Analyst Forecast Dispersion and Aggregate Stock Returns

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Abstract

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Starting from Diether *et al.* (2002), a prolific body of literature reports evidence on and makes different interpretations to the negative relation between dispersion in analysts' earnings forecasts and cross-sectional stock returns. Diether *et al.* (2002) attribute this negative relation to market frictions that drive stocks overpriced. Specifically, based on Miller (1977), prices will reflect a more optimistic valuation because pessimistic investors are kept out of the market by high short-sale costs. As a result, higher dispersion causes higher overpricing, and therefore predicts lower stock returns in the future as the overpricing is corrected over time. They conclude that dispersion in analysts' forecasts is a proxy for differences in opinion, and reject the interpretation of dispersion as a measure of risk. Boehme *et al.* (2006) confirm Diether *et al.* (2002)'s findings and show that high dispersion and short-sale constraints are two necessary but not sufficient conditions for firm stocks to be overpriced.

Johnson (2004), however, develops an asset pricing model in which idiosyncratic risk increases the option value of the firm, and interprets dispersion as a proxy for this idiosyncratic parameter risk. Sadka and Scherbina (2007) suggest illiquidity as an explanation for the persistence of the dispersion effect. They show that the most illiquid high-dispersion stocks are the most severely mispriced, and returns on high-dispersion stocks are negatively correlated with changes in aggregate liquidity. However, they note that their results are not necessarily inconsistent with Johnson (2004) in the sense that illiquidity might be another indicator of idiosyncratic risk. Avramova *et al.* (2009) provide another explanation, financial distress, as proxied by credit rating downgrades. Viewing forecast dispersion as a measure of uncertainty about firm's future earnings, which is a component of default risk, they show that the profitability of dispersion-based trading strategies concentrates in a small number of the worst-rated firms and is significant only during periods of deteriorating credit conditions. They infer that the negative dispersion-return relation emerges because the price drop of low-rated firms happens together with increase in forecast dispersion. They further show that the dispersion-return relation disappears when adjusting for credit risk. Güntay and Hackbarth (2010) examine dispersion effects on corporate bond credit spreads and find that dispersion is positively associated with credit spreads and changes in dispersion reliably predict changes in credit spreads. They conclude that their evidence suggests a limited role of short-sale constraints and provides little support for interpretation of idiosyncratic risk, but consistent with a rational explanation, that dispersion appears to proxy largely for future cash flow uncertainty in corporate bond markets.

Barron *et al.* (2009) decompose dispersion into "uncertainty" and "information asymmetry" components utilizing the framework in Barron *et al.* (1998), and examine the relation between dispersion and returns around earnings announcements. They demonstrate that the "uncertainty" component explains the negative correlation between dispersion and future returns, rather than the "information asymmetry" component. They further show a negative correlation between change in "information asymmetry" component of dispersion and contemporaneous abnormal returns. They conclude that levels of dispersion reflect levels of uncertainty while changes in dispersion reflect changes in information asymmetry.

Ali *et al.* (2010) provide an explanation from the perspective of corporate disclosure. They argue that firms withholding bad news leads to greater dispersion in analysts' forecasts, and those firms are more likely to experience poor earnings in subsequent quarters, which in turn triggers lower returns. They find evidence supporting their argument, and they further show that the negative dispersion-return relation disappears after controlling for the relation between forecast dispersion and future earnings.

While prior studies propose different explanations for the cross-sectional negative relation between dispersion and future returns, they share some similarities in common: dispersion is a proxy for something non-systematic. In this paper, I test whether the negative relation extends to the aggregate level, and provide evidence on whether the dispersion effects can be diversified away at the aggregate level. Specifically, I test the relation between future aggregate returns and aggregate forecast dispersion, and further test the relation between innovations in aggregate dispersion and contemporaneous aggregate returns, and discount rate shocks.

In a complete and rational aggregate market, where information is transparent and investors rationally update their expectations, any idiosyncratic risks or mispricing at firm level will be diversified away when aggregated. And even in presence of heterogeneous opinions, the market prices will be unbiased, as suggested in Diamond and Verrecchia (1991), and Hong and Stein (2003). Short-sale constraint may be immaterial at the aggregate level since it is more binding for small firms (Jones and Lamont (2002); Asquith *et al.* (2005)), and options and futures for market indices would seem to reduce transaction costs and short-sale restrictions (Kothari *et al.* (2006)). Therefore, it is reasonable to expect that the dispersion effects do not extend to the aggregate level and there is no relation between aggregate returns and forecast dispersions, no matter whether it proxies for divergent opinions or idiosyncratic risks.

On the other hand, if individual stocks are overpriced because of pessimistic investors holding back from short-selling, then the aggregate market reflects optimistic opinions only and thus overpriced as well. Using survey data from foreign exchange, Ito (1990) and Elliott and Ito (1999) show that heterogeneous expectations exist in aggregate financial markets. In addition, short sales are not pervasive in the aggregate market and might be constrained at the aggregate level too. D'Avolio (2002) reports that although aggregate market is easy to borrow: the value-weighted cost to borrow the sample loan portfolio is 25 basis points per annum, but only 7% of loan supply (by value) is borrowed during the period April 2000 through September 2001. The latest aggregate data from The Risk Management

Association show this number around 9% in 2009 and 2010.[1] And institutional investors like mutual funds face various restrictions and usually do not go short (Almazana *et al.* (2004)). Therefore, the dispersion effects at firm level might extend to the aggregate market level as well.

It is also possible that the negative relation between dispersion and return reverses at the aggregate level. If analyst forecast dispersion measures the divergence in investor's opinions, it is less likely that investor's opinions will converge when aggregated. That is, the divergence in investor's opinions is less likely to be diversified away when aggregated, and it is reasonable to expect that the aggregated divergence in investor's opinions becomes a systematic risk and requires return compensation.

Ali *et al.* (2010) show that analyst forecast dispersion is negatively associated with future earnings at the firm level, and Kothari *et al.* (2006) show that earnings surprise is negatively associated with contemporaneous returns at the aggregate level. Combining their evidence, it is possible that analyst forecast dispersion predicts positively future returns at the aggregate level, if the dispersion-return is relation is driven by firms' selective disclosures.

Therefore, the relation between dispersion and aggregate returns is an empirical question.

Using data from I/B/E/S for the period from January 1976 to November 2010, I construct monthly equal-weighted, value-weighted, and coverage-weighted averages of forecast dispersions as measures of aggregate dispersion[2], and regress aggregate returns on dispersions. I find that aggregate dispersions have predictive power to market returns, and the relation is significantly positive, statistically and economically. Correcting finite sample biases following Stambaugh (1999) and Lewellen (2004) does

[1] Data available at: http://www.rmahq.org/RMA/SecuritiesLending/DataDecisionSupportCenter/SecuritiesLendingQuarterlyAggregateComposite/.

[2] The dispersion in analysts' forecasts is also viewed as the second moment of analysts' earnings forecasts, instead of a single measure of uncertainty, divergence in opinions, or default risk, etc. Aggregating the second moment of random variables may be difficult, and requires assumptions on the covariance structure between random variables. However, I view the dispersion as a random variable as well, not a second moment of some variable else. And this view can find its support in prior studies. On the other hand, aggregation of second moment is feasible if I assume the covariance structure is stable over time, and this assumption will bias against finding significant coefficients.

not qualitatively change my results. In multivariate regressions, I control for other macroeconomic variables suggested in prior literature, such as aggregate dividend yield, aggregate earnings change, treasury bill rate, term spread, yield spread, default spread, industrial production growth rate, GDP growth rate, inflation rate, and new equity shares issued. The coefficient before aggregate dispersion remains significantly positive. The results are robust to inclusion of other measures of market volatility: the volatility of daily returns for CRSP Index, the cross-sectional dispersion of earnings change, CBOE implied volatility index, and value-weighted average of monthly trading volume for all CRSP firms. Instead, none of these volatility measures shows consistent significance in presence of the dispersion measures.

The predictive regressions show contradiction with prior firm-level studies. I further test whether innovations in aggregate dispersions are positively associated with contemporaneous discount rate shocks, in spirit of Campbell (1991), Kothari *et al.* (2006) and Hirshleifer *et al.* (2009), and find confirmative evidence that innovations in dispersions are negatively related to contemporaneous aggregate returns, and positively related to contemporaneous changes in discount rates, which are proxied by treasury bill rate, term spread, yield spread, and default spread. These findings suggest that positive innovations in aggregate dispersions are associated with increase in discount rates, which leads to a price drop contemporaneously and a larger expected return in the future.

Barron *et al.* (2009) find that the negative dispersion-return relation at firm level is due to the "uncertainty" component, and the relation between future returns and the "information asymmetry" component is positive. It is of interest to ask which component drives the positive relation at the aggregate level. Is the "uncertainty" component diversified away at the aggregate level while the "information asymmetry" component remains unchanged? Or does the sign of the effects of "uncertainty" component flip over at the aggregate level? I decompose dispersion into two components in the same manner and find that both components contribute to the positive dispersion-return relation at the aggregate level. The coefficients before two components are both significantly positive, which suggests that the reversal of dispersion-return relation at the aggregate level is mainly due to the “uncertainty” component. Contemporaneous regressions of innovations in these two components and discount rate news show that they are both positively correlated with discount rate news. But regressions of contemporaneous returns on fitted and residual innovations in these two components show that the uncertainty component is more significant and negative, and the information asymmetry component is not statistically significant, which suggests that the uncertainty component explains more about the dispersion-return relation at the aggregate level.

To cast more light on the dispersion-return relation, I conduct similar analyses at the industry level. I find that dispersion positively predicts industry returns in most industries, and the relation is negative for only a few industries and insignificant. Decomposing industry dispersion into uncertainty and information asymmetry, I find that both components positively predict future industry returns, and again, none is significantly negatively associated with future returns. This evidence is opposite to what has been documented at firm level and provides little support for idiosyncratic risk hypothesis or mispricing hypothesis for dispersion-return relation.

I am not the first one to examine the dispersion-return relation at the aggregate level. Park (2005) studies analyst forecast dispersion for S&P 500 Index. A group of I/B/E/S analysts make forecasts for the S&P 500 Index (Ticker: SPX) like they do for individual stocks. Park (2005) uses the forecast dispersion of this particular security as a measure of aggregate dispersion and examines its relation to S&P 500 Index returns. Not surprisingly, he finds negative relation, similar to firm-level studies. And he interpret the forecast dispersion as a measure of differences of opinion rather than risk, similar to Diether *et al.* (2002). Different from Park (2005), I construct measures of aggregate dispersion from individual stocks, which might be a better representative of dispersion at the aggregate level. Especially, if the forecast dispersion proxies for divergence in investors’ opinions, then the aggregate divergence in opinions should represent most investors in the market. The S&P 500 Index forecast dispersion, however, represents only a very small group of analysts who are making forecasts for it. In the period from January 1982 to November 2010, for which the index forecast is available, the average (median) number of analyst forecasts each month used to calculate the dispersion is 17 (16), which casts great doubt on the representativeness of this measure. However, I believe my measures are more representative. The average (median) number of forecasts I use to calculate the aggregate dispersions each month is 12,389 (12,929), the average (median) number of firms is 1,312 (1,307), and the average (median) ratio of sample market value to total CRSP market value is 48.75% (48.61%). In addition, controlling for the forecast dispersion for S&P 500 Index does not significantly change my results.

The evidence presented in this paper is of interest to accounting and finance researchers. First, I add more evidence to the relation between forecast dispersion and stock returns. Prior studies focusing on firm-level analyses show consistent negative relation, and provide various explanations and hypotheses for it. I document a positive relation at the aggregate level, however. As noted by Kothari *et al.* (2006), "(i)f a theory explains both firm and aggregate returns, we are more confident that it captures a pervasive phenomenon", and "(i)f a theory explains one but not the other, we can reject it as a general description of prices". The evidence I present enhances the interpretation of default risk, such as Avramova *et al.* (2009), but challenges the interpretation of idiosyncratic risk, or mispricing proposed by Diether *et al.* (2002) and Johnson (2004). Second, I add to the literature of predicting market returns. Prior studies show that macroeconomic variables such as interest rates and default spreads, and financial variables such as earnings-price ratio and dividend yield, have predictive power for future stock returns (Fama and Schwert (1977); Campbell (1987); Campbell and Shiller (1988); Fama and French (1988); Kothari and Shanken (1997); Lamont (1998); Lewellen (2004)), although some researchers do not agree (Bali *et al.* (2008)). I add to this literature by presenting substantial predictive power of aggregate forecast dispersion, after controlling for other measures of market volatility and macroeconomic variables. Third, I provide additional evidence on examining whether firm-level anomalies extend to aggregate level, complementary to Kothari *et al.* (2006), Hirshleifer *et al.* (2009), and Kang *et al.* (2010). My study further enhances the understanding of market price movement. Specifically, my evidence suggests that discount-rate shocks explain a significant fraction of aggregate returns, confirming Kothari *et al.* (2006). Lastly, my evidence may shed some light on the long-debated question whether information risk is systematic. Viewing analyst forecast dispersion as a proxy for information risk (Barry and Brown (1985); Cohen (2006)), the evidence I present confirms that information risk is not diversifiable and thus a systematic risk factor.

The paper proceeds as follows. Section II discusses the data sources and how to construct my measures of dispersion. Section III examines the abilities of aggregate dispersions to predict aggregate returns. Section IV examines the contemporaneous relation between innovations in dispersions and discount rate shocks. Section V decomposes dispersion into uncertainty and information asymmetry components. Section VI presents evidence of dispersion's predicting power on industry levels. Section VII concludes.

II. Data and Variable Construction

I extract all earnings forecasts for horizon year 1 (FPI=1) from the Summary Unadjusted database in the Institutional Brokers Estimate System (I/B/E/S). I/B/E/S starts providing monthly summary of forecasts from January 1976, and therefore my data span the period from January 1976 to December 2010. The dispersion for firm *i* at month *t* is defined as the standard deviation in analysts' earnings forecasts for firm *i* at month *t*, scaled by firm *i*'s stock price at the end of month *t-1*, following Thomas (2002), Zhang (2006), Barron *et al.* (2009), and Güntay and Hackbarth (2010). Scaling the standard deviation by lagged price makes dispersion magnitudes comparable across firms and facilitates aggregation in the following[3]. The forecast horizon is set at year 1 because it is most frequent in I/B/E/S, and I can make my aggregate measures most representative. Prices, index levels, dividends and monthly returns are extracted from the Center for Research in Security Prices (CRSP). Accounting information including earnings and book value of equity is obtained from Standard and Poor's Compustat Fundamentals North America database. I require the availability of all information of any observation to be included, and drop observations with stock price lower than $5 or higher than $10,000. For each month, I also exclude firms in top percentile of standard deviations, and in top and bottom percentiles of market value, to rule out possible effects of extreme values. I further restrict my sample to firms with December fiscal year end, and update accounting numbers in each April. This restriction aligns the horizon of forecasts, and accounting periodicity across individual firms. My final sample includes 549,808 firm-month observations spanning from January 1976 to November 2010. December 2010 is dropped because I require one-month-ahead returns available.

I then take equal-weighted, value-weighted (using market capitalization at the beginning of the month as weight), and coverage-weighted (using analyst coverage in the month as weight) averages of scaled dispersion across all firms in my sample to form my aggregate series of dispersion (denoted *EWDISP*, *VWDISP*, and *CWDISP*, respectively). The return measures include two sets: equal-weighted and value-weighted returns for all firms within my sample (*EWSAMPRET*, *VWSAMPRET*), and equal-weighted and value-weighted returns for CRSP Index (*EWCRSPRET*, *VWCRSPRET*).

In addition, I control for other variables that have been documented to have predictive power on aggregate returns. These variables include dividend yield (*DY*) which is defined as total dividends paid by all CRSP firms over the year prior divided by current level of CRSP index, 90-day Treasury bill rate (*TBILL*), term spread (*TERM*) which is defined as the difference between yields on a 10-year

[3] Alternatively, I scale the standard deviation of forecasts by the absolute value of consensus forecast as in Diether *et al.* (2002), and my results are qualitatively similar.

maturity treasury bond and on a 3-month maturity treasury bill, yield spread (*YS*) defined as the difference between the Federal Funds rate and the yield on a 3-month maturity treasury bill, default spread (*DEF*) which is defined as the difference in interest rates between Moody's BAA bonds and AAA bonds, industrial production growth (*INDPROD*) which is defined as the growth rate of industrial production in the prior year, GDP growth rate (*GDP*), and inflation rate (*INF*) (Kothari *et al.* (2006); Hirshleifer *et al.* (2009); Cready and Gurun (2010))[4]. I also include new equity shares issued in the prior year divided by total equity and debt issues, as in Baker and Wurgler (2000)[5]. To test whether the dispersion-return relation at the aggregate level is robust to other measures of market volatility and disagreement among investors, I include volatility of daily CRSP index returns (*VOL*), value-weighted trading volume (*TRADE*), CBOE volatility index (*VIX*), and cross-sectional dispersion of earnings changes across firms (σEC) (Harris and Raviv (1993); Lee and Swaminathan (2000); Jorgensen *et al.* (2009)). See the appendix for other variable definitions.

