What Drives the Dispersion Anomaly?

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Abstract

This paper shows that the stock return predictability of analysts' earnings forecast dispersion is driven by the information content of dispersion about future firm profitability. Greater dispersion predicts lower future profitability, and the return predictability of dispersion disappears after controlling for future profitability. We propose disclosure manipulation as an explanation for the relation between dispersion and future profitability. Disclosure quality is inversely related to forecast dispersion. Moreover, the return predictability of dispersion decreases in disclosure quality, and is no longer significant in the post-Sarbanes-Oxley period. Our results are robust to consideration of previously suggested explanations for the dispersion anomaly.

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

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1. Introduction

Diether, Malloy, and Scherbina (2002) show that firms with higher analysts' earnings forecast dispersion have lower subsequent 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 compensation for bearing greater uncertainty.[1] As such, the negative relation between dispersion and stock returns is anomalous. Subsequent studies further assess the link between forecast dispersion and stock returns. Bali, Bodnaruk, Scherbina, and Tang (2018) show that volatility shocks, which temporary increase forecast dispersion, negatively predict the cross-section of stock returns. Chatterjee, John, and Yan (2012) show that takeover premium (i.e., cumulative target return in the takeover announcement window) is positively associated with the dispersion of analysts' forecasts on the target's one-year-ahead earnings.[2]

This paper shows that the stock return predictability of analysts' earnings forecast dispersion is driven by the information content of dispersion about future firm profitability. We hypothesize that analysts' earnings forecast dispersion contains information about future profitability. Our hypothesis builds on two strands of the literature. First, the disclosure literature shows that low expected future profitability leads to low disclosure quality due to disclosure manipulation by corporate managers. Prior studies document managers' substantial discretion in earnings disclosure and strong incentives

[1] Guntay and Hackbarth (2010) examine whether forecast dispersion plays a role in corporate bond markets similar to the one it plays in equity markets. They find that bonds of firms with higher dispersion have greater credit spreads and earn higher subsequent returns than otherwise similar bonds, suggesting that forecast dispersion proxies for future cash flow uncertainty in corporate bond markets.

[2] Hwang, Lou, and Yin (2017) propose that offsetting disagreement helps explain why portfolios often trade below the sums of their parts (e.g., closed-end funds).

related to career and compensation to engage in disclosure manipulation (e.g., see Armstrong, Guay, and Weber 2010 for a review). Managers' information about future profitability is superior to that of corporate outsiders such as equity analysts (e.g., managers can directly observe customer orders). When future profitability is expected to be high, managers tend to release good news in a timely manner, often providing detailed supplementary information. When future profitability is expected to be low, managers tend to withhold bad news and/or disclose relatively vague information (e.g., Hong, Lim, and Stein, 2000; Jin and Myers, 2006; Kothari, Shu, and Wysocki, 2009). For example, Graham, Harvey, and Rajgopal (2005) provide survey evidence that CFOs sometimes withhold bad news in the hope that they may not have to disclose it at all if their firms' situations improve prior to mandatory disclosure.

Second, the literature shows that low disclosure quality leads to high forecast dispersion. In the absence of accurate public information for forecasting firms' future earnings prospects (i.e., when disclosure quality deteriorates), analysts are likely to place less weight on available public information, and more weight on their private information, about a firm's future earnings prospects, which in turn increases forecast dispersion. Lang and Lundholm (1996), for example, find firms with lower levels of information disclosure to exhibit greater analyst forecast dispersion, and Rajgopal and Venkatachalam (2011) document financial reporting quality to be inversely related to analyst forecast dispersion.

Building on these two strands of literature, we thus hypothesize that forecast dispersion negatively predicts future profitability due to selective disclosure. Consistent with our prediction, we find that analysts' forecast dispersion has strong predictive power for future return on assets (ROA) and return on equity (ROE), 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 a -0.66% (-1.26%) drop in one-quarter-ahead ROA (ROE).

We further hypothesize that firms with high forecast dispersion should have low expected stock returns because of their low expected future profitability. Recent asset pricing theories propose that expected profitability is an important determinant of expected stock returns in the cross-section. The *q*-factor model proposed by Hou, Xue, and Zhang (2015) predicts that, for a given investment, firms with high expected future profitability should earn higher expected returns than firms with low expected profitability. Using the dividend discount model in conjunction with clean surplus accounting, 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 in the cross-section. If high dispersion stocks have low expected profitability, they should earn low expected returns according to these asset pricing theories.

We conduct three sets of tests to examine this prediction. First, we examine whether a profitability factor helps explain the dispersion anomaly. If the dispersion-return relation is driven by the profitability-return relation, a profitability factor should substantially reduce the magnitude of the dispersion anomaly. Using the profitability factors proposed in the recent asset pricing literature, including the ROE (Return-On-Equity) factor (Hou, Xue, and Zhang, 2015) and PMU (Profitable-Minus-Unprofitable) 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 the four-factor models of Hou, Xue, and Zhang (2015) and Novy-Marx (2013) to also make the low-minus-high dispersion hedge portfolio alpha insignificantly different from zero.

Second, when we control for future profitability, the predictive power of dispersion for stock returns changes sign, becoming positive and 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. This suggests that among variables known to predict cross-sectional stock returns, future profitability subsumes only the explanatory power of dispersion. Third, we perform sequential portfolio double sorts first by future profitability (ROA or ROE) and then by dispersion. Consistent with the Fama-MacBeth cross-sectional regression results, in each future profitability quintile, stocks with higher analysts' earnings forecast dispersion have higher, not lower, subsequent raw returns as well as Carhart (1997) four-factor alphas. These results collectively suggest that the anomalous negative relation between forecast dispersion and subsequent stock returns is mainly driven by the information content of forecast dispersion on future firm profitability.

The disclosure manipulation explanation for the dispersion-future profitability relation has cross-sectional as well as time-series implications for the dispersion anomaly. If the dispersion anomaly is driven by managerial disclosure manipulation in anticipation of low future profitability, we expect the return predictive power of dispersion to be stronger for firms with lower earnings disclosure quality.[3] When we double sort stocks into quintile portfolios first by disclosure quality and then by dispersion, 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 is significant and drives out dispersion 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 further verifying the proposed disclosure manipulation explanation for the dispersion anomaly. The

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

most important disclosure reform in the U.S. corporate history, SOX significantly reduced earnings disclosure manipulation and increased disclosure quality for publicly listed firms (e.g., Lobo and Zhou, 2006; Cohen, Dey, and Lys, 2008; Iliev 2010). We hence hypothesize 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, in the post-2003 period, the relation between analyst earnings forecast dispersion and future stock returns to no longer be statistically significant.

Several explanations for the dispersion anomaly have been proposed in the literature. Diether, Malloy, and Scherbina (2002), positing analysts' earnings forecast dispersion to be a measure of the divergence of investor opinions, interpret their findings as evidence favoring 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 initially overpriced and hence leads to lower subsequent returns as the overpricing is corrected over time. In contrast, our explanation does not rely on mispricing and market friction. Instead, we argue that high dispersion stocks earn low subsequent returns due to the equilibrium relation between expected firm profitability and expected stock returns.[4] Johnson (2004) offers the 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 its assets, firms with higher dispersion are likely to have higher current equity value and, hence, lower expected returns. This explanation relates dispersion only to future stock returns, not future profitability. Avramov, Chordia, Jostova, and Philipov (2009) suggest that the dispersion-return relation can be explained by the credit risk-return relation; they show the profitability of dispersion-based trading

[4] Diether et al. (2002) find that analyst forecast dispersion is negatively related to analyst forecast errors and interpret their finding as evidence that analyst dispersion is positively related to the upward bias in analyst forecasts.

strategies to be driven mainly by a small number of the worst-rated firms, and significant only during periods of deteriorating credit conditions as proxied by credit rating downgrades.

