The Forecast Dispersion Anomaly Revisited: Time-Series Mean Forecast Dispersion and the Cross-Section of Stock Returns

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Keywords: Analysts' earnings forecasts; Time-series mean forecast dispersion; Cross-sectional forecast dispersion; Systematic risk components; Macroeconomic conditions

JEL classification: G12, G14

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Abstract

Previous researches focus on examining only the relation between cross-sectional earnings forecast dispersion and stock returns and on providing explanations for the negative dispersion-return relation. This paper attempts to examine how time-series mean forecast dispersion is distinct in the relation to stock returns from the cross-sectional forecast dispersion effect. We find that contrary to the standard analyst dispersion effect, there is a strong positive relation between time-series mean forecast dispersion and stock returns. We also find that time-series mean forecast dispersion apparently contains systematic risk components and that such risk is priced in stock returns.

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1. Introduction

Recent literature reports that there is a negative relationship between cross-sectional dispersion in analysts' earnings forecasts and future stock returns. In other words, firms with high forecast dispersion earn lower future stock returns. In particular, Diether, Malloy, and Scherbina (2002) report that stocks in the highest quintile of dispersion substantially underperform stocks in the lowest quintile of dispersion and that this inverse relation is found in all size quintile portfolios. This dispersion-return relation is anomalous, since investors pay a premium for stocks with high forecast dispersion rather than discounting uncertainty. This negative relation can also be used as evidence to strongly reject the notion that cross-sectional dispersion in analysts' earnings forecasts can be viewed as a proxy for (non-diversifiable) risk. In other words, analysts' forecasts are not informative in terms of pricing ability. This casts some doubt on the role of analysts as information agents.[1]

Since Diether, Malloy, and Scherbina (2002), recent researches focus mainly on providing explanations for the negative dispersion-return relation. For example, Diether et al (2002) attribute this negative dispersion-return relation to mispricing due to agents' different beliefs and market frictions such as short-sales constraints.[2] The authors thus interpret dispersion in analysts' forecasts as a proxy for differences of opinion about a stock due to asymmetric information. Johnson (2004) argues that dispersion in analysts' forecasts reflects

[1] Altinkiliç, Balashov, and Hansen (2013) report evidence that analysts' forecast revisions are not informative in intraday returns and, further, revisions are virtually information free in the cross-section of returns around announcements.

[2] Berkman, Dimitrov, Jain, Koch, and Tice (2009) also provide evidence that stocks with high differences of opinion among investors and more binding short-sales constraints earn lower returns around earnings announcements than other stocks. As proxies for differences of opinion, they use dispersion of analysts' earnings forecasts, earnings volatility, return volatility, firm age, and share turnover, and as a proxy for short-sale constraint, they use institutional ownership.

idiosyncratic risk about cash flows which increases the option value of equity and that expected returns should decrease with idiosyncratic risk.[3] By linking the negative dispersion-return relation to the negative distress-return relation, Avramov, Chordia, Jostova, and Philipov (2009) argue that forecast dispersion may be related to financial distress.[4]

As discussed above, most prior papers focus on examining the relation between the cross-sectional forecast dispersion and stock returns. There are, however, few papers that examine the relation between *time-series* forecast dispersion and stock returns. Note that the anomalous negative relation is a result from examining only the relation between the *cross-sectional* forecast dispersion and stock returns. The purpose of this paper is therefore twofold: First, we examine how time-series dispersion around mean forecast (or time-series mean forecast dispersion) is distinct in the relation to stock returns from the standard analyst dispersion effect. Second, we examine if time-series mean forecast dispersion can be used as a proxy for risk. In other words, we examine if this relation is positive and time-series mean forecast dispersion contains non-diversifiable risk components. This is an important issue to both investors and analysts.

To address the above-mentioned issue, we perform several tests. First, we examine how stock prices react to earnings signals conditionally on (time-series or cross-sectional) forecast dispersion. Since for a given level of earnings signal, stock price reaction differs according to whether earnings information uncertainty is attributable to noise in the earnings signal or to the

[3] Barron, Stanford, and Yu (2009) provide evidence supporting the Johnson (2004) argument. These authors separate dispersion into its two components, uncertainty and information asymmetry, by using the Barron, Kim, Lim, and Stevens (1998) model, and they report that the negative dispersion-return relation is explained by the uncertainty components of dispersion.

[4] However, the profitability of dispersion-based trading strategies concentrates only in a small number of the worst-rated firms, which account for less than 5% of the overall market capitalization of rated firms. In contrast, this profitability is non-existent among higher quality firms. These results are robust to previously proposed explanations for the negative dispersion-return relation such as short-sale constraints and leverage.

fundamental uncertainty of the firm's future cash flows due to business environment, it may be determined, by examining the pattern of returns across forecast dispersion, whether forecast dispersion is caused by idiosyncratic noise or by fundamental uncertainty.

Second, we re-examine the relation between (time-series or cross-sectional) forecast dispersion and stock return after adjusting for some systematic risk components. If a particular dispersion-return relation is caused by systematic risk components of stock returns, the particular relation should disappear after the systematic risk is appropriately adjusted. Otherwise, the relation will remain unchanged. We use firm size, book-to-market ratio, and market beta as appropriate systematic risk components according to Fama and French (1992, 1993).

Third, we relate payoffs to time-series mean forecast dispersion-based factors to macroeconomic conditions. As a final test, we conduct cross-sectional regression tests to examine whether risk components contained in time-series mean forecast dispersion are priced in stock returns.

Based on these tests, we find that there is a strong positive relation between time-series mean forecast dispersion and stock returns. Further, we find that time-series mean forecast dispersion apparently contains systematic risk components and that such risk is priced in stock returns. In other words, time-series dispersion around mean forecast contains fundamental and non-diversifiable risk components and is informative in terms of pricing ability.

The remainder of this paper proceeds as follows. Section 2 describes the data and methodology for computing time-series mean forecast dispersion. Section 3 presents the characteristics of portfolios sorted by the forecast dispersion. Section 4 presents empirical evidence showing that time-series mean forecast dispersion contains systematic risk components. Section 5 set forth our conclusions.

2. Data and Methodology

2.1. Computing Cross-Sectional and Time-Series Forecast Dispersions

We obtain analysts' quarterly earnings forecasts data for all NYSE, AMEX, and NASDAQ stocks from the Institutional Brokers Estimate System (I/B/E/S) for the period 1984–2012. According to Diether, Malloy, and Scherbina (2002) and Payne and Thomas (2003), since the standard deviation of analysts' earnings forecasts computed from the adjusted file in I/B/E/S is subject to the rounding error issue and the rounding problem becomes more severe in the summary file, we use the Unadjusted Detailed History File.[5]

Every month we calculate cross-sectional standard deviations and means by using analysts' current-fiscal-quarter earnings forecasts which are available up to the month (contained in the fiscal quarter) by updating on a monthly basis.[6] If there are more than one forecast from each brokerage firm for the same firm and the same forecast period, only the latest estimate is used. If the forecast is voided by I/B/E/S with an "Excluded" or "Stopped" flag, then it is excluded.[7] We also exclude firms whose number of analyst forecasts available for a given month equals 1 and whose previous month price is less than 5 dollars. We use standard deviation scaled

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[5] In the case of firms that have gone through multiple stock splits, rounding the stock split-adjusted forecasts to the nearest penny causes this problem.