[Insert Fig 1a and Fig 1b here]

[Insert Table I here]

Figure 1 and Table I Panel A show the composition of my sample and firm characteristics. The final sample consists of 549,808 firm-month observations in the period from January 1976 to November 2010. The mean (median) return is 1.3% (1.0%) contemporaneously and 1.1% (0.9%) one-month ahead. The mean (median) dispersion is 0.6% (0.3%) with standard deviation of 0.8%. The mean (median) logarithm of market capitalization is 13.54 (13.42) with standard deviation of 1.52. It shows that my sample consists of larger firms, confirming evidence documented in prior studies that analysts tend to follow larger firms (Bhushan (1989); Barth *et al.* (2001)). The mean (median) number

[4] The interest rate variables are obtained from the St. Louis Federal Reserve Economic Database (FRED). Available at: http://research.stlouisfed.org/fred2/.
[5] The new equity issuance is downloaded from Jeffery Wurgler's website: http://pages.stern.nyu.edu/~jwurgler/.

of forecasts I use to calculate the aggregate dispersions each month is 12,389 (12,929), the mean (median) number of firms is 1,312 (1,307), and the mean (median) ratio of sample market value to total CRSP market value is 48.75% (48.61%). Fig 1a shows the time series of percentage of number of firms and market value in my sample to entire CRSP universe, and Fig 1b shows the total number of forecasts used in calculating aggregate dispersions. While the percentage of firm number and total coverage is increasing over time, the percentage of market value stays quite stable around 50%. The total coverage is steadily increasing from 1976 to 1985 and stays rather high after 1985[6].

[Insert Fig 2a to Fig 2d here]

Figure 2 and Table I Panel B show time series and summary statistics of aggregate variables I construct. The mean (median) monthly aggregate returns are 1.38% (1.68%) for equal-weighted sample portfolio, 1.57% (1.88%) for value-weighted sample portfolio, 1.35% (1.66%) for equal-weighted CRSP index, and 1.00% (1.41%) for value-weighted CRSP index. They seem very close to each other except for value-weighted CRSP index, which is slightly lower than the other three aggregate returns. The mean (median) aggregate dispersion is 0.65% (0.61%) if equal-weighted, 0.47% (0.44%) if value-weighted, and 0.59% (0.56%) if coverage-weighted. The change in dispersion has a mean of -0.01% and a median of -0.02%, which are very close to zero, despite weighting schemes. Fig 2a shows that the series of dispersion peak at August 1982 and February 2009 and stay quite stable otherwise. However, they do show strong seasonality. To remove the effects of seasonality or coincidence with economic cycles that dispersion measures might capture, I deseason the series of raw dispersions by running an auto-regression with 12-month lagged dispersion as independent variable, and obtaining the residuals. Specifically, I obtain residuals from the regression $DISP_t = \pi_0 + \pi_1 DISP_{t-12} + \epsilon_t$. The deseasoned series of dispersion are shown in Fig 2b. The deseasoned dispersion

[6] Deleting the earlier years from 1976 to 1985 with fewer firms and lower coverage does not significantly change my results and inferences.

shows variability, especially around 1983 and 2009. I also calculate the change in deseasoned dispersions and present along with change in raw dispersions in Fig 2c and Fig 2d. The change in raw dispersion does not show apparent seasonality but shows large variability than level of dispersion.

[Insert Table II here]

Table II reports Pearson/Spearman correlations between returns and dispersions. The correlation between the three measures of dispersions is significantly high, above 0.97, and the correlation between three changes in dispersions is significantly high as well, above 0.88, which suggests that the weighting schemes do not matter very much. Panel A shows that the correlation between forwarded returns and level of dispersions is significantly positive, while the correlation between forwarded returns and change in dispersions is positive but insignificant. Panel B shows that the correlation between contemporaneous returns and change in dispersions is significantly negative, which suggests that innovations in dispersions might be positively correlated with discount rate news.

III. Predicting Aggregate Returns with Aggregate Dispersions

My main tests explore whether the negative dispersion-return relation at firm level extends to aggregate level. I first replicate the findings in prior studies at firm level. Then I run both univariate and multivariate regressions of one-month-ahead aggregate returns on level of dispersions, and test whether aggregate dispersions have predictive power to aggregate returns. Next, I examine whether the predictive power of dispersion is robust to inclusion of other measures of market volatility. And in the last subsection, I compare my results with Park (2005).

A. Dispersion-return relation at firm level

I first replicate the dispersion-return relation at firm level, documented in prior literature. I run a Fama-MacBeth regression of one-month-ahead individual stock returns on forecast dispersion and other control variables, using my sample. Specifically, I run the following regression:

$$R_{t+1} = \alpha + \theta_1 Beta_t + \theta_2 \log ME_t + \theta_3 \log BM_t + \theta_4 MOM_{t-12,t} + \theta_5 COV_t + \lambda_1 DISP_t + \varepsilon_{t+1} \quad (1),$$

where $Beta_t$ is the market beta, estimated from a regression of stock returns on value-weighted market returns for the period from month *t-60* to month *t-1*; $\log ME_t$ is logarithm of market capitalization at the end of month *t*; $\log BM_t$ is logarithm of book-to-market ratio, calculated as the ratio of book value of equity to market value of equity at the end of month *t*; $MOM_{t-12,t}$ is the cumulative returns from month *t-12* to month *t*; and COV_t is analyst coverage, the number of outstanding forecasts in moth *t*. The estimation is reported in Table III.The coefficients before dispersion is significantly negative (-0.198 with t-statistic -3.45 in column 1), consistent with prior studies, and the magnitude does not change much with inclusion of additional control variables. The average R^2 is 7.3% when all control variables are included. This replication procedure ensures my following analyses free of sample selection bias.

[Insert Table III here]

B. Forecasting aggregate returns: univariate tests

Table IV reports univariate regressions of one-month-ahead aggregate stock returns on raw aggregate dispersions (Panel A), or deseasoned aggregate dispersions (Panel B), specifically,

$$R_{t+1} = \alpha + \beta DISP_t + \varepsilon_{t+1} \quad (2).$$

[Insert Table IV here]

OLS estimation shows that when raw dispersion is the independent variable, the coefficient is significantly positive (Panel A1). The positive coefficient is robust to different weighting schemes and sample portfolio returns as well as CRSP index returns. Generally, the coefficient is smallest when value-weighted sample returns are the dependent variable (2.016 for EWDISP, 2.089 for VWDISP, and 2.141 for CWDISP), and largest when equal-weighted sample returns are the dependent variable (2.383 for EWDISP, 2.514 for CWDISP, and 2.512 for VWDISP). Among three weighting schemes of dispersion, value-weighting generally is most conservative with the smallest *t*-statistics. When deseasoned dispersions are applied to regression (2), the coefficients remain significantly positive, and the magnitude becomes larger. For example, when *EWSAMPRET* is regressed on *EWDISP_DS*, the coefficient is 5.288 with t-statistic 3.045, compared with 2.383 with t-statistic 2.762 when raw dispersion is used. Similar pattern also exists in Panel B1. Economically, when equal-weighted dispersion increases from 0.42% at the first quartile to 0.85% at the third quartile, the equal-weighted sample return one month later increases by 1.02%; when deseasoned equal-weighted dispersion increases from -0.08% at the first quartile to 0.05% at the third quartile, the equal-weighted sample return once month later increases by 0.69%. This evidence shows that the economic significance of dispersion effects on aggregate stock returns since the mean equal-weighted sample return is only 1.38%.

As noted by Stambaugh (1986), Mankiw *et al.* (1991), and Nelson and Kim (1993), and later formulated by Stambaugh (1999), finite sample bias could severely bias predictive regressions toward find predictability, especially when the predictor follows an auto-regressive process. To address the potential finite-sample bias in the OLS estimates, I follow Lewellen (2004) to correct for biases and adjust *t*-statistics. For the regression (2) and an AR(1) process of dispersion, $DISP_t = \phi + \rho DISP_{t-1} + \mu_t$, I can show that the bias-adjusted estimator $\hat{\beta}_{adj} = \hat{\beta} - \gamma(\hat{\rho} - \rho)$, with variance $\sigma_v^2(DISP'DISP)^{-1}$, where $\varepsilon_t = \gamma\mu_t + v_t$. Obviously, assuming $\rho = 1$ gives the most conservative estimate of $\hat{\beta}_{adj}$, as derived in Lewellen (2004). I report the AR(1) time series regression of dispersions in Panels A2 and B2, Table IV, and subsequent finite-sample-bias adjusted coefficients in Panels A3 and B3. The first-order auto-regressive coefficient is as high as 0.948 for raw dispersions, and 0.901 for deseasoned dispersions, which is statistically significant. The coefficient is smaller than one, suggesting that the series of dispersions are smooth. Under the normality assumption, a well-known approximation for the bias in $\hat{\rho}$, to order 1/T, is given by $-(1+3\rho)/T$, as shown by Marriott and Pope (1954) and Kendall (1954). Thus, the bias in $\hat{\rho}$ assuming the true parameter $\rho = 1$ is $\hat{\rho} - 1 - (1+3\hat{\rho})/T$, which is always negative for smooth time series. Therefore, when $\gamma < 0$, i.e., the covariance between residual returns and residual dispersions is negative, β is biased upward toward finding predictability, but when $\gamma > 0$, i.e., the covariance between residual returns and residual dispersions is positive, β is biased downward toward rejecting predictability.

From Table IV Panel A3 I see that the covariance between residual returns and residual raw dispersions is positive, suggesting the predictive coefficient β is biased downward toward rejecting predictability, and the OLS estimation is more conservative. As shown in Panel A3, both the magnitude and *t*-statistics of β increase after adjusting for finite-sample bias, relative to the corresponding OLS estimates in Panel A1. Panel B3, however, shows that the covariance between residual returns and residual deseasoned dispersion is negative, suggesting β is biased upward toward finding predictability. Correcting finite-sample bias is more crucial for deseasoned series of dispersions. In general, the finite-sample bias is not significantly changing my inferences based OLS estimation. The *t*-statistics remain large after correcting biases, suggesting aggregate dispersions have predictive power to aggregate stock returns.

In summary, Table IV illustrates that the relation between dispersions and future returns at the aggregate level is significantly positive, in sharp contrast with the strong negative firm-level relations in prior literature. The arguments for dispersions proposed in prior literature include idiosyncratic risks (idiosyncratic uncertainty), mispricing, divergent opinions (information asymmetry), and default risks. The evidence I present here provides little support for the former two explanations, but is in favor of the default risk explanation. I will further examine the contemporaneous relation between innovations in dispersion and change in discount rates in Section IV.

C. Forecasting aggregate returns: multivariate tests

[Inset Table V here]

Table V reports the estimation for multivariate regressions of one-month-ahead aggregate stock returns on aggregate forecast dispersions, controlling for macroeconomic variables identified in prior studies. Specifically, I include aggregate dividend yield, aggregate earnings changes, Treasury bill rates, term spreads, yield spreads, default spreads, industrial production growth rates, GDP growth rates, inflation rates, and new equity shares issued. To better align the dispersion measures with returns, I use equal-weighted (value-weighted) dispersions when equal-weighted (value-weighted) returns are regressed. Coverage-weighted dispersions have similar properties to value-weighted returns and generally have more significant coefficients, and therefore I do not report them separately in the following analyses. Since the series of new equity shares issued, obtained from Baker and Wurgler (2000), cover the period only through April 2008, I list regressions with and without new equity shares (*ESHARE*) separately. Specifically, I run the following regression:

$$R_{t+1} = \alpha + \beta DISP_t + \gamma_1 DY_t + \gamma_2 EC_t + \gamma_3 TBILL_t + \gamma_4 TERM_t + \gamma_5 YS_t + \gamma_6 DEF_t + \gamma_7 INDPROD_t + \gamma_8 GDP + \gamma_9 INF_t + \gamma_{10} ESHARE_t + \varepsilon_{t+1} \quad (3).$$

Table V Panel A shows estimation for raw dispersion measures. Consistent with prior studies, I find that dividend yield, term spreads, yield spreads, industrial production growth rates, and new equity shares do not show any significance in predicting aggregate returns. Default spreads, GDP growth rates, and inflation rates show some significance but are not consistently significant. Treasury bill rates show strong significance in regressions of equal-weighted returns, consistent with Hirshleifer *et al.* (2009). Note that earnings changes show some significance too, but it might be due to the fact that earnings changes keep constant over a year and it may capture some year fixed effects. Most importantly, my measures of dispersion are strongly significant in all regressions, with *t*-statistics from 2.35 for value-weighted sample returns to 3.73 for equal-weighted sample returns. The magnitude of the coefficient on dispersions is economically large too, compared with univariate regressions in Table 4. It is more than doubled, suggesting that the incremental effects of dispersion in predicting future aggregate returns are even larger, after removing the influence of macroeconomic variables. For example, holding all macroeconomic variables constant, an increase of value-weighted dispersion from 0.27% (the first quartile) to 0.62% (the third quartile) predicts an increase of value-weighted CRSP index return by 2.46%, which is practically huge for monthly returns. The reduction of sample size by including *ESHARE* does not significantly change my results, suggesting my results are not driven by the peak of forecast dispersion in late 2008 and 2009, when the financial crisis broke out (Schwert (2011)).

I conduct similar analyses for deseasoned dispersions, and the results in Table V Panel B are qualitatively similar to those in Panel A. GDP growth rates load more significantly than in Panel A, but the coefficients on deseasoned dispersions, of the interest, are consistently significant across eight regressions. One interesting phenomenon is that the coefficients on deseasoned dispersions are very close to those on raw dispersion in Panel A, suggesting that when macroeconomic conditions are controlled, the seasonal components of dispersions do not matter. In other words, the contribution of dispersions to predicting future aggregate returns does not result from coincidence with economic cycles or seasonality.

D. Multivariate regressions: controlling for market volatility

Prior studies have interpreted forecast dispersions as divergence in investors' opinions, or uncertainty about future cash flows, and hence the concepts of forecast dispersion and market volatility are naturally connected. It is reasonable to think that when investors have more divergent beliefs or are more uncertain about future cash flows, the market volatility of stocks might increase at the same time, as argued by Park (2005). I include the volatility of CRSP index returns (*VOL*), and CBOE implied volatility index (*VIX*) as additional controls in my multivariate regression (3). In analytical models, Harris and Raviv (1993) and Hong and Stein (2003) show that trading volume is high when disagreement among investors is high. Besides, Lee and Swaminathan (2000) empirically find that trading volume predicts cross-sectional stock returns. To take care of the relation between trading volume and forecast dispersion, I add value-weighted trading volume (*TRADE*) as another control variable. Jorgensen *et al.* (2009) show that cross-sectional earnings dispersion is positively related to contemporaneous stock returns, and argue that higher earnings dispersion is associated with higher expected returns. It is possible that aggregate dispersion is related to cross-sectional earnings dispersion and I take care of this issue by adding the cross-sectional earnings dispersion (σEC_t) as an additional control.

[Insert Table VI]

The estimates are reported in Table VI, in which Panel A regresses sample returns and Panel B regresses CRSP Index returns. The coefficient on dispersions is significantly positive, consistent across all model specifications. And, the magnitude of the coefficient is much larger, in most cases, than when excluding these volatility variables, as shown in Table V. For example, when all these four volatility measures are included, the coefficient on dispersion is 13.438 (*t*-value 4.01) when value-weighted CRSP Index returns are regressed on value-weighted raw dispersions, 17.862 (*t*-value 3.23) when value-weighted CRSP index returns are regressed on value-weighted deseasoned dispersions, compared with 5.243 (*t*-value 2.45) and 6.122 (*t*-value 1.96) in Table V. Individually, cross-sectional earnings dispersion and CBOE volatility index do not show any significance, CRSP Index volatility is significant when value-weighted returns are regressed on deseasoned dispersions, and trading volume is significant when sample returns are regressed. None of them shows consistent significance across all model specifications. Interestingly, when added together, CRSP Index volatility and VIX are both significant but in different signs. It is possible due to the high correlation between them. Actually, the Pearson (Spearman) correlation between VOL and VIX is 0.89 (0.87), and statistically significant. Note that VIX is available after January 1986, and therefore the evidence presented in Table 6 also suggests that my results are not driven by observations in years before 1986. In particular, my results are not driven by the peak of aggregate dispersion in 1983.

In summary, the relation between dispersion and future returns at the aggregate level is robust to inclusion of market volatility, and aggregate dispersion contains more information other than market volatility or trading volume.