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. To distinguish our explanation from the aforementioned explanations in the literature, we partition our full sample into subsamples based on short-sale constraints, firm leverage, or credit rating. Then, we form the dispersion quintile portfolios using each subsample and run factor regressions for the low-minus-high dispersion hedge portfolio constructed from each subsample. Similar to the earlier findings, for each subsample considered we find that controlling for the profitability factor substantially reduces the magnitude of the dispersion anomaly, often to insignificant levels. For example, the augmented CAPM with the PMU factor reduces the alpha of the dispersion hedge portfolio to an insignificant level for all of the subsamples except two. Most notably, the Novy-Marx four-factor model successfully explains the dispersion-return relation (i.e., reducing the alpha to an insignificant level) for *all* subsamples. We further estimate the Fama-MacBeth cross-sectional regressions of subsequent returns on analyst forecast dispersion with and without future profitability. We similarly find, across all subsamples, that controlling for future profitability results in the dispersion-return relation disappearing or changing sign. The proposed profitability-based explanation for the dispersion effect is thus not captured by the alternative explanations in the literature.

The remainder of the paper proceeds as follows. Section 2 develops the testable hypotheses. Section 3 describes the data. Section 4 documents the empirical evidence on dispersion, future profitability, and future stock returns. Section 5 provides the evidence on the dispersion anomaly and disclosure manipulation. Section 6 presents the evidence that helps distinguish our explanation from the alternative explanations. Section 7 concludes. Detailed definitions of all variables and their data sources are in Table A1 in the Appendix.

2. Hypothesis Development

In this section, we develop testable hypotheses to guide the subsequent empirical analyses. The first hypothesis builds on two strands of the literature. The disclosure literature documents a strong relation between disclosure quality and future profitability. Corporate managers' engagement in disclosure manipulation responds to incentives, career- and compensation-wise (Armstrong, Guay, and Weber, 2010), and position, their insider status affording access to more accurate information about future firm profitability than is available to corporate outsiders. As noted earlier, managers anticipating strong future profitability tend to willingly release good news in a timely manner, often accompanied by detailed supplementary information. By contrast, managers anticipating weak future profitability tend to withhold bad news and/or disclose relatively vague information (e.g., Jin and Myers, 2006). Kothari, Shu, and Wysocki (2009) present empirical evidence of managers' tendency to withhold bad news from, but immediately reveal good news to, investors. Graham, Harvey, and Rajgopal (2005) provide survey evidence that CFOs sometimes withhold bad news in the hope that circumstances may improve before disclosure becomes mandatory.

The literature shows a strong relation between disclosure quality and forecast dispersion. The intuition is that if disclosure quality deteriorates, analysts are likely to place less weight on available public information, and more weight on their private information, about a firm's future earnings prospects, which in turn increases forecast dispersion. Lang and Lundholm (1996), for example, show firms with less informative disclosure policies to have greater analyst forecast dispersion, and Rajgopal and Venkatachalam (2011) document financial reporting quality to be inversely associated with dispersion in analysts' forecasts. Combining these two strands of literature leads to the first hypothesis:

Hypothesis 1: *Analysts' earnings forecast dispersion should contain information about future firm profitability.*

The second hypothesis is developed from recent asset pricing models which predict that expected firm profitability is an important determinant of expected stock returns in the cross-section. Hou, Xue, and Zhang (2015) propose the *q*-factor model based on investment-based asset pricing. To illustrate the key intuitions behind the *q*-factor model, they consider a simple economic model in which a firm chooses investment to maximize its firm value, and derive the following first-order condition:

$$1 + \mathrm{a}(I_{it}/A_{it}) = \frac{E[\Pi_{it+1}]}{E\left[R^S_{it+1}\right]}, \tag{1}$$

where I_{it}, A_{it}, and Π_{it+1} denote firm *i*'s investment, productive assets, and profitability at time *t*, respectively, R^S_{it+1}denotes firm *i*'s stock return, and $\mathrm{a} > 0$ is a constant parameter. Intuitively, firm *i* will keep investing until the marginal costs of investment at time *t*, $1 + \mathrm{a}(I_{it}/A_{it})$, equal the expected marginal benefit of investment at time *t* + 1, $E[\Pi_{it+1}]$, discounted to time *t* with the expected stock return, $E\left[R^S_{it+1}\right]$, as the discount rate. The key prediction of Equation (1) is that, all else equal (in particular, holding firm investment constant), firms with high expected future profitability should earn higher expected returns than firms with low expected profitability.[5] Combining Hypothesis 1 with the positive expected profitability-expected return relation leads to the following hypothesis:

[5] Another key prediction from Equation (1) is that, all else equal, high investment stocks should earn lower expected returns than low investment stocks. Fama and French (2015) also propose that higher expected future profitability is related to higher expected stock returns. They illustrate this point using the Miller-Modigliani (1961) valuation model.

Hypothesis 2: *Firms with high forecast dispersion should earn low expected stock returns because of their low expected future profitability.*

If disclosure manipulation results in the relation between forecast dispersion and future profitability, both time-series and cross-sectional variation of disclosure quality should affect the strength of the dispersion anomaly. We use the 2002 Sarbanes-Oxley Act (SOX), arguably the most important disclosure reform in U.S. corporate history, as a quasi-natural experiment. SOX significantly tightens corporate governance and internal controls, enhances financial disclosure, and imposes substantial penalties on managers caught manipulating information disclosure. Thus, it significantly reduces earnings disclosure manipulation and increases disclosure quality for publicly listed firms (e.g., Lobo and Zhou, 2006; Cohen, Dey, and Lys, 2008; Iliev, 2010). To capture cross-sectional variation in disclosure quality, we use accrual-based measures of earnings quality that are often interpreted as financial reporting quality (Francis et al, 2005; Rajgopal and Venkatachalam, 2011; Chaney, Faccio, and Parsley, 201; Bhattacharya, Desai, and Venkatachalam, 2013). Based on this discussion we develop the following hypothesis:

Hypothesis 3: *The dispersion anomaly should be stronger for firms with lower earnings disclosure quality and substantially weakened in the post-SOX period.*

3. Data

Monthly analysts' 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) point out that the adjusted file is subject to the rounding error issue. The I/B/E/S data being 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 including 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 for number of firms, forecast dispersion, and market capitalization for the various sub-periods 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 variable definitions. Similar to other studies, the average of market capitalization of stocks increases over time. Averages of forecast dispersion and number of forecasts, in contrast, are relatively stable. Consistent with prior studies (e.g., Gu and Wu, 2003; Verardo, 2009), forecast dispersion is highly skewed, the mean substantially greater than the median.