[6] For example, the standard deviation for October 2005 of a firm whose fiscal quarter is a March–June–September–December cycle is computed by using analysts' earnings forecasts made for the fourth quarter of 2005, which are available up to this month. The standard deviation for February 2006 of the same firm is also computed by using analysts' earnings forecasts made for the first quarter of 2006 which are available up to this month.

[7] To reconstruct the dataset as closely to the summary statistics from the unadjusted detailed history file as possible, we follow the procedure introduced in the I/B/E/S Manual provided by Wharton Research Data Services, "A Note on Recreating Summary Statistics from Detail History."

by the average of the absolute forecast values used to compute the standard deviation, as a proxy for cross-sectional dispersion in analysts' earnings forecasts, *DISP_CS*.

As a proxy for time-series mean forecast dispersion, we use the standard deviation of time-series quarterly mean forecast errors. To obtain time-series quarterly mean forecast errors of firm i, as in Foster, Olsen, and Shelvin (1984), Bernard and Thomas (1989), and Kim (2006), we first estimate the following AR(1) process by using the mean values of analysts' quarterly earnings forecasts of the most recent 20 quarters at a given quarter q (a minimum of 8 quarters' data at the given quarter),

$$\overline{\mathrm{Q}}_{i,q} - \overline{\mathrm{Q}}_{i,q-4} = \phi_{i0} + \phi_{i1}\left(\overline{\mathrm{Q}}_{i,q-1} - \overline{\mathrm{Q}}_{i,q-5}\right) + \eta_{i,q}, \tag{1}$$

where $\overline{\mathrm{Q}}_{i,q}$ is the mean value of analysts' quarterly earnings forecasts for firm i at quarter q. In fact, this is the mean value of analysts' current-fiscal-quarter earnings forecasts which are available up to the last month of the quarter. The time-series mean forecasts error is then defined as

$$FE_{i,q} = \overline{\mathrm{Q}}_{i,q} - E\left(\overline{\mathrm{Q}}_{i,q} | I_{i,q-1}\right), \tag{2}$$

where $E\left(\overline{\mathrm{Q}}_{i,q} | I_{i,q-1}\right)$ is the time-series estimate of the mean value of analysts' earnings forecasts for quarter q defined as

$$E\left(\overline{\mathrm{Q}}_{i,q} | I_{i,q-1}\right) = \overline{\mathrm{Q}}_{i,q-4} + \widehat{\Phi}_{\mathrm{i1}}\left(\overline{\mathrm{Q}}_{i,q-1} - \overline{\mathrm{Q}}_{i,q-5}\right) + \hat{\phi}_{i0}. \tag{3}$$

We use the standard deviation of the time-series quarterly mean forecasts errors defined in equation (2), scaled by the stock price at the previous quarter-end, as a proxy for time-series mean forecast dispersion, *DISP_TS*, for quarter q. In fact, this is a measure of the dispersion in the time-series of the mean forecast. Note that *DISP_CS* and *DISP_TS* measure the degree of cross-sectional and intertemporal deviations from the mean value of analysts' earnings forecasts, respectively, and do not use actual earnings.

2.2. Summary Statistics of Dispersion in Analysts' Earnings Forecasts

Table 1 presents the averages of cross-sectional and time-series forecast dispersions (DISP_CS and DISP_TS), number of earnings forecasts, number of sample firms, actual earnings, and forecast earnings over the entire sample period 1986–2012 and several subperiods (Panel A) and business cycles (Panel B). Note that since the minimum required number of quarterly mean forecast earnings in computing DISP_TS through equation (1) is eight, the sample period begins in 1986. There is no particular trend in both dispersions over the subperiods. However, the average values of both DISP_CS and DISP_TS are larger in contractionary than in expansionary periods. Figure 1 shows aggregate DISP_CS and DISP_TS over time. Both dispersion measures tend to sharply increase during recessions and have their highest value during the global financial crisis of the period 2008–2009. This figure also shows that these two measures of forecast dispersions seem to move in a similar pattern. The correlation coefficient between these two dispersion measures is 0.1605 (with p-value less than 0.0001).

3. Portfolios Sorted by Dispersion in Analysts' Forecasts

3.1. Firm Characteristics of Dispersion-Sorted Portfolios

To take a preliminary look at the relation between the dispersion measures, *DISP_TS* and *DISP_CS*, and firm characteristics, we sort all firms every month by assigning them into one of five quintile portfolios according to the magnitude of *DISP_TS* or *DISP_CS* which are most recently available up to the portfolio formation month. The portfolios are equally-weighted and held for the next one–month period. Table 2 presents the averages of the two dispersion measures and firm characteristic variables such as firm size, book-to-market, market beta, and price per share of the DISP_TS- or DISP_CS-sorted portfolios. This table shows that both dispersion measures have a negative relation with firm size and price per share, but a positive relation with book-to-market ratio and market beta. In other words, firms with greater dispersion, cross-sectional or time-series, tend to be small size, high book-to-market ratio, high market beta, and low priced.

3.2. Relationship Between Analysts' Forecast Dispersion and Stock Returns

To examine how dispersions in analysts' earnings forecasts are related to stock returns, we form portfolios every month by assigning all firms into one of 25 (=5×5) portfolios according to the magnitude of *DISP_TS* and *DISP_CS* which are most recently available up to the portfolio formation month. Five break-points for *DISP_TS* and *DISP_CS* are independently determined. Note that although the results for the cross-sectional forecast dispersion effect have mostly been already reported in the literature, we report these results as well together with the results for the time-series mean forecast dispersion effect throughout the paper to show how the latter (time-series) effect is distinct from the former (cross-sectional) effect.

Panel A of Table 3 presents average monthly returns and standard deviations of these 25 portfolios over the entire sample period January 1986 to December 2012 (324 months). Consistent with the literature (e.g., Diether, Malloy, and Scherbina, 2002; Johnson, 2004; Barron, Stanford, and Yu, 2009; Berkman et al., 2009), we find an inverse relation between cross-sectional forecast dispersion and subsequent stock returns. That is, average monthly returns decrease monotonically with cross-sectional forecast dispersion from 1.20 percent (t-statistic of 4.08) to 0.80 percent (t-statistic of 1.89). The difference in average return between the largest (DISP_CS5) and smallest (DISP_CS1) quintile portfolios sorted by *DISP_CS* is negative and statistically significant at the 5 percent level; it is -0.40 percent, with t-statistic of -2.00. This negative relation is maintained within each DISP_TS-sorted quintile portfolio and is especially strong when time-series mean forecast dispersion is large. The differences in average return within each of the five *DISP_TS*-sorted quintile portfolios are all negative. This negative relation (or the negative arbitrage return) is puzzling, since dispersion in analysts' forecasts is usually perceived as a proxy for information-related risk (information uncertainty or information asymmetry) and the characteristic variables of firms with greater cross-sectional forecast dispersion point toward higher risk, as shown in Table 2.