E. Aggregate dispersion and the dispersion for S&P 500 Index

Starting from January 1982, a group of I/B/E/S analysts report forecasts for S&P 500 Index (Ticker: SPX), as they do for individual firms. In practice, investors trade on futures, options, and funds based on S&P 500 Index. It is reasonable to believe that some analysts make forecasts for the index to meet investors' demand. Park (2005) utilizes this dispersion measure and examines the relation between the SPX dispersion and index returns. He finds similar results to prior firm-level studies, at intermediate horizons, that is, negative relation between SPX dispersion and future index returns, especially at horizons longer than 24 months.

[Insert Fig 3 here]

However, the small number of analysts who make forecasts for SPX casts some doubt on the representativeness of SPX dispersion to aggregate market. Fig 3 shows the time series of coverage on

S&P 500 Index. The maximum coverage is only 47, the mean (median) forecasts each month is 17 (16) for the index, and the coverage is becoming lower and close to one in recent years. While SPX dispersion might be correlated with aggregate dispersion, I empirically test which one dominates the other.

[Insert Table VII here]

In Table VII Panel A, I first regress aggregate dispersions on SPX dispersions. The coefficient on SPX dispersion is statistically significant and positive, suggesting they are positively correlated as I conjecture. I then obtain residuals from the above regression, and put into the regression of future returns along with SPX dispersions. By doing this procedure, I separate the effects of SPX dispersion from aggregate dispersion, and help make clean inferences. The estimation of the second stage regression is reported in Table VII Panel B. Instead of using CRSP Index returns, I use S&P 500 Index returns to make fair comparison. No matter which measure of aggregate dispersions I use, the coefficient on aggregate dispersion is statistically significant and positive, consistent across all model specifications and variable definitions. Although the coefficient on SPX dispersion is negative, consistent with Park (2005), it is never statistically significant. The largest *t*-value for SPX dispersion is -0.849, far from significance.

In summary, the aggregate dispersion measures I construct are more representative, compared with SPX dispersions. And I provide little evidence for Park (2005)'s interpretation of dispersion in analysts' forecasts as a measure of the differences in investors' expectations rather than the risk.

IV. Contemporaneous Relations between Innovations in Aggregate Dispersions and Discount Rate Shocks

To address whether forecast dispersion proxies for risk, divergent opinions, or idiosyncratic risk, I examine the contemporaneous relation between innovations in aggregate dispersions and returns, and discount rate shocks, following Kothari *et al.* (2006) and Hirshleifer *et al.* (2009). In an efficient market, *ceteris paribus*, when the discount rate increases, the expected return in the future increases, and thus the contemporaneous stock price drops, i.e., the contemporaneous stock return decreases. So, if innovations in aggregate dispersion is positively associated with discount rate shocks, and negatively associated with contemporaneous aggregate returns, then it can explain the positive relation between aggregate dispersions and future aggregate returns.

It is reasonable to expect that innovations in aggregate dispersion are positively associated with discount rate shocks. Avramova *et al.* (2009) and Güntay and Hackbarth (2010) show that dispersion is positively related to default risk at firm level. Chan and Chen (1991) and Fama and French (1996) argue that firms with higher default risk[7] are compensated with higher expected returns. To test this prediction, I examine the contemporaneous relation between returns and innovations in dispersion. I further run a regression of innovations in dispersion on discount rate shocks, proxied by changes in Treasury bill rate, term spread, yield spread, and default spread, and obtain the fitted and residual innovations in dispersion. I then run the contemporaneous regression of returns again, on fitted and residual innovations in dispersion. If the positive dispersion-return relation at the aggregate level is due to positive association between dispersion and discount rates, then the residual innovations in dispersion does not load in the contemporaneous regression of returns.

I calculate innovations in dispersion either as the equal-weighted/value-weighted average of individual changes (referred as “Change” in Table VIII) or as the change in deseasoned aggregate dispersion relative to one month before (referred as “Innovation” in Table VIII).

[Insert Table VIII here]

[7] Chan and Chen (1991) use the term “marginal firms” and Fama and French (1996) use the term “relative distress”.

Table VIII Panel A shows that innovations in aggregate dispersion are negatively associated with contemporaneous returns, consistent with my expectation. And the coefficient is statistically significant except when equal-weighted sample returns are regressed on "Innovation". In Panel B, the innovations in dispersion are positively correlated with change in default spread (*DEF*) and statistically significant across four measures of innovation. The coefficient is around 0.001 with *t*-values higher than 3.2. "Change" in dispersions is also positively associated with change in yield spread (*YS*), and the coefficient is around 0.0003 with *t*-values higher than 2.1. This evidence suggests that aggregate dispersions are positively associated discount rates, especially the component attributable to default risk. Panel C shows the second stage regression of contemporaneous returns on fitted ($\Delta\widehat{DISP}_t$) and residual ($\widehat{e_t}$) innovations in dispersion. $\Delta\widehat{DISP}_t$ shows significantly negative coefficient, and the magnitude is large, above -40. The residuals, $\widehat{e_t}$, however, do not show consistent significance. It has a significant coefficient only when *EWCRSPRET* is regressed on "Change" in dispersion.

The evidence above suggests that innovations in dispersion are highly positively associated with discount rate shocks, and the discount rate shocks explain a majority stake, if not all, of the negative relation between innovations in dispersion and contemporaneous returns. It supports my expectation that the positive dispersion-return predictive relation at the aggregate level is mostly due to the positive association of dispersion with discount rates. It lends little support for interpretations of dispersion as idiosyncratic risk.

V. Decompose Dispersion into Uncertainty and Information Asymmetry

Barron *et al.* (2009) decompose forecast dispersion into *uncertainty* and *information asymmetry* components and show that the negative dispersion-return relation at firm level is purely due to *uncertainty* component, which is idiosyncratic. They further show that the *information asymmetry* component is positively associated with future returns, and change in *information asymmetry* is negatively associated with contemporaneous returns. Then I would expect that the dispersion-return relation I find is purely due to the *information asymmetry* component. Specifically, the *uncertainty* component is diversified away when aggregated since it is idiosyncratic, and therefore the effects I present above are fully attributable to the *information asymmetry* component. I empirically test the prediction that the coefficient before *uncertainty* is indifferent from zero at the aggregate level.

Following Barron *et al.* (2009), I decompose the variance of earnings forecasts into *UNCERT* and *InfoAsym* based on the following formulae:

$$VAR = \sum_{i=1}^{n} \frac{(F_i - \bar{F})^2}{n-1} \tag{4}$$

$$UNCERT = \sum_{i=1}^{n} \frac{(F_i - A)^2}{n} = (1-n) \cdot VAR + (A - \bar{F})^2 \tag{5}$$

$$InfoAsym = (1-\rho) = \frac{VAR}{(1-n) \cdot VAR + (A - \bar{F})^2} = \frac{VAR}{UNCERT} \tag{6}$$

where F_i is individual forecasts, $\bar{F}$ is the consensus forecast (mean), A is actual earnings, and n is the coverage. All these three variables are scaled by price. I then calculate the equal-weighted and value-weighted average of these three variables to get my aggregate measures.

[Insert Table IX here]

I first run the predictive regressions including *UNCERT* and *InfoAsym* at firm level, and the estimation is reported in Table IX Panel A. To be comparable with Barron *et al.* (2009), I use the quintile ranks of *VAR*, *UNCERT*, and *InfoAsym*, divided by 5, as independent variables, instead of levels. Using forecast variance instead of dispersion does not change the negative relation between dispersion and future returns at firm level. Columns (2) and (4) show the regression of one-month-ahead returns on *UNCERT* and *InfoAsym.* Consistent with Barron *et al.* (2009), the coefficient on *UNCERT* is significantly negative, -0.010 ($t = -4.72$) in column (2) and -0.009 ($t = -5.73$) in column (4), while the coefficient on *InfoAsym* is significantly positive, 0.003 ($t = 2.15$) in column (2) and 0.004 ($t = 3.25$) in column (4), confirming Barron *et al.* (2009) that the negative cross-sectional dispersion-return relation is due to the uncertainty component of dispersion. The magnitudes of *UNCERT* and *InfoAsym* are also comparable to Barron *et al.* (2009).

I next examine whether the effects of *uncertainty* are diversified away when aggregated and the positive dispersion-return relation at the aggregate level is due to *information asymmetry* only. I notice that *UNCERT* is more volatile in early years, while *InfoAsym* is more volatile in recent years. To take care of their variances changing over time, I take the natural logarithm of both variables. In Table IX Panel B, I regress one-month-ahead aggregate returns on two components, *UNCERT* and *InfoAsym*. *InfoAsym* loads significantly and positively, 0.036 ($t = 3.10$) for *EWSAMPRET*, 0.039 ($t = 2.21$) for *EWCRSPRET*, 0.023 ($t = 2.62$) for *VWSAMPRET*, and 0.022 ($t = 2.44$) for *VWCRSPRET*. However, *UNCERT* loads significantly and positively too, 0.005 ($t = 2.71$) for *EWSAMPRET*, 0.005 ($t = 1.99$) for *EWCRSPRET*, 0.003 ($t = 2.15$) for *VWSAMPRET*, and 0.003 ($t = 2.05$) for *VWCRSPRET*.

Next I run the contemporaneous analyses as I do in Section IV. In the first stage, I regress innovations in *uncertainty* and *information asymmetry* on changes in discount rates, and report in Panel C of Table IX. Both innovations in *uncertainty* and *information asymmetry* are positively associated with changes in default spread. In addition, innovations in uncertainty are positively related to changes in Treasury bill rate, term spread, and yield spread. This suggests that both innovations in *uncertainty* and *information asymmetry* are positively associated with discount rate shocks. Which one explains more on the dispersion-return relation at the aggregate level? In the second stage, I put fitted and residual innovations in *uncertainty* and *information asymmetry* altogether in regressions of contemporaneous aggregate returns, and the results are reported in Panel D. Fitted $\Delta UNCERT_t$ is significantly negatively related to contemporaneous returns, which suggests that it is the uncertainty component of dispersion that reverses the dispersion-return relation at the aggregate level. By contrary, fitted $\Delta InfoAsym_t$ does not load significantly negative, and it is even positively significant when equal-weighted sample returns are regressed. Both residuals do not show consistent significance yet remain negative.

In summary, decomposing dispersions into uncertainty and information asymmetry components, I show that both components contribute to the positive relation between dispersion and future returns at the aggregate level. Furthermore, innovations in the uncertainty component are negatively related to contemporaneous returns and discount rate shocks, which suggests that the uncertainty component might have more explanatory power.

VI. Industry-level Evidence

To further explore the predictive relation between dispersion and future returns, I conduct similar analyses at the industry level. I run regressions of one-month-ahead returns on dispersions, and two components of dispersions, *uncertainty* and *information asymmetry* for each of 48 industries classified by Fama and French (1997). Table X Panel A shows the coefficient on dispersions for each industry. Again, I report estimation based on both equal-weighted and value-weighted measures. The coefficient is significantly positive for 26 industries if equal-weighted dispersions and returns are used, and 24 industries if value-weighted dispersions and returns are used. Out of 48 industries, only five industries have negative coefficients when equal-weighted dispersions and returns are used, and three industries with negative coefficients when value-weighted dispersions and returns are used, and none of them is statistically significant.

[Insert Table X here]

Panel B of Table X reports the estimation when I decompose dispersions into *uncertainty* and *information asymmetry* components. Similar to the treatment in aggregate analyses, I take natural logarithm of both components. For uncertainty component, 7 (10) industries have significant positive coefficients for equal-weighted (value-weighted) measures, and the Computers industry shows significant negative coefficient for value-weighted measures. For information asymmetry, 19 (20) industries have significant positive coefficients for equal-weighted (value-weighted) measures, and the Beer/Liquor industry shows significant negative coefficient for equal-weighted measures. The industry-level evidence in Table X further confirms my aggregate-level findings. And it seems that the information asymmetry component plays a bigger role in the positive dispersion-return relation at industry level.

VII. Conclusion

This paper explores the relation between forecast dispersion and stock returns at the aggregate market level. I provide evidence that aggregate dispersion positively forecasts aggregate returns, and this relation is robust to different aggregation methods, various model specifications, and inclusion of common control variables and forecast dispersions for S&P 500 Index. I further show that innovations in forecast dispersions are negatively associated with contemporaneous aggregate returns and positively associated with changes in discount rates. Decomposing forecast dispersion into “uncertainty” and “information asymmetry” components, I find that reversion of the relation between forecast dispersion and future stock returns is due to the “uncertainty” component, which turns positive at the aggregate level. Industry-level analyses further validate the findings above.

Prior studies find negative relation between forecast dispersions and future individual stock returns at firm level, and provide various explanations. My results suggest that forecast dispersion is closely related to default spreads, and its effects are not diversified away at the aggregate level, and lend little support to interpretations of forecast dispersion as proxies for idiosyncratic risk or mispricing. Viewing analyst forecast dispersion as a measure of information risk, my results also shed some light on the question whether information risk is systematic. The evidence is also consistent with the explanation of dispersion-return relation attributable to firms' selective disclosure practices.

The positive dispersion-return relation at the aggregate level may not be inconsistent with a negative dispersion-return relation at firm level, however. Firm-level studies focus on the cross-sectional variation of forecast dispersions, and aggregate-level analysis focuses on common factors behind forecast dispersions. Individual forecast dispersions at firm level might contain information about future cash flows as well as discount rates. They may capture different uncertainties about firms' future cash flow and therefore explain cross-sectional returns in a different way (Campbell (1991)).

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Appendix. Variable Definitions

Variable Name	Definitions
Firm-Level	
R_t	Stock return during month *t*, obtained from CRSP monthly database.
$STDEV_t$	Standard deviation of analyst forecasts in month t, obtained from I/B/E/S Summary Unadjusted database.
$DISP_t$	Analyst forecast dispersion in month *t*, defined as $STDEV_t/P_{t-1}$.
$Beta_t$	Market beta, estimated from regressing firm stock returns on value-weighted market returns for the period from month *t-60* to month *t-1*.
$\log ME_t$	Logarithm of market value at the end of month *t*.
$\log BM_t$	Logarithm of book-to-market ratio, calculated as the ratio of book value of equity to market value of equity at the end of month *t*. Book value of equity is obtained from the closest annual financial report. Year 2000's book value of equity is used in the period from April 2001 to March 2002.
$MOM_{t-12,t}$	Momentum, the cumulative returns from month *t-12* to month *t*.
COV_t	Analyst coverage, the number of outstanding forecasts in moth *t*, extracted from I/B/E/S Summary Unadjusted database.
VAR_t	Variance of analyst forecasts, scaled by stock price at the beginning of month *t*.
$UNCERT_t$	Uncertainty, the mean of squared differences between individual analysts' forecasts (F_i) and reported earnings per share (A), scaled by lagged price, i.e., $\sum_i (F_i - A)^2/(COV_t * P_{t-1}) = [(1 - COV_t) * VAR_t + (A - \bar{F})^2]/P_{t-1}$.
$InfoAsym_t$	Information asymmetry, the ratio of variance and uncertainty, $VAR_t/UNCERT_t$.
Aggregate Level	
$EWSAMPRET_t$	Equal-weighted average of sample returns for month *t*.
$VWSAMPRET_t$	Value-weighted average of sample returns for month *t*.
$EWCRSPRET_t$	Equal-weighted average of CRSP index returns for month *t*.
$VWCRSPRET_t$	Value-weighted average of CRSP index returns for month *t*.
$EWDISP_t$	Equal-weighted average of forecast dispersion for month *t*.
$CWDISP_t$	Coverage-weighted average of forecast dispersion for month *t*.
$VWDISP_t$	Value-weighted average of forecast dispersion for month *t*.
$EWUNCERT_t$	Natural logarithm of equal-weighted average of uncertainty for month *t*.
$EWASYM_t$	Natural logarithm of equal-weighted average of information asymmetry for month *t*.
$VWUNCERT_t$	Natural logarithm of value-weighted average of uncertainty for month *t*.
$VWASYM_t$	Natural logarithm of value-weighted average of information asymmetry for month *t*.
$EWDISP\_DS_t$	Deseasoned equal-weighted average of forecast dispersion for month *t*, defined as the residuals from the regression $EWDISP_t = \pi_0 + \pi_1 EWDISP_{t-12} + \epsilon_t$.
$CWDISP\_DS_t$	Deseasoned coverage-weighted average of forecast dispersion for month *t*, defined as the residuals from the regression $CWDISP_t = \pi_0 + \pi_1 CWDISP_{t-12} + \epsilon_t$.
$VWDISP\_DS_t$	Deseasoned value-weighted average of forecast dispersion for month *t*, defined as the residuals from the regression $VWDISP_t = \pi_0 + \pi_1 VWDISP_{t-12} + \epsilon_t$.
DY_t	Dividend yield, defined as dividends paid by all CRSP firms over the year prior to month *t*, divided by the current level of CRSP index.
$ESHARE_t$	New equity shares issued in the prior year, divided by total equity and debt issues, as in Baker and Wurgler (2000), available till April 2008.

