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Why Do Analysts Disagree ?

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Abstract:
This paper finds that about one-quarter of analyst forecast dispersion and one-half of the dispersion-return relationship between 1985 and 2012 are explained by analyst overconfidence. In particular, the firm's analyst overconfidence mean and analyst overconfidence dispersion are the two most significant determinants of analyst forecast dispersion. Together, these two variables capture 77% of the explained variation in analyst forecast dispersion when all known determinants are considered. With respect to the dispersion-return relationship, the analyst forecast dispersion predicted by analyst overconfidence leads to a monthly hedging portfolio profit of 0.35% compared to a profit of 0.37% for the analyst forecast dispersion not predicted by analyst overconfidence.

Keywords: Analyst Overconfidence, Self-Attribution Bias, Analyst Forecast Dispersion, Stock Returns

JEL Classification: G12, G14, G24

1. Introduction

Recent papers have debated the reason for the negative relationship between analyst forecast dispersion and future stock returns (e.g. Diether, Malloy and Scherbina, 2002; Johnson, 2004; Sadka and Scherbina, 2007; Avramov, Chordia, Jostova and Philipov, 2009); yet very little has been said about why analysts disagree to begin with, and how this relates to stock market returns. This paper fills this void by providing a simple explanation for why analysts might disagree: overconfidence. This not only allows us to explain why analysts might disagree, but also to explain a large portion of the dispersion-return relationship.

We find that about one-quarter of analyst forecast dispersion and one-half of the dispersion-return relationship between 1985 and 2012 are explained by analyst overconfidence. In particular, analyst overconfidence explains 23.5% of the variation in analyst forecast dispersion, while including all other known determinants of analyst forecast dispersion only explains an additional 7.1% of the variation in analyst forecast dispersion. With respect to the dispersion-return relationship, the analyst forecast dispersion predicted by analyst overconfidence leads to a monthly hedging portfolio profit of 0.35% compared to a profit of 0.37% for the analyst forecast dispersion not predicted by analyst overconfidence. Moreover, the predicted and residual portions of analyst forecast dispersion have greater explanatory power than analyst forecast dispersion does by itself, suggesting that analyst overconfidence captures a facet of analyst disagreement that is more sensitive to stock returns. These results are robust to various specifications and methodologies.

Our measure of analyst overconfidence is based on biased self-attribution, whereby analysts become overconfident after a short series of successes. We define overconfidence, in the same way as Daniel, Hirshleifer and Subrahmanyam (1998), as an individual who overestimates the precision of her private information signal, but not of public information signals. Meanwhile, individuals subject to self-attribution bias tend to attribute good outcomes to their own abilities and bad outcomes to external circumstances. Overconfidence and biased self-attribution are therefore static and dynamic counterparts; self-attribution bias causes individuals to learn to be overconfident rather than converging to an accurate self-assessment (Hirshleifer, 2001). Hilary and Menzly (2006) find that analysts are more overconfident in their ability to forecast future earnings after making a short series of accurate predictions. Our results show that some analysts are overconfident such that their success and accuracy both decrease subsequent to a successful year of forecasting. Specifically, the analysts in the top quintile of forecasting success over the past year are 26.7% less successful and 60.6% less accurate in the subsequent quarter.

We hypothesize that analyst overconfidence affects analyst forecast dispersion in two ways. First, if some analysts are overconfident about future earnings relative to other analysts at the same firm, then these analysts should arrive at differing forecasts since overconfident analysts overweight their private information compared to non-overconfident analysts. Therefore, a firm's analyst overconfidence dispersion should explain a portion of its analyst earnings forecast dispersion. Second, even if a firm's analysts do not differ on the basis of their overconfidence, such that there is no dispersion in their overconfidence, overconfident analysts should still arrive at differing forecasts as long as their private information is less than perfectly correlated. Therefore, a firm's analyst overconfidence mean should also explain a portion of its analyst earnings forecast dispersion. Our results support these hypotheses. In particular, we find that the top analyst overconfidence mean quintile has 135% more analyst forecast dispersion than the bottom analyst overconfidence mean quintile, and the top analyst overconfidence dispersion quintile has 300% more analyst forecast dispersion than the bottom analyst overconfidence dispersion quintile. These results remain similar when both analyst overconfidence mean and analyst overconfidence dispersion are included along side other control variables in a multivariate framework.

We make two main contributions to the literature in this paper. First, we provide a first-order explanation of why analysts disagree in the earnings forecasts they provide for the firms they cover. Most of the research so far has correlated disagreement with differences in firm or market characteristics, whereas the analyst overconfidence shown in this paper provides an analyst-specific explanation for analyst disagreement. Second, our analyst overconfidence explanation contributes to the debate on what drives the negative dispersion-return relationship, and while the analyst overconfidence-return relationship we document remains consistent with a Miller (1977) overvaluation story, it is also consistent with two other stories: overreaction and information risk.

The rest of this paper is structured as follows. Section 2 summarizes the literature on overconfidence and analyst forecast dispersion. Section 3 explains our research design and data sample. We report the analyst-level relationship between short-term success and subsequent performance in Section 4. Section 5 examines the determinants of analyst forecast dispersion. In Section 6, the relationship between the predicted and residual portions of analyst forecast dispersion and stock returns is reported. Section 7 discusses the possible interpretations of our results, while Section 8 concludes.

2. Related Literature

2.1. Overconfidence and Self-Biased Attribution

Perhaps the most robust finding in the psychology of judgment is that people are overconfident (Debondt and Thaler, 1995). In particular, calibration studies examining subjective probabilities find that people tend to overestimate the precision of their knowledge, especially for difficult tasks, for forecasts with low predictability, and for undertakings lacking timely and clear feedback (Alpert and Raiffa, 1982; Fischhoff, Slovic, and Lichtenstein, 1977). Furthermore, it has been shown that traders in experimental markets do not place enough weight on the information and actions of others (Bloomfield, Libby, and Nelson, 1999).

Past research on analyst behavior suggests that analysts are not immune to this bias. Chen and Jiang (2006) use linear regression and probability-based methods to find that on average, analysts overweight their private information when they forecast corporate earnings. This evidence is consistent with the Daniel, Hirshleifer, and Subrahmanyam (1998) definition of overconfidence. Friesen and Weller (2006) develop a model of analyst earnings forecasts that discriminates between rational behavior and that induced by cognitive biases. The authors find strong empirical evidence that analysts are overconfident about the precision of their own information. Montgomery and Bradlow (1999) develop a theoretical explanation of why analyst overconfidence about the functional form of demand models can lead to overpricing. In their setup, the analyst's overconfidence can stem from their ignorance of model misspecification, structural changes in the marketplace, or omitted variables.

The analyst overconfidence we have in mind in this paper is derived from an attribution bias. According to the self-attribution theory, individuals too strongly attribute events that confirm the validity of their own actions to their ability while attributing events that disconfirm their actions to external noise (Bem, 1965; Hastorf, Schneider and Polefka, 1970). The empirical evidence appears to support the existence of this bias (e.g. Langer and Ross, 1975; Miller and Ross, 1975). Furthermore, Miller (1976) finds that tendencies toward self-attribution are stronger when the task is important for the subject. Daniel et al. (1998) and Gervais and Odean (2001) assume the dynamic complement of overconfidence, biased self-attribution, in their models. An investor's confidence in her precision rises too much when she receives confirming news, and declines too little when there is disconfirming news. Hilary and Menzly (2006) find that analysts in particular are more overconfident in their ability to forecast future earnings after making a short series of accurate predictions. This overconfidence is specific to a firm at a point in time.

We take the Hilary and Menzly (2006) result a step further by showing that attribution-induced overconfidence exists at the analyst level. In other words, analysts are not only overconfident about specific firms, but can also be overconfident about the entire portfolio of firms they cover. Our analyst-specific overconfidence is therefore a bias that is directly attributable to an individual.

2.2. Analyst Forecast Dispersion

Recent research has begun to shed light on the negative cross-sectional relationship between analyst forecast dispersion and future stock returns. Diether et al.