At the end of month *t*, we sort all stocks into equally weighted quintile portfolios based on the analysts' earnings forecast dispersion in month *t*. The quintile portfolios are 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, average portfolio returns decreasing monotonically as we move from the lowest (Quintile 1) to the highest (Quintile 5) dispersion portfolio. As such, the low-minus-high dispersion hedge portfolio (Quintile 1 – Quintile 5) earns an average return of 0.44% per month, the (Newey and West (1987) adjusted) *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. The table 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 (MKT), size (SMB), book-to-market (HML), and momentum (UMD) factors. 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 exposures to the four factors does not weaken (in fact, strengthens) the dispersion effect.

4. Dispersion, Future Profitability, and Future Stock Returns

This section tests Hypotheses 1 and 2. Section 4.1 examines whether dispersion predicts future firm profitability. Section 4.2 investigates whether the return predictive power of dispersion is driven by its information content about future firm profitability.

4.1. Dispersion and Future Profitability

To test our prediction of a negative relation between analysts' earnings forecast dispersion and future firm profitability, we run Fama and MacBeth (1973) cross-sectional regressions of future firm profitability on 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).[6] Table 3 reports 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 *t*-value being –28.39 (–35.10). A one-standard-deviation increase in DISP is related to a -0.66% (-1.26%) drop in one-quarter-ahead ROA (ROE).

Results do not change when we include other firm characteristics (e.g., 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, and results for other firm characteristics are intuitive and consistent with prior studies. That size and momentum predict future profitability positively, and book-to-market ratio predicts future profitability negatively, is, for example, consistent with Fama and French (1995). We also document that investment is negatively related to future profitability in the cross-section. To control for the persistency in firm profitability, we include the most recently disclosed ROA or ROE as an additional control variable and find qualitatively similar results (columns 3 and 6). To summarize, consistent with Hypothesis 1, we find a strong inverse relation between analyst forecast dispersion and future firm profitability.

4.2. The Dispersion Effect after Controlling for Future Profitability

To examine whether the return predictive power of analysts' earnings forecast dispersion derives from its information content about future firm profitability, we conduct three sets of tests.

[6] Our results remain qualitatively similar when we use one-year-ahead ROA and ROE.

First, we examine whether a profitability factor helps to explain the dispersion-return relation. As noted earlier, recent asset pricing studies propose the equilibrium relation between expected profitability and expected stock returns and suggest profitability factors that can help explain the cross section of expected stock returns. Hou, Xue, and Zhang (2015) propose the *q*-factor model, which predicts that, for a given investment, firms with high expected future profitability (i.e., low dispersion stocks) should earn higher expected stock returns than firms with low expected profitability (i.e., high dispersion stocks). 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 stock returns. If the dispersion-return relation is driven by the profitability-return relation, a profitability factor should substantially reduce the magnitude of the alpha of the low-minus-high dispersion hedge portfolio. We augment the CAPM with a profitability factor and examine the ability of the model in explaining the dispersion anomaly. We consider two profitability factors: the ROE (Return-On-Equity) factor proposed by Hou, Xue, and Zhang (2015), and the PMU (Profitable-Minus-Unprofitable) factor proposed by Novy-Marx (2013).[7]

Table 4 reports thee alphas and factor loadings from time-series regressions of the five dispersion quintile portfolio excess returns and of the low-minus-high dispersion hedge portfolio (Quintile 1 – Quintile 5) return on the market factor augmented by a profitability factor. Panels A and B present the results for using the ROE and PMU factors, respectively. From Panel A, we see that the factor loading of ROE is highly significant for all the dispersion quintile portfolios, and it decreases monotonically from 0.15 for the lowest (Quintile 1) to –0.76 for the highest (Quintile 5) dispersion portfolio. This suggests that a firm's exposure to the ROE factor varies systematically with its analyst

[7] The ROE factor is provided by Lu Zhang, and the PMU factor is obtained from Robert Novy-Marx's webpage. We use the industry-adjusted PMU factor, which is shown by Novy-Marx (2013) to have greater power than the straight PMU factor in explaining the cross section of expected stock returns.

forecast dispersion, which helps to explain the dispersion anomaly.[8] Moreover, the augmented CAPM with the ROE factor reduces the alpha of the low-minus-high dispersion hedge portfolio to an insignificant 0.07% (*t*-value = 0.51), and the alphas do not show any systematic pattern across dispersion quintile portfolios. Thus, the augmented CAPM with the profitability factor well explains the dispersion anomaly.

Panel B of Table 4 shows that the PMU factor also explains well the dispersion anomaly. The PMU factor loadings are again all highly significant and decrease monotonically with dispersion from 0.42 (for the lowest dispersion quintile) to –1.10 (for the highest dispersion quintile). The dispersion hedge portfolio alpha from the augmented CAPM with the PMU factor is 0.09% (*t*-value = 0.50), which suggests that the dispersion-based trading strategy generates an insignificant payoff after controlling for portfolio exposure to the PMU factor.[9]

We examine as well the ability of the recently developed asset pricing models (i.e., Hou, Xue, and Zhang (2015) four-factor model and Novy-Marx (2013) four-factor model) to explain the dispersion anomaly.[10] The results, also reported in Table 4, are qualitatively similar to those for the simple two-factor models. For instance, the alpha of the low-minus-high dispersion hedge portfolio obtained from the Hou, Xue, and Zhang four-factor model is 0.16% (*t*-value = 1.36), and that obtained from the Novy-Marx four-factor model is -0.08 (*t*-value = -0.41). Moreover, the loadings of the

[8] 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.

[9] We also examine the results using the augmented CAPM with the RMW factor from Fama and French (2015). We find that the factor loading of RMW is highly significant for all the dispersion quintile portfolios, and it decreases monotonically with dispersion from 0.16 (for the lowest dispersion quintile) to –0.74 (for the highest dispersion quintile). Further, the augmented CAPM with the RMW factor substantially attenuates the alpha of the low-minus-high dispersion hedge portfolio (0.28%), which is less than half of the Carhart alpha (0.61% in Table 2). These results are omitted for brevity (but are available on request). Prior studies (e.g., Hou, Xue, and Zhang, 2016; Ball, Gerakos, Linnainmaa, and Nikolaev, 2016) show the empirical performance of the RMW factor to be weaker than that of the ROE and PMU factors in explaining the cross-section of stock returns. For instance, the RMW cannot explain the momentum portfolios, which can be explained by either of the other factors.

