme. All variables are winsorized at 1 and 99 percentiles of the sample. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: DISP	(1)	(2)	(3)	(4)
DA_Quality	0.106***	0.060***		
	(5.70)	(4.65)		
Abs_DA			0.106***	0.033***
			(8.28)	(3.16)
Size		-0.032***		-0.032***
		(-19.71)		(-20.23)
Industry Indicators	yes	yes	yes	yes
Adj.R^2	0.056	0.081	0.054	0.080

Table 8. Earnings Disclosure Quality and Future Profitability

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of future firm profitability on earnings disclosure quality (EDQ). The regression model is specified as follows:

$$ROE_{t+1}(\text{or } ROA_{t+1}) = a + b * EDQ_t + c * Control_t + \varepsilon_{t+1}$$

We use DA_Quality and Abs_DA as proxies of earnings disclosure quality (EDQ). Size, book-to-market, momentum, investment, and current profitability are used as control variables. All variables are winsorized at 1 and 99 percentiles of the sample. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Future ROE		Future ROA	
	(1)	(2)	(3)	(4)
DA_Quality	-0.239		-0.264***	
	(-1.28)		(-4.17)	
Abs_DA		-0.606**		-0.378***
		(-2.38)		(4.20)
Size	0.244***	0.242***	0.089***	0.089***
	(11.72)	(11.68)	(9.52)	(9.65)
BM	-1.289***	-1.285***	-0.596***	-0.589***
	(-12.78)	(-12.50)	(-11.37)	(-11.17)
Momentum	1.978***	1.959***	0.860***	0.857***
	(12.99)	(13.00)	(14.00)	(13.93)
Investment	-0.181***	-0.154**	-0.131***	-0.114***
	(-2.62)	(-2.12)	(-5.56)	(-4.99)
ROE	0.494***	0.498***		
	(25.58)	(26.17)		
ROA			0.580***	0.585***
			(44.42)	(45.25)
Adj. R^2	0.353	0.357	0.434	0.439

Table 9. The Dispersion Effect Conditional on Earnings Disclosure Quality

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of future stock returns in month *t*+1 on dispersion measured in month t, conditional on earnings disclosure quality. The regression model is specified as follows:

$$R_{t+1} = a + b * DISP_t + c * DISP_t * EDQ_t + d * EDQ_t + e * Control_t + \varepsilon_{t+1}$$

We use DA_Quality, Abs_DA and Size as proxies of earnings disclosure quality (EDQ). Size, book-to-market, momentum, and investment are used as control variables. All variables are winsorized at 1 and 99 percentiles of the sample. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Return	(1)	(2)	(3)	(4)
DISP	-0.589***	-0.186	-0.183	-1.609
	(-3.60)	(-0.74)	(-0.73)	(-1.60)
DISP * DA_Quality		-3.450**		
		(-1.98)		
DA_Quality		0.17		
		(0.51)		
DISP * Abs_DA			-4.813**	
			(-2.08)	
Abs_DA			0.061	
			(0.12)	
DISP * Size				0.080
				(0.91)
Size	-0.090**	-0.091**	-0.093**	-0.100**
	(-2.22)	(-2.24)	(-2.40)	(-2.43)
BM	0.066	0.061	0.049	0.069
	(0.38)	(0.37)	(0.29)	(0.41)
Momentum	0.912***	0.866***	0.904***	0.925***
	(3.65)	(3.60)	(3.73)	(3.78)
Inv	-0.501***	-0.574***	-0.485***	-0.503***
	(-4.09)	(-5.62)	(-4.92)	(-4.71)
Adj. R^2	0.042	0.044	0.045	0.043