(2002) is the first paper to empirically test this relationship. Employing dispersion in analysts' earnings forecasts as a proxy for divergence of opinion, the authors find that stocks with higher dispersion in analysts' earnings forecasts earn significantly lower future returns than otherwise similar stocks, consistent with the Miller (1977) framework. The divergence of opinion theory first proposed by Miller (1977) and further formalized by Harrison and Kreps (1978) and Morris (1996), posits that the prices for risky securities reflect the most optimistic valuations if pessimistic investors are kept off the market due to short-sales constraints. Optimistic investors (who hold the stock) suffer losses in expectation as short-sales constraints or limits to arbitrage (Shleifer and Vishny, 1997) are relaxed over time. The empirical prediction from these studies is a negative cross-sectional relationship between heterogeneous beliefs (i.e. divergence of opinion) and future stock returns.

Several empirical studies have since shed further light on this seemingly anomalous negative dispersion-return relationship. For example, Johnson (2004) reconciles the negative relationship between the dispersion in analysts' earnings forecasts and stock returns by arguing that dispersion is a proxy for unpriced information risk, which arises when asset values are unobservable. Therefore expected returns should always decrease (for a levered firm) with the level of idiosyncratic risk, since adding idiosyncratic uncertainty about cash flows increases the option value of equity. Sadka and Scherbina (2007) draw a link between dispersion and liquidity and show that high disagreement coincides with high transaction costs. The authors find that the returns of high-disagreement stocks are negatively related to changes in liquidity, and as a result, the differential sensitivity to changes in liquidity explain a significant portion of the cross-sectional variation in the returns of portfolios sorted by analyst disagreement.

More recently, Avramov et al. (2009) show that the negative dispersion-return relationship is explained by financial distress, as proxied by credit rating downgrades. In particular, strategies that buy low dispersion stocks and sell high dispersion stocks yield a statistically insignificant payoff of 31 basis points per month for investment grade firms. In contrast, dispersion strategies are significantly profitable across non-investment grade firms; for such firms, the return differential between the lowest and highest dispersion stocks is a highly significant 101 basis points per month. Controlling for the findings in Johnson (2004) and Sadka and Scherbina (2007), Avramov et al. (2009) find that the dispersion effect is indistinguishable across levered and unlevered firms, and liquidity proxies do not capture the dispersion effect either.

We control for all of the explanations above and find that the firm's analyst overconfidence mean and analyst overconfidence dispersion are the two most significant determinants of analyst forecast dispersion. Together, these two variables capture 77% of the explained variation in analyst forecast dispersion when all known determinants are considered. Furthermore, we find that analyst overconfidence captures a facet of analyst disagreement that is more sensitive to stock returns than analyst forecast dispersion is by itself.

3. Overconfidence Measures and Data

3.1. Overconfidence Measures

In order to examine the impact of analyst overconfidence on analyst forecast dispersion at the firm level, we must first define a measure of overconfidence at the analyst level. We begin with the Hilary and Menzly (2006) definition of a successful forecast: an analyst's forecast error is less than the median forecast error for the same firm in the same quarter. Otherwise, this forecast is deemed to be unsuccessful. The forecast error is the difference between the EPS forecast and the realized value. Our measure of an analyst's overconfidence is the proportion of her successes relative to the number of trials over the past four quarters, which we name *Success*. We require that the analyst have at least 4 trials, although our results are similar if 2 or 8 trials are required. In order to calculate the median forecast error, we further require that at least 3 analysts provide a forecast for a firm in a given quarter. Our results are similar if we require a minimum of 2 or 4 analysts. Unlike Hilary and Menzly (2006), we consider all of the analyst's forecasts for every firm she covers in the past year, not just the forecasts for a specific firm. Our analyst-quarter measure has two benefits. First, it is consistent with overconfidence being a behavioral trait attributable to an individual, and not firm specific. Second, it allows us to aggregate analyst *Success* at the firm level in order to assess its impact on analyst forecast dispersion.

To aggregate analyst overconfidence at the firm level, we first use all CRSP firm-month returns, and then find all of the analysts providing a forecast for these firms in the 3 months prior. Our results remain similar if we restrict the sample to analyst coverage within the 2 or 6 months prior. We then associate the most recent analyst-quarter *Success* to these firms and aggregate it in two ways. First, we average the firm's analyst *Success* to capture the level of analyst overconfidence, which we denote as *Success Mean*.

Second, we take the standard deviation of the firm's analyst *Success* and scale it by the stock price in the prior month to capture the dispersion in analyst overconfidence, which we denote as *Success Dispersion*.

3.2. Data

Our analyst-level sample is composed of all quarterly analyst EPS forecasts from the I/B/E/S unadjusted detail dataset. We only retain the first forecasts made prior to the fiscal quarter end and quarters ending in March, June, September and December. These restrictions allow us to avoid issues relating to earnings management and to create balanced portfolios, respectively. However, removing these restrictions does not change the results qualitatively. We merge in realized quarterly EPS from the I/B/E/S actuals dataset to calculate the forecast error. We also merge in prices at the end of the prior quarter from CRSP in order to scale the forecast errors. Given the restrictions for calculating *Success* described above, our final analyst-level dataset has 144,196 observations from 1984 to 2012, which represent analyst-quarter forecasts.

Our firm-level sample is composed of all CRSP monthly returns.[1] We only retain the firms covered by analysts for which *Success* is defined. We merge in data from CRSP on price, shares outstanding and volume in the month prior to returns. We also merge in data from the I/B/E/S unadjusted summary dataset on the standard deviation of annual EPS forecasts. Finally, we merge in data from Compustat on credit rating, long-term debt, book value of equity, and institutional ownership. Given the restrictions for calculating *Success* described above, our final firm-level dataset has 492,666 observations from 1985 to 2012, which represent firm-month returns. We start this

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[1] We truncate returns outside the 1st and 99th percentiles in order to minimize the effect of outliers as in Avramov et al. (2009). However, our results are qualitatively similar when returns are not truncated.

sample one year later than the analyst-level sample because *Success* is defined over the prior 4 quarters.

4. Analyst-Level Success

In this section we show that attribution-induced overconfidence exists at the analyst level such that analysts are not only overconfident about specific firms as in Hilary and Menzly (2006), but can also be overconfident about the entire portfolio of firms they cover.

4.1. Summary Statistics

In Table 1 we first present analyst-level performance summary statistics and correlations for our sample. Panel A presents the summary statistics and Panel B presents a correlation matrix for our variables of interest. The Panel A summary statistics show that *Success* at time *t* has a mean of 0.34 and a median of 0.33, indicating that on average, a third of analyst forecasts are successful. To demonstrate that analysts are overconfident, we examine an analyst's performance in the subsequent period by measuring *Success* at time *t+1* and *Error/Price* at time *t+1*, where time *t+1* is the subsequent quarter, *Error* is the absolute value of the difference between actual and forecasted quarterly earnings, and *Price* is the firm's share price at the end of the prior quarter. In addition to the level of success and forecast error in the subsequent quarter, we also examine the percentage change in success ($\Delta Success_{t,t+1}$) and the percentage change in forecast error ($\Delta Error/Price_{t,t+1}$). We find $Success_{t+1}$ to have a mean of 0.34 and a median of 0.33, and $\Delta Success_{t,t+1}$ to have a mean of 12.29% and a median of −4.17%, and exhibiting considerable variability with a standard deviation of 106.92%. Moreover, $Error/Price_{t+1}$

has a mean of 0.75 and a median of 0.30, which is slightly higher than the firm-specific analyst error-to-price ratio in Hilary and Menzly (2006), while $\Delta Error/Price_{t,t+1}$ has a mean of 44.48% and a median of −14.05%, exhibiting considerable variability with a standard deviation of 416.14%. We note that while Hilary and Menzly (2006) also examine subsequent forecast error, they do not examine subsequent success or the percentage change in analyst performance, which are novel elements to this study.[2] Examining the percentage change in performance is important on two dimensions. First, it captures the rate of change, which can be notably different for successful analysts versus unsuccessful analysts even while the level of performance is unchanged. Second, it controls for analyst-specific characteristics – such as analyst ability or skill – that could alternatively explain analyst performance and hence the overconfidence we document.