[10] Note that Hou, Xue, and Zhang (2015), Fama and French (2015) and Novy-Marx (2013) do not examine whether their asset pricing models explain the dispersion anomaly.

profitability factor continue to monotonically decrease from dispersion Quintile 1 to Quintile 5, with a large loading spread (ranging from 0.82 to 1.48) in these asset pricing models, suggesting that the profitability factor well explains the dispersion-return relation. The other factors do not help to explain the dispersion anomaly.[11]

Second, for robustness, we run Fama-MacBeth (1973) monthly cross-sectional regressions of subsequent stock returns on forecast dispersion and other control variables, including future profitability. The results are reported in Table A2 in the Appendix. Column 1 shows that, in the univariate regression specification, dispersion has strong negative predictive power for future stock returns. The coefficient on dispersion is -0.541 and highly significant (*t*-value = -3.31). A one-standard-deviation increase in DISP is related to a -0.17% drop in one-month-ahead stock return. This economic magnitude is consistent with the portfolio results in Table 2. In column 2 of Table A2, we control for standard firm characteristics that have been shown to affect the cross-section of future stock returns including size, book-to-market equity ratio, momentum, and investment. The coefficient of dispersion remains negative at -0.589 and statistically significant at the 1% level, suggesting that these standard control variables do not have an impact on the significance of the dispersion coefficient. Our primary interest is to include future ROA (ROE) as an additional control variable, reported in column 3 (column 4). We see that, in the presence of future profitability measure, dispersion has no statistical or economic power to explain the cross-section of subsequent returns. The coefficient of dispersion changes sign, becoming positive, and is statistically insignificant, at 0.113 (*t*-value = 0.78) and 0.131 (*t*-value = 0.89) when controlling for future ROA and ROE, respectively. As expected, the coefficient of future ROA (ROE) in column 3 (4) is positive and highly significant. Combined with the earlier finding of a strong and inverse relation between analyst forecast dispersion and future

[11] We also find that the Fama and French (2015) five-factor model reduces the dispersion hedge portfolio alpha, but performs worse than the other models, consistent with the results from the augmented CAPM with the RMW factor. These results are omitted for brevity (but are available on request).

profitability, this finding suggests that the information content of dispersion about future profitability well explains the dispersion anomaly in the cross-section of stock returns. Thus, consistent with our findings from earlier factor regressions, the Fama-MacBeth cross-sectional regression results in Table A2 strongly support the conjecture that the anomalous stock return predictability of analyst forecast dispersion reflects mainly its information content about future firm profitability.

Third, we further 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, measured by one-quarter ahead ROA or ROE. In each of the future profitability quintiles, we then sort stocks equally into quintile portfolios based on analysts' earnings forecast dispersion in month *t*. The 25 profitability-dispersion portfolios are rebalanced each month. Table A3 in the Appendix presents average monthly risk-adjusted and raw returns for the 25 portfolios. We also present the risk-adjusted and raw returns for the low-minus-high dispersion hedge portfolio (Quintile 1 – Quintile 5) across future profitability quintiles. Panel A reports risk-adjusted returns (or time-series alphas) using the Carhart four-factor model, and Panel B reports raw returns. Results obtained using ROA and ROE are reported in each panel.

Panel A clearly shows that after controlling for future profitability, there is no longer a negative relation between dispersion and subsequent risk-adjusted returns. In each future ROA quintile, risk-adjusted returns tend to *increase* with dispersion (results are similar for the ROE quintiles). For instance, in the highest future ROA quintile, risk-adjusted returns increase from 0.99% per month for the lowest to 1.84% per month for the highest dispersion quintile. As such, the low-minus-high dispersion hedge portfolio (Quintile 1 – Quintile 5) alphas are negative across all future ROA quintiles, and statistically significant at the 1% level in all but the lowest future ROA quintile. We also aggregate each dispersion quintile risk-adjusted returns across five future ROA (ROE) quintiles using equal weight. We find that risk-adjusted returns of these profitability-adjusted dispersion portfolios increase with dispersion, the difference between the low and high dispersion portfolios being negative at -0.62% per month, with *t*-value of -4.47. Panel B shows that the results for raw returns are qualitatively similar. Overall, the results from our portfolio double sort further confirm that the dispersion-return relation changes sign after controlling for future profitability: lower dispersion stocks have lower, not higher, subsequent raw and risk-adjusted returns.

To summarize, the empirical results of the three sets of tests performed in this section consistently and strongly support Hypothesis 2 that the return predictive power of dispersion reflects mainly its information content about future firm profitability.

5. Dispersion, Disclosure Quality, and Future Stock Returns

This section tests Hypothesis 3. Section 5.1 presents evidence that lower disclosure quality is associated with lower future profitability as well as greater forecast dispersion. Section 5.2 examines whether the dispersion anomaly is stronger for firms with lower earnings disclosure quality. Section 5.3 investigates whether the anomaly is substantially weakened in the post-SOX period.

5.1. Dispersion and Earnings Disclosure Quality

We first examine whether lower earnings disclosure quality leads to greater analysts' earnings forecast dispersion 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 analysts' private information due to a lack of accurate public information that can be used to forecast a firm's future earnings (e.g., Lang and Lundholm, 1996; Dhaliwal, Li, Tsang, and Yang, 2011; Rajgopal and Venkatachalam, 2011). Following 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 (median absolute value) of discretionary accruals over the past five fiscal years. Larger values of DA_Quality or Abs_DA imply *lower* earnings disclosure quality and, hence, noisier earnings disclosure.

We calculate discretionary accruals for each firm-year using the model suggested by Dechow, Sloan, and Sweeney (1995), a modified version of the Jones' (1991) model, to decompose total accruals into non-discretionary and discretionary components. Following Kothari, Leone, and Wasley (2005), we add to the model, as a regressor, return on assets, that is, earnings before extraordinary items (Compustat item: IB) scaled by lagged total assets, 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 eight firms in the full Compustat universe during a year:

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

In equation (2), 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), and DP is depreciation and amortization (Compustat item: DP). For each year, equation (2) 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), and 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 follows:

$$NDA_{i,t} = b_1 \frac{1}{Assets_{i,t-1}} + b_2 \frac{\Delta Sales_{i,t} - \Delta AR_{i,t}}{Assets_{i,t-1}} + b_3 \frac{PPE_{i,t}}{Assets_{i,t-1}} + b_4 \frac{IB_{i,t}}{Assets_{i,t-1}}. \qquad (3)$$

Discretionary accruals (DA) are then defined as

$$DA_{i,t} = \frac{TA_{i,t}}{Assets_{i,t-1}} - NDA_{i,t}. \qquad (4)$$

Diamond and Verrecchia (1991) and many others suggesting that disclosure quality is worse among small firms, we further use market capitalization (Size) as an alternative simple proxy for disclosure quality. Fama-MacBeth regression results are reported in Table A4 in the Appendix. 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 accounting data are publicly available). Industry fixed effects are included in all regressions to account for potential cross-industry heterogeneity in dispersion (we use the Fama-French 48-industry classification scheme).

Consistent with findings reported in the literature (e.g., Rajopal and Venkatachalam 2011), DA_Quality and Abs_DA are both strongly and positively related to dispersion, the Newey-West adjusted *t*-value being 5.70 and 8.28 in columns 1 and 3, respectively. Results are qualitatively unchanged when we control for firm size in the regressions (columns 2 and 4). A one-standard-deviation increase in DA_Quality (Abs_DA) is, 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.

We next examine whether lower future profitability is related to poorer disclosure quality. We regress 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 A5 in the Appendix show that, similar to dispersion, both DA_Quality and Abs_DA negatively predict future ROA at the 1% level (columns

3 and 4). The predictive power of DA_Quality and Abs_DA for future ROE is qualitatively similar to, but somewhat weaker than, that for future ROA (columns 1 and 2). The coefficients of the other variables in Table A5 show signs similar to those in Table 3. In particular, Size positively predicts future profitability at the 1% level.

Consistent with the disclosure manipulation explanation, we find that lower earnings disclosure quality is related to greater analysts' earnings forecast dispersion. Furthermore, lower future profitability is related to poor earnings disclosure quality.