$TBILL_t$	90-day treasury bill rate in month *t*.
$TERM_t$	Term spread, defined as the yield spread on a 10-year maturity treasury bond and a 3-month maturity treasury bill in month *t*.
YS_t	Yield spread, defined as the difference between the Federal Funds rate and the yield on a 3-month maturity treasury bill in month *t*.
DEF_t	Default spread, defined as the difference in interest rates between Moody's BAA bonds and AAA bonds in month *t*.
$INDPROD_t$	The growth rate of industrial production in the prior year, with rolling window.
GDP_t	GDP growth rate, defined as the latest quarterly GDP growth rate prior to month *t*.
INF_t	Inflation rate, defined as the growth of CPI relative to the same month last year.
VOL_t	The volatility of daily CRSP index returns in month *t*.
EC_t	Value-weighted annual earnings change, I scale individual EPS by price, and then calculate the market-value-weighted average. From April in year *q+1* to March in year *q+2*, I use year *q*'s earnings change.
σEC_t	The cross-sectional standard deviation of price scaled earnings changes, calculated using the latest earnings changes for each individual firm. I update earnings starting from each April 1st.
$TRADE_t$	Value-weighted daily average of trading volume of all individual stocks in CRSP, during month *t*.
VIX_t	CBOE Volatility Index for month *t*, available from January 1986.
$\sigma F_t^{S\&P500}$	Forecast dispersion for S&P 500 Index, defined as the standard deviation of forecasts for S&P 500 Index for fiscal year 1, scaled by level of the index at the beginning of the month *t*.

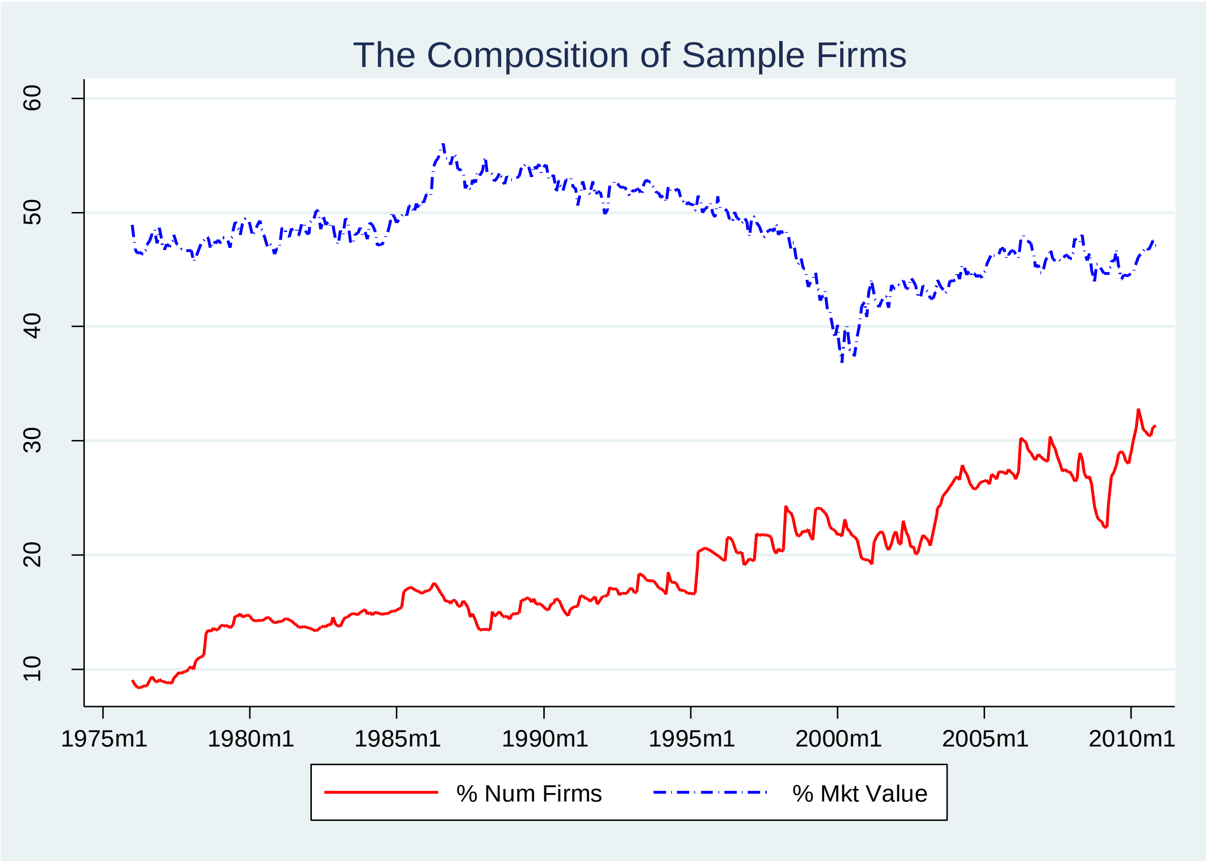

Fig 1a. The Composition of Sample Firms.

This figure shows the composition of my sample. I calculate the ratio of number of firms in my sample to number of firms in CRSP index, and the ratio of total market value of my sample to total market value of CRSP index firms.

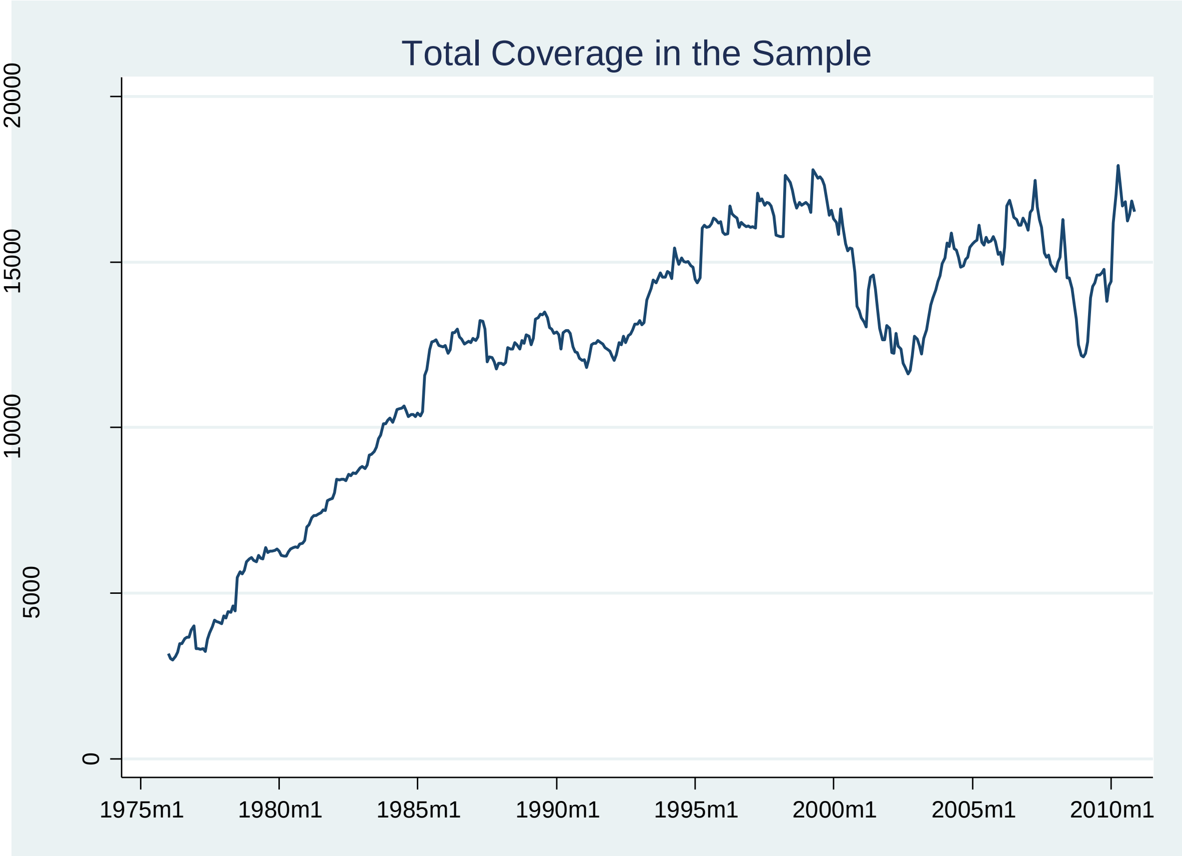

Fig 1b. Total Coverage of the Sample.

This figure shows the time series of total number of forecasts in my sample from 1976 to 2010.

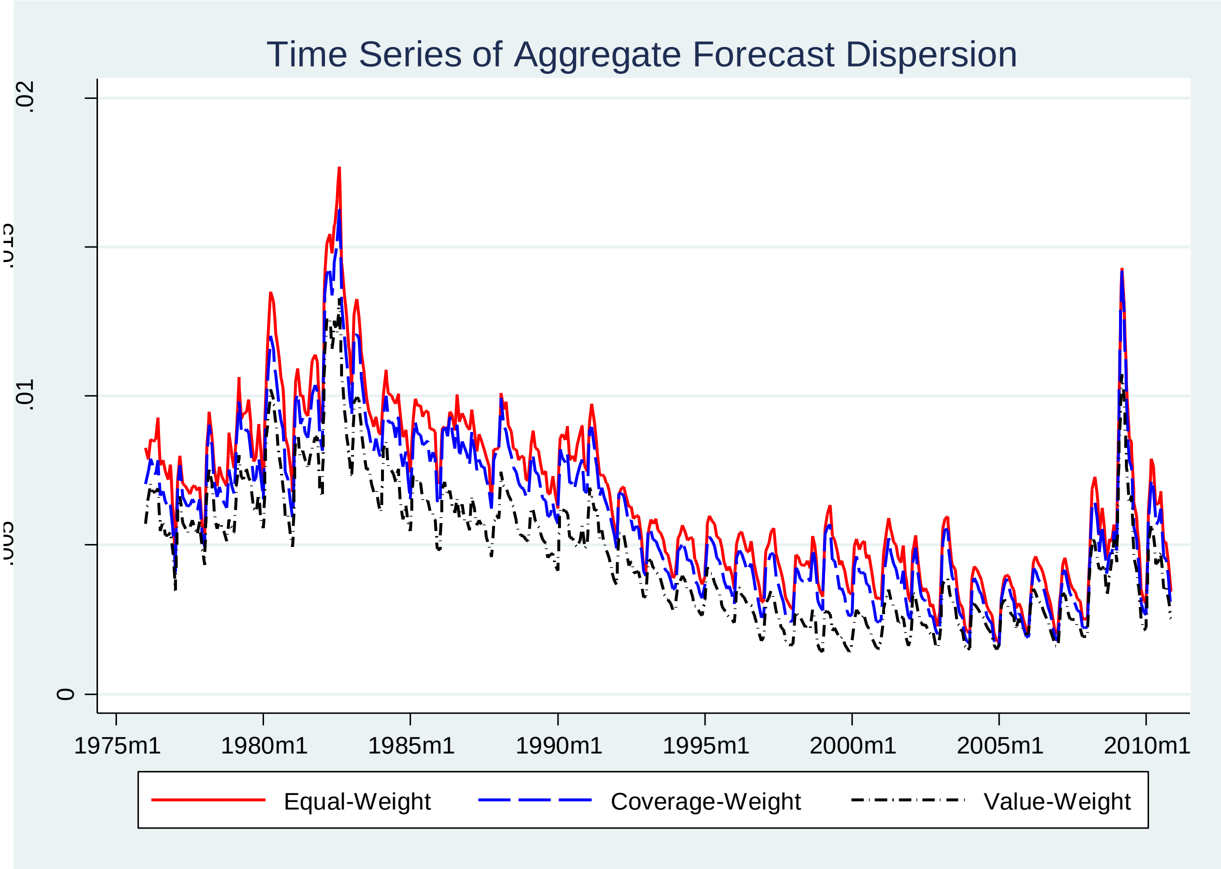

Fig 2a. Time Series of Aggregate Forecast Dispersion

This figure depicts the time series of aggregate forecast dispersion for the period 1976 to 2010. Analyst forecast dispersion for firm *i* in month *t* is defined as the standard deviation of analyst forecasts for firm *i* in month *t*, extracted from I/B/E/S Summary Unadjusted dataset, scaled by the lagged stock price. Aggregating forecast dispersion across firms in month *t* generates the aggregate forecast dispersion measures. Three weighting schemes are employed, equal-weight, coverage-weight (using analyst coverage for firm *i* in month *t* as a weight), and value-weight (using market value of firm *i* at the beginning of month *t* as a weight).

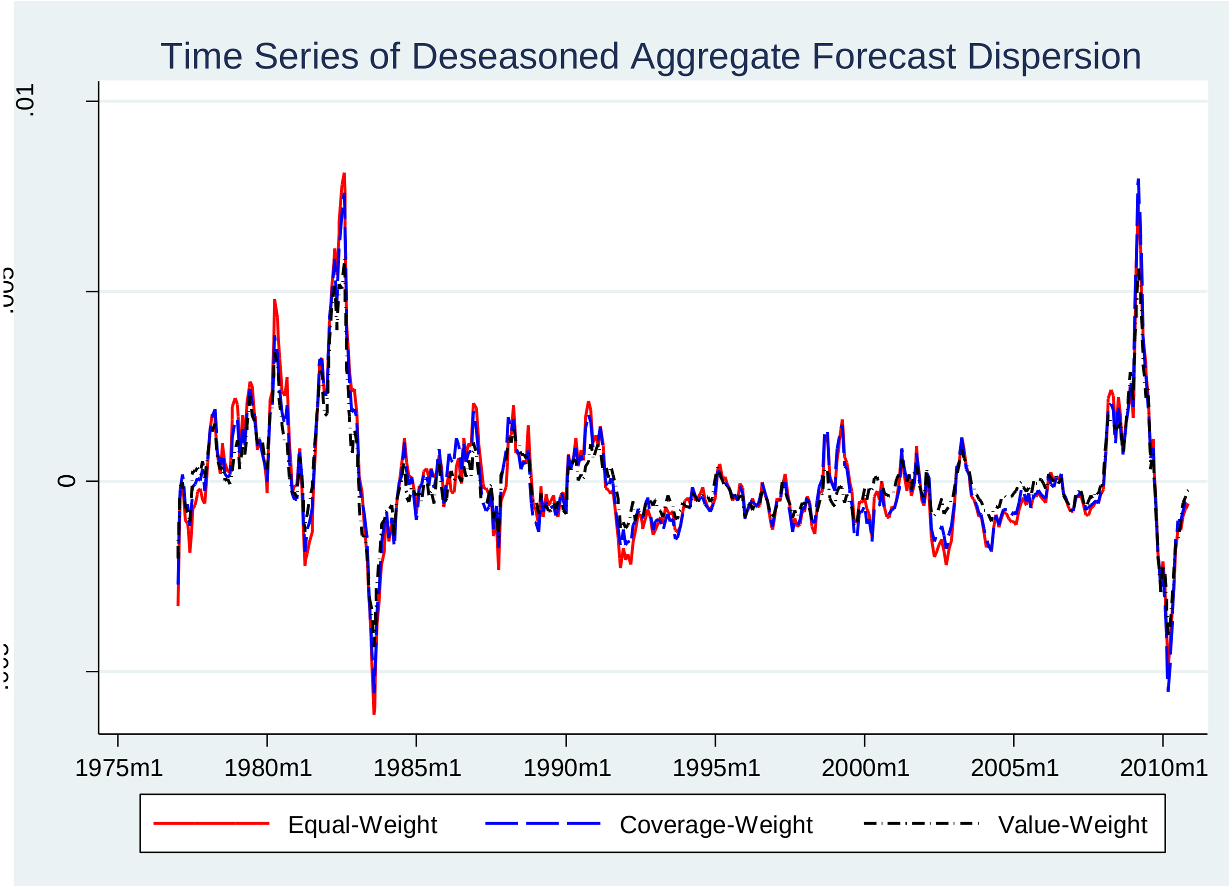

Fig 2b. Time Series of Deseasoned Aggregate Forecast Dispersion

I deseason aggregate forecast dispersion by running a time-series regression for each aggregate forecast dispersion measure: $DISP_t = \pi_0 + \pi_1 DISP_{t-12} + \epsilon_t$, and obtaining the residuals.