In Panel B we present Pearson correlation coefficients between the variables in Panel A. Interestingly, we find the correlation between $Success_t$ and $Success_{t+1}$ to be a positive 0.15, suggesting that successful analysts are more successful in the subsequent quarter. However, we also find that the correlation between $Success_t$ and $\Delta Success_{t,t+1}$ is a strongly negative −0.35. The contrasting results between the level of *Success* and the percentage change in *Success* implies that successful analysts tend to still be more successful than unsuccessful analysts in the subsequent quarter, but the rate of *Success* for successful analysts decreases by substantially more than for unsuccessful analysts. This finding further highlights the importance of examining the percentage change in performance versus the level of performance. We also find that the correlation between $Success_t$ and $Error/Price_{t+1}$ is a positive 0.04, which implies that an analyst's accuracy

[2] Hilary and Menzly (2006) also examine the deviation from the consensus as an alternative ex-post measure, which they interpret as a proxy for the likelihood of an analyst to discount public information.

decreases subsequent to a successful year of forecasting. This is further supported by the positive 0.02 correlation we find between $Success_t$ and $\Delta Error/Price_{t,t+1}$. We note that the Pearson correlations in Panel B are all statistically significant at the 1% level of significance and that eliminating outliers does not qualitatively affect our results.

In Figure 1, we also present an analyst-level frequency distribution of our *Success* measure. We find *Success* to be fairly normally distributed, with spikes at specific integer values, which is consistent with the fractional nature of our measure.

4.2. Analyst Performance

In Table 2, we provide further support for attribution-induced analyst overconfidence by sorting the sample into *Success* quintiles quarterly and examining the mean analyst performance by *Success* portfolios. Not surprisingly and by construction, we find that mean $Success_t$ is monotonically increasing by *Success* quintile, and the high minus low mean $Success_t$ difference is 0.39 and highly statistically significant. We further find that $Success_{t+1}$ is monotonically increasing by *Success* quintile, and the high minus low mean $Success_{t+1}$ difference of 0.09 is statistically significant at the 1% level of significance. Thus, similar to the correlation matrix in Panel B of Table 1, there is a positive relation between $Success_t$ and $Success_{t+1}$. While this result might seem to contradict the notion of analyst overconfidence, we again note that the level of performance fails to capture the rate of change in performance, or control for analyst-specific characteristics. Hence, turning to the percentage change in *Success*, we indeed find that mean $\Delta Success_{t,t+1}$ is monotonically decreasing by *Success* quintile, and the high minus low $\Delta Success_{t,t+1}$ difference is −115.20% and highly statistically significant. As before, the positive $Success_t$-$Success_{t+1}$ relation and negative $Succes_{t+1}$-$\Delta Success_{t,t+1}$

suggests that while successful analysts remain successful in the subsequent quarter, their rate of success declines by substantially more than for unsuccessful analysts. The results for *Error/Price*$_{t+1}$ and *ΔError/Price*$_{t,t+1}$ also support the analyst overconfidence hypothesis. In particular, we find that mean *Error/Price*$_{t+1}$ is monotonically increasing by *Success* quintile, and the high minus low mean *Error/Price*$_{t+1}$ is 0.31 and highly statistically significant. Similarly, *ΔError/Price*$_{t,t+1}$ is monotonically increasing by *Success* quintile, and the mean high minus low *ΔError/Price*$_{t,t+1}$ difference of 23.56% is also highly statistically significant.

To summarize, the analyst-level correlations in Table 1 and the portfolio results in Table 2 support the idea that analysts become overconfident in their ability to predict future earnings after a series of successful predictions. More specifically, we show that analysts in the top quintile of forecast success over the past year are 26.7% less successful and 60.6% less accurate in the subsequent quarter. These results are consistent with overconfidence induced by self-attribution bias.

5. Firm-Level Success Mean and Success Dispersion

In this section, we turn to a firm-level analysis of analyst overconfidence. We examine the relationship between analyst *Success* and *Forecast Dispersion* at the firm level in order to determine whether analyst overconfidence can explain analyst disagreement.

5.1. Summary Statistics

In Table 3, we present firm-level summary statistics for the variables used throughout the remainder of the paper. Our two firm-level overconfidence measures are

Success Mean, defined as the mean of a firm's analyst *Success*, and *Success Dispersion*, defined as the standard deviation of a firm's analyst *Success*, scaled by the firm's stock price, where *Success* is as defined in the analyst-level analysis in the previous section. We find *Success Mean* to have a mean of 0.34 and a median of 0.35, indicating that on average, a firm's analyst success is about one-third. Meanwhile, *Success Dispersion* has a mean of 0.56% and a median of 0.52%. We define *Forecast Dispersion* as the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. *Forecast Dispersion* has a mean of 0.55% and a median of 0.23%, and exhibits considerable variability, with a standard deviation of 1.51%. We also include several known determinants of *Forecast Dispersion* and returns in the paper, including: (1) *Market Cap*, defined as the number of shares outstanding multiplied by the price, in millions of dollars; (2) *Book-to-Market*, defined as the book value of common equity divided by the market capitalization; (3) *Momentum*, defined as the firm's buy-and-hold return over the prior 6 months; (4) *Illiquidity*, defined as the absolute value of the stock return scaled by the product of volume and price; (5) *Leverage*, defined as the long-term debt scaled by the sum of long-term debt and market capitalization; (6) *Residual Volatility*, defined as the root mean squared error from regressing daily stock returns on daily Fama-French-Carhart factors in the prior month; (7) *Institutional Ownership*, defined as institutional share holdings scaled by shares outstanding; and (8) *Rated*, which is a dummy variable equal to 1 if the firm has an S&P credit rating, and 0 otherwise. The Table 3 summary statistics for these controls are consistent with prior studies.

In Figure 2, we present distributions for the main variables of interest: *Success Mean*, *Ln(Success Dispersion)*, and *Ln(Forecast Dispersion)*. The distributions for the natural logarithm of *Success Dispersion* and *Forecast Dispersion* are shown to remain consistent with the regression analysis below, and to dampen the effects of large outliers. Also, the natural logarithms of the numbers rather than the percentages are presented. The Figure 2 distributions show that *Success Mean* and *Ln(Forecast Dispersion)* are quite normally distributed around their means, while *Ln(Success Dispersion)* has a somewhat negatively skewed distribution.

5.2. Earnings Forecast Dispersion

As noted, we are interested in determining whether analyst overconfidence can explain analyst disagreement. Therefore, in this subsection, we examine the relationship between our firm-level analyst overconfidence measures, *Success Mean* and *Success Dispersion*, and *Forecast Dispersion*. In Table 4, we form portfolios of *Success Mean* and *Success Dispersion* by sorting the sample monthly, and presenting the mean *Forecast Dispersion* by *Success Mean* and *Success Dispersion* quintiles, respectively. Focusing on *Success Mean*, we find that the mean *Forecast Dispersion* is monotonically increasing in *Success Mean* portfolios, and the high minus low *Success Mean* difference is 0.51% and highly statistically significant at the 1% level of significance. This indicates that a high level of overconfidence among a firm's analysts, as measured by analyst *Success Mean*, is strongly associated with greater analyst forecast dispersion. Turning to the *Success Dispersion* portfolios, we also find that mean *Forecast Dispersion* is monotonically increasing by *Success Dispersion* portfolios, and the high minus low *Success Dispersion* difference of 0.83% is highly statistically significant at the 1% level of significance. The significantly positive *Forecast Dispersion*-*Success Dispersion* relationship indicates that a larger gap between overconfident and non-overconfident analysts is also strongly associated with greater analyst forecast dispersion.