5.2. The Dispersion Effect Conditional on Earnings Disclosure Quality

If the dispersion anomaly is driven by managerial disclosure manipulation in anticipation of low future profitability, we expect the return predictive power of dispersion to be stronger for firms with lower earnings disclosure quality. We examine this conjecture using the Fama-MacBeth regressions in Table 5.

Column 1 of Table 5 shows that dispersion has significantly negative predictive power for future stock returns at the 1% level even after controlling for other common cross-sectional return predictors, such as size, book-to-market equity ratio, momentum, and investment. When we include a disclosure quality proxy (i.e., DA_Quality, Abs_DA or Size) and its interaction term with dispersion in columns 2-4, the interaction term DISP*DA_Quality (DISP*Abs_DA) in column 2 (column 3) has a significantly negative coefficient at the 5% level while the coefficient of dispersion becomes statistically insignificant. These results suggest that the return predictive power of dispersion is stronger for firms with lower earnings disclosure quality. Similarly, the interaction term DISP*Size in column 4 has a positive, albeit insignificant, coefficient, and the coefficient of dispersion is also statistically insignificant. The insignificant coefficient of DISP*Size likely reflects the fact that firm size as a measure of earnings disclosure quality is noisier than DA_Quality and Abs_DA.

As a complementary analysis, 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 quintile portfolios. That is, we examine the return predictive power of dispersion conditional on earnings disclosure quality. The portfolio sorting results are reported in Table 6. 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 for firms with lower earnings disclosure quality (recall that DA_Quality is an inverse proxy for earnings disclosure quality). Panel B reports qualitatively similar results for 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 poorer disclosure quality. Thus, consistent with our expectation, the stock return predictive power of analysts' earnings forecast dispersion is, indeed, stronger for firms with lower earnings disclosure quality.

5.3. SOX and the Dispersion Effect

We use the 2002 Sarbanes-Oxley Act (SOX) as a quasi-natural experiment. 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 pre- and post-SOX subsamples and re-run the Fama-MacBeth cross-sectional return predictive regressions for each subsample. Results are reported in Table 7.

Panel A of Table 7 shows that dispersion has strong, negative return predictive power in the pre-SOX subsample, and its regression coefficient changes sign and is statistically insignificant when we control for future firm profitability. By contrast, Panel B shows that dispersion has no return predictive power in the post-SOX subsample, even absent 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.

The empirical results of the three sets of tests performed in this section support Hypothesis 3 that the dispersion anomaly is stronger for firms with lower earnings disclosure quality and substantially weakened in the post-SOX period.

6. Alternative Explanations

As noted earlier, Diether, Malloy, and Scherbina (2002) suggest that analysts' earnings forecast dispersion is a measure of divergence of investor opinions. Stock prices will reflect the valuation of more optimistic investors in the presence of heterogeneous investors' beliefs and short-sale constraints (Miller, 1977). The latter prevent pessimistic investors from selling, while optimistic investors can buy and bid prices up. As such, greater divergence of investor opinions (proxied by higher forecast dispersion) causes stocks to be initially overpriced and hence leads to lower subsequent returns as the overpricing is corrected over time. One prediction of this explanation is that the dispersion anomaly should be more pronounced for firms with more stringent short-sale constraints. In contrast, our explanation does not rely on mispricing and market friction. Instead, we argue that high dispersion stocks earn low subsequent returns due to the equilibrium relation between expected profitability and expected stock returns. Johnson (2004) proposes that forecast 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 its assets, levered firms with higher dispersion are likely to have higher current equity value and, hence, lower expected stock returns. This explanation predicts that the dispersion-return relation should be stronger as firm leverage increases. Johnson's explanation, however, does not relate dispersion to future firm profitability. Avramov, Chordia, Jostova, and Philipov (2009) suggest that the dispersion-return relation can be explained by the credit risk-return relation.[12] Avramov et al. (2009) show that the dispersion effect concentrates in a small number of the worst-rated firms and exists only during periods of financial distress as proxied by credit rating downgrades.

In order to distinguish our explanation for the dispersion anomaly, that it is driven by the information content of dispersion about future firm profitability due to disclosure manipulation, from other explanations offered in the literature, we partition our full sample into subsamples based on short-sale constraints, firm leverage, or credit rating. We then examine the dispersion-return relation in each subsample to check whether these firm characteristics indeed affect the dispersion anomaly. More importantly, we investigate whether the profitability-based explanation is captured by the previously proposed explanations by controlling for the profitability factor in each subsample.

Prior studies suggest 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). It is further shown that put options trading alleviates short-sale constraints (e.g., Danielsen and Sorescu, 2001; Guo and Qiu, 2014). Both institutional ownership and put option trading are hence used as proxies for short-sale constraints. To examine whether short-sale constraints play an important role in the dispersion effect (Diether, Malloy, and Scherbina, 2002), we split our full sample, for each month, into subsamples based on median institutional ownership and whether a stock has put options trading. Institutional ownership is computed as the fraction of a stock's outstanding shares held by all institutional shareholders constructed using the most recent 13f filings obtained from the Thomson Financial 13f database. A

[12] Campbell, Hilscher, and Szilagyi (2008) document a negative relation between credit risk and future returns, which has been considered an anomalous pattern in the cross-section of stock returns.

stock is classified as having put options trading in a month if there exists a put option contract with non-zero trading volume for that stock in that month. Option data is obtained from OptionMetrics.

To determine whether the dispersion-return relation strengthens with greater firm leverage (Johnson, 2004), we partition our full sample into subsamples in each month based on the median market leverage ratio. Market leverage (debt-to-equity ratio) is measured 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. To test whether financial distress is a driver of the dispersion anomaly (Avramov et al., 2009), we consider credit rating level as a proxy for credit risk and 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 in each month. Following Avramov et al. (2009), we classify non-investment grade as credit ratings BB+ or worse and investment grade as ratings BBB- or better, using the S&P Long-Term Domestic Issuer Credit Rating obtained from Compustat.[13]

Table 8 reports the factor regression results from the subsample analyses. We first split the full sample into subsamples based on the median institutional ownership (Low IO vs. High IO), whether a stock has put options trading (No PUT vs. PUT), the median market leverage ratio (High LEV vs. Low LEV), and the S&P Long-Term Domestic Issuer Credit Rating (Non-Inv Grade vs. Inv Grade vs. Unrated). We then form the dispersion quintile portfolios using each subsample and run factor regressions for the low-minus-high dispersion quintile hedge portfolio of each subsample. The table reports the low-minus-high dispersion hedge portfolio alphas obtained from various asset

[13] The sample periods for the subsample analyses differ due to data availability. The sample period for the analysis based on institutional ownership (put options) 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 based on leverage is from January 1976 to December 2014. The sample period for the analysis based on credit rating is from January 1986 to December 2014 due to the availability of the S&P Long-Term Domestic Issuer Credit Rating data.

pricing models, including the Carhart (1997) four-factor model, augmented CAPM with the ROE factor, the Hou, Xue, and Zhang (2015) four-factor model, augmented CAPM with the PMU factor, and Novy-Marx (2013) four-factor model.