Contrary to the case of cross-sectional forecast dispersion, time-series mean forecast dispersion has a positive and strong monotonic relation with stock returns. That is, average monthly returns increase monotonically with time-series mean forecast dispersion from 1.04 percent (t-statistic of 4.00) to 1.63 percent (t-statistic of 3.68). The difference in average return between the largest (DISP_TS5) and smallest (DISP_TS1) quintile portfolios is positive and statistically significant at the 5-percent level; it is 0.59 percent, with t-statistic of 2.13. This positive relation is also maintained within each *DISP_CS*-sorted quintile portfolio. The differences in average return within each of the 5 *DISP_CS*-sorted quintile portfolios are all positive and mostly statistically significant.[8]

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[8] The above-mentioned negative and positive relations of cross-sectional and time-series forecast dispersions with subsequent stock returns are also similarly obtained when firms are dependently sorted; all firms are first sorted into

Panel B of Table 3 presents average monthly returns of the 25 portfolios sorted by DISP_TS and DISP_CS over business cycles. It shows that the negative (positive) relation between cross-sectional (time-series) forecast dispersion is prominently maintained over business cycles. The magnitude and statistical significance of the differences in average return between DISP_CS5 and DISP_CS1 and between DISP_TS5 and DISP_TS1 in expansionary periods (290 months) are similar to those in the whole periods; these are -0.35 percent (with t-statistic of -1.91) and 0.60 percent (with t-statistic of 2.38), respectively. However, the magnitude of these differences is greater in contraction (34 months) than in expansion periods, although their statistical significance is weaker because of smaller sample size; these are -0.70 percent (with t-statistic of -0.68) and 1.49 percent (with t-statistic of 1.04) in contraction periods, respectively.

4. Tests of Whether Forecast Dispersion Contains Systematic Risk Components

4.1. Forecast Dispersion, Earnings Surprise, and Stock Returns

Earnings information uncertainty is attributable to noise in the earnings signal and/or the fundamental uncertainty of the firm's future cash flows due to business environment. When investors receive noise in the earnings signal, they translate it into transitory earnings changes that do not persist into future cash flows, and they do not react as strongly to the earnings signal. As a result, stock price reaction to earnings innovations (proxied by earnings surprise, *ES*) is dampened. Therefore, if earnings information uncertainty is attributable to noise in the earnings

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one of five quintile portfolios according to the magnitude of *DISP_TS* and the firms within each *DISP_TS*-sorted quintile portfolio are then sorted into one of five portfolios according to the magnitude of *DISP_CS*, and vice versa. The results are available upon request.

signal, the greater the earnings information uncertainty, the smaller the price reaction for a given level of earnings surprise. On the other hand, if earnings information uncertainty is attributable to the fundamental uncertainty of firm future cash flows, earnings surprise is more permanent than transitory and a current earnings surprise would be more informative about future growth opportunities. As a result, a given level of earnings surprise has a greater effect on stock price when there is greater uncertainty about firm earnings prospects.

In this section, we examine how stock prices differentially react to news about earnings innovations according to the degree of earnings information uncertainty, which is proxied by cross-sectional and time-series forecast dispersions. To do this, we form portfolios by sorting all firms for each month, first by five break-points of time-series mean or cross-sectional forecast dispersion. Within each *DISP_TS*- or *DISP_CS*-sorted quintile portfolio, firms are then re-assigned into one of three *ES*-sorted portfolios according to the sign of earnings surprise (negative, zero, or positive) which is most recently available up to the portfolio formation month. Earnings surprise is defined as the difference between actual earnings and the mean value of analysts' earnings forecasts, scaled by stock price at the end of the preceding quarter. Then, the negative *ES*-sorted portfolio is split into two subgroups, $\mathrm{ES}^{(-2)}$ and $\mathrm{ES}^{(-1)}$, according to whether firms are below or above the median value of negative earnings surprises. The positive ES-sorted portfolio is also similarly split into two subgroups, $\mathrm{ES}^{(+1)}$ and $\mathrm{ES}^{(+2)}$.

Panel A of Table 4 presents average monthly returns of those 25 (5×5) portfolios sorted by *DISP_CS* and *ES*. Consistent with Berkman et al. (2009), average returns mostly decrease with cross-sectional forecast dispersion within each ES-sorted portfolio. That is, the greater the cross-sectional forecast dispersion, the smaller the stock return for a given level of earnings surprise.[9] This may be evidence indicating that cross-sectional forecast dispersion contains components attributable to noise in the earnings signal rather than fundamental uncertainty in a firm's future cash flows. On the contrary, average returns increase with time-series mean forecast dispersion within each ES-sorted portfolio, as shown in Panel B of Table 4. In other words, the greater the time-series mean forecast dispersion, the greater the price return for a given level of earnings surprise. Therefore, this positive relation indicates that time-series mean forecast dispersion contains components attributable to fundamental uncertainty in a firm's future cash flows. As expected, average returns increase with the magnitude of earnings surprise.

4.2. Dispersion-Return Relations After Controlling for Some Systematic Risk Components

If the negative relation between cross-sectional forecast dispersion and stock returns is caused by a systematic risk component of stock returns, this negative arbitrage return should disappear after the systematic risk is *appropriately* controlled. If the negative relation and the negative arbitrage return still persist even after controlling for the systematic risk, it would be argued that these may not be caused by systematic risk components but by idiosyncratic components. In the context of Fama and French (1993), we adopt firm size, book-to-market, and market beta as systematic risk components of stock returns.

To examine whether the negative relation persists after controlling for the systematic risk components, we first sort all firms into one of five portfolios according to the magnitude of firm size (book-to-market or market beta) and then sort the firms within each size-sorted portfolio into

[9] By using daily returns and the IBES Summary file, Kim and Kim (2003) report that average stock returns increase with cross-sectional forecast dispersion when the smallest dispersion quintile portfolio containing zero dispersion is excluded.

one of five quintile portfolios according to the magnitude of cross-sectional forecast dispersion.[10] We use NYSE-breakpoints for firm size and book-to-market ratio to allocate all sample firms into one of five size (or book-to-market) portfolios. Portfolios are equally weighted. Table 5 presents average monthly returns of 25 portfolios sorted first by firm size and then by *DISP_CS*. The negative relation between cross-sectional forecast dispersion and stock returns is still maintained within each of all five size-sorted portfolios. Specifically, the differences in average return between the largest (DISP_CS5) and smallest (DISP_CS1) portfolios within each of the five size-sorted portfolios are all negative. The negative difference is particularly large and statistically significant for small firms.[11] The overall difference in average return between DISP_CS5 and DISP_CS1 is negative and statistically significant at the 1 percent level; it is -0.40 percent, with t-statistic of -2.44. This is an (negative) arbitrage return of the zero-investment portfolio based on *DISP_CS*, after controlling for firm size.