Table 10. Sequential Double Sorts on Earnings Disclosure Quality and Dispersion

The table reports the results of sequential portfolio double sorts on earnings disclosure quality and dispersion. At the end of each month *t*, we first sort stocks equally into quintile portfolios based on the most recent earnings disclosure quality. In each disclosure quality quintile, we then sort stocks equally into quintile portfolios based on analyst forecast dispersion in month *t*. The 25 portfolios are rebalanced each month. We calculate Carhart four-factor alphas from their one-month-ahead equal-weighted portfolio returns. Panel A (B) reports the 4-factor alphas for 25 portfolios based on DA_Quality (Abs_DA) measure and analyst forecast dispersion. Panel C reports the 4-factor alphas for 25 portfolios based on the Size measure and analyst forecast dispersion. Newey and West (1987) *t*-statistics are reported in parentheses. The sample period is from January 1976 to December 2014. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: DA_Quality								
		DISP						
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
DA_Quality quintile	1 (L)	0.26	0.19	0.24	0.10	-0.10	0.36***	(2.62)
	2	0.27	0.24	0.21	0.06	-0.16	0.43***	(2.62)
	3	0.24	0.21	0.06	-0.01	-0.27	0.51***	(3.85)
	4	0.18	0.04	0.03	0.11	-0.41	0.59***	(3.65)
	5 (H)	0.08	-0.07	-0.27	-0.34	-0.64	0.72***	(3.77)
Controlling for DA_Quality		0.21	0.12	0.05	-0.01	-0.31	0.52***	(4.03)
Panel B: Abs_DA								
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
Abs_DA quintile	1 (L)	0.27	0.17	0.15	-0.04	-0.08	0.35**	(2.42)
	2	0.28	0.22	0.16	0.20	-0.28	0.56***	(3.28)
	3	0.21	0.23	0.05	-0.03	-0.23	0.44***	(2.89)
	4	0.24	0.06	0.18	-0.05	-0.24	0.48***	(3.21)
	5 (H)	-0.03	-0.04	-0.21	-0.32	-0.79	0.77***	(3.60)
Controlling for Abs_DA		0.19	0.13	0.07	-0.05	-0.33	0.52***	(3.88)
Panel C: Size								
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
Size quintile	1 (L)	0.42	0.37	-0.02	-0.16	-0.64	1.06***	(6.80)
	2	0.18	0.27	0.03	-0.10	-0.49	0.67***	(4.37)
	3	0.13	0.13	0.04	0.02	-0.31	0.43**	(2.38)
	4	0.20	0.12	-0.10	0.02	-0.23	0.42**	(2.57)
	5 (H)	0.16	0.08	0.05	0.01	-0.15	0.31*	(1.79)
Controlling for Size		0.22	0.19	0.00	-0.04	-0.36	0.58***	(4.31)

Table 11. The Dispersion Effect: Pre-SOX Subsample and Post-SOX Subsample

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of future stock returns in month *t*+1 on dispersion measured in month *t*, controlling for future profitability. We split our full sample into a pre-SOX subsample and a post-SOX subsample. The regression model is specified as follows:

$$r_{t+1} = a + b * DISP_t + c * ROE_{t+1}(\text{or } ROA_{t+1}) + d * Control_t + \varepsilon_{t+1}$$

The sample period for the analysis in Panel A is from January 1976 to December 2002 (pre-SOX period). The sample period for the analysis in Panel B is from January 2003 to December 2014 (post-SOX period). Size, book-to-market, momentum, and investment are used as control variables. All variables are winsorized at 1 and 99 percentiles of the sample. Newey and West (1987) *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Panel A: Pre-SOX Subsample				Panel B: Post-SOX Subsample			
Return	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DISP	-0.652***	-0.681***	0.149	0.177	-0.231	-0.290	0.033	0.027
	(-3.28)	(-3.27)	(0.77)	(0.90)	(-0.87)	(-1.57)	(0.18)	(0.15)
Size		-0.113**	-0.169***	-0.185***		-0.040	-0.126**	-0.136**
		(-2.12)	(-3.30)	(-3.63)		(-0.68)	(-2.21)	(-2.41)
BM		0.087	0.760***	0.674***		0.042	0.371*	0.428**
		(0.39)	(3.07)	(2.75)		(0.20)	(1.89)	(2.22)
Mom		1.258***	0.378	0.278		0.192	-0.043	-0.056
		(5.03)	(1.31)	(0.96)		(0.39)	(-0.08)	(-0.10)
Inv		-0.555***	-0.419***	-0.513***		-0.368***	-0.293***	-0.276***
		(-3.81)	(-2.67)	(-3.64)		(-3.33)	(-3.15)	(-2.96)
Future ROA			50.211***				24.655***	
			(14.88)				(12.48)	
Future ROE				27.540***				12.466***
				(15.29)				(11.83)
Adj.R^2	0.005	0.048	0.062	0.063	0.004	0.027	0.038	0.038

Table 12. Subsample Analyses Based on Short-Sale Constraints, Firm Leverage, and Credit Rating

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of future stock returns in month *t*+1 on dispersion measured in month *t*, controlling for future profitability. We split the full sample into subsamples based on the median institutional ownership (Panel A), whether a stock has put options trading (Panel B), the median market leverage ratio (Panel C), or the S&P Long-Term Domestic Issuer Credit Rating from Compustat (Panel D). The regression model is specified as follows:

$$r_{t+1} = a + b * DISP_t + c * ROE_{t+1} (\text{or } ROA_{t+1}) + d * Control_t + \varepsilon_{t+1}$$