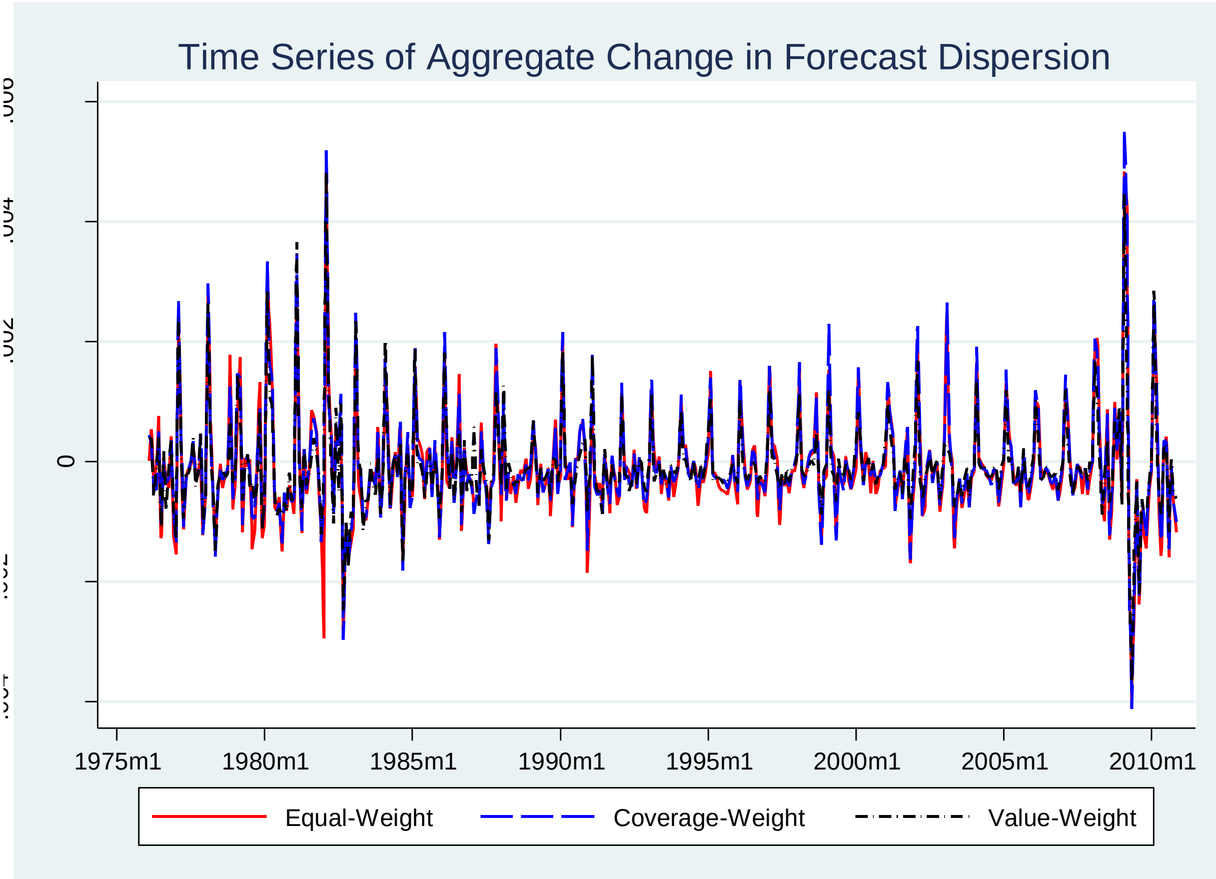

Fig 2c. Time Series of Aggregate Change in Forecast Dispersion

This figure depicts the time series of aggregate change in forecast dispersion for the period 1976 to 2010. Analyst forecast dispersion for firm *i* in month *t* is defined as the standard deviation of analyst forecasts for firm *i* in month *t*, extracted from I/B/E/S summary unadjusted dataset, scaled by the lagged stock price. The change of forecast dispersion for firm *i* in month *t* is obtained by subtracting dispersion in month *t-1* from dispersion in month *t*. Aggregating dispersion changes across firms in month *t* generates the aggregate change in forecast dispersion. Three weighting schemes are employed, equal-weight, coverage-weight (using analyst coverage for firm *i* in month *t* as a weight), and value-weight (using market value of firm *i* at the beginning of month *t* as a weight).

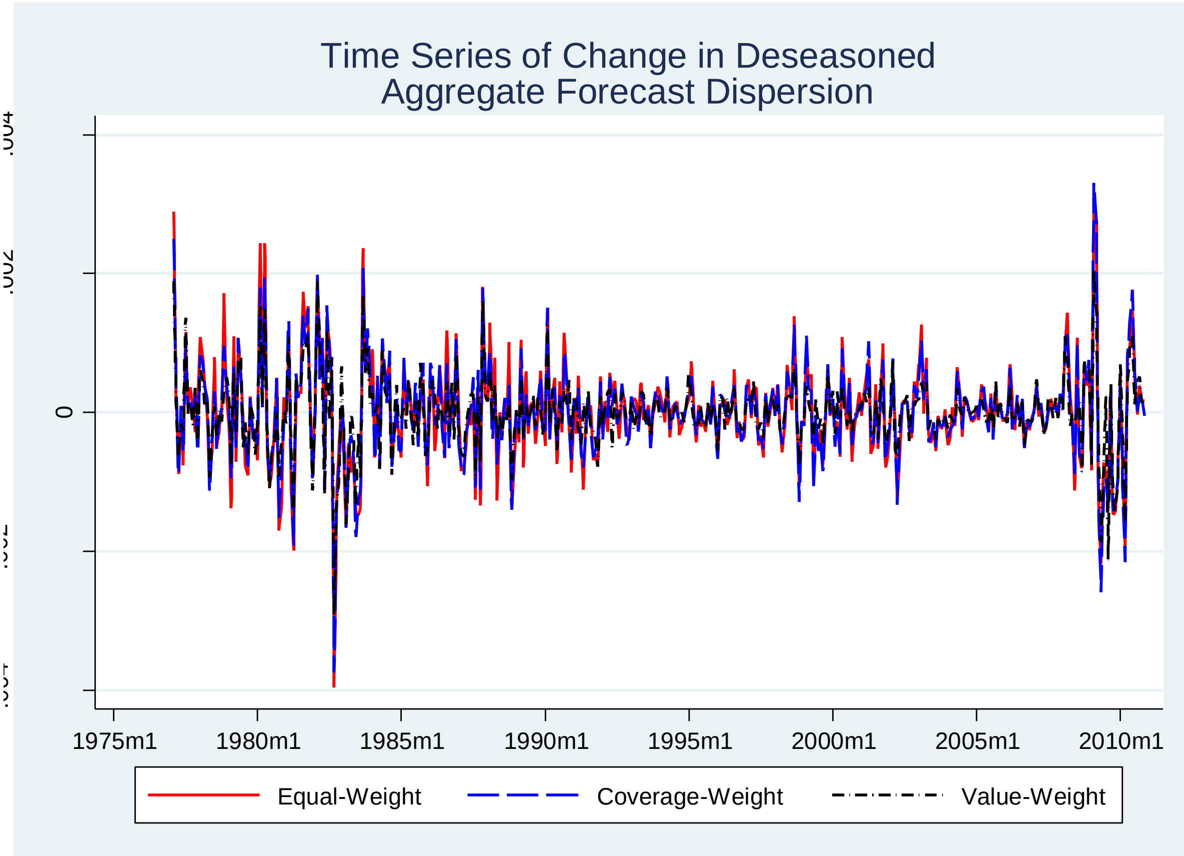

Fig 2d. Time Series of Change in Deseasoned Aggregate Forecast Dispersion

I deseason the aggregate forecast dispersion by running a time-series regression for each aggregate forecast dispersion measure: $DISP_t = \pi_0 + \pi_1 DISP_{t-12} + \epsilon_t$, and obtaining the residuals. Subtracting deseasoned dispersion in month *t-1* from dispersion in month *t*, $\hat{\epsilon}_t - \hat{\epsilon}_{t-1}$, generates monthly change in deseasoned aggregate forecast dispersion.

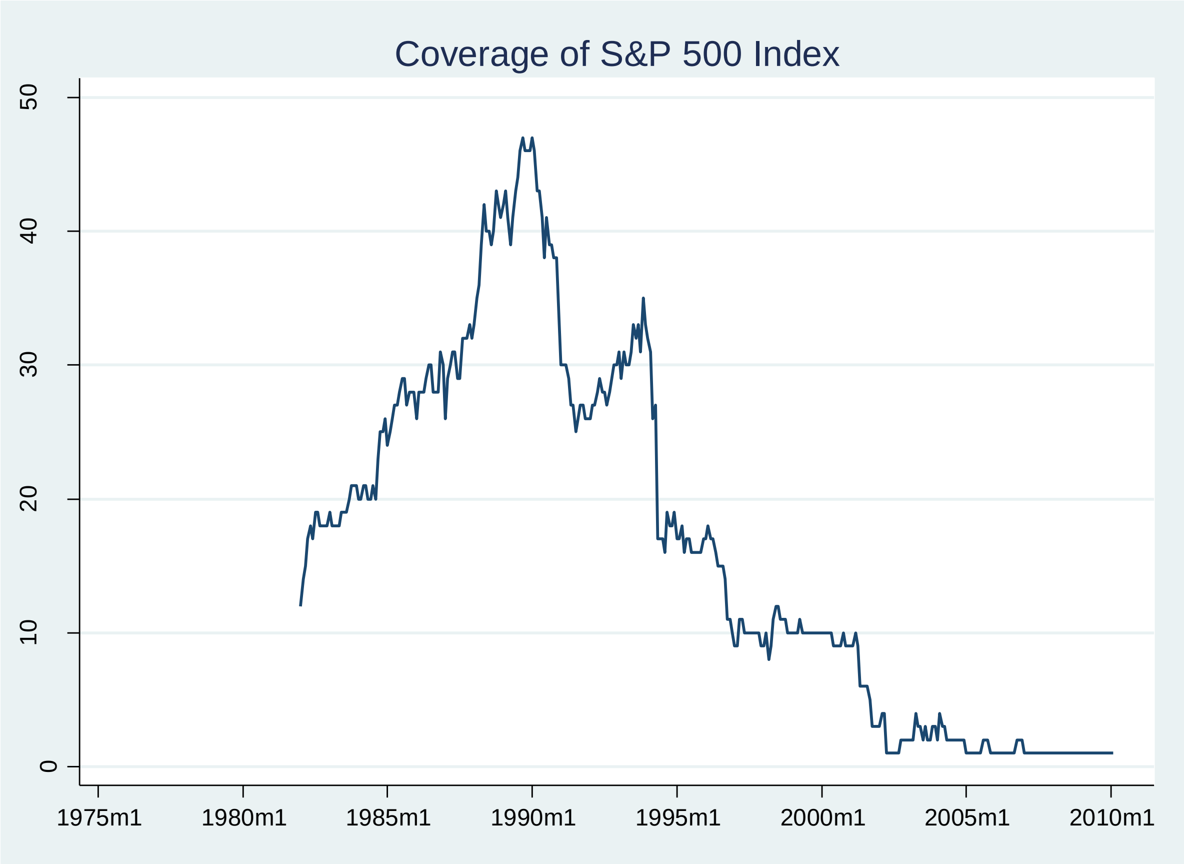

Fig 3. Coverage of S&P 500 Index.

This figure shows number of forecasts for S&P 500 Index for year 1, obtained from I/B/E/S Summary Unadjusted, 1982-2009.

Table I. Descriptive Statistics of Individual Firms and Aggregate Variables

This table reports the descriptive statistics for firms in my sample and the aggregate measures I construct. Panel A reports summary statistics for individual firms while Panel B reports summary statistics for aggregate measures. The sample period spans from January 1976 to November 2010. See the Appendix for variable definitions.

Panel A. Descriptive Statistics for the Firm Sample

	count	mean	sd	p25	p50	p75
R_t	549808	0.013	0.119	-0.047	0.010	0.069
R_{t+1}	549808	0.011	0.120	-0.048	0.009	0.068
$STDEV_t$	549808	0.128	0.167	0.030	0.070	0.160
$DISP_t$	549808	0.006	0.008	0.001	0.003	0.007
$Beta_t$	548766	1.085	0.704	0.618	0.994	1.409
$\log ME_t$	549808	13.54	1.52	12.43	13.42	14.54
$\log BM_t$	549808	-7.52	0.95	-8.03	-7.50	-7.01
$MOM_{t-12,t}$	549576	0.207	0.624	-0.090	0.126	0.376
COV_t	549808	9.44	7.20	4.00	7.00	13.00
VAR_t	549808	0.002	0.007	0.000	0.000	0.001
$UNCERT_t$	515201	0.158	1.186	0.000	0.002	0.013
$InfoAsym_t$	513758	0.018	0.026	0.001	0.007	0.024

Panel B. Descriptive Statistics for Aggregate Variables

	count	mean	sd	p25	p50	p75
$EWSAMPRET_t$	419	0.0138	0.0497	-0.0160	0.0168	0.0453
$VWSAMPRET_t$	419	0.0157	0.0449	-0.0117	0.0188	0.0438
$EWCRSPRET_t$	419	0.0135	0.0557	-0.0176	0.0166	0.0463
$VWCRSPRET_t$	419	0.0100	0.0457	-0.0164	0.0141	0.0400
$EWDISP_t$	419	0.0065	0.0029	0.0042	0.0061	0.0085
$CWDISP_t$	419	0.0059	0.0027	0.0037	0.0056	0.0078
$VWDISP_t$	419	0.0047	0.0024	0.0027	0.0044	0.0062
$EWUNCERT_t$	419	-3.0349	2.0521	-4.6762	-3.7164	-1.1414
$EWASYM_t$	419	-4.1379	0.3562	-4.4084	-4.1118	-3.8517
$VWUNCERT_t$	419	-2.9618	2.3345	-4.8098	-3.6764	-1.0045
$VWASYM_t$	419	-4.5698	0.3787	-4.8217	-4.5406	-4.2969
$EWDISP\_DS_t$	407	-0.0000	0.0017	-0.0008	-0.0003	0.0005
$CWDISP\_DS_t$	407	-0.0000	0.0016	-0.0008	-0.0003	0.0006
$VWDISP\_DS_t$	407	0.0000	0.0013	-0.0006	-0.0003	0.0004
$\Delta EWDISP_t$	418	-0.0001	0.0009	-0.0005	-0.0002	0.0001
$\Delta CWDISP_t$	418	-0.0001	0.0009	-0.0005	-0.0002	0.0001
$\Delta VWDISP_t$	418	-0.0001	0.0008	-0.0004	-0.0002	0.0000
$\Delta EWDISP\_DS_t$	406	0.0000	0.0007	-0.0004	-0.0000	0.0004
$\Delta CWDISP\_DS_t$	406	0.0000	0.0007	-0.0003	-0.0000	0.0003
$\Delta VWDISP\_DS_t$	406	0.0000	0.0006	-0.0002	0.0000	0.0002
DY_t	419	0.0649	0.0186	0.0504	0.0636	0.0774
$ESHARE_t$	388	0.1632	0.0901	0.0966	0.1467	0.2041
$TBILL_t$	419	5.4786	3.2777	3.3600	5.0900	7.2400
$TERM_t$	419	1.7672	1.3093	0.7500	1.9100	2.8000
YS_t	419	-0.5507	0.6457	-0.8200	-0.3800	-0.1200
DEF_t	419	1.1133	0.4833	0.7800	0.9600	1.2900
$INDPROD_t$	419	2.3764	4.4586	0.5000	2.8000	5.3000
GDP_t	419	6.5024	4.1418	4.5000	6.0000	8.4000
INF_t	419	4.1258	2.8998	2.5000	3.3000	4.8000
VOL_t	419	0.0090	0.0056	0.0057	0.0074	0.0101
EC_t	419	0.0060	0.0148	0.0015	0.0085	0.0156
σEC_t	419	0.0719	0.0411	0.0522	0.0628	0.0810
$TRADE_t$	419	5.4716	3.9925	2.8994	4.0760	6.7298
VIX_t	251	20.4305	8.0094	14.4200	19.2600	24.2500
$\sigma F_t^{S\&P500}$	274	0.0028	0.0013	0.0019	0.0026	0.0035

Table II. Correlation Matrix for Aggregate Returns and Forecast Dispersions

This table reports the Pearson (above the diagonal) and Spearman (below the diagonal) correlations between aggregate returns and forecast dispersions. Panel A reports the correlations between forwarded returns and forecast dispersions, while Panel B reports the correlations between contemporaneous returns and forecast dispersions. See the Appendix for detailed variable definitions.