The Carhart four-factor alpha for the low-minus-high dispersion hedge portfolio is positive and highly significant at the 1% level for both the Low and High IO subsamples, the No PUT subsample, both the High and Low LEV subsamples, and the Unrated subsample, while it is positive and insignificant for the other subsamples. Consistent with the extant explanations for the dispersion anomaly, the Carhart alpha for the hedge portfolio is greater in the Low IO (No PUT) subsample than in the High IO (PUT) subsample. It is also greater in the High LEV subsample than in the Low LEV subsample. Finally, the Carhart alpha for the hedge portfolio is greater in the Unrated subsample than in the subsamples with credit ratings. And it is greater in the Non-Inv Grade subsample than in the Inv Grade subsample.

When we add the profitability factor (either the ROE or PMU factor) in the CAPM, the alpha of the dispersion hedge portfolio is substantially reduced and becomes insignificant in most of the subsamples considered. For instance, the augmented CAPM with the PMU factor reduces the alpha of the dispersion hedge portfolio to an insignificant level for all of the subsamples except the Low IO subsample and the High LEV subsample. Results are similar for the augmented CAPM with the ROE factor. Most notably, the Novy-Marx (2013) four-factor model successfully explains the dispersion-return relation (i.e., reducing the alpha to an insignificant level) for *all* subsamples. The results suggest that the profitability factor well explains the dispersion anomaly in subsamples sorted on short-sale constraints, firm leverage, or credit rating.

For robustness, Table A6 in the Appendix presents the results from the Fama-MacBeth cross-sectional regressions of subsequent returns on forecast dispersion, standard firm characteristics (i.e., size, book-to-market equity ratio, momentum, and investment), and future profitability for each partitioned subsample. Similar to the subsample results using factor regressions, Panels A, B, C, and D of Table A6 show that when we control for future ROA or ROE, the return predictive power of dispersion disappears or the coefficient on dispersion changes sign across all subsamples, suggesting that the profitability-based explanation for the dispersion effect holds irrespective of the degree of short-sale constraints, firm leverage, and credit rating.

Panel E shows the impact of credit rating downgrades on the dispersion-return relation. In a subsample of rated firms, the coefficient on dispersion is statistically insignificant when a dummy variable for credit rating downgrades is included, consistent with Avramov et al. (2009). When we re-do, as a robustness check, the analyses for all (rated and unrated) firms, coefficients on both the downgrades dummy variable and dispersion are significantly negative. However, when we control for future profitability, the coefficient on dispersion again changes sign and becomes positive across all regressions (columns 3, 4, 7, and 8 of Panel E).

To summarize, our results show that the profitability-based explanation for the dispersion effect is not captured by alternative explanations in the literature.

7. Conclusion

In this paper, we show that the dispersion anomaly, that is, the cross-sectional stock return predictive power of analysts' earnings forecast dispersion documented by Diether, Malloy, and Scherbina (2002), is driven by the information content of dispersion about expected future profitability consequent to disclosure manipulation. We hypothesize that high dispersion stocks have low expected stock returns because they have low expected future profitability due to disclosure manipulation. Consistent with this prediction, we find that greater dispersion strongly predicts lower future profitability and that the dispersion effect derives from the information content of dispersion about future profitability. We show that the augmented CAPM with a profitability factor well explains the dispersion effect. Loadings on the profitability factor monotonically decrease from the lowest to the highest dispersion quintile portfolios. Consequently, the profitability factor substantially reduces the alpha of the low-minus-high dispersion hedge portfolio, often to insignificant levels. Moreover, when we control for future profitability in Fama-MacBeth regressions and portfolio double sorting, the dispersion-return relation disappears.

The literature suggests that when future profitability is expected to be low, managers tend to withhold bad news and/or disclose relatively vague information (e.g., Hong, Lim, and Stein, 2000; Graham, Harvey, and Rajgopal, 2005; Jin and Myers, 2006; Kothari, Shu, and Wysocki, 2009). Such disclosure manipulation increases analysts' earnings forecast dispersion, the source of which is mainly the differences in analysts' private information. When there is a lack of accurate public information, analysts place less weight on common public information and rely more on heterogeneous private information to forecast future earnings, thereby engendering greater forecast dispersion (e.g., Lang and Lundholm, 1996; Dhaliwal, Li, Tsang, and Yang, 2011; Rajgopal and Venkatachalam, 2011).

Consistent with the proposed disclosure manipulation explanation of the dispersion anomaly, we document that earnings disclosure 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 earnings disclosure quality and then by dispersion, we find that the return predictive power of dispersion increases monotonically as disclosure quality worsens. Similarly, the interaction term between disclosure quality and dispersion drives out dispersion in the Fama-MacBeth regressions of predicting future stock returns. The 2002 Sarbanes-Oxley Act (SOX) provides us a quasi-natural experiment to further verify the proposed disclosure manipulation explanation of the dispersion anomaly. SOX, the most important disclosure reform in U.S. corporate history, 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.

To distinguish our proposed explanation from alternative explanations suggested in the literature, we examine the dispersion anomaly in subsamples sorted on short-sale constraints, firm leverage, or credit rating, all of which have been suggested to be related to the dispersion anomaly. We find that controlling for the profitability factor substantially reduces the magnitude of the dispersion anomaly, often to insignificant levels, across different subsamples. Therefore, our profitability-based explanation for the dispersion effect is not captured by alternative explanations.

Reference

Armstrong, C., W. Guay, and J. Weber, 2010, The role of information and financial reporting in corporate governance and debt contracting, *Journal of Accounting and Economics* 50(2-3): 179-234.

Asquith, P., P. Pathak, and J. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78(2): 243-276.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov, 2009, Dispersion in analysts' earnings forecasts and credit rating, *Journal of Financial Economics* 91(1): 83-101.

Bali, T. G., A. Bodnaruk, A. Schernina, and Y. Tang, 2018, Unusual news events and the cross-section of stock returns, *Management Science* 64(9): 3971-4470.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. Nikolaev, 2016, Accruals, cash flows, and operating profitability in the cross section of stock returns, *Journal of Financial Economics* 121(1): 28-45.

Bhattacharya, N., H. Desai, and K. Venkataraman, 2013, Does earnings quality affect information asymmetry? Evidence from trading costs, *Contemporary Accounting Research* 30(2): 482-516.

Campbell J. Y., J. Hilscher, and J. Szilagyi, 2008, In search of distress risk. *Journal of Finance* 63(6): 2899-2939.

Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52(1): 57-82.

Chaney, P., M. Faccio, and D. Parsley, 2011, The quality of accounting information in politically connected firms, *Journal of Accounting and Economics* 51(1-2): 58-76.

Chatterjee, S., K. John, and A. Yan, 2012, Takeovers and divergence of opinion, *Review of Financial Studies*, 25(1): 227-277.

Chen, J., H. Hong, and J. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66(2-3): 171-205.

Cohen, D., A. Dey, and T. Lys, 2008, Real and accrual–based earnings management in the pre- and post-Sarbanes Oxley periods, *The Accounting Review* 82(3): 757-787.

Danielsen, B., and S. Sorescu, 2001, Why do option introductions depress stock prices? A study of diminishing short-sale constraints, *Journal of Financial and Quantitative Analysis* 36(4): 451-484.

D'Avolio, G., 2002, The market for borrowing stock, *Journal of Financial Economics* 66(2-3): 271-306.

Dechow, P., R. Sloan, and A. Sweeney, 1995, Detecting earnings management. *The Accounting Review* 70(2): 193-225.

Dhaliwal, D., O. Li, A. Tsang, and Y. Yang, 2011, Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review* 86(1): 59-100.