In Table 5, we report multivariate OLS regressions to better determine the explanatory power of *Success Mean* and *Success Dispersion* on *Forecast Dispersion*. We report t-statistics that are two-way clustered by firm and year in all specifications. In Model 1, we regress *Ln(Forecast Dispersion)* on *Success Mean* only, and find that the coefficient is positive and highly statistically significant at the 1% level, indicating that high average analyst overconfidence in a firm is a strong determinant of analyst forecast dispersion. Moreover, the model has respectable explanatory power, with an adjusted R^2 of 9.20%. In Model 2, we regress *Ln(Forecast Dispersion)* on *Ln(Success Dispersion)* only, and also find a positive and highly statistically significant coefficient at the 1% level of significance. This indicates that a firm's analyst overconfidence dispersion is also a strong determinant of analyst earnings forecast dispersion. Moreover, the adjusted R^2 of 13.29% in Model 2 shows that *Ln(Success Dispersion)* provides relatively more explanatory power than *Success Mean* on its own. In Model 3, we include both *Success Mean* and *Ln(Success Dispersion)*, and once again find positive and highly statistically significant coefficients on each explanatory variable. In addition, including both variables provides remarkably strong explanatory power, with an adjusted R^2 of 23.47%, which implies that high average analyst overconfidence and high dispersion in analyst overconfidence in a firm are both independently important determinants of analyst forecast dispersion. To put the explanatory power of Model 3 in context, in Model 4 we regress *Ln(Forecast Dispersion)* on several firm characteristics that are known determinants of analyst forecast dispersion in the literature, but exclude *Success Mean* and *Ln(Success Dispersion)*. We find significance among several of the variables, consistent with prior studies, but remarkably, we find an adjusted R^2 of 16.72%, which is about 7 percentage points *lower* than the adjusted R^2 in Model 3, which only includes *Success Mean* and *Success Dispersion*. This indicates that analyst overconfidence is a much stronger determinant of analyst disagreement than prior known firm-level determinants of analyst disagreement. Finally, in Model 5 we present a complete model that includes *Success Mean* and *Ln(Success Dispersion)* and the control variables from Model 4. We find that while several of the control variables are statistically significant, they do not explain away *Success Mean* or *Success Dispersion*. Furthermore, the inclusion of these other known determinants of analyst forecast dispersion only explains an additional 7.1% of the variation in analyst forecast dispersion.

In sum, the Table 4 and Table 5 results show a strong positive relationship between analyst overconfidence and analyst forecast dispersion. In particular, the univariate portfolio results indicate that the top analyst overconfidence mean quintile has 135% more analyst forecast dispersion than the bottom analyst overconfidence mean quintile, and the top analyst overconfidence dispersion quintile has 300% more analyst forecast dispersion than the bottom analyst overconfidence dispersion quintile. Furthermore, the regression analysis shows that almost a quarter of analyst forecast dispersion is explained by analyst overconfidence mean and analyst overconfidence dispersion, and including other known determinants of analyst forecast dispersion does not markedly improve explanatory power.

In the appendix (Table A1), we also report quarterly and long-term growth forecast dispersion multivariate regressions, and show that the positive analyst overconfidence-analyst forecast dispersion relationship we document above is not specific to annual earnings forecasts. We find that *Success Mean* and *Ln(Success Dispersion)* explain 25.96% of the variation in quarterly forecast dispersion and 34.14% of the variation in long-term growth forecast dispersion. This generalizes our results and provides further evidence that analyst overconfidence is an important determinant of analyst forecast dispersion.

6. Stock Returns

The literature documents a strong negative relationship between analyst forecast dispersion and future stock returns, and our evidence in the prior section shows that analyst overconfidence is a strong determinant of analyst forecast dispersion. Therefore, in this section we examine whether a portion of the dispersion-return relationship is driven by analyst overconfidence.

Specifically, we examine the relationship between analyst forecast dispersion predicted by analyst overconfidence (*Predicted Forecast Dispersion*) and stock returns as well as the relationship between analyst forecast dispersion not predicted by analyst overconfidence (*Residual Forecast Dispersion*) and stock returns. We compute *Predicted Forecast Dispersion* and *Residual Forecast Dispersion* from Model 3 of Table 5, in which the natural logarithm of *Forecast Dispersion* is regressed on *Success Mean* and the natural logarithm of *Success Dispersion*. However, instead of a pooled regression, we run monthly regressions in order to avoid incorporating a look-ahead bias in our *Predicted Forecast Dispersion* and *Residual Forecast Dispersion* measures. Thus, *Predicted Forecast Dispersion* captures the portion of *Forecast Dispersion* that is related to analyst overconfidence, and the *Residual Forecast Dispersion* captures the portion of *Forecast Dispersion* that is unrelated to analyst overconfidence.

6.1. Portfolio Returns

In Table 6, we report the mean one-month returns for portfolios that are formed by sorting the sample monthly into *Forecast Dispersion*, *Predicted Forecast Dispersion* and *Residual Forecast Dispersion* quintiles, respectively. Focusing first on the *Forecast Dispersion* portfolios, we find that the mean portfolio return is monotonically decreasing by *Forecast Dispersion* quintile. In addition, the high minus low *Forecast Dispersion* return difference is −0.48% monthly, or −5.76% annually (−0.48% × 12), and statistically significant at the 1% level of significance. This negative relationship between *Forecast Dispersion* and future returns is consistent with the prior literature (e.g. Diether et al., 2002; Avramov et al., 2009). Turning to the *Predicted Forecast Dispersion* portfolios, we also find that the mean return is monotonically decreasing in the *Predicted Forecast Dispersion* quintiles. Moreover, firms in the top *Predicted Forecast Dispersion* quintile underperform firms in the bottom *Predicted Forecast Dispersion* quintile by a highly statistically significant 0.35% monthly (4.20% annually), indicating that analyst forecast dispersion predicted by analyst overconfidence leads to a respectable monthly hedging portfolio profit. Lastly, in Table 6 we examine *Residual Forecast Dispersion* portfolios and also find that the mean portfolio return is decreasing by *Residual Forecast Dispersion* quintile, and the high minus low *Residual Forecast Dispersion* return difference is −0.37% monthly (−4.44% annually) and statistically significant at the 1% level of significance.

Overall, the Table 6 results are quite telling. The results reveal that analyst forecast dispersion predicted by analyst overconfidence leads to a monthly hedging portfolio profit of 0.35%, compared to a profit of 0.37% for the analyst forecast dispersion not predicted by analyst overconfidence. Thus, about one-half of the dispersion-return relationship is explained by analyst overconfidence. In addition, the predicted and residual portions of analyst forecast dispersion have greater explanatory power than analyst forecast dispersion does by itself, suggesting that analyst overconfidence captures a facet of analyst forecast dispersion that is more sensitive to stock returns. The Table 6 results do not control for other potentially important determinants of returns, and so we turn to tests that control for other factors in the following subsections.

6.2. Calendar-Time Factor-Adjusted Return Regressions

In Table 7, we report the coefficients from regressions of monthly portfolio returns on Fama and French (1993) three-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Panels A, B and C report the portfolio regression results for *Forecast Dispersion*, *Predicted Forecast Dispersion* and *Residual Forecast Dispersion*, respectively.

Focusing on the Panel A *Forecast Dispersion* results, we find a general decrease in the intercept across the five portfolios, Q1 to Q5, but the intercepts are only statistically significant in the first, fourth and fifth quintiles. To gauge the magnitude of the differential performance, we also examine the return performance of a hedge portfolio that consists of buying the high *Forecast Dispersion* portfolio and shorting the low *Forecast Dispersion* portfolio. As the tabulated results in Panel A of Table 7 indicate, the estimated excess return from such a portfolio in a five-factor model is −0.54% per month, or −6.48% annually (−0.54% × 12), and statistically significant at the 1% level of significance. We note that while the zero-investment hedge portfolio's loadings are statistically significant on each of the factors, they do not subsume the significance of the intercept. In Panel B we report the results for *Predicted Forecast Dispersion*, and again find a general decrease in the intercept across the five portfolios, but the intercepts are only statistically significant in the first and fifth quintiles. We are particularly interested in the zero-investment hedge portfolio that buys the high *Predicted Forecast Dispersion* portfolio and shorts the low *Predicted Forecast Dispersion* portfolio. As the results in Panel B indicate, the estimated intercept from this strategy translates into a return of −0.30% per month (−3.60% annually) that is statistically significant at the 5% level of significance. This result is telling, and implies that the portion of analyst forecast dispersion that is related to analyst overconfidence yields a significant return difference between the top *Predicted Forecast Dispersion* quintile and low *Predicted Forecast Dispersion* quintile. Moreover, while the loadings on each of the factors are statistically significant, with the exception of the liquidity factor, they do not explain away the significance of the intercept. Lastly, in Panel C we present the factor-adjusted regression results for *Residual Forecast Dispersion*, and similar to Panels A and B, we find a generally monotonically decreasing intercept across the five quintiles, but the intercepts are only statistically significant in the first, fourth and fifth quintiles. As before, we are interested in the zero-investment hedge portfolio that buys the high *Residual Forecast Dispersion* portfolio and shorts the low *Residual Forecast Dispersion* portfolio. The results in Panel C indicate that this strategy yields a −0.46% monthly return (−5.52%

annually) that is statistically significant at the 1% level of significance, even while each of the factor loadings are statistically significant. This suggests that the portion of analyst forecast dispersion that is unrelated to analyst overconfidence also provides a significant return difference between the top *Residual Forecast Dispersion* quintile and the low *Residual Forecast Dispersion* quintile.