Table 5 also presents average monthly returns of 25 portfolios sorted first by book-to-market ratio (or market beta, β) and then by DISP_CS. The similar negative pattern in average returns across *DISP_CS* within each of the *BM*-sorted and β-sorted portfolios is also observed. We also find that the higher the book-to-market ratio, the stronger the negative dispersion-return relation. This result is consistent with the Johnson (2004) model which predicts that the negative dispersion–return relation should strengthen with leverage. Note that there is a strong association between leverage and book-to-market, as noted by Fama and French (1992). The overall differences in average return between DISP_CS5 and DISP_CS1 after controlling for book-to-

[10] This is a two-way dependent sorting that is used to control one characteristic.

[11] Diether, Malloy, and Scherbina (2002) also report that the negative dispersion-return relation is strongest in small stocks. Sadka and Scherbina (2007) also report that the negative dispersion-return relation is especially prominent among illiquid stocks which are usually small-sized.

market and market beta are also negative and statistically significant; they are -0.34 percent (with t-statistic of-1.91) and -0.42 percent (with t-statistic of-2.93), respectively. The magnitude and statistical significance of these negative arbitrage returns based on *DISP_CS* (even after controlling for firm size, book-to-market, and market beta) are qualitatively almost unchanged from those of the original (uncontrolled) arbitrage return, which is -0.40 percent (t-statistic of -2.00), as shown in Table 3.

We similarly construct portfolios to examine whether the positive relation between time-series mean forecast dispersion and stock returns (or positive arbitrage return) is explained by the systematic risk components. Table 5 presents average monthly returns of 25 portfolios sorted first by firm size (book-to-market ratio or market beta) and then by DISP_TS. Contrary to the case of cross-sectional forecast dispersion, arbitrage returns of the zero-investment based on *DISP_TS* become all statistically insignificant within each of the five portfolios sorted by firm size, book-to-market ratio, or market beta, after controlling for firm size, book-to-market, and market beta. Overall differences in average return between DISP_TS5 and DISP_TS1 are also statistically insignificant; they are 0.34 percent, with t-statistic of 1.34 (size-controlled), 0.41 percent, with t-statistic of 1.49 (book-to-market-controlled), and 0.34 percent, with t-statistic of 1.61 (market beta-controlled), respectively. These arbitrage returns based on *DISP_TS* are much smaller in magnitude than the original (uncontrolled) arbitrage return of 0.59 percent, with t-statistic of 2.13, as shown in Table 3. Furthermore, the statistical significance of these arbitrage returns largely declines after controlling for the systematic risk components of stock returns.

The above results indicate that the positive relation between time-series mean forecast dispersion and stock return is related to firm size, book-to-market, and/or market beta, while the negative (cross-sectional forecast) dispersion-return relation is at least hardly related to these systematic risk components.

4.3. Dispersion–Return Relations After Applying for the Risk Factor Models

To further examine whether the relations between the (cross-sectional and time-series) forecast dispersions and stock returns are explained by systematic risk components, we conduct time-series tests by estimating the widely used risk factor models: the Fama and French (1993) three-factor model (FF3).

Table 6 presents the estimates of the intercept (or Jensen alpha) (Panel A) and factor loadings (Panel B) from FF3 for 25 portfolios double-sorted by *DISP_TS* and *DISP_CS* as in Table 3. The differences in the intercept estimate between the largest (DISP_CS5) and smallest (DISP_CS1) quintile portfolios within each of the five *DISP_TS*-sorted portfolios are all negative and are statistically significant for large *DISP_TS*. A joint null hypothesis on whether all intercept estimates of the five overall *DISP_CS*-sorted quintile portfolios are different from zero (i.e., $\widehat{\alpha}_{\mathrm{CS1}} = \cdots = \widehat{\alpha}_{\mathrm{CS5}} = 0$) is strongly rejected. The Gibbons, Ross, and Shanken (1989) (GRS) *F*-statistic for the joint null hypothesis is 5.476 (with p-value < 0.001). This joint null hypothesis is also rejected with respect to the Hansen-Jagannathan (1997) (HJ) distance which is 0.155 (with p-value of 0.009).[12] Furthermore, the intercept estimates of these five overall *DISP_CS*-sorted quintile portfolios monotonically decrease with DISP_CS. In particular, the overall

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[12] The HJ distance is defined as $\delta = [\mathrm{Min}_{\theta}\ \mathrm{g}(\theta)'\, W\, \mathrm{g}(\theta)]^{1/2}$, where $\mathrm{g}(\theta) = E(m_t \boldsymbol{R}_t) - 1_N, m_t = b_0 + b_1' \boldsymbol{F_t}$, $\theta = (b_0, b_1')$ is a vector of parameters to be estimated, $\boldsymbol{R}_t$ is a $(N \times 1)$ vector of gross returns of test portfolios, $\boldsymbol{F_t}$ is the factor portfolio return, and W is a weighting matrix. $E[\boldsymbol{R}_t \boldsymbol{R}_t']^{-1}$ is used for the weighting matrix to compute the HJ distance. The HJ distance can be interpreted as the maximum pricing error for the set of assets mispriced by the model (Campbell and Cochrane, 2000). The *p*-value for the null hypothesis $\mathrm{H}_0\colon \delta = 0$ is computed based on Jagannathan and Wang (1996).

difference in the intercept estimate, $\hat{\alpha}_{\mathrm{CS5}} - \hat{\alpha}_{\mathrm{CS1}}$, is -0.50 ($t$-statistic of -3.48). This (adjusted) overall difference is even greater in negative value than the unadjusted overall difference in average raw returns which is -0.40 percent (t-statistic of -2.00), as shown in Table 3. In short, the negative (cross-sectional) dispersion-return relation and the negative arbitrage return are not explained by FF3, which indicates that cross-sectional forecast dispersion does at least not contain the widely-accepted risk components.

On the contrary, the differences in intercept estimates between the largest (DISP_TS5) and smallest (DISP_TS1) quintile portfolios within each of the five DISP_CS-sorted portfolios are all statistically insignificant. A joint null hypothesis on whether all intercept estimates of the five overall DISP_TS-sorted quintile portfolios are different from zero (i.e., $\hat{\alpha}_{\mathrm{TS1}} = \cdots = \hat{\alpha}_{\mathrm{TS5}} = 0$) is not rejected with respect to the HJ distance which is 0.063 (with p-value of 0.278), although it is rejected with respect to the GRS test statistic. Further, the overall difference in the intercept estimate, $\hat{\alpha}_{\mathrm{TS5}} - \hat{\alpha}_{\mathrm{TS1}}$, is statistically insignificant; it is only 0.14 percent (t-statistic of 0.67). That is, the unadjusted overall difference in average raw returns which is 0.59 percent (with t-statistic of 2.13), as shown in Table 3, and the positive relation between time-series mean forecast dispersion and average return are well explained by FF3, which indicates that time-series mean forecast dispersion contains the widely-accepted systematic risk components.