Panel A. Correlation between forwarded returns and forecast dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)$EWSAMPRET_{t+1}$		0.930	0.905	0.940	0.102	0.102	0.088	0.060	0.075	0.070
		(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.07)	(0.22)	(0.13)	(0.16)
(2)$VWSAMPRET_{t+1}$	0.948		0.788	0.975	0.088	0.090	0.079	0.075	0.083	0.070
	(0.00)		(0.00)	(0.00)	(0.07)	(0.06)	(0.11)	(0.13)	(0.09)	(0.15)
(3)$EWCRSPRET_{t+1}$	0.910	0.815		0.838	0.091	0.092	0.086	-0.034	-0.007	-0.002
	(0.00)	(0.00)		(0.00)	(0.06)	(0.06)	(0.08)	(0.48)	(0.89)	(0.96)
(4)$VWCRSPRET_{t+1}$	0.948	0.981	0.855		0.093	0.094	0.077	0.056	0.067	0.061
	(0.00)	(0.00)	(0.00)		(0.06)	(0.06)	(0.12)	(0.25)	(0.17)	(0.22)
(5)$EWDISP_t$	0.133	0.124	0.117	0.131		0.995	0.970	0.078	0.042	-0.010
	(0.01)	(0.01)	(0.02)	(0.01)		(0.00)	(0.00)	(0.11)	(0.39)	(0.83)
(6)$CWDISP_t$	0.135	0.127	0.119	0.132	0.996		0.980	0.093	0.061	0.010
	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)		(0.00)	(0.06)	(0.21)	(0.84)
(7)$VWDISP_t$	0.117	0.107	0.107	0.112	0.979	0.985		0.090	0.060	0.014
	(0.02)	(0.03)	(0.03)	(0.02)	(0.00)	(0.00)		(0.07)	(0.22)	(0.78)
(8)$\Delta EWDISP_t$	0.069	0.071	0.012	0.049	0.128	0.157	0.163		0.959	0.882
	(0.16)	(0.15)	(0.81)	(0.31)	(0.01)	(0.00)	(0.00)		(0.00)	(0.00)
(9)$\Delta CWDISP_t$	0.075	0.075	0.029	0.055	0.109	0.142	0.151	0.981		0.936
	(0.13)	(0.13)	(0.56)	(0.27)	(0.03)	(0.00)	(0.00)	(0.00)		(0.00)
(10)$\Delta VWDISP_t$	0.060	0.051	0.023	0.036	0.081	0.115	0.134	0.923	0.956	
	(0.22)	(0.30)	(0.64)	(0.47)	(0.10)	(0.02)	(0.01)	(0.00)	(0.00)	

Panel B. Correlation between contemporaneous returns and forecast dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)$EWSAMPRET_t$		0.939	0.905	0.940	0.102	0.094	0.074	-0.068	-0.067	-0.051
		(0.00)	(0.00)	(0.00)	(0.04)	(0.06)	(0.13)	(0.17)	(0.17)	(0.30)
(2)$VWSAMPRET_t$	0.950		0.799	0.978	0.088	0.079	0.055	-0.027	-0.023	-0.016
	(0.00)		(0.00)	(0.00)	(0.07)	(0.11)	(0.26)	(0.59)	(0.64)	(0.74)
(3)$EWCRSPRET_t$	0.910	0.819		0.839	0.091	0.088	0.083	-0.156	-0.141	-0.112
	(0.00)	(0.00)		(0.00)	(0.06)	(0.07)	(0.09)	(0.00)	(0.00)	(0.02)
(4)$VWCRSPRET_t$	0.947	0.977	0.857		0.108	0.100	0.077	-0.044	-0.039	-0.022
	(0.00)	(0.00)	(0.00)		(0.03)	(0.04)	(0.12)	(0.37)	(0.43)	(0.65)
(5)$EWDISP_t$	0.126	0.118	0.103	0.134		0.995	0.970	0.078	0.042	-0.010
	(0.01)	(0.02)	(0.03)	(0.01)		(0.00)	(0.00)	(0.11)	(0.39)	(0.83)
(6)$CWDISP_t$	0.121	0.113	0.102	0.128	0.996		0.980	0.093	0.061	0.010
	(0.01)	(0.02)	(0.04)	(0.01)	(0.00)		(0.00)	(0.06)	(0.21)	(0.84)
(7)$VWDISP_t$	0.101	0.088	0.093	0.107	0.979	0.985		0.090	0.060	0.014
	(0.04)	(0.07)	(0.06)	(0.03)	(0.00)	(0.00)		(0.07)	(0.22)	(0.78)
(8)$\Delta EWDISP_t$	-0.106	-0.090	-0.166	-0.103	0.128	0.157	0.163		0.959	0.882
	(0.03)	(0.07)	(0.00)	(0.04)	(0.01)	(0.00)	(0.00)		(0.00)	(0.00)
(9)$\Delta CWDISP_t$	-0.103	-0.085	-0.147	-0.096	0.109	0.142	0.151	0.981		0.936
	(0.04)	(0.08)	(0.00)	(0.05)	(0.03)	(0.00)	(0.00)	(0.00)		(0.00)
(10)$\Delta VWDISP_t$	-0.094	-0.083	-0.135	-0.091	0.081	0.115	0.134	0.923	0.956	
	(0.05)	(0.09)	(0.01)	(0.06)	(0.10)	(0.02)	(0.01)	(0.00)	(0.00)	

Table III. Fama-MacBeth Regressions: Individual Stock Returns and Forecast Dispersion

Fama-MacBeth cross-sectional regressions are run every month from January 1976 to November 2010.

$$R_{t+1} = \alpha + \theta_1 Beta_t + \theta_2 \log ME_t + \theta_3 \log BM_t + \theta_4 MOM_{t-12,t} + \theta_5 COV_t + \lambda_1 DISP_t + \lambda_2 STDEV_t + \lambda_3 MeanEst_t + \varepsilon_{t+1}$$

$STDEV_t$ is the standard deviation of analyst forecasts for current fiscal year in month t. $DISP_t$ is analyst forecast dispersion in month *t*, defined as $STDEV_t/P_{t-1}$. $Beta_t$ is the market beta, estimated from regressing firm stock returns on value-weighted market returns for the period from month *t-60* to month *t-1*. $\log ME_t$ is logarithm of market value at the end of month t. $\log BM_t$ is logarithm of book-to-market ratio, calculated as the ratio of book value of equity to market value of equity at the end of month *t*. Book value of equity is obtained from the closest annual financial report. For example, year 2000's book value of equity is used in the period from April 2001 to March 2002. $MOM_{t-12,t}$ is the cumulative returns from month *t-12* to month t. COV_t is analyst coverage, the number of outstanding forecasts in moth *t*, extracted from I/B/E/S Summary Unadjusted database. * indicates 10% significance, ** 5%, and *** 1%.

	(1)	(2)	(3)
Constant	0.036***	0.040***	0.044***
	(5.90)	(7.36)	(8.02)
$Beta_t$	0.001	0.001	0.001
	(0.55)	(0.39)	(0.36)
$\log ME_t$	-0.001***	-0.001***	-0.001***
	(-2.61)	(-2.66)	(-3.32)
$\log BM_t$	0.001**	0.002***	0.002***
	(2.09)	(3.83)	(3.75)
$MOM_{t-12,t}$		0.005***	0.005***
		(3.14)	(3.26)
COV_t			0.000*
			(1.77)
$DISP_t$	**-0.198*** **	**-0.172*** **	**-0.174*** **
	(-3.45)	**(-3.10)**	**(-3.17)**
Avg R^2	0.059	0.071	0.073
N	548766	548766	548766

Table IV. Univariate Regressions of One-Month-Ahead Aggregate Returns on Forecast Dispersion, 1976-2010.

This table reports the univariate predictive regression of one-month-ahead aggregate returns on forecast dispersions. Specifically, I run the following regression:

$$R_{t+1} = \alpha + \beta DISP_t + \varepsilon_{t+1}$$

The dependent variable is equal-weighted (value-weighted) average of sample returns (CRSP index returns), and the independent variable in equal-weighted, value-weighted, and coverage-weighted forecast dispersion for year 1 in month *t*. Two sets of dispersion measures are used, Panel A applies the raw dispersion measures, and Panel B applies the deseasoned dispersion measures, which are residuals from the time-series regression $DISP_t = \pi_0 + \pi_1 DISP_{t-12} + \epsilon_t$. I correct the infinite sample bias utilizing Lewellen (2009). Specifically, I run the AR(1) time series regressions for forecast dispersions, $DISP_t = \phi + \rho DISP_{t-1} + \mu_t$, and assume the true parameter $\rho \approx 1$. A1 and B1 report the OLS estimates, A2 and B2 report the AR(1) estimates, and A3 and B3 report the infinite-sample-bias adjusted coefficients. *t*-values are based on Huber-White heteroskedasticity consistent standard errors.

Panel A. Predictive Regressions of Aggregate Returns on Raw Dispersions

A1. OLS estimation of univariate predictive regressions.

	EWDISP			*VWDISP*			*CWDISP*		
	β	$t(\beta)$	$AdjR^2$	β	$t(\beta)$	$AdjR^2$	β	$t(\beta)$	$AdjR^2$
EWSAMPRET	2.383	2.762	0.016	2.512	2.377	0.011	2.514	2.754	0.016
EWCRSPRET	2.323	2.396	0.012	2.547	2.099	0.009	2.452	2.353	0.012
VWSAMPRET	2.016	2.558	0.014	2.089	2.168	0.009	2.141	2.580	0.014
VWCRSPRET	2.131	2.723	0.015	2.191	2.258	0.010	2.234	2.703	0.015

A2. AR(1) time series regression of dispersions.

$DISP_t = \phi + \rho DISP_{t-1} + \mu_t$							
	ρ	$t(\rho)$	Bias	$-(1+3\rho)/T$	$AdjR^2$	$\sigma(\mu)$	$\sqrt{(DISP'DISP)^{-1}}$
EWDISP	0.948	60.513	-0.0612	-0.0092	0.898	0.000901	17.364
VWDISP	0.948	60.362	-0.0612	-0.0092	0.897	0.000745	21.055
CWDISP	0.943	57.292	-0.0662	-0.0092	0.887	0.000903	18.204

A3. Finite-sample-bias adjusted coefficients.

	EWDISP				*VWDISP*				*CWDISP*			
	β_{adj}	$t(\beta_{adj})$	γ	σ_v	β_{adj}	$t(\beta_{adj})$	γ	σ_v	β_{adj}	$t(\beta_{adj})$	γ	σ_v
EWSAMPRET	2.59	3.04	3.30	0.05	2.70	2.57	3.12	0.05	2.72	3.05	3.09	0.05
EWCRSPRET	2.41	2.53	1.44	0.06	2.63	2.27	1.40	0.06	2.55	2.55	1.50	0.06
VWSAMPRET	2.19	2.80	2.81	0.05	2.23	2.35	2.28	0.05	2.31	2.82	2.61	0.05
VWCRSPRET	2.25	2.87	1.87	0.05	2.27	2.40	1.27	0.05	2.35	2.87	1.71	0.05

Panel B. Predictive Regressions of Aggregate Returns on Deseasoned Dispersions

B1. OLS estimation of univariate predictive regressions.

	EWDISP_DS			*VWDISP_DS*			*CWDISP_DS*		
	β	$t(\beta)$	$AdjR^2$	β	$t(\beta)$	$AdjR^2$	β	$t(\beta)$	$AdjR^2$
EWSAMPRET	5.288	3.045	0.027	5.600	2.330	0.017	5.382	2.881	0.025
EWCRSPRET	6.283	3.357	0.032	6.906	2.684	0.021	6.447	3.190	0.030
VWSAMPRET	4.218	2.693	0.021	4.081	1.901	0.010	4.243	2.536	0.019
VWCRSPRET	4.677	3.109	0.025	4.460	2.157	0.012	4.678	2.921	0.022

B2. AR(1) time series regression of deseasoned dispersions.

$DISP\_DS_t = \phi + \rho DISP\_DS_{t-1} + \mu_t$							
	ρ	$t(\rho)$	Bias	$-(1+3\rho)/T$	$AdjR^2$	$\sigma(\mu)$	$\sqrt{(DISP'DISP)^{-1}}$
EWDISP_DS	0.894	41.025	-0.1148	-0.0088	0.806	0.000715	30.464
VWDISP_DS	0.901	42.399	-0.1079	-0.0089	0.816	0.000532	39.951
CWDISP_DS	0.896	41.406	-0.1128	-0.0088	0.809	0.000674	32.120

B3. Finite-sample-bias adjusted coefficients.

	EWDISP_DS				*VWDISP_DS*				*CWDISP_DS*			
	β_{adj}	$t(\beta_{adj})$	γ	σ_v	β_{adj}	$t(\beta_{adj})$	γ	σ_v	β_{adj}	$t(\beta_{adj})$	γ	σ_v
EWSAMPRET	4.97	3.29	-2.79	0.05	5.23	2.62	-3.43	0.05	5.17	3.24	-1.84	0.05
EWCRSPRET	5.70	3.43	-5.12	0.06	6.13	2.80	-7.18	0.06	5.89	3.36	-4.90	0.06
VWSAMPRET	4.00	2.93	-1.94	0.05	3.83	2.13	-2.36	0.05	4.14	2.87	-0.96	0.05
VWCRSPRET	4.35	3.15	-2.84	0.05	4.06	2.23	-3.69	0.05	4.45	3.05	-2.03	0.05

Table V. Multivariate Predictive Regressions of Returns on Forecast Dispersions, Controlling for Macroeconomic Conditions

This table reports multivariate regressions of one-month-ahead aggregate returns on forecast dispersions, controlling for macroeconomic conditions. Specifically, the following regression is estimated using raw dispersion measures (Panel A) and deseasoned dispersion measures (Panel B):

$$R_{t+1} = \alpha + \beta DISP_t + \gamma_1 DY_t + \gamma_2 EC_t + \gamma_3 TBILL_t + \gamma_4 TERM_t + \gamma_5 YS_t + \gamma_6 DEF_t + \gamma_7 INDPROD_t + \gamma_8 GDP + \gamma_9 INF_t + \gamma_{10} ESHARE_t + \varepsilon_{t+1}$$

Dependent variable is equal-weighted (value-weighted) average of sample returns (CRSP index returns), and the variable of interest, $DISP$, is equal-weighted (value-weighted) average of individual forecast dispersion when the dependent variable is equal-weighted (value-weighted) returns. See the Appendix for other variable definitions. *t*-values are reported in parentheses and based on Huber-White heteroskedasticity consistent standard errors.

Panel A. Raw Dispersion

	α	β_{EW}	β_{VW}	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	γ_9	γ_{10}	$Adj\ R^2$
$EWSAMPRET_{t+1}$	0.017	**7.397**		-0.123	0.320	-0.004	-0.004	-0.006	-0.015	-0.001	0.001	-0.003		0.034
	(1.27)	**(3.73)**		(-0.66)	(1.63)	(-2.08)	(-1.17)	(-1.00)	(-1.49)	(-1.18)	(1.88)	(-1.74)		
$EWSAMPRET_{t+1}$	0.005	**5.788**		-0.021	0.520	-0.004	-0.003	-0.002	0.004	0.000	0.001	-0.002	-0.025	0.027
	(0.37)	**(3.31)**		(-0.12)	(2.20)	(-2.09)	(-0.91)	(-0.42)	(0.36)	(-0.43)	(1.22)	(-1.04)	(-0.47)	
$EWCRSPRET_{t+1}$	0.026	**7.752**		-0.340	0.316	-0.005	-0.005	-0.002	-0.005	-0.001	0.002	-0.002		0.043
	(2.00)	**(3.59)**		(-1.52)	(1.52)	(-2.46)	(-1.63)	(-0.32)	(-0.54)	(-1.75)	(2.11)	(-1.10)		
$EWCRSPRET_{t+1}$	0.014	**5.678**		-0.152	0.514	-0.007	-0.005	0.002	0.013	-0.001	0.001	0.000	0.009	0.043
	(1.04)	**(2.85)**		(-0.66)	(1.97)	(-2.89)	(-1.42)	(0.28)	(1.16)	(-1.03)	(1.56)	(-0.08)	(0.15)	
$VWSAMPRET_{t+1}$	0.018		**7.051**	-0.016	0.243	-0.002	-0.003	-0.006	-0.017	-0.001	0.001	-0.004		0.024
	(1.52)		**(3.31)**	(-0.10)	(1.41)	(-1.16)	(-0.99)	(-1.04)	(-1.78)	(-0.94)	(1.41)	(-2.36)		
$VWSAMPRET_{t+1}$	0.005		**4.964**	0.060	0.414	-0.002	-0.002	-0.003	0.001	0.000	0.001	-0.002	-0.036	0.010
	(0.41)		**(2.35)**	(0.36)	(1.90)	(-1.01)	(-0.53)	(-0.46)	(0.12)	(-0.17)	(0.86)	(-1.57)	(-0.76)	
$VWCRSPRET_{t+1}$	0.017		**7.034**	-0.034	0.231	-0.002	-0.003	-0.007	-0.015	-0.001	0.001	-0.003		0.021
	(1.47)		**(3.32)**	(-0.19)	(1.34)	(-1.37)	(-0.99)	(-1.21)	(-1.62)	(-0.84)	(1.40)	(-2.16)		
$VWCRSPRET_{t+1}$	0.004		**5.243**	0.047	0.386	-0.003	-0.002	-0.003	0.004	0.000	0.001	-0.002	-0.040	0.011
	(0.33)		**(2.45)**	(0.26)	(1.74)	(-1.25)	(-0.61)	(-0.61)	(0.41)	(-0.02)	(0.89)	(-1.36)	(-0.82)	