6.3. Fama-MacBeth Return Regressions

In Table 8, we report the results from monthly cross-sectional Fama and MacBeth (1973) regressions of one-month returns on *Forecast Dispersion*, *Predicted Forecast Dispersion*, *Residual Forecast Dispersion* and other control variables. We include the standard controls that have been shown to impact the cross-section of returns, such as *Market Cap*, *Book-to-Market* and *Momentum*. In addition, we include *Illiquidity*, *Leverage*, *Residual Volatility*, *Institutional Ownership*, and a dummy variable for firms that have an S&P credit rating (*Rated*). Each of these variables has been shown to be an important determinant of the forecast dispersion-return relationship (see Diether et al., 2002; Johnson, 2004; Sadka and Scherbina, 2007; Avramov et al., 2009).

In Model 1 of Table 8, we first show that the negative forecast dispersion-return relationship holds for our sample. We regress one-month returns on the natural logarithm of *Forecast Dispersion* and our control variables, but exclude *Predicted Forecast Dispersion* and *Residual Forecast Dispersion*. We find the coefficient on *Ln(Forecast Dispersion)* to be a negative −0.17 and statistically significant at the 1% level of significance, confirming the negative forecast dispersion-return relationship found in prior studies. We also find several of the other firm characteristics to explain returns. In particular, *Ln(Market Cap)* is negative and statistically significant, *Book-to-Market* is positive and statistically significant, *Ln(Illiquidity)* is negative and statistically significant, and *Residual Volatility* is negative and statistically significant. In Model 2, we regress returns on *Predicted Forecast Dispersion* and *Residual Forecast Dispersion*, which are the portions of *Forecast Dispersion* that are related to and unrelated to analyst overconfidence, respectively. We again include the firm characteristics from Model 1, but exclude *Ln(Forecast Dispersion)*. The results show that the coefficient on *Predicted Forecast Dispersion* is a negative −0.24 and highly statistically significant at the 1% level of significance. In addition, the coefficient on *Residual Forecast Dispersion* is a negative −0.16 and also statistically significant at the 1% level of significance. Importantly, while we find the coefficients and statistical significance on the other control variables to be similar to Model 1, they do not explain away the relationship between *Predicted Forecast Dispersion* and future returns or the relationship between *Residual Forecast Dispersion* and future returns.

Overall, the Table 8 regression results support the baseline Table 6 univariate portfolio results after controlling for other important determinants of returns. The results therefore provide robust evidence that analyst overconfidence captures a facet of analyst forecast dispersion that is sensitive to stock returns.

7. Discussion

Our results show that analyst overconfidence is associated with higher analyst forecast dispersion and lower future stock market returns. As such, our results are consistent with the divergence of opinion theory first proposed by Miller (1977), and shown empirically by Diether et al. (2002) more recently. In our setting this means that analyst overconfidence increases differences in opinion. In the presence of short sales constraints or limits to arbitrage, the most optimistic valuations are impounded in market prices but the most pessimistic valuations are not. This leads to overvaluation followed by a correction as the true value of the firm is discovered.

However, the new findings we present leave open other possible explanations as well. Given that investors rely on analyst forecasts in their decision to buy and sell stocks[3], an alternative explanation is that investors overreact to recently successful, and therefore overconfident analysts. This overreaction explanation is in the spirit of DeBondt and Thaler (1985), who document investor overreaction among winner and loser portfolios. Furthermore, Debondt and Thaler (1990) find that the actual expectations of professional security analysts and economic forecasters display the same overreaction bias, and since analysts issue positively biased forecasts on average (Abarbanell, 1991), investor overreaction to these forecasts would lead to negative returns on average.

Yet another possible explanation is that analyst overconfidence is associated with higher information risk. The risk investors face is being unable to detect overconfident analysts, and therefore being unable to ascertain whether or not the information the analyst is providing is overweighting the analyst's private information. The investor would require a higher expected return in order to be compensated for this increased risk, which would lead to a decrease in stock prices. Empirically, higher information risk would be associated with higher expected returns, but lower realized returns. In an efficient market, the lower realized returns would occur almost immediately and not in the following month. However, if investors misunderstand this risk or if investor learning

[3] Beyer, Cohen, Lys, and Walther (2010) find that 22% of quarterly abnormal stock returns are explained by the abnormal returns surrounding analyst forecasts, suggesting that investors do indeed rely heavily on analyst forecasts to make their investment decisions.

is delayed, lower realized returns may occur later. We note that while we control for the information risk described in Johnson (2004) by including idiosyncratic volatility and leverage as control variables, it is possible that the analyst overconfidence we document is associated with information risk that is not captured by these two measures.

8. Conclusions

In this paper, we test and confirm that analysts disagree in their earnings forecasts due to overconfidence. We first develop a measure of analyst overconfidence that is based on biased self-attribution in the spirit of Hilary and Menzly (2006), whereby analysts become overconfident after a short series of successes. Consistent with overconfidence, our results show that analyst success and accuracy both decrease subsequent to a successful year of forecasting. Next, we show that a firm's analyst overconfidence mean and analyst overconfidence dispersion are the two strongest determinants of analyst forecast dispersion, explaining about one-quarter of the variation in dispersion. Finally, we show that analyst overconfidence explains about one-half of the negative analyst forecast dispersion-return relationship, and furthermore that analyst overconfidence captures a facet of analyst forecast dispersion that is more sensitive to stock returns.

Overall, the evidence in this paper strongly supports the notions that analyst forecast dispersion and stock returns are largely explained by analyst overconfidence. However, our tests are joint tests of overconfidence and the correctness of the models we are using. Therefore, it is always possible that our results are due to model misspecification. We mitigate this concern by using multiple specifications and methodologies in testing our analyst overconfidence hypothesis and the relationship between analyst overconfidence and stock-market performance.

References

Abarbanell, J. S., 1991, Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes?, *Journal of Accounting and Economics* 14, 147–165.

Alpert, M., and H. Raiffa, 1982, A Progress Report on the Training of Probability Assessors, in D. Kahneman, P. Slavic, L. A. Tversky (Eds.), Judgment under Uncertainty: Heuristics and Biases, 294–305, Cambridge, England: Cambridge University Press.

Bem, D. J., 1965, An Experimental Analysis of Self-Persuasion, *Journal of Experimental SocialPsychology* 1, 199–218.

Beyer, A., D. A. Cohen, T. Z. Lys, and B. R. Walther, 2010, The Financial Reporting Environment: Review of the Recent Literature, *Journal of Accounting and Economics* 50, 296–343.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov, 2009, Dispersion in Analysts' Earnings Forecasts and Credit Rating, *Journal of Financial Economics* 91, 83–101.

Bloomfield, R., R. Libby, and M. W. Nelson, 1999, Confidence and the Welfare of Less-Informed Investors, *Accounting, Organizations and Society* 24, 623–647.

Carhart, M. M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57–82.

Chen, Q., and W. Jiang, 2006, Analysts' Weighting of Private and Public Information, *Review of Financial Studies* 19, 319–355.

Daniel, K. D., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *Journal of Finance* 53, 1839–1886.

DeBondt, W., and R. Thaler, 1985, Does the Stock Market Overreact?, *Journal of Finance* 40, 793–805.

DeBondt, W., and R. Thaler, 1990, Do Security Analysts Overreact?, *American Economic Review* 80, 52–57.