Table 6 also reports the estimates of the three factor loadings estimates for market beta, firm size, and book-to-market, $\hat{\beta}_{\mathrm{MKT}}$, $\hat{\beta}_{\mathrm{SMB}}$, and $\hat{\beta}_{\mathrm{HML}}$, for the 25 portfolios. All three factor loading estimates monotonically increase with time-series mean forecast dispersion within any DISP_CS-sorted quintile portfolios. That is, time-series mean forecast dispersion is strongly positively correlated with these factor loadings, as it is with average stock returns. However, cross-sectional forecast dispersion shows no or a weak, if any, pattern in the relation to these factor loading estimates. In particular, it shows no pattern in the relation to $\hat{\beta}_{\mathrm{HML}}$.

The above results, together with those of the previous section, confirm that time-series mean forecast dispersion contains the widely-accepted risk components such as market beta, firm size, and book-to-market, while cross-sectional forecast dispersion does not. It could be argued, however, that the above assertion may be a result from applying a mis-specified asset pricing model in the analyses. To examine this argument, we relate the arbitrage returns of the zero-investment based on time-series mean forecast dispersion and cross-sectional forecast dispersion, respectively, to macroeconomic conditions, rather than attempting to identify and apply a well-specified asset pricing model which is a more daunting task. If ~~a~~ (time-series or cross-sectional) forecast dispersion contains systematic risk components, the arbitrage return based on the forecast dispersion should be related to macroeconomic variables, since these are the most plausible candidates for the state variables in the context of the Intertemporal CAPM of Merton (1973). We examine this argument in the following section.

4.4. Forecast Dispersion-Related Returns and the Macroeconomy

4.4.1. Constructing Dispersion-Related Factors

To relate the arbitrage returns of the zero-investment based on time-series and cross-sectional forecast dispersions (or dispersion-based payoffs) to macroeconomic variables, we first construct factors related to time-series and cross-sectional forecast dispersions. All firms are assigned for each month into one of three portfolios based on top 30 percent (H), middle 40 percent (M), and bottom 30 percent (L) break-points of time-series mean forecast dispersion. The factor related to time-series mean forecast dispersion, referred to as TS, is the difference between the equally weighted return of the top 30-percent group and the equally weighted return of the bottom 30-percent group (H-L). The factor related to cross-sectional forecast dispersion, referred to as CS, is also similarly constructed using 30-40-30 percent break-points of cross-sectional forecast dispersion.[13]

4.4.2. Dispersion-Related Payoffs and Future Innovations in Macroeconomic Conditions

In this section, we examine whether payoffs to TS and CS are related to future innovations in macroeconomic variables. For macroeconomic variables, we consider the following seven variables: real GDP growth rate, real consumption (nondurable and services) growth rate, term spread (TERM), default spread (DEF), inflation rate (based on CPI-all items), three-month Treasury bill yield, and dividend yield.[14] In particular, TERM, DEF, inflation rate, interest rate, and dividend yield are frequently used in the literature as proxies for time-varying risk premia.

To control for mutual influence among the macroeconomic variables, following Petkova (2006), we first estimate a vector autoregressive (VAR) process specification with order of one containing quarterly growth rates for all seven variables.[15] We then extract seven series of residuals, which represent innovation or surprise in each macroeconomic variable. This VAR(1) represents a joint specification of the dynamics of all seven candidate state variables. Then, we

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[13] The correlation coefficient between TS and CS is 0.134.

[14] GDP, consumption, CPI, Aaa- and Baa-rated corporate bond yields, and 3-month and 10-year Treasury yields are obtained from the Federal Reserve Bank of St. Louis Economic Data website (http://research.stlouisfed.org/fred2/). Dividend yield is the CRSP value-weighted market dividend yield. GDP, consumption, and CPI are seasonally adjusted.

[15] For GDP, consumption, and inflation, which are of quarterly frequency, quarterly growth rates are computed as the difference between two quarterly log (seasonally adjusted) values. For T-bill yield, term spread, default spread, and dividend yield, which are of monthly frequency, quarterly rates are computed by continuously compounding monthly rates.

relate the future value of the residuals to TS and CS. Following Chen (1991), Liew and Vassalou (2000), and Chordia and Shivakumar (2006), we regress future quarterly growth rates of innovation (i.e., residuals from the VAR(1)) in the macroeconomic variables on lagged payoff to CS and TS. Specifically,

$$u^K_{q+1,q+4} = \theta_0 + \theta_1 \mathrm{TS}_{q-3,q} + \theta_2 \mathrm{TS}_{q-3,q}\mathrm{D}_q + \theta_3 \mathrm{CS}_{q-3,q} + \theta_4 \mathrm{CS}_{q-3,q}\mathrm{D}_q$$

$$+\theta_{C1}\Lambda_{q-3,q} + \theta_{C2}\Lambda_{q-3,q}\mathrm{D}_q + \varepsilon_\mathrm{q}, \qquad (4)$$

where $u^K_{q+1,q+4}$ is the continuously compounded value of innovation in a macroeconomic variable K over quarters q+1 through q+4, $\mathrm{TS}_{q-3,q}$ and $\mathrm{CS}_{q-3,q}$ are the continuously compounded returns of TS and CS over quarters q-3 through q, D_q is a business cycle dummy variable that equals 1 for expansion periods and 0 for contraction periods, and $\Lambda_{q-3,q}$ is a vector of control risk factors which are continuously compounded over quarters q-3 through q. The Fama and French three factors are used as control risk factors. This equation measures how TS and CS are related to future innovations in the macroeconomic variables.

Table 7 presents the coefficient estimates (×100) of equation (4) for future innovations in each of the seven macroeconomic variables over the whole sample period 1986:Q1 to 2012:Q4.[16] In a partial model of equation (4) where TS and CS are alone in the model (without the business cycle dummy) and with the Fama and French three factors controlled, the coefficients on TS ($\hat{\theta}_1$) are positively statistically significant at the 5-perent level for future innovations in GDP growth ($\hat{\theta}_1 = 4.03$, t-statistic of 2.37), consumption growth ($\hat{\theta}_1 = 2.61$, t-statistic of 2.15), and inflation ($\hat{\theta}_1 = 3.13$, t-statistic 2.63), while they are negatively moderately

[16] All t-statistics of the coefficient estimates are based on the autocorrelation-consistent Newey-West standard errors.

significant for future innovations in three-month Treasury bill rate ($\hat{\theta}_1 = -0.71$, t-statistic of -1.70). This negative sign for this short-term interest rate benchmark is consistent with the positive sign for GDP growth rate, consumption growth rate, and inflation rate, since short-term interest rates tend to show a countercyclical pattern, while these three variables tend to show a pro-cyclical pattern. These results indicate that positive (negative) payoffs to TS are a preemptive signal of an improving (deteriorating) economy. On the other hand, payoffs to CS are related to future innovations in only two macroeconomic variables (GDP and consumption growth rates) with an inverse relation. Specifically, the coefficients on CS ($\hat{\theta}_3$) are negatively statistically significant for future innovations in GDP growth ($\hat{\theta}_3 = -8.31$, t-statistic of -3.27) and consumption growth ($\hat{\theta}_3 = -5.08$, t-statistic of -2.84). If cross-sectional forecast dispersion contains systematic risk components, these inverse relations are hardly justifiable in a rational economy.