Panel B. Deseasoned Dispersion

	α	β_{EW}	β_{VW}	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	γ_8	γ_9	γ_{10}	$Adj\ R^2$
$EWSAMPRET_{t+1}$	0.026	**8.722**		-0.179	0.111	0.001	0.003	-0.006	-0.011	-0.001	0.002	-0.003		0.033
	(1.93)	**(3.61)**		(-0.91)	(0.54)	(0.42)	(0.97)	(-0.91)	(-0.97)	(-0.82)	(2.52)	(-1.91)		
$EWSAMPRET_{t+1}$	0.013	**6.783**		-0.070	0.367	-0.001	0.001	-0.001	0.005	-0.001	0.001	-0.002	-0.011	0.029
	(0.90)	**(2.87)**		(-0.37)	(1.49)	(-0.30)	(0.50)	(-0.25)	(0.41)	(-0.59)	(1.95)	(-1.37)	(-0.20)	
$EWCRSPRET_{t+1}$	0.037	**9.577**		-0.406	0.077	0.000	0.001	-0.002	-0.001	-0.001	0.002	-0.003		0.044
	(2.68)	**(3.85)**		(-1.74)	(0.36)	(-0.04)	(0.31)	(-0.24)	(-0.10)	(-1.21)	(2.72)	(-1.34)		
$EWCRSPRET_{t+1}$	0.024	**7.213**		-0.215	0.339	-0.003	-0.001	0.003	0.014	-0.001	0.002	-0.001	0.022	0.045
	(1.59)	**(3.09)**		(-0.91)	(1.31)	(-1.33)	(-0.29)	(0.47)	(1.11)	(-1.01)	(2.19)	(-0.48)	(0.35)	
$VWSAMPRET_{t+1}$	0.019		**7.693**	-0.077	0.122	0.001	0.002	-0.005	-0.010	-0.001	0.001	-0.004		0.014
	(1.56)		**(2.69)**	(-0.44)	(0.65)	(0.92)	(0.84)	(-0.78)	(-1.01)	(-0.68)	(2.03)	(-2.23)		
$VWSAMPRET_{t+1}$	0.006		**5.890**	-0.003	0.375	0.001	0.001	-0.001	0.005	0.000	0.001	-0.003	-0.025	0.006
	(0.45)		**(1.83)**	(-0.02)	(1.63)	(0.32)	(0.50)	(-0.11)	(0.48)	(-0.22)	(1.42)	(-1.62)	(-0.51)	
$VWCRSPRET_{t+1}$	0.018		**7.930**	-0.095	0.112	0.001	0.002	-0.006	-0.009	-0.001	0.001	-0.004		0.013
	(1.55)		**(2.86)**	(-0.52)	(0.60)	(0.71)	(0.82)	(-0.97)	(-0.92)	(-0.61)	(2.01)	(-2.10)		
$VWCRSPRET_{t+1}$	0.005		**6.122**	-0.017	0.347	0.000	0.001	-0.002	0.008	0.000	0.001	-0.002	-0.029	0.007
	(0.38)		**(1.96)**	(-0.09)	(1.49)	(0.09)	(0.43)	(-0.27)	(0.71)	(-0.10)	(1.44)	(-1.45)	(-0.57)	

Table VI. Multivariate Predictive Regressions of Returns on Forecast Dispersions: Controlling for Market Volatility

This table reports the predictive regressions of one-month-ahead aggregate returns on forecast dispersions, controlling for other measures of market volatility. Specifically,

$$R_{t+1} = \alpha + \beta DISP_t + \theta_1 VOL_t + \theta_2 \cdot \sigma(EC_t) + \theta_3 VIX_t + \theta_4 TRADE_t + \gamma_1 DY_t + \gamma_2 EC_t + \gamma_3 TBILL_t + \gamma_4 TERM_t + \gamma_5 YS_t + \gamma_6 DEF_t + \gamma_7 INDPROD_t + \gamma_8 GDP + \gamma_9 INF_t + \varepsilon_{t+1}$$

Where R_{t+1} is either sample returns or CRSP index returns, $DISP_t$ is equal-weighted (value-weighted) raw dispersions or deseasoned dispersions when the dependent variable is equal-weighted (value-weighted). VOL_t is the volatility of CRSP index returns during month *t*. $\sigma(EC_t)$ is the cross-sectional dispersion of latest earnings changes. VIX_t is CBOE implied volatility index. $TRADE_t$ is the value-weighted daily average of trading volume of individual stocks in CRSP, during month *t*. See the Appendix for other variable definitions. *t*-values are reported in parentheses and based on Huber-White heteroskedasticity consistent standard errors.

Panel A. Sample Returns as Dependent Variables

	Raw Dispersion							Deseasoned Dispersion						
	β_{EW}	β_{VW}	θ_1	θ_2	θ_3	θ_4	$Adj\ R^2$	β_{EW}	β_{VW}	θ_1	θ_2	θ_3	θ_4	$Adj\ R^2$
$EWSAMPRET_{t+1}$	**7.290**		-0.753				0.044	**9.113**		-0.863				0.046
	(3.45)		(-0.87)					**(3.72)**		(-0.99)				
$EWSAMPRET_{t+1}$	**8.232**			-0.104			0.045	**9.756**			0.023			0.041
	(3.94)			(-1.20)				**(3.72)**			(0.29)			
$EWSAMPRET_{t+1}$	**7.746**				0.001		0.034	**15.322**				0.001		0.056
	(2.18)				(0.77)			**(2.91)**				(0.61)		
$EWSAMPRET_{t+1}$	**6.757**					**-0.004**	0.068	**8.459**					**-0.004**	0.069
	(3.08)					**(-2.74)**		**(3.41)**					**(-2.75)**	
$EWSAMPRET_{t+1}$	**9.516**		-1.561	-0.088	0.002	**-0.004**	0.060	**14.658**		-1.317	0.080	0.001	-0.003	0.067
	(3.09)		(-1.02)	(-0.92)	(1.18)	**(-1.91)**		**(2.54)**		(-0.60)	(0.87)	(0.93)	(-1.32)	
$VWSAMPRET_{t+1}$		**6.343**	-0.780				0.024		**7.528**	**-1.077**				0.021
		(3.01)	(-1.17)						**(2.76)**	**(-1.70)**				
$VWSAMPRET_{t+1}$		**7.245**		-0.042			0.020		**8.486**		0.049			0.013
		(3.50)		(-0.54)					**(2.89)**		(0.67)			
$VWSAMPRET_{t+1}$		**11.203**			0.001		0.062		**16.851**			0.000		0.058
		(3.29)			(1.51)				**(3.33)**			(0.63)		
$VWSAMPRET_{t+1}$		**7.127**				**-0.004**	0.062		**7.331**				**-0.003**	0.028
		(2.73)				**(-3.07)**			**(2.68)**				**(-2.12)**	
$VWSAMPRET_{t+1}$		**13.165**	**-2.582**	-0.095	**0.003**	-0.001	0.094		**17.167**	**-3.127**	0.068	**0.003**	0.000	0.083
		(4.03)	**(-1.85)**	(-1.05)	**(2.51)**	(-0.88)			**(3.22)**	**(-2.07)**	(0.87)	**(2.23)**	(0.23)	

Panel B. CRSP Returns as Dependent Variables

	Raw Dispersion							*Deseasoned Dispersion*						
	β_{EW}	β_{VW}	γ_1	γ_2	γ_3	γ_4	$Adj\ R^2$	β_{EW}	β_{VW}	γ_1	γ_2	γ_3	γ_4	$Adj\ R^2$
$EWCRSPRET_{t+1}$	**7.099**		-0.487				0.033	**8.386**		-0.627				0.033
	(3.62)		(-0.63)					**(3.50)**		(-0.82)				
$EWCRSPRET_{t+1}$	**7.607**			-0.046			0.033	**9.294**			0.073			0.033
	(3.99)			(-0.52)				**(3.62)**			(0.89)			
$EWCRSPRET_{t+1}$	**9.004**				0.001		0.030	**15.450**				0.001		0.046
	(2.77)				(0.99)			**(3.21)**				(0.73)		
$EWCRSPRET_{t+1}$	**6.862**					-0.002	0.042	**8.110**					-0.002	0.040
	(3.39)					(-1.53)		**(3.34)**					(-1.56)	
$EWCRSPRET_{t+1}$	**10.129**		-1.754	-0.082	0.002	-0.002	0.044	**15.175**		-1.526	0.096	0.002	-0.001	0.050
	(3.64)		(-1.27)	(-0.94)	(1.53)	(-1.06)		**(2.87)**		(-0.82)	(1.06)	(1.26)	(-0.52)	
$VWCRSPRET_{t+1}$		**6.412**	-0.721				0.026		**7.306**	**-1.038**				0.021
		(3.01)	(-1.09)						**(2.59)**	**(-1.66)**				
$VWCRSPRET_{t+1}$		**7.126**		-0.015			0.021		**8.545**		0.075			0.015
		(3.40)		(-0.19)					**(2.80)**		(1.02)			
$VWCRSPRET_{t+1}$		**11.885**			0.001		0.068		**17.094**			0.000		0.059
		(3.43)			(1.43)				**(3.25)**			(0.46)		
$VWCRSPRET_{t+1}$		**6.832**				-0.002	0.032		**7.237**				-0.002	0.022
		(3.21)				(-1.63)			**(2.55)**				(-1.59)	
$VWCRSPRET_{t+1}$		**13.438**	**-2.437**	-0.085	**0.003**	-0.001	0.092		**17.862**	**-2.989**	0.083	**0.002**	0.001	0.082
		(4.01)	**(-1.83)**	(-0.93)	**(2.42)**	(-0.63)			**(3.23)**	**(-2.04)**	(1.06)	**(2.13)**	(0.53)	

Table VII. Predicting Aggregate Returns: Aggregate Forecast Dispersion and SPX Dispersion

In panel A, I regress aggregate forecast dispersion on the forecast dispersion for S&P 500 Index, and obtain the residuals, $\hat{\delta}_t$. I/B/E/S analysts make forecasts for the S&P 500 Index (ticker: SPX), and the forecast dispersion for SPX is collected from I/B/E/S Summary Unadjusted dataset. $\sigma F_t^{S\&P500}$ is defined as the standard deviation of forecasts for SPX for year 1 in month *t*, scaled by the index level at the beginning of month *t*. In panel B, I regress one-month-ahead returns on forecast dispersion of S&P 500 Index, $\sigma F_t^{S\&P500}$, and the residual aggregate dispersion, $\hat{\delta}_t$. *t*-values are based on Huber-White heteroskedasticity consistent standard errors.

Panel A. Regression of Aggregate Dispersion on S&P 500 Index Dispersion

$DISP_t = \alpha + \beta \cdot \sigma F_t^{S\&P500} + \delta_t$

	α	$t(\alpha)$	β	$t(\beta)$	$Adj\ R^2$
EWDISP	0.0027	6.700	**1.294**	7.823	0.354
VWDISP	0.0014	4.151	**1.077**	7.681	0.355
EWDISP_DS	-0.0016	-6.035	**0.508**	4.657	0.192
VWDISP_DS	-0.0012	-6.417	**0.386**	4.718	0.212

Panel B. Predictive Regression Using $\sigma F_t^{S\&P500}$ and $\hat{\delta}_t$ from the First Stage

$R_{t+1} = \alpha + \beta_1 \cdot \hat{\delta}_t + \beta_2 \cdot \sigma F_t^{S\&P500} + \varepsilon_{t+1}$

	α	$t(\alpha)$	β_1^{EW}	$t(\beta_1^{EW})$	β_1^{VW}	$t(\beta_1^{VW})$	β_2	$t(\beta_2)$	$Adj\ R^2$
Raw Dispersion									
EWSAMPRET	0.018	2.813	**2.237**	1.661			-1.469	-0.636	0.006
VWSAMPRET	0.018	3.058			**2.832**	1.996	-1.768	-0.849	0.012
EWSP500RET	0.017	2.621	**2.440**	1.765			-0.949	-0.402	0.007
VWSP500RET	0.016	2.725			**2.875**	2.084	-1.290	-0.627	0.010
Deseasoned Dispersion									
EWSAMPRET	0.018	2.827	**6.237**	2.808			-1.469	-0.637	0.027
VWSAMPRET	0.018	3.031			**6.561**	2.194	-1.768	-0.839	0.018
EWSP500RET	0.017	2.621	**5.835**	2.492			-0.949	-0.402	0.021
VWSP500RET	0.016	2.703			**6.377**	2.175	-1.290	-0.621	0.015

Table VIII. Dispersion and Contemporaneous Returns/Discount Rates

Panel A reports the regressions of aggregate stock returns on contemporaneous innovation in aggregate forecast dispersion, $R_t = \alpha + \beta \Delta DISP_t + \epsilon_t$. "Change" is the equal-weighted/value-weighted individual change in forecast dispersion relative to the value one month before. "Innovation" is the change in deseasoned aggregate equal-weighted/value-weighted forecast dispersion relative to the value one month before. Panel B reports the regressions of innovation in aggregate forecast dispersion on change in discount rates. Panel C reports regression of contemporaneous returns on fitted and residual innovation in dispersion obtained from Panel B. See the Appendix for other variable definitions. *t*-values are based on Huber-White heteroskedasticity consistent standard errors.

Panel A. Regression of Contemporaneous Returns on Innovation in Forecast Dispersion.

	Change					Innovation				
	α	$t(\alpha)$	β	$t(\beta)$	$Adj\ R^2$	α	$t(\alpha)$	β	$t(\beta)$	$Adj\ R^2$
EWSAMPRET	0.013	5.190	**-5.747**	-1.947	0.009	0.014	5.510	-4.645	-1.385	0.002
EWCRSPRET	0.012	4.343	**-10.063**	-2.962	0.025	0.013	4.691	**-9.070**	-2.054	0.012
VWSAMPRET	0.015	6.881	**-4.709**	-1.658	0.004	0.016	7.089	**-7.559**	-1.858	0.006
VWCRSPRET	0.009	4.133	**-5.264**	-1.760	0.005	0.010	4.364	**-8.471**	-1.859	0.008

Panel B. Innovation in Dispersion and Contemporaneous Discount Rate Shocks

$\Delta DISP_t = \alpha + \beta_1 \Delta TBILL_t + \beta_2 \Delta TERM_t + \beta_3 \Delta YS_t + \beta_4 \Delta DEF_t + e_t$

	α	$t(\alpha)$	β_1	$t(\beta_1)$	β_2	$t(\beta_2)$	β_3	$t(\beta_3)$	β_4	$t(\beta_4)$	$Adj\ R^2$
$EW\Delta DISP$	-0.00011	-2.641	0.00023	1.620	0.00012	0.720	**0.00029**	2.178	**0.00133**	3.568	0.025
$VW\Delta DISP$	-0.00008	-2.158	0.00018	1.442	0.00009	0.639	**0.00032**	2.815	**0.00102**	3.205	0.026
$\Delta EWDISP\_DS$	0.00001	0.237	0.00012	0.997	0.00016	1.145	0.00012	1.115	**0.00137**	4.468	0.041
$\Delta VWDISP\_DS$	0.00001	0.225	0.00012	1.365	0.00014	1.325	0.00008	0.983	**0.00099**	4.335	0.037

Panel C. Contemporaneous Returns and Fitted and Residual Innovation in Dispersion

$R_t = \alpha + \beta_{Fitted} \widehat{\Delta DISP}_t + \beta_{Residual} \hat{e}_t + \epsilon_t$

	α	$t(\alpha)$	β_{Fitted}	$t(\beta_{Fitted})$	$\beta_{Residual}$	$t(\beta_{Residual})$	$Adj\ R^2$
Change in Dispersion							
EWSAMPRET	0.008	2.14	**-44.642**	-1.97	-4.347	-1.40	0.024
EWCRSPRET	0.006	1.47	**-60.643**	-2.65	**-8.241**	-2.33	0.047
VWSAMPRET	0.012	4.89	**-37.972**	-2.51	-3.099	-1.26	0.014
VWCRSPRET	0.006	2.54	**-39.225**	-2.54	-3.796	-1.52	0.016
Innovation in Deseasoned Dispersion							
EWSAMPRET	0.014	5.71	**-42.223**	-1.66	-2.649	-0.60	0.016
EWCRSPRET	0.013	4.95	**-67.371**	-2.88	-5.973	-1.25	0.041
VWSAMPRET	0.016	7.30	**-57.237**	-1.85	-5.127	-1.05	0.022
VWCRSPRET	0.010	4.55	**-64.671**	-2.09	-5.719	-1.19	0.027

Table IX. Decompose Dispersion into Uncertainty and Information Asymmetry

I decompose forecast dispersion into *uncertainty* and *information asymmetry*, following Barron, Stanford, and Yu (2010), and calculate equal-weighted (value-weighted) averages across individual firms in each month. Panel A reports the Fama-MacBeth regressions of one-month-ahead returns on *uncertainty* and *information asymmetry* for individual firms. In Panel B, aggregate returns are regressed on *uncertainty* and *information asymmetry*, $R_{t+1} = \alpha + \beta_1 VAR_t + \beta_2 UNCERT_t + \beta_3 InfoAsym_t + e_{t+1}$. Weighting schemes are aligned with returns. Panel C reports the regressions of innovations in *uncertainty* and *information asymmetry* on innovations in discount rates. Panel D reports the regressions of returns on contemporaneous fitted and residual innovations in *uncertainty* and *information asymmetry* obtained from Panel C. VAR_t is the variance of analyst forecasts, scaled by stock price at the beginning of month *t*. *Uncertainty*, $UNCERT_t$, is the mean of squared differences between individual analysts' forecasts (F_i) and reported earnings per share (A), scaled by lagged price, i.e., $\sum_i (F_i - A)^2/(COV_t * P_{t-1}) = [(1 - COV_t) * VAR_t + (A - \bar{F})^2]/P_{t-1}$. *Information Asymmetry*, $InfoAsym_t$, is the ratio of variance and uncertainty, scaled by price. I take natural logarithm of *UNCERT* and *InfoAsym*. *t*-values are reported in parentheses and based on Huber-White heteroskedasticity consistent standard errors.