DeBondt, W.F., and R. Thaler, 1995, Financial Decision-making in Markets and Firms: A Behavioral Perspective, *Handbooks in OR & MS* 9, 385–410.

Diether, K. B., C. J. Malloy, and A. Scherbina, 2002, Differences of Opinion and the Cross Section of Stock Returns, *Journal of Finance* 57, 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, 3–56.

Fama, E. F., and J. D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607–636.

Fischhoff, B., P. Slovic, and S. Lichtenstein, 1977, Knowing with Certainty: The Appropriateness of Extreme Confidence, *Journal of Experimental Psychology: Human Perception and Performance* 3, 552–564

Friesen, G., and P. A. Weller, 2006, Quantifying Cognitive Biases in Analyst Earnings Forecasts, *Journal of Financial Markets* 9, 333–365.

Gervais, S., and T. Odean, 2001, Learning to be Overconfident*, Review of Financial Studies* 14, 1–27.

Harrison, M. J., and D. M. Kreps, 1978, Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations, *Quarterly Journal of Economics* 92, 323–336.

Hastorf, A., D. Schneider, and J. Polefka, 1970, Person Perception, Addison-Wesley, Reading, PA.

Hilary, G., and L. Menzly, 2006, Does Past Success Lead Analysts to Become Overconfident?, *Management Science* 52, 489–500.

Hirshleifer, D., 2001, Investor Psychology and Asset Pricing, *Journal of Finance* 56, 1533–1597.

Johnson, T. C., 2004, Forecast Dispersion and the Cross Section of Expected Returns, *Journal of Finance* 59, 1957–1978.

Langer, E. J.. and J. Roth, 1975*,* Heads I Win Tails It's Chance: The Illusion of Control as a Function of the Sequence of Outcomes in a Purely Chance Task, *Journal of Personality and Social Psychology* 32, 951–955.

Miller, D. T., 1976, Ego Involvement and Attributions for Success and Failures, *Journal of Personality and Social Psychology* 34, 901–906.

Miller, D. T., and M. Ross, 1975, Self-Serving Bias in Attribution of Causality: Fact or Fiction?, *Psychological Bulletin* 82, 213–225.

Miller, E. M., 1977, Risk, Uncertainty, and Divergence of Opinion, *Journal of Finance* 32, 1151–1168.

Montgomery, A. L., and E. T. Bradlow, 1999, Why Analyst Overconfidence about the Functional Form of Demand Can Lead to Overpricing, *Marketing Science* 18, 569–583.

Morris, S., 1996, Speculative Investor Behavior and Learning, *The Quarterly Journal of Economics* 111, 1111–1133.

Pastor, L., and R. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642–685.

Sadka, R., and A. Scherbina, 2007, Analyst Disagreement, Mispricing, and Liquidity, *Journal of Finance* 62, 2367–2403.

Shleifer, A., and R. W. Vishny, 1997, The Limits of Arbitrage, *Journal of Finance* 52, 35–55.

Table 1: Analyst-Level Performance Summary Statistics and Correlations

Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. Error is the absolute value of the difference between actual and forecasted quarterly earnings. Price is the firm's share price at the end of the prior quarter. The Pearson correlations in Panel B are all statistically significant at the 1% level of significance.

	$Success_t$	$Success_{t+1}$	$\Delta Success_{t,t+1}$	$Error/Price_{t+1}$	$\Delta Error/Price_{t,t+1}$
Panel A: Analyst-Level Summary Statistics					
Mean	0.34	0.34	12.29	0.75	44.48
Std Dev	0.14	0.25	106.92	3.90	416.14
Median	0.33	0.33	−4.17	0.30	−14.05
Min	0.00	0.00	−100.00	0.00	−100.00
Max	1.00	1.00	2,700.00	390.15	44,324.02
N	144,196	144,196	140,863	144,195	144,191
Panel B: Correlations					
$Success_t$	1.00				
$Success_{t+1}$	0.15	1.00			
$\Delta Success_{t,t+1}$	−0.35	0.71	1.00		
$Error/Price_{t+1}$	0.04	0.01	−0.01	1.00	
$\Delta Error/Price_{t,t+1}$	0.02	−0.03	−0.03	0.61	1.00

Table 2: Analyst-Level Performance by Success Portfolios

Portfolios are formed by sorting the sample into Success quintiles quarterly. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. Error is the absolute value of the difference between actual and forecasted quarterly earnings. Price is the firm's share price at the end of the prior quarter. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% two-tailed level, respectively.

	$Success_t$	$Success_{t+1}$	$Error/Price_{t+1}$	$\Delta Success_{t,t+1}$	$\Delta Error/Price_{t,t+1}$
Q1	0.15	0.30	0.57	88.43	37.03
Q2	0.27	0.32	0.67	21.07	41.10
Q3	0.34	0.34	0.77	2.39	39.07
Q4	0.40	0.36	0.85	−10.53	43.84
Q5	0.54	0.39	0.87	−26.74	60.59
Q5−Q1	0.39***	0.09***	0.31***	−115.20***	23.56***
	(554.08)	(41.97)	(10.72)	(−101.47)	(7.64)

Table 3: Firm-Level Summary Statistics

Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. Forecast Dispersion is the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. Market Cap is the number of shares outstanding multiplied by the price, in millions of dollars. Book-to-Market is the book value of common equity divided by the market capitalization. Momentum is the firm's buy-and-hold return over the prior 6 months. Illiquidity is the absolute value of the stock return scaled by the product of volume and price. Leverage is long-term debt scaled by the sum of long-term debt and market capitalization. Residual Volatility is the root mean squared error from regressing daily stock returns on daily Fama-French-Carhart factors in the prior month. Institutional Ownership is institutional share holdings scaled by shares outstanding. Rated is a dummy variable equal to 1 if the firm has an S&P credit rating, and 0 otherwise.

	N	Mean	Std Dev	Median	Min	Max
Success Mean	492,666	0.34	0.07	0.35	0.03	0.71
Success Dispersion (%)	492,666	0.56	0.52	0.39	0.00	8.73
Forecast Dispersion (%)	492,666	0.55	1.51	0.23	0.00	153.40
Market Cap (MM$)	492,664	5,667.24	18,986.09	1,259.29	3.07	626,550.33
Book-to-Market	492,666	0.39	0.39	0.34	−9.43	21.06
Momentum (%)	492,666	8.10	38.07	5.04	−98.79	2,167.47
Illiquidity (%)	492,664	24.44	152.40	3.28	0.00	51,452.19
Leverage (%)	492,666	14.96	19.12	6.61	−5.75	98.45
Residual Volatility (%)	492,666	2.20	1.51	1.80	0.03	52.86
Institutional Ownership (%)	492,666	3.03	16.23	0.00	0.00	4.66
Rated	492,666	0.37	0.48	0.00	0.00	1.00

Table 4: Mean Portfolio Forecast Dispersion

This table reports the mean portfolio Forecast Dispersion. Portfolios are formed by sorting the sample monthly into Success Mean and Success Dispersion quintiles. Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. The t-statistics are in parentheses. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% two-tailed level, respectively.

	Success Mean Portfolios	Success Dispersion Portfolios
Q1	0.37	0.28
Q2	0.41	0.34
Q3	0.50	0.42
Q4	0.62	0.60
Q5	0.87	1.12
Q5−Q1	0.51***	0.83***
	(69.49)	(97.29)

Table 5: Forecast Dispersion Multivariate OLS Regressions

The dependent variable is the natural logarithm of Forecast Dispersion. Forecast Dispersion is the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. Market Cap is the number of shares outstanding multiplied by the price, in millions of dollars. Book-to-Market is the book value of common equity divided by the market capitalization. Momentum is the firm's buy-and-hold return over the prior 6 months. Illiquidity is the absolute value of the stock return scaled by the product of volume and price. Leverage is long-term debt scaled by the sum of long-term debt and market capitalization. Residual Volatility is the root mean squared error from regressing daily stock returns on daily Fama-French-Carhart factors in the prior month. Institutional Ownership is institutional share holdings scaled by shares outstanding. Rated is a dummy variable equal to 1 if the firm has an S&P credit rating, and 0 otherwise. The t-statistics in parentheses are two-way clustered by firm and year in all specifications. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% two-tailed level, respectively.