To examine whether payoffs to TS and CS are differentially related to future innovations in macroeconomic variables across business cycles, we estimate the full model of equation (4) using the business cycle dummy and the Fama and French three factors controlled. Table 7 shows that payoffs to TS react to future innovations in macroeconomic variables differently across business cycles, while payoffs to CS do not. During contraction periods, the coefficient estimates on TS ($\hat{\theta}_1$) are positively statistically significant for future innovations in all seven macroeconomic variables, except for the three-month Treasury bill rate. Specifically, the coefficient estimates are 29.12 (t-statistic of 3.02) for GDP growth rate, 16.24 (t-statistic of 2.35) for consumption growth rate, 1.09 (t-statistic of 1.44) for term spread, 5.94 (t-statistic of 2.83) for default spread, 12.26 (t-statistic of 2.40) for inflation rate, and 0.24 (t-statistic of

1.56) for dividend yield. The differences in the coefficient estimate on TS between expansion and contraction periods (measured by $\hat{\theta}_2$) are negatively statistically significant for future innovations in the above-mentioned six macroeconomic variables. The differences are -26.12 (t-statistic of -2.69) for GDP growth rate, -13.83 (t-statistic of -1.97) for consumption growth rate, -1.20 (t-statistic of -1.56) for term spread, -6.20 (t-statistic of -2.95) for default spread, -10.32 (t-statistic of -1.98) for inflation rate, and -0.48 (t-statistic of -1.83) for dividend yield. However, the coefficient estimates for future innovations in three-month Treasury bill rate are opposite to the case of the six macroeconomic variables. That is, the coefficient estimates on TS ($\hat{\theta}_1$) are negatively statistically significant ($\hat{\theta}_1 =$ -8.10, t-statistic of -5.06), and the difference in the coefficient estimate on TS between expansion and contraction periods is positively statistically significant ($\hat{\theta}_2 = 7.68$, t-statistic of 4.54). In sum, payoffs to TS are positively more sensitive to future innovations in the six macroeconomic variables and negatively more sensitive to future innovations in the three-month Treasury bill rate during contraction than during expansion periods.

The above results indicate that payoffs to TS are more volatile and riskier during contraction than expansion periods. Investors would thus require greater premium for risks contained in TS during contraction than expansion periods. In fact, Table 3 shows that the arbitrage return on the zero-investment based on *DISP_TS* is greater in contraction than expansion periods. This is quite consistent with the pattern that payoffs generated from a source containing systematic risk components typically show. On the other hand, payoffs to CS do not show such pattern. The coefficient estimates on CS ($\hat{\theta}_3$) during contraction periods and the differences in the coefficient estimate on CS between expansion and contraction periods (measured by $\hat{\theta}_4$) are mostly insignificant.

4.5. Predicted Payoffs by Macroeconomic Conditions Across Dispersions

Another approach toward examining whether dispersion-based arbitrage payoffs are related to macroeconomic conditions is to adjust raw returns for prediction by macroeconomic variables and to check whether the adjusted arbitrage payoffs remain significant. According to Chordia and Shivakumar (2002), if arbitrage payoffs of the zero-investment based on some characteristic are entirely explained by predicted returns by a set of standard macroeconomic variables, the arbitrage payoffs may be attributable to conditionally expected returns that are predicted by standard macroeconomic variables and are caused by a source of systematic risk. On the other hand, if the arbitrage payoffs remain significant even after adjusting for the predicted returns, then the arbitrage payoffs may be caused by firm-specific idiosyncratic components.

To adjust raw returns for prediction by a set of standard macroeconomic variables, we first obtain the one-period-ahead predicted return from the following time-series regression model.

$$R_{i,q} = \lambda_{i0} + \lambda_{i1} X_{q-1} + \lambda_{i2} D_{q-1} + \varepsilon_{i,q}, \tag{5}$$

where $R_{i,q}$ is raw return of firm i at quarter q, X_{q-1} is a vector containing the seven macroeconomic variables used in the previous section, and D_{q-1} is a business cycle dummy variable that equals 1 during expansionary periods and 0 otherwise. The parameters are estimated each quarter for each firm by using the preceding 20 quarters data from $q-20$ to $q-1$ (a minimum of 8 quarters). The parameter estimates of the model are then used to compute the one-quarter-ahead predicted return for each stock. The unexplained portion of returns, which is defined as the sum of the intercept and the residual, represents returns after adjusting raw returns for the predicted returns by the set of macroeconomic variables. As in Table 3, we construct portfolios sorted by *DISP_TS* and *DISP_CS* by using these adjusted returns (the sum of the intercept and the residual) instead of raw returns.

Table 8 presents the differences in average adjusted (quarterly) return between the largest and smallest quintile portfolios (P5-P1) sorted by *DISP_TS* and *DISP_CS*, respectively. When the adjusted returns are sorted by *DISP_TS*, the differences in average adjusted return are insignificantly different from zero; they are 6.91 percent (t-statistic of 0.98) and 4.20 percent (t-statistic of 0.60), respectively. However, when the adjusted returns are sorted by *DISP_CS*, the differences in average adjusted return are still negative and statistically significant; they are -9.91 percent (t-statistic of -1.93) and -10.82 percent (t-statistic of -2.21), respectively, depending on the inclusion of the business cycle dummy variable in the model. These results indicate that payoffs to the zero-investment strategy based on *DISP_TS* are well explained by the prediction from the macroeconomic variables, while (negative) payoffs to the zero-investment strategy based on *DISP_CS* are not. The above results therefore constitute further evidence suggesting that arbitrage payoffs based on time-series mean forecast dispersion are explained by time-varying expected returns and can be attributed to systematic risk components, while arbitrage payoffs based on cross-sectional forecast dispersion can be attributable to firm-specific idiosyncratic components.

4.6. Cross-Sectional Regression Tests with Dispersion-Related Factor Loadings

The results thus far show that arbitrage returns based on time-series mean forecast dispersion are related to future innovations in macroeconomic variables. In other words, time-series mean forecast dispersion may contain components of nondiversifiable risk. To examine whether such risk contained in time-series mean forecast dispersion is priced in stock returns, we perform cross-sectional regression (CSR) tests by regressing cross-sectionally excess returns on factor loadings on the factor within the Fama-MacBeth (1973) two-stage methodology framework. That is, we estimate the following CSR model at month t:

$$R_{pt} - R_{ft} = \gamma_{0t} + \gamma_{1t}\hat{\beta}_{1p,t-1} + \cdots + \gamma_{Kt}\hat{\beta}_{Kp,t-1} + \varepsilon_{pt}, \qquad p = 1, \cdots, N, \tag{6}$$

where $\hat{\beta}_{kp,t-1}$ is test asset p's factor loading estimate (or beta estimate) on the k-th factor which is estimated by rolling month-by-month the previous five-year monthly returns available up to month t-1, and γ_{kt} is the risk premium of the k-th factor (or gamma) to be estimated. Thus, the beta variables are predictive betas.