Diamond, D., and R. Verrecchia, 1991, Disclosure, liquidity, and the cost of capital, *Journal of Finance* 46(4): 1325-1359.

Diether, K., C. Malloy, and A. Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57(5): 2113-2141.

Fama, E. F., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33(1): 3-56.

Fama, E. F., and K. R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50(1): 131-155.

Fama, E. F., and K. R. French, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82(3): 491-518.

Fama, E. F., and K. R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116(1): 1-22.

Fama, E. F., and J. D. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81(3): 607-636.

Francis, J., R. LaFond, P. Olsson, and K. Schipper, 2005, The market pricing of accruals quality, *Journal of Accounting and Economics* 39(2): 295-327.

Graham, J. R., C. R. Harvey, and S. Rajgopal, 2005, The economic implications of corporate financial reporting, *Journal of Accounting and Economics* 40(1-3): 3-73.

Gu, Z., and J. S. Wu, 2003, Earnings skewness and analyst forecast bias, *Journal of Accounting Economics* 35(1): 5-29.

Guntay, L., and D. Hackbarth, 2010, Corporate bond credit spreads and forecast dispersion, *Journal of Banking and Finance* 34: 2327-2345.

Guo, H., and B. Qiu, 2014, Options-implied variance and future stock returns, *Journal of Banking and Finance* 44: 93-113.

Guo, H., and B. Qiu, 2016, A better measure of institutional informed trading, *Contemporary Accounting Research* 33(2): 815-850.

Hong, H., T. Lim, and J. C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55(1): 265-295.

Hou, K., C. Xue, and L. Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28(3): 650-705.

Hou, K., C. Xue, and L. Zhang, 2016, A comparison of New Factor Models, Working paper, Ohio State University.

Hwang, B.-H., D. Lou, and C. A. Yin, 2017, "Offsetting Disagreement and Security Prices," Working paper, Cornell University.

Iliev, P., 2010, The effect of SOX Section 404: Costs, earnings quality and stock prices, *Journal of Finance* 65(3): 1163-1196.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48(1): 65-91.

Jegadeesh, N., and S. Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56(2): 699-720.

Jin, L., and S. C. Myers, 2006, R^2 around the world: New theory and new tests. *Journal of Financial Economics* 79(2): 257-292.

Johnson, T., 2004, Forecast dispersion and the cross section of expected returns, *Journal of Finance* 59(5): 1957-1978.

Kothari, S. P., A. J. Leone, and C. E. Wasley, 2005, Performance matched discretionary accrual measures, *Journal of Financial Economics* 39(1): 163-197.

Kothari, S. P., S. Shu, and P. D. Wysocki, 2009, Do managers withhold bad news? *Journal of Accounting Research* 47(1): 241-276.

Lang, M., and R. Lundholm, 1996, Corporate disclosure policy and analyst behavior. *The Accounting Review* 71(4): 467-492.

Lobo, G. L., and J. Zhou, 2006, Did conservatism in financial reporting increase after the Sarbanes-Oxley Act? Initial evidence, *Accounting Horizons* 20(1): 57-73.

Miller, E., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32(4): 1151-1168.

Nagel, S., 2005, Short sales, institutional investors, and the cross-section of stock returns, *Journal of Financial Economics* 78(2): 277-309.

Newey, W., and K. West, 1987, A simple, positive, semi-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55(3): 703-708.

Novy-Marx, R., 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108(1): 1-28.

Rajgopal, S., and M. Venkatachalam, 2011, Financial reporting quality and idiosyncratic return volatility, *Journal of Accounting and Economics* 51(1-2): 1-20.

Saffi, P., and J. Sturgess, 2009, Equity lending markets and ownership structure, Working paper, IESE Business School.

Verardo, M., 2009, Heterogeneous beliefs and momentum profits, *Journal of Financial and Quantitative Analysis* 44(4): 795-822.

Table 1. Summary Statistics of Dispersion and Other Firm Characteristics

This table reports summary statistics of characteristics of sample stocks during sub-periods 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 no less than $5. We exclude firms with negative book value of equity as well as firms for which 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 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. 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, obtained from the regression of excess returns of dispersion portfolios 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

This 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 the 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. Factor Regressions of Dispersion Portfolio Returns on a Profitability Factor

This table reports the results of factor regressions of the dispersion quintile portfolios on a profitability factor. In Panels A and B, the upper tables report factor regression results for the augmented CAPM models with a profitability factor. Panel A uses the ROE (Return-On-Equity) factor proposed by Hou, Xue, and Zhang (2015), and Panel B the PMU (Profitable-Minus-Unprofitable) factor proposed by Novy-Marx (2013). The lower tables in Panels A and B report factor regression results for the recent asset pricing models with a profitability factor: the Hou, Xue, and Zhang (2015) four-factor model and 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: Hou, Xue, and Zhang Profitability Factor (ROE)						
	D1	D2	D3	D4	D5	D1 - D5
	The augmented CAPM with the ROE factor					
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 4. Factor Regressions of Dispersion Portfolio Returns on a Profitability Factor (Continued)

Panel B: Novy-Marx Profitability Factor (PMU)						
	D1	D2	D3	D4	D5	D1 - D5
	The augmented CAPM with the PMU factor					
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 5. The Dispersion Effect Conditional on Earnings Disclosure Quality

This 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 for earnings disclosure quality (EDQ). Size, book-to-market, momentum, and investment are used as control variables. All variables are winsorized at the 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 6. Sequential Double Sorts on Earnings Disclosure Quality and Dispersion

This 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. The Carhart four-factor alphas are calculated from the one-month-ahead equal-weighted portfolio returns. Panel A (B) reports the four-factor alphas for 25 portfolios based on the DA_Quality (Abs_DA) measure and analyst forecast dispersion. Panel C reports the four-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 7. The Dispersion Effect: Pre-SOX Subsample and Post-SOX Subsample

This 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 pre-SOX and post-SOX subsamples. 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 the 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 8. Subsample Factor Regression Analyses Based on Short-Sale Constraints, Firm Leverage and Credit Rating

This table reports the factor regression results from subsample analyses based on short-sale constraints, firm leverage, and credit rating. We first split the full sample into subsamples based on the median institutional ownership (Low IO versus High IO), whether a stock has put options trading (No PUT vs. PUT), the median market leverage ratio (High LEV vs. Low LEV), and the S&P Long-Term Domestic Issuer Credit Rating from Compustat (Non-Inv Grade vs. Inv Grade vs. Unrated). We then form the dispersion quintile portfolios using each subsample and run factor regressions for the low-minus-high dispersion hedge portfolio of each subsample. 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 the Thomson Financial 13f database. A stock has put options trading in a month if there exists a put option contract with non-zero trading volume for that stock. Option data is from OptionMetrics. Market leverage is defined as the ratio of most recent book value of debt to the sum of book value of debt and market value of equity. Book value of debt is the sum of long-term debt (Compustat quarterly item: DLTTQ) and debt in current liabilities (Compustat quarterly item: DLCQ). The sample period for the analysis based on institutional ownership (put options) 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 based on leverage is from January 1976 to December 2014. The sample period for the analysis based on credit rating is from January 1986 to December 2014 due to the availability of the S&P Long-Term Domestic Issuer Credit Rating data. The table reports the low-minus-high dispersion hedge portfolio alphas obtained from various asset pricing models, including the Carhart (1997) four-factor model, augmented CAPM with the ROE factor, Hou, Xue, and Zhang (2015) four-factor model, augmented CAPM with the PMU factor, and Novy-Marx (2013) four factor model. Newey and West (1987) *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Subsample Factor Regression Analyses Based on Short-Sale Constraints, Firm Leverage and Credit Rating (Continued)