	Model 1	Model 2	Model 3	Model 4
Success Mean	5.12***		5.39***	5.40***
	(24.02)		(28.20)	(30.76)
Ln(Success Dispersion)		0.53***	0.55***	0.34***
		(24.14)	(28.02)	(18.51)
Ln(Market Cap)				−0.14***
				(−11.17)
Book-to-Market				0.23***
				(7.16)
Ln(1+Momentum)				−0.28***
				(−6.37)
Ln(Illiquidity)				0.01*
				(1.66)
Leverage				0.77***
				(11.56)
Residual Volatility				4.14*
				(1.93)
Ln(1+Institutional Ownership)				−0.07
				(−1.03)
Rated				−0.02
				(−0.62)
Intercept	−7.78***	−3.09***	−4.84***	−5.29***
	(−86.95)	(−26.84)	(−56.35)	(−36.55)
N	492,666	492,666	492,666	492,664
Adj. R^2 (%)	9.20	13.29	23.47	30.53

Table 6: Mean Portfolio Returns

This table reports mean one-month portfolio returns. Portfolios are formed by sorting the sample monthly into Forecast Dispersion, Predicted Forecast Dispersion and Residual Forecast Dispersion quintiles, respectively. Forecast Dispersion is the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. Predicted and Residual Forecast Dispersion are based on Model 3 of Table 5, in which the natural logarithm of Forecast Dispersion is regressed monthly on Success Mean and the natural logarithm of Success Dispersion. Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. The t-statistics are in parentheses. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% two-tailed level, respectively.

	Forecast Dispersion Portfolios	Predicted Forecast Dispersion Portfolios	Residual Forecast Dispersion Portfolios
Q1	0.98	1.00	0.98
Q2	0.95	0.89	0.90
Q3	0.92	0.78	0.87
Q4	0.74	0.77	0.74
Q5	0.50	0.65	0.61
Q5−Q1	−0.48***	−0.35***	−0.37***
	(−8.49)	(−6.18)	(−6.65)

Table 7: Calendar-Time Factor-Adjusted Return Portfolio Regressions

This table reports the coefficients from regressions of monthly portfolio returns on Fama and French (1993) three-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Forecast Dispersion is the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. Predicted and Residual Forecast Dispersion are based on Model 3 of Table 5, in which the natural logarithm of Forecast Dispersion is regressed monthly on Success Mean and the natural logarithm of Success Dispersion. Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. The t-statistics are in parentheses. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% two-tailed level, respectively.

	Intercept	MKT	SMB	HML	MOM	LIQ
Panel A: Forecast Dispersion						
Q1	0.16**	1.03***	0.32***	−0.18***	0.11***	−0.03
Q2	0.10	1.07***	0.34***	0.03	−0.06***	0.01
Q3	0.05	1.08***	0.43***	0.17***	−0.13***	0.05***
Q4	−0.14*	1.13***	0.49***	0.21***	−0.21***	0.07***
Q5	−0.38***	1.24***	0.68***	0.21***	−0.34***	0.06**
Q5−Q1	−0.54***	0.22***	0.36***	0.39**	−0.45***	0.09***
	(−4.54)	(8.14)	(9.48)	(9.40)	(−18.14)	(2.85)
Panel B: Predicted Forecast Dispersion						
Q1	0.12**	1.04***	0.36***	−0.06	0.11***	0.02
Q2	0.02	1.07***	0.36***	0.06	−0.04***	0.02
Q3	−0.06	1.10***	0.37***	0.11***	−0.15***	0.04*
Q4	−0.11	1.13***	0.51***	0.15***	−0.21***	0.04*
Q5	−0.18*	1.21***	0.66***	0.18***	−0.34***	0.04
Q5−Q1	−0.30**	0.17***	0.30***	0.24***	−0.44***	0.01
	(−2.56)	(6.22)	(7.80)	(5.88)	(−18.12)	(0.43)
Panel C: Residual Forecast Dispersion						
Q1	0.18**	1.05***	0.37***	−0.11***	0.00	−0.03
Q2	0.05	1.07***	0.41***	0.05**	−0.07***	0.01
Q3	0.01	1.09***	0.38***	0.12***	−0.14***	0.05***
Q4	−0.16**	1.14***	0.47***	0.18***	−0.18***	0.07***
Q5	−0.28***	1.20***	0.63***	0.20	−0.24***	0.06***
Q5−Q1	−0.46***	0.15***	0.27***	0.31***	−0.24***	0.08***
	(−4.72)	(6.70)	(8.37)	(8.90)	(−11.86)	(3.23)

Table 8: Return Multivariate Fama-MacBeth Regressions

This table reports the average coefficients from monthly OLS regressions of one-month returns on Dispersion and control variables. Forecast Dispersion is the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. Predicted and Residual Forecast Dispersion are based on Model 3 of Table 5, in which the natural logarithm of Forecast Dispersion is regressed monthly on Success Mean and the natural logarithm of Success Dispersion. Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. Market Cap is the number of shares outstanding multiplied by the price, in millions of dollars. Book-to-Market is the book value of common equity divided by the market capitalization. Momentum is the firm's buy-and-hold return over the prior 6 months. Illiquidity is the absolute value of the stock return scaled by the product of volume and price. Leverage is long-term debt scaled by the sum of long-term debt and market capitalization. Residual Volatility is the root mean squared error from regressing daily stock returns on daily Fama-French-Carhart factors in the prior month. Institutional Ownership is institutional share holdings scaled by shares outstanding. Rated is a dummy variable equal to 1 if the firm has an S&P credit rating, and 0 otherwise. The t-statistics are in parentheses. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% two-tailed level, respectively.

	Model 1	Model 2
Ln(Forecast Dispersion)	−0.17***	
	(−3.85)	
Predicted Forecast Dispersion		−0.24***
		(−3.10)
Residual Forecast Dispersion		−0.16***
		(−3.85)
Ln(Market Cap)	−0.10**	−0.10**
	(−2.26)	(−2.34)
Book-to-Market	0.24***	0.24***
	(2.79)	(2.82)
Ln(1+Momentum)	0.31	0.30
	(1.15)	(1.13)
Ln(Illiquidity)	−0.04***	−0.04**
	(−2.61)	(−2.54)
Leverage	−0.09	−0.09
	(−0.41)	(−0.41)
Residual Volatility	−22.02***	−21.73***
	(−4.15)	(−4.14)
Ln(1+Institutional Ownership)	−403.00	−395.55
	(−1.00)	(−1.00)
Rated	0.05	0.05
	(0.89)	(0.89)
N	336	336

Table A1: Quarterly and Long-Term Growth Forecast Dispersion Multivariate OLS Regressions
The dependent variable is the natural logarithm of Quarterly and Long-Term Growth Forecast Dispersion. Forecast Dispersion is the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. Market Cap is the number of shares outstanding multiplied by the price, in millions of dollars. Book-to-Market is the book value of common equity divided by the market capitalization. Momentum is the firm's buy-and-hold return over the prior 6 months. Illiquidity is the absolute value of the stock return scaled by the product of volume and price. Leverage is long-term debt scaled by the sum of long-term debt and market capitalization. Residual Volatility is the root mean squared error from regressing daily stock returns on daily Fama-French-Carhart factors in the prior month. Institutional Ownership is institutional share holdings scaled by shares outstanding. Rated is a dummy variable equal to 1 if the firm has an S&P credit rating, and 0 otherwise. The t-statistics in parentheses are two-way clustered by firm and year in all specifications. ***, **, or * signify that the test statistic is significant at the 1, 5 or 10% two-tailed level, respectively.