Table 9 presents times-series averages ($\bar{\hat{\gamma}}_{\mathrm{k}}$) of the month-by-month CSR coefficient estimates or risk premia estimates of each factor over the entire sample period January 1986 to December 2012 (324 months). The first set of test assets is 100 size-BM equally weighted portfolios (Panel A) which are formed by sorting all NYSE, AMEX, and NASDAQ firms at the end of every June based on the intersection of 10 firm size break-points and 10 book-to-market break-points. The second set of test assets is individual stocks (Panel B).

The factor related to time-series mean forecast dispersion, TS, is significantly priced in most of the cases considered. Regardless of whether the Fama and French (1993) three factors are controlled, the risk premium estimates of TS $\left(\bar{\hat{\gamma}}_{\mathrm{TS}}\right)$ are positive and statistically significant in all test assets considered. Specifically, when TS is alone in the model, $\bar{\hat{\gamma}}_{\mathrm{TS}}$'s are 0.54 percent ($t$-statistic of 2.36) and 0.13 percent (t-statistic of 2.08), respectively, using 100 size-BM portfolios and individual stocks as test assets. Even when the Fama and French three factors are controlled, $\bar{\bar{\gamma}}_{\mathrm{TS}}$'s are 0.60 percent ($t$-statistic of 2.72) and 0.13 percent (t-statistic of 2.26), respectively. When the factor related to cross-sectional forecast dispersion, CS, is added to the models, the economic and statistical significance of TS remains qualitatively unchanged. On the other hand, Table 9 shows no evidence that CS is priced, even negatively. Its risk premium estimates $\left(\bar{\bar{\gamma}}_{\mathrm{CS}}\right)$ are statistically insignificant in all cases considered.

5. Conclusions

This paper attempts to address the issue on whether time-series mean forecast dispersion contains systematic risk components and whether such risk is priced in stock returns. To do this, we perform several tests by i) examining the pattern of stock returns across forecast dispersions; ii) examining the relation between time-series mean forecast dispersion and stock return after adjusting for several systematic risk components; iii) relating payoffs to time-series mean forecast dispersion-based factors to macroeconomic conditions; and iv) conducting CSR tests to examine whether risk components contained in time-series mean forecast dispersion are priced in stock returns.

We find that there is a strong positive relation between time-series mean forecast dispersion and stock returns. Further, we find that time-series mean forecast dispersion apparently contains systematic risk components and that such risk is priced in stock returns, while cross-sectional forecast dispersion does not contain such risk. In other words, time-series dispersion around mean forecast is informative in terms of pricing ability, but cross-sectional dispersion around mean forecast is not so. Each analyst observes two signals about a firm's future earnings: one is the public one which is common across all analysts, and the other is the private one which is idiosyncratic and unique to a particular analyst. Cross-sectional forecast dispersion is the measure of deviation of idiosyncratic signals around the common and public signal at a given time, while time-series forecast dispersion is the measure of deviation of public signals over time. Put differently, analysts are *individually* non-informative, but *collectively* informative in terms of pricing ability. This may be the reason that time-series mean forecast dispersion contains systematic risk components, while cross-sectional forecast dispersion does not such components.

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Table 1 Summary Statistics of Cross-Sectional and Time-Series Dispersions in Analysts' Earnings Forecasts

This table presents summary statistics of cross-sectional and time-series dispersions in analysts' earnings forecasts. Cross-sectional dispersion in analysts' earnings forecasts (*DISP_CS*) is measured as standard deviation of analysts' current-fiscal-quarter EPS forecasts, scaled by the mean value of the absolute analyst forecasts. Time-series mean forecast dispersion (*DISP_TS*) is measured as standard deviation of the time-series mean forecast errors obtained from using quarterly mean values of analysts' earnings forecasts, scaled by the stock price at the previous quarter-end. Analysts' earnings forecasts are obtained from the I/B/E/S Unadjusted Detail History File. 'Ave #estimates' indicates the average number of analysts' earnings forecasts in computing cross-sectional forecasts dispersion. 'Earnings surprise' indicates the difference between average actual earnings and average forecast earnings available on the I/B/E/S File. The sample period is January 1986 to December 2012.

Periods	#Months	Cross-sectional dispersion (DISP_CS)	Ave #estimates	Time-series forecast dispersion (DISP_TS)	# Firms	Ave actual earnings	Ave forecast earnings	Earnings surprise	Ave market return
				Panel A: Over the whole calendar years					
1986-1990	60	0.2385	4.35	0.0103	2,345	0.5907	0.6430	-0.0523	0.4780
1990-1995	60	0.1784	4.58	0.0085	3,291	0.4492	0.4636	-0.0145	1.0500
1996-2000	60	0.1615	4.63	0.0068	5,235	0.4044	0.3956	0.0089	1.0169
2001-2005	60	0.1669	6.04	0.0089	3,991	0.5419	0.5478	-0.0059	0.0731
2005-2010	60	0.2390	7.07	0.0090	3,868	1.0083	0.9455	0.0628	0.2082
2011-2012	24	0.2228	8.40	0.0104	2,886	1.0532	1.0549	-0.0017	0.7280
Whole period	324	0.1983	5.92	0.0087	9,584	0.7109	0.6972	0.0137	0.5773
				Panel B: Over business cycles					
				Expansionary periods					
01/86-07/90	55	0.2404	4.33	0.0101	2,244	0.6047	0.6576	-0.0530	0.6916
04/91-03/01	120	0.1672	4.63	0.0075	6,221	0.4210	0.4209	0.0000	0.7939
12/01-12/07	73	0.1726	6.30	0.0079	4,196	0.7721	0.7338	0.0383	0.4261
07/09-12/12	42	0.2427	8.22	0.0108	3,225	1.0495	1.0119	0.0376	1.3384
Overall	290	0.1908	5.86	0.0085	9,516	0.7055	0.6868	0.0187	0.7608
				Contractionary Periods					
08/90-03/91	8	0.2310	4.70	0.0130	1,416	0.4961	0.5424	-0.0463	0.6469
04/01-11/01	8	0.1837	5.65	0.0086	2,583	0.3510	0.3451	0.0059	-0.1334
01/08-06/09	18	0.2808	6.88	0.0102	2,949	0.8934	0.9167	-0.0234	-2.0935
Overall	34	0.2533	6.35	0.0103	4,980	0.7491	0.7701	-0.0210	-0.9875

Table 2 Characteristics of the Portfolios Sorted by Cross-Sectional or Time-Series Dispersion in Analysts' Earnings Forecasts

This table presents average values of several characteristics of portfolios sorted by time-series mean forecast dispersion (DISP_TS) or cross-sectional forecast dispersion (DISP_CS). All stocks are assigned every month into one of five equally-weighted quintile portfolios according DISP_CS or DISP_TS over the entire sample period 1986-2012. Numbers are the averages of the firm characteristic values on the portfolio formation months. Firm size is the market capitalization (in million dollars). 'P5-P1' indicates the difference in average value between the largest and smallest quintile portfolios.