The institutional ownership is the fraction of a stock's outstanding shares held by all institutional shareholders constructed using the most recent 13f filings obtained from Thomson Financial 13f database. A stock has put options trading in a month if there exist a put option contract with non-zero trading volume for that stock. The option data is from OptionMetrics. The market leverage (debt-to-equity ratio) is defined as the ratio of the sum of long-term debt (Compustat quarterly item: DLTTQ) and debt in current liabilities (Compustat quarterly item: DLCQ) to market equity. The sample period for the analysis in Panel A (B) is from January 1980 (January 1996) to December 2014 due to the availability of the institutional ownership (put option) data. The sample period for the analysis in Panel C is from January 1976 to December 2014. The sample period for the analysis in Panel D is from January 1986 to December 2014 due to the availability of the S&P Long-Term Domestic Issuer Credit Rating data. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 12. Subsample Analyses Based on Short-Sale Constraints, Firm Leverage and Credit Rating (Continued)

Panel A: Institutional ownership								
Dependent Variable:	Low Institutional Ownership				High Institutional Ownership			
Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISP	-0.808***	-0.813***	-0.053	-0.061	-0.417***	-0.403***	0.288**	0.264**
	(-3.54)	(-3.91)	(-0.25)	(-0.29)	(-2.78)	(-2.97)	(2.42)	(2.19)
Size		-0.140**	-0.254***	-0.251***		-0.059	-0.144***	-0.125***
		(-2.39)	(-3.98)	(-3.96)		(-1.45)	(-3.37)	(-2.92)
BM		0.288	0.442*	0.471*		-0.026	0.553***	0.593***
		(1.21)	(1.70)	(1.82)		(-0.14)	(2.85)	(3.00)
Mom		1.477***	0.797***	0.811***		0.797***	0.065	0.108
		(5.79)	(3.32)	(3.44)		(2.83)	(0.22)	(0.36)
Inv		-0.619***	-0.554***	-0.530***		-0.550***	-0.452***	-0.452***
		(-3.92)	(-3.25)	(-3.11)		(-5.13)	(-4.32)	(-4.28)
Future ROE			21.898***				21.261***	
			(13.07)				(11.12)	
Future ROA				42.421***				40.058***
				(11.21)				(11.84)
Adj.R^2	0.006	0.044	0.066	0.067	0.004	0.042	0.054	0.054

Table 12. Subsample Analyses Based on Short-Sale Constraints, Firm Leverage and Credit Rating (Continued)

Panel B: Availability of put options trading								
Dependent Variable:	No Put Option				Put Option			
Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISP	-0.669**	-0.697***	-0.025	-0.033	-0.075	-0.078	0.346*	0.359*
	(-2.26)	(-2.73)	(-0.13)	(-0.17)	(-0.31)	(-0.38)	(1.68)	(1.71)
Size		-0.149**	-0.282***	-0.260***		-0.067	-0.200***	-0.185***
		(-2.05)	(-3.64)	(-3.46)		(-0.99)	(-2.85)	(-2.65)
BM		0.011	0.258	0.241		-0.015	0.352	0.307
		(0.04)	(0.97)	(0.91)		(-0.05)	(1.00)	(0.88)
Mom		1.410***	1.019**	1.071**		0.189	-0.155	-0.140
		(3.71)	(2.48)	(2.57)		(0.46)	(-0.34)	(-0.31)
Inv		-0.696***	-0.626***	-0.589***		-0.544***	-0.392***	-0.409***
		(-5.81)	(-4.58)	(-4.30)		(-3.71)	(-3.49)	(-3.65)
Future ROE			20.487***				13.888***	
			(11.77)				(7.61)	
Future ROA				37.051***				27.082***
				(11.33)				(9.06)
Adj.R^2	0.004	0.033	0.051	0.052	0.004	0.047	0.059	0.059

Table 12. Subsample Analyses Based on Short-Sale Constraints, Firm Leverage and Credit Rating (Continued)

Panel C: Firm Leverage								
Dependent Variable:	High Leverage				Low Leverage			
Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DISP	-0.524***	-0.525***	0.127	0.206	-0.409	-0.640**	0.372	0.438
	(-2.83)	(-3.30)	(0.83)	(1.37)	(-1.50)	(-2.17)	(1.33)	(1.55)
Size		-0.077*	-0.135***	-0.137***		-0.107**	-0.201***	-0.177***
		(-1.75)	(-3.19)	(-3.24)		(-2.52)	(-4.76)	(-4.13)
BM		0.110	0.619***	0.532***		0.188	0.761***	0.730***
		(1.04)	(5.96)	(5.15)		(0.86)	(3.27)	(3.10)
Mom		0.717**	-0.229	-0.167		1.020***	0.348	0.454*
		(2.48)	(-0.73)	(-0.54)		(4.38)	(1.45)	(1.88)
Inv		-0.603***	-0.564***	-0.534***		-0.411***	-0.349***	-0.280**
		(-4.37)	(-4.14)	(-3.97)		(-3.23)	(-3.05)	(-2.21)
Future ROE			22.524***				25.577***	
			(14.98)				(10.46)	
Future ROA				60.421***				41.055***
				(17.11)				(11.26)
Adj.R^2	0.007	0.044	0.059	0.060	0.004	0.038	0.054	0.054