	Carhart alpha	CAPM with the ROE alpha	Hou-Xue-Zhang alpha	CAPM with the PMU alpha	Novy-Marx alpha
Low IO	1.00%***	0.69%***	0.68%***	0.64%**	0.41%
	(4.24)	(2.66)	(2.83)	(2.04)	(1.18)
High IO	0.53%***	0.00%	0.07%	0.01%	-0.18%
	(3.76)	(0.02)	(0.61)	(0.06)	(-0.93)
No PUT	0.81%***	0.40%	0.50%**	0.27%	0.23%
	(3.80)	(1.57)	(2.27)	(0.80)	(0.71)
PUT	0.32%	-0.24%	-0.11%	-0.41%	-0.66%**
	(1.57)	(-1.05)	(-0.56)	(-1.26)	(-1.99)
High LEV	0.69%***	0.28%**	0.43%***	0.33%*	0.25%
	(4.47)	(2.05)	(3.12)	(1.69)	(1.40)
Low LEV	0.45%***	-0.08%	-0.08%	-0.02%	-0.37%
	(2.98)	(-0.36)	(-0.46)	(-0.06)	(-1.49)
Non-Inv Grade	0.28%	-0.20%	-0.11%	-0.37%	-0.43%
	(1.10)	(-0.97)	(-0.47)	(-1.40)	(-1.53)
Inv Grade	0.19%	-0.11%	0.01%	-0.21%	-0.09%
	(1.26)	(-0.76)	(0.05)	(-1.09)	(-0.56)
Unrated	0.47%***	0.00%	0.01%	-0.04%	-0.29%
	(2.92)	(0.01)	(0.05)	(-0.14)	(-1.09)

Appendix
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	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 exists a put option contract with non-zero trading volume for that stock.

Table A2. The Dispersion Effect after Controlling for Future Profitability

This 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 the 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 A3. Sequential Double Sorts on Future Profitability and Dispersion

This 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 their Carhart four-factor alphas (Panel A) and one-month-ahead equal-weighted portfolio returns (Panel B) are calculated. 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)
Future 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 future ROE		-0.15	-0.17	-0.13	0.07	0.47	-0.62***	(-4.47)
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
Future 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 future 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)
Future 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 future ROE		0.54	0.53	0.61	0.84	1.35	-0.81***	(-5.52)
		D1	D2	D3	D4	D5	D1 - D5	(t-value)
Future 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 future ROA		0.58	0.56	0.58	0.80	1.35	-0.78***	(-5.20)

Table A4. Dispersion and Earnings Disclosure Quality

This table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of analyst forecast dispersion (DISP) on proxies for 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 for earnings disclosure quality (EDQ). DA_Quality (Abs_DA) is the standard deviation (median absolute value) of discretionary accruals over the past five fiscal years. Size is logarithm of market cap. To account for potential cross-industry heterogeneity in dispersion, we control for industry fixed effects in the regressions. We use the Fama-French 48-industry classification scheme. All variables are winsorized at the 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 FE	Yes	Yes	Yes	Yes
Adj.R^2	0.056	0.081	0.054	0.080

Table A5. Earnings Disclosure Quality and Future Profitability

This 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 for earnings disclosure quality (EDQ). Size, book-to-market, momentum, investment, and current profitability are used as control variables. All variables are winsorized at the 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 A6. Subsample Fama-MacBeth Regression Analyses Based on Short-Sale Constraints, Firm Leverage, Credit Rating and Credit Rating Downgrades

This 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 median institutional ownership (Panel A), whether a stock has put options trading (Panel B), the median market leverage ratio (Panel C), and the S&P Long-Term Domestic Issuer Credit Rating from Compustat (Panel D). Panel E reports the results of the Fama and MacBeth (1973) cross-sectional regressions of future stock returns on dispersion and *Downgrade Dummy*. *Downgrade Dummy* takes the value of one for the period from three months before to three months after a downgrade. The left side of Panel E uses rated firms and the right side of Panel E uses both rated and unrated firms. The regression model is specified as follows.

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

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 the Thomson Financial 13f database. A stock has put options trading in a month if there exists a put option contract with non-zero trading volume for that stock. Option data is from OptionMetrics. Market leverage is defined as the ratio of most recent book value of debt to the sum of book value of debt and market value of equity. Book value of debt is the sum of long-term debt (Compustat quarterly item: DLTTQ) and debt in current liabilities (Compustat quarterly item: DLCQ). 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 analyses in Panel D and Panel E 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 A6. Subsample Fama-MacBeth Regression Analyses Based on Short-Sale Constraints, Firm Leverage, Credit Rating and Credit Rating Downgrades (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 A6. Subsample Fama-MacBeth Regression Analyses Based on Short-Sale Constraints, Firm Leverage, Credit Rating and Credit Rating Downgrades (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 A6. Subsample Fama-MacBeth Regression Analyses Based on Short-Sale Constraints, Firm Leverage, Credit Rating and Credit Rating Downgrades (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 A6. Subsample Fama-MacBeth Regression Analyses Based on Short-Sale Constraints, Firm Leverage, Credit Rating and Credit Rating Downgrades (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 A6. Subsample Fama-MacBeth Regression Analyses Based on Short-Sale Constraints, Firm Leverage, Credit Rating and Credit Rating Downgrades (Continued)

Panel E: Credit Rating Downgrades

Dependent Variable:	Rated Firms				All (Rated and Unrated) Firms			
Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downgrade Dummy	-1.325***	-1.395***	-1.031***	-0.971***	-1.268***	-1.293***	-0.847***	-0.892***
	(-7.81)	(-9.48)	(-7.03)	(-6.71)	(-6.35)	(-7.75)	(-5.14)	(-5.45)
DISP	-0.142	-0.185	0.250*	0.303**	-0.372**	-0.589**	0.320**	0.315**
	(-0.77)	(-1.24)	(1.77)	(2.13)	(-2.19)	(-2.38)	(2.40)	(2.35)
Size		0.001	-0.072	-0.111		-0.018	-0.123***	-0.106**
		(0.03)	(-1.44)	(-2.21)		(-0.44)	(-2.84)	(-2.47)
BM		0.143	0.694***	0.706***		0.096	0.479**	0.490**
		(1.12)	(4.93)	(5.19)		(0.46)	(2.16)	(2.20)
Mom		0.163	-0.476	-0.483		0.675**	0.166	0.184
		(0.44)	(-1.18)	(-1.21)		(2.39)	(0.54)	(0.60)
Inv		-0.627***	-0.472***	-0.502***		-0.545***	-0.412***	-0.428***
		(-4.73)	(-3.81)	(-4.14)		(-5.66)	(-5.12)	(-5.36)
Future ROE			15.334***				18.301***	
			(11.13)				(11.33)	
Future ROA				47.777***				34.765***
				(12.71)				(11.52)
Adj.R^2	0.012	0.054	0.066	0.066	0.005	0.037	0.050	0.050