Panel A. Firm Level Regression of One-Month-Ahead Returns on Uncertainty and Information Asymmetry.

	(1)	(2)	(3)	(4)
Constant	0.013***	0.012***	0.009***	0.009***
	(3.97)	(4.16)	(3.50)	(3.52)
VAR_t	**-0.004****		**-0.004*****	
	(-2.47)		**(-2.97)**	
$UNCERT_t$		**-0.010*****		**-0.009*****
		(-4.72)		**(-5.73)**
$InfoAsym_t$		**0.003****		**0.004*****
		(2.15)		**(3.25)**
$\log ME_t$	-0.004*	-0.003	-0.006***	-0.004**
	(-1.75)	(-1.63)	(-2.83)	(-2.12)
$\log BM_t$	0.006**	0.007***	0.007***	0.008***
	(2.16)	(2.64)	(3.73)	(4.18)
$Beta_t$			0.001	0.001
			(0.30)	(0.24)
MOM_t			0.007***	0.006**
			(3.14)	(2.47)
$Coverage_t$			0.002	0.000
			(1.31)	(0.07)
Avg R^2	0.035	0.042	0.070	0.080
N	549808	513758	548766	512766

Panel B. Regression of One-Month-Ahead Returns on Uncertainty and Information Asymmetry.

$R_{t+1} = \alpha + \beta_1 VAR_t + \beta_2 UNCERT_t + \beta_3 InfoAsym_t + e_{t+1}$

	α	$t(\alpha)$	β_1	$t(\beta_1)$	β_2	$t(\beta_2)$	β_3	$t(\beta_3)$	$Adj\ R^2$
Equal-Weight									
$EWSAMPRET_{t+1}$	0.005	1.46	**3.073**	2.35					0.010
$EWSAMPRET_{t+1}$	0.175	3.33			**0.005**	2.71	**0.036**	3.10	0.021
$EWCRSPRET_{t+1}$	0.006	1.46	**3.363**	2.35					0.010
$EWCRSPRET_{t+1}$	0.189	2.38			**0.005**	1.99	**0.039**	2.21	0.020
Value-Weight									
$VWSAMPRET_{t+1}$	0.006	1.63	**2.678**	1.73					0.005
$VWSAMPRET_{t+1}$	0.124	2.87			**0.003**	2.15	**0.023**	2.62	0.015
$VWCRSPRET_{t+1}$	0.005	1.34	**2.905**	1.87					0.006
$VWCRSPRET_{t+1}$	0.117	2.68			**0.003**	2.05	**0.022**	2.44	0.013

Panel C: Contemporaneous Regressions of Innovations in Uncertainty and Information Asymmetry on Innovations in Discount Rates.

$\Delta UNCERT_t(\Delta InfoAsym_t) = \alpha + \beta_1 \Delta TBILL_t + \beta_2 \Delta TERM_t + \beta_3 \Delta YS_t + \beta_4 \Delta DEF_t + e_t$

	α	$t(\alpha)$	β_1	$t(\beta_1)$	β_2	$t(\beta_2)$	β_3	$t(\beta_3)$	β_4	$t(\beta_4)$	$Adj\ R^2$
Equal-weight											
$\Delta UNCERT_t$	0.0002	0.082	**0.0167**	1.746	**0.0205**	1.758	0.0074	0.833	**0.0584**	2.326	0.009
$\Delta InfoAsym_t$	0.0001	0.429	-0.0004	-0.840	-0.0005	-0.875	0.0003	0.633	**0.0031**	2.827	0.018
Value-weight											
$\Delta UNCERT_t$	0.0006	0.085	0.0295	1.323	**0.0568**	2.089	**0.0565**	2.718	**0.1524**	2.607	0.031
$\Delta InfoAsym_t$	0.0001	0.805	-0.0001	-0.196	-0.0001	-0.228	0.0001	0.193	**0.0028**	3.773	0.033

Panel D: Contemporaneous Regressions of Returns on Fitted and Residual Innovations in Uncertainty and Information Asymmetry

$R_t = \alpha + \beta_1 \Delta \widehat{UNCERT}_t + \beta_2 Res.\Delta UNCERT_t + \beta_3 \Delta \widehat{InfoAsym}_t + \beta_4 Res.\Delta InfoAsym_t + e_t$

	α	$t(\alpha)$	β_1	$t(\beta_1)$	β_2	$t(\beta_2)$	β_3	$t(\beta_3)$	β_4	$t(\beta_4)$	$Adj\ R^2$
$EWSAMPRET_t$	0.018	5.606	**-6.425**	-3.799	-0.125	-0.753	**13.524**	2.000	-1.316	-1.303	0.031
$EWCRSPRET_t$	0.013	3.718	**-5.457**	-2.904	-0.259	-1.407	-0.290	-0.039	**-2.993**	-2.668	0.046
$VWSAMPRET_t$	0.014	6.381	**-1.533**	-2.064	-0.024	-0.319	-0.650	-0.096	-0.093	-0.072	0.006
$VWCRSPRET_t$	0.008	3.728	**-1.497**	-1.977	-0.016	-0.204	-4.108	-0.598	0.365	0.277	0.010

Table X. Regressions of One-Month-Ahead Industry-Level Returns on Forecast Dispersions, 1976-2010

This table reports the predictive regressions of one-month-ahead returns on forecast dispersions for each of Fama-French 48 industries, in the period 1976 to 2010. Panel A reports regression of returns on dispersions, and Panel B decomposes dispersion into *Uncertainty* and *Information Asymmetry*, as Barron et. al. (2010). t-values are based on Huber-White heteroskedasticity consistent standard errors.

	Panel A. $R_{t+1} = \alpha + \beta_1 DISP_t + \gamma_1 DY_t + \gamma_2 EC_t + \gamma_3 TBILL_t + \gamma_4 TERM_t + \gamma_5 YS_t + \gamma_6 DEF_t + \gamma_7 INDPROD_t + \gamma_8 GDP + \gamma_9 INF_t + \varepsilon_{t+1}$						Panel B. $R_{t+1} = \alpha + \beta_1 UNCERT_t + \beta_2 INFOASYM_t + \gamma_1 DY_t + \gamma_2 EC_t + \gamma_3 TBILL_t + \gamma_4 TERM_t + \gamma_5 YS_t + \gamma_6 DEF_t + \gamma_7 INDPROD_t + \gamma_8 GDP + \gamma_9 INF_t + \varepsilon_{t+1}$									
	Equal-weight			Value-weight			Equal-weight					Value-weight				
	β_1	$t(\beta_1)$	$AdjR^2$	β_1	$t(\beta_1)$	$AdjR^2$	β_1	$t(\beta_1)$	β_2	$t(\beta_2)$	$AdjR^2$	β_1	$t(\beta_1)$	β_2	$t(\beta_2)$	$AdjR^2$
Agriculture	-1.38	-0.80	0.01	0.84	0.44	-0.01	-0.008	-1.59	-0.003	-0.48	0.001	-0.004	-0.86	0.004	0.55	0.004
Food Pd.	0.65	0.50	0.02	2.39	1.03	0.03	0.001	0.34	0.002	0.50	0.023	0.000	0.01	0.001	0.26	0.025
Candy/Soda	1.27	0.95	0.00	3.24	1.60	0.01	-0.003	-0.87	0.003	0.87	0.002	0.000	0.03	0.000	0.07	-0.000
Beer/Liquor	-0.30	-0.19	-0.01	**10.06**	2.51	0.01	-0.000	-0.24	**-0.005**	-1.90	0.011	0.001	0.82	-0.002	-0.74	0.002
Tobacco	0.95	0.48	-0.02	4.15	1.19	-0.00	0.002	1.03	**0.003**	1.66	-0.006	0.004	1.56	**0.005**	2.09	0.009
Recreation	-0.13	-0.11	0.00	0.10	0.14	-0.01	0.003	1.07	**0.019**	3.05	0.031	-0.000	-0.08	**0.011**	1.87	0.008
Entertainment	**2.45**	1.69	0.01	**6.04**	2.27	0.02	0.001	0.54	**0.011**	1.97	0.008	0.002	0.68	**0.012**	1.73	0.013
Publishing	0.70	0.24	0.02	3.17	1.01	0.00	-0.001	-0.37	0.003	0.41	0.022	0.001	0.62	0.006	1.09	0.005
Consumer Gd.	**6.35**	3.14	0.05	**5.51**	2.19	0.04	0.003	1.15	0.005	0.80	0.022	-0.001	-0.27	-0.003	-0.79	0.022
Apparel	**3.19**	2.71	0.03	**2.78**	2.22	0.02	**0.004**	1.78	**0.022**	3.87	0.049	**0.005**	2.17	**0.021**	3.73	0.044
Healthcare	1.31	1.25	0.01	**4.08**	2.01	0.02	0.003	1.14	**0.008**	1.98	0.020	0.003	1.19	**0.008**	2.16	0.016
Medical Eq.	1.94	1.20	0.01	**8.52**	2.20	0.02	-0.000	-0.16	0.003	0.68	0.009	0.001	0.46	0.002	0.54	0.003
Drugs	1.22	0.81	-0.01	4.90	1.09	0.00	0.000	0.00	0.006	0.67	-0.016	0.001	0.62	0.005	0.93	-0.005
Chemicals	**5.36**	2.73	0.03	**5.53**	2.96	0.03	0.005	1.38	0.009	1.23	0.007	**0.007**	2.33	**0.026**	3.14	0.044
Rubber/Plastic	2.04	1.33	0.02	2.16	1.26	0.02	0.000	0.15	**0.006**	1.74	0.017	0.003	1.12	0.003	0.75	0.012
Textiles	**1.84**	1.81	0.01	2.14	1.53	0.07	-0.002	-0.55	**0.008**	2.55	0.024	0.001	0.21	**0.007**	2.23	0.064
Construction Mt.	**3.27**	2.24	0.02	**3.97**	2.27	0.02	**0.005**	2.05	**0.026**	2.99	0.024	0.004	1.35	**0.022**	2.24	0.024
Construction	0.79	0.80	-0.00	**2.52**	2.25	0.01	0.003	0.87	0.000	0.09	-0.003	0.002	0.56	-0.000	-0.10	-0.006
Steel Works	**1.25**	1.69	0.01	1.11	1.55	0.00	0.005	1.48	**0.027**	3.12	0.038	0.003	0.80	**0.021**	2.70	0.019
Fabricated Pd.	1.01	1.21	0.00	0.38	0.66	-0.00	0.004	0.84	0.005	0.99	0.004	0.004	0.84	0.004	0.77	0.001
Machinery	**3.26**	2.52	0.00	**3.80**	2.93	0.01	**0.007**	2.09	**0.028**	2.76	0.011	**0.008**	2.69	**0.028**	2.71	0.018
Electrical Eq.	**4.19**	2.25	0.00	3.37	1.53	-0.01	**0.003**	1.01	**0.022**	2.44	0.010	0.000	0.16	**0.018**	2.19	0.000
Autos	**2.77**	2.82	0.04	0.53	0.59	0.01	**0.005**	1.72	**0.017**	2.52	0.036	0.003	0.71	**0.022**	3.07	0.036
Aircraft	**2.11**	1.87	0.01	**3.40**	2.21	0.00	0.005	2.02	0.010	1.40	0.008	**0.007**	2.57	**0.011**	1.65	0.006
Ships	1.05	0.80	0.03	-0.92	-0.54	0.03	-0.005	-1.25	-0.004	-0.77	0.024	-0.003	-0.95	-0.005	-1.04	0.029
Defense	0.73	0.34	-0.00	1.80	0.90	-0.01	0.003	0.54	0.007	1.12	-0.002	-0.000	-0.09	-0.000	-0.02	-0.022
Precious metals	**2.33**	1.88	0.02	1.13	0.97	0.00	**0.015**	2.45	0.016	1.57	0.024	**0.009**	1.77	0.013	1.36	0.008
Mining	0.97	1.12	0.02	1.42	1.25	0.03	0.002	0.73	**0.021**	2.71	0.054	0.002	0.65	**0.018**	2.05	0.046
Coal	-0.83	-0.57	-0.01	-0.68	-0.52	-0.01	-0.002	-0.44	-0.017	-1.50	0.022	-0.002	-0.49	-0.015	-1.47	0.009
Oil/Gas	**2.64**	2.42	0.01	**2.80**	2.54	0.01	**0.012**	2.91	**0.028**	2.58	0.011	**0.006**	2.55	0.011	1.50	0.004
Utilities	**4.61**	2.30	0.02	**5.05**	2.46	0.01	-0.002	-1.08	-0.004	-0.44	0.000	-0.000	-0.01	0.009	0.94	0.001
Communication	2.22	1.22	-0.00	**6.20**	2.32	0.01	-0.002	-0.78	-0.004	-0.56	-0.008	-0.002	-0.74	-0.001	-0.16	-0.003
Personal Sv.	**2.29**	1.86	0.03	**5.44**	2.93	0.04	0.004	1.53	0.000	0.15	0.018	0.003	1.02	0.002	0.72	0.006
Business Sv.	**6.28**	3.90	0.02	**7.30**	3.87	0.02	0.001	0.41	**0.010**	1.65	-0.012	**0.004**	1.76	**0.015**	2.70	-0.001
Computers	1.10	0.66	0.00	2.25	0.71	0.01	-0.004	-1.10	-0.002	-0.41	0.002	**-0.005**	-1.79	-0.008	-1.46	0.017
Electronic Eq.	2.24	1.27	-0.02	3.78	1.53	-0.01	0.001	0.19	-0.000	-0.01	-0.022	0.004	0.99	0.000	0.03	-0.016
Lab Eq.	**3.31**	2.08	-0.01	**3.96**	1.82	-0.01	0.001	0.17	**0.014**	1.95	-0.013	-0.000	-0.15	0.011	1.49	-0.019
Business Su.	**3.48**	2.38	0.03	**4.12**	2.04	0.03	0.003	0.82	0.012	1.25	0.012	**0.004**	1.65	**0.014**	1.90	0.023
Boxes	**2.29**	1.96	0.03	2.14	1.40	0.03	0.000	0.19	0.004	0.77	0.022	0.002	0.93	0.006	1.14	0.026
Transportation	**3.93**	3.26	0.04	**4.81**	3.47	0.04	0.001	0.41	0.017	1.55	0.015	**0.005**	1.89	0.007	1.07	0.008
Wholesale	**3.25**	2.69	0.01	**4.28**	2.87	0.01	-0.000	-0.05	**0.011**	2.03	0.001	0.003	0.77	**0.017**	2.22	0.001
Retail	**4.42**	3.88	0.04	**5.97**	3.73	0.05	0.001	0.28	0.001	0.22	0.010	0.002	0.87	0.005	1.17	0.016
Rest./Hotels	1.20	1.00	0.01	1.08	0.62	0.02	0.000	0.02	0.002	0.55	0.011	-0.000	-0.03	-0.004	-0.93	0.017
Banking	**3.76**	2.74	0.05	**4.84**	2.82	0.04	-0.001	-0.46	**0.025**	2.64	0.050	0.000	0.15	**0.027**	3.17	0.044
Insurance	**3.66**	2.86	0.02	**3.59**	2.13	0.01	-0.001	-0.32	0.010	1.30	0.006	0.000	0.17	**0.013**	1.86	0.005
Real estate	-0.05	-0.11	-0.01	-0.38	-0.54	-0.02	-0.005	-1.35	0.003	0.70	0.008	-0.006	-1.63	-0.001	-0.22	-0.007
Trading	**2.36**	2.17	0.02	**2.01**	1.92	-0.00	-0.001	-0.37	0.004	1.33	0.005	0.000	0.08	0.005	1.55	-0.010
Other	**3.54**	2.44	0.01	5.03	1.64	0.01	0.002	0.60	**0.012**	2.59	0.007	**0.007**	2.04	**0.014**	3.18	0.024