Table 12. Subsample Analyses Based on Short-Sale Constraints, Firm Leverage and Credit Rating (Continued)

Panel D: Credit Rating

Dependent Variable:	High Credit Risk (Non-investment Grade)				Low Credit Risk (Investment Grade)				Unrated			
Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DISP	-0.228*	-0.232*	0.362***	0.352***	-0.424	-0.798	-0.443	-0.411	-0.490***	-0.433***	0.326**	0.344**
	(-1.67)	(-1.93)	(2.83)	(2.89)	(-0.82)	(-1.46)	(-0.78)	(-0.72)	(-3.32)	(-2.96)	(2.27)	(2.40)
Size		-0.038	-0.112	-0.143		-0.026	-0.057	-0.068		-0.034	-0.176***	-0.193***
		(-0.41)	(-1.30)	(-1.64)		(-0.55)	(-1.16)	(-1.34)		(-0.75)	(-3.44)	(-3.77)
BM		-0.020	0.498***	0.461***		0.100	0.646	0.624***		0.046	0.361	0.398
		(-0.14)	(3.24)	(2.98)		(1.01)	(5.89)	(5.69)		(0.23)	(1.44)	(1.57)
Mom		1.133***	0.328	0.348		-0.709*	-1.260	-1.302***		0.867***	0.366	0.403
		(3.34)	(0.85)	(0.89)		(-1.88)	(-3.21)	(-3.29)		(3.15)	(1.35)	(1.48)
Inv		-0.598***	-0.456***	-0.508***		-0.221**	-0.235**	-0.272***		-0.517***	-0.358***	-0.360***
		(-4.46)	(-3.17)	(-3.70)		(-2.06)	(-2.24)	(-2.73)		(-5.44)	(-4.52)	(-4.54)
Future ROE			18.299***				12.277***				20.268***	
			(10.17)				(9.13)				(10.42)	
Future ROA				51.217***				30.942***				35.514***
				(10.12)				(9.92)				(10.49)
Adj.R^2	0.004	0.041	0.058	0.058	0.011	0.056	0.063	0.064	0.003	0.029	0.044	0.044

Table A1. Description of Variables

Variable	Data Sources	Period for Data Availability	Description
DISP	I/B/E/S	1976-2014	The standard deviation of analyst earnings forecasts in a month divided by the absolute value of the mean forecast in that month
ROE	Compustat Quarterly	1976-2014	Income before extraordinary items (IBQ) divided by one-quarter-lagged book equity. Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use stockholders' equity (SEQQ), or common equity (CEQQ) plus the carrying value of preferred stock (PSTKQ), or total assets (ATQ) minus total liabilities (LTQ) in that order as shareholders' equity. We use redemption value (PSTKRQ) if available, or carrying value for the book value of preferred stock.
ROA	Compustat Quarterly	1976-2014	Income before extraordinary items (IBQ) divided by one-quarter-lagged total assets (ATQ)
Size	CRSP	1976-2014	The logarithm of market cap (Number of shares (CSHO) multiplied by the closing price (PRC))
BM	CRSP, Compustat Annual	1976-2014	Market cap divided by one-year-lagged book equity.
Momentum	CRSP	1976-2014	Prior (2-7) Returns
Investment	Compustat Annual	1976-2014	The annual change in total assets (AT) divided by one-year-lagged total assets
Abs_DA	Compustat Annual	1976-2014	See Section 4.1 for detailed construction
DA_Quality	Compustat Annual	1976-2014	See Section 4.1 for detailed construction
Institutional Ownership	Thomson Financial 13f	1980-2014	
Market Leverage	CRSP, Compustat Quarterly	1976-2014	The ratio of the sum of long-term debt (DLTTQ) and debt in current liabilities (DLCQ) to market cap
Credit Rating	Compustat Ratings	1986-2014	The S&P Long-Term Domestic Issuer Credit Rating (SPLTICRM)
Put Option Availability	Optionmetrics	1996-2014	A stock has put options trading in a month if there exist a put option contract with non-zero trading volume for that stock