	Quarterly Forecast Dispersion		Long-Term Growth Forecast Dispersion	
	Model 1	Model 2	Model 1	Model 2
Success Mean	4.77***	4.76***	−0.89***	−0.14
	(23.09)	(30.68)	(−4.24)	(−0.58)
Ln(Success Dispersion)	0.54***	0.32***	0.68***	0.48***
	(28.17)	(18.91)	(27.24)	(20.90)
Ln(Market Cap)		−0.14***		−0.14***
		(−12.88)		(−10.56)
Book-to-Market		0.21***		0.28***
		(7.10)		(4.87)
Ln(1+Momentum)		−0.31***		−0.21***
		(−7.40)		(−2.99)
Ln(Illiquidity)		0.01		−0.03***
		(1.59)		(−7.33)
Leverage		0.81***		−0.06
		(12.81)		(−0.50)
Residual Volatility		4.02**		16.30***
		(2.20)		(11.47)
Ln(1+Institutional Ownership)		−0.08		0.38***
		(−1.40)		(6.42)
Rated		−0.03		−0.17***
		(−1.18)		(−4.50)
Intercept	−5.45***	−5.89***	2.08***	1.47***
	(−66.37)	(−44.85)	(10.72)	(8.18)
N	453,785	453,784	60,586	60,586
Adj. R^2 (%)	25.96	35.23	34.14	47.10

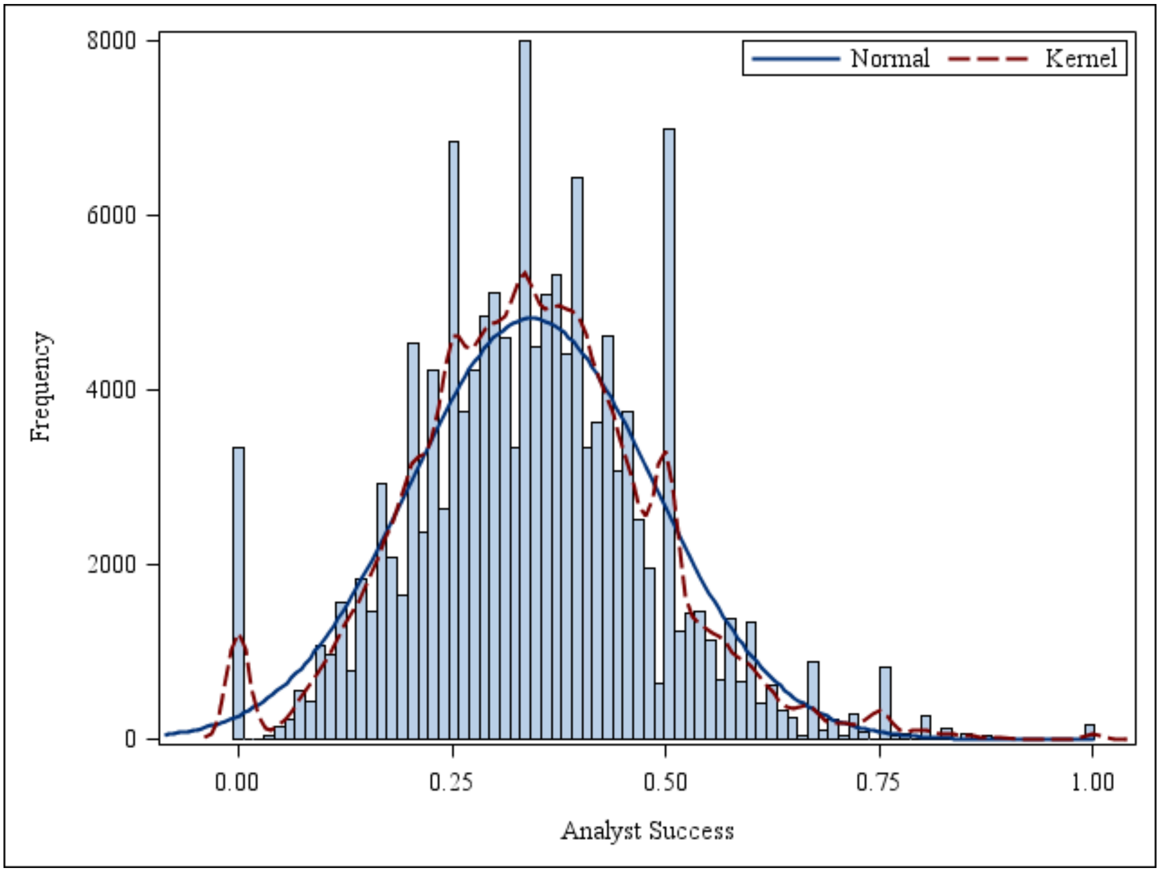

Figure 1: Analyst-Level Success Distribution
Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter. Error is the absolute value of the difference between actual and forecasted quarterly earnings.

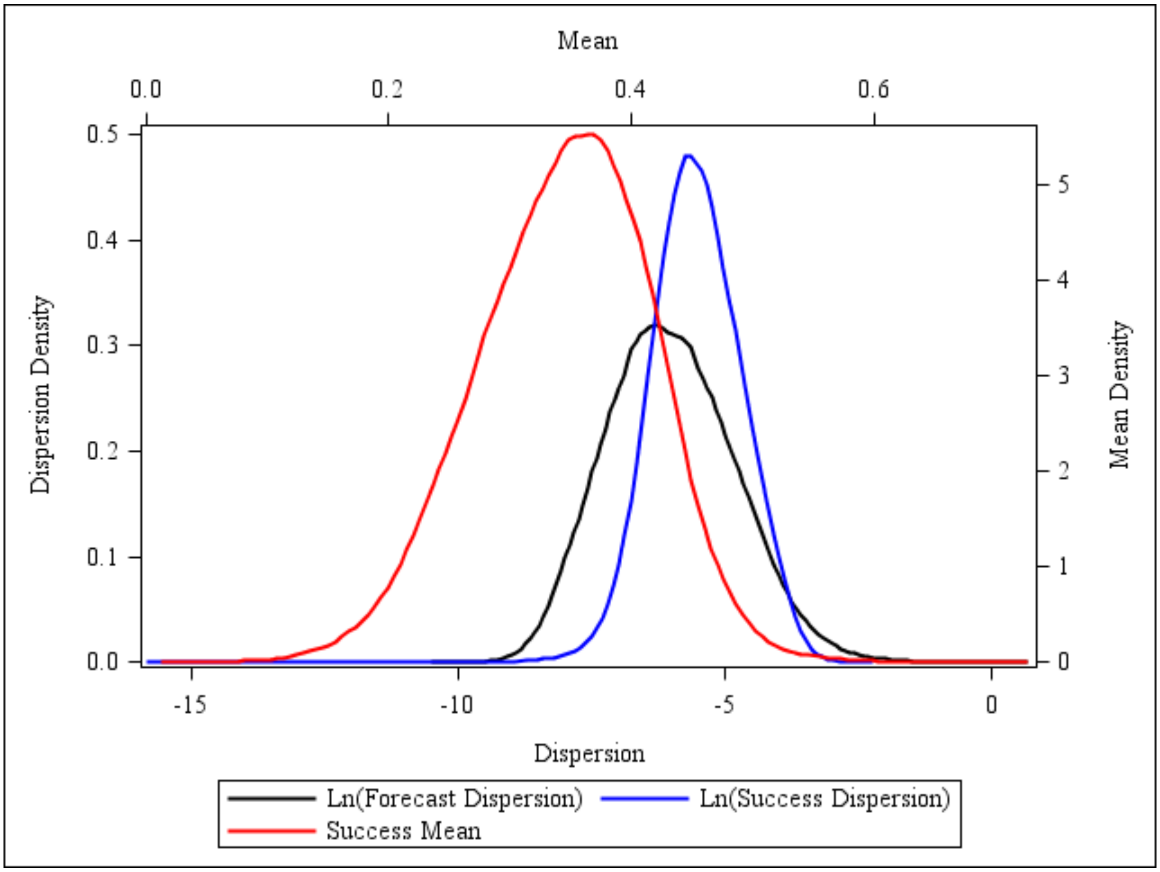

Figure 2: Forecast Dispersion, Success Mean, and Success Dispersion Distributions
Forecast Dispersion is the standard deviation of a firm's analyst forecasts, scaled by the firm's stock price. Success Mean is the mean of a firm's analyst Success. Success Dispersion is the standard deviation of a firm's analyst Success, scaled by the firm's stock price. Success is an analyst's fraction of successful forecasts in the past 4 quarters, where a forecast is successful if an analyst's error is below the median error for the same firm in the same quarter.