	Time-series forecast dispersion (DISP_TS)	Cross-sectional dispersion (DISP_CS)	Firm size	Book-to-market	Market beta	Price per share
	Sorted by time-series mean forecast dispersion (DISP_TS)					
DISP_TS1	0.0011	0.0578	9,462.85	0.37	1.0264	87.79
DISP_TS2	0.0025	0.0963	6,256.21	0.48	1.0826	39.70
DISP_TS3	0.0043	0.1553	5,000.54	0.56	1.1705	60.77
DISP_TS4	0.0076	0.2482	3,541.82	0.66	1.2834	27.01
DISP_TS5	0.0278	0.4031	2,592.10	0.83	1.4874	18.37
P5-P1			-6870.75	0.46	0.4609	-69.42
	Sorted by cross-sectional forecast dispersion (DISP_CS)					
DISP_CS1	0.0040	0.0140	8,055.48	0.47	1.0413	56.16
DISP_CS2	0.0046	0.0378	7,073.26	0.49	1.1115	50.61
DISP_CS3	0.0066	0.0693	5,599.84	0.55	1.2018	62.49
DISP_CS4	0.0101	0.1406	4,028.74	0.63	1.2879	43.56
DISP_CS5	0.0158	0.6848	2,623.82	0.71	1.3757	25.09
P5-P1			-5,431.66	0.24	0.3344	-31.07

Table 3 Average Returns and Standard Deviations of Portfolios Sorted by Cross-Sectional and Time-Series Dispersions in Analysts' Earnings Forecasts

Portfolios are formed every month by sorting all firms according to the magnitude of time-series mean forecast dispersion (DISP_TS) and cross-sectional forecast dispersion (DISP_CS) over the entire sample period 1986-2012. Five break-points for DISP_CS and DISP_TS are independently determined. Portfolios are equally weighted. 'P5-P1' indicates an arbitrage portfolio that buys long Portfolio 5 (the largest dispersion) and sells short Portfolio 1 (the smallest dispersion). Analysts' earnings forecasts are obtained from the I/B/E/S Unadjusted Detail History File. Numbers in parentheses indicate t-statistics.

	DISP_CS1	DISP_CS2	DISP_CS3	DISP_CS4	DISP_CS5	P5-P1	Overall
Panel A: Whole periods (January 1986 - December 2012; 324 months)							
Average return (%)							
DISP_TS1	0.98	1.09	1.13	0.80	0.77	-0.21(-0.69)	1.04(4.00)
DISP_TS2	1.18	0.98	1.23	0.90	0.98	-0.20(-0.63)	1.05(3.88)
DISP_TS3	1.08	1.11	0.97	0.93	1.04	-0.04(-0.16)	1.06(3.56)
DISP_TS4	1.66	1.23	1.25	1.26	0.96	-0.70(-3.15)	1.14(3.35)
DISP_TS5	1.98	1.90	1.39	1.47	1.07	-0.91(-2.74)	1.63(3.68)
P5-P1	1.00	0.81	0.26	0.67	0.30		**0.59(2.13)**
	(2.46)	(2.02)	(0.71)	(1.76)	(0.74)		
Overall	1.20	1.10	1.05	1.08	0.80	**-0.40**	
	(4.08)	(3.6)	(3.02)	(2.79)	(1.89)	**(-2.00)**	
Standard deviation (%)							
DISP_TS1	4.55	4.83	5.33	6.37	7.55	5.41	4.67
DISP_TS2	4.96	5.19	5.33	5.59	7.04	5.56	4.85
DISP_TS3	5.57	5.92	6.09	6.01	6.63	4.06	5.33
DISP_TS4	6.36	6.29	6.56	6.80	7.14	3.97	6.10
DISP_TS5	9.36	9.46	9.20	9.24	8.98	5.89	7.96
P5-P1	7.22	7.16	6.40	6.76	7.20		4.97
Overall	5.27	5.47	6.22	6.94	7.62	3.55	

Panel B: Average returns over business cycles							
			Expansionary periods (290 months)				
DISP_TS1	1.13	1.14	1.01	1.10	0.98	-0.15(-0.49)	1.11(4.38)
DISP_TS2	1.35	1.17	1.21	1.00	1.35	-0.00(-0.01)	1.16(4.49)
DISP_TS3	1.36	1.31	1.24	1.19	0.96	-0.41(-1.75)	1.21(4.33)
DISP_TS4	1.48	1.28	1.20	1.35	1.24	-0.24(-1.06)	1.28(4.05)
DISP_TS5	2.03	1.81	1.38	1.45	1.08	-0.95(-2.74)	1.71(4.15)
P5-P1	0.90	0.67	0.37	0.35	0.10		**0.60(2.38)**
	(2.14)	(1.65)	(1.12)	(0.94)	(0.26)		
Overall	1.33	1.20	1.16	1.23	0.98	**-0.35**	
	(4.63)	(4.15)	(3.58)	(3.43)	(2.46)	**(-1.91)**	
			Contractionary periods (34 months)				
DISP_TS1	0.00	0.06	-0.13	-1.89	-1.79	-1.78(-1.80)	-0.15(-0.13)
DISP_TS2	0.15	-0.18	0.32	-0.69	-0.37	-0.52(-0.61)	-0.03(-0.02)
DISP_TS3	-0.37	0.43	-0.04	-0.91	0.12	0.49(0.48)	-0.08(-0.05)
DISP_TS4	0.85	0.70	0.79	0.34	-0.58	-1.43(-1.47)	0.08(0.05)
DISP_TS5	1.40	3.05	0.64	2.00	0.07	-1.33(-1.08)	1.34(0.57)
P5-P1	1.40	3.00	0.78	3.89	1.85		**1.49(1.04)**
	(0.91)	(2.05)	(0.48)	(2.31)	(1.15)		
Overall	0.33	0.41	0.32	-0.10	-0.37	**-0.70**	
	(0.25)	(0.27)	(0.18)	(-0.05)	(-0.17)	**(-0.68)**	

Table 4 Average Returns of Portfolios Sorted by Dispersion in Analysts' Earnings Forecasts and Earnings Surprise

This table presents average returns of portfolios sorted by time-series mean forecast dispersion (DISP_TS) or cross-sectional forecast dispersion (DISP_CS) and earnings surprise. Earnings surprise (*ES*) is defined as the difference between actual earnings and the mean value of analysts' earnings forecasts, scaled by stock price at the end of the previous quarter. Firms are first sorted into one of three *ES* portfolios according to the sign of earnings surprise (negative, zero, positive). Then, the negative (positive) ES portfolio, $\mathrm{ES} < 0$ $(\mathrm{ES} > 0)$, is split into two subgroups, $\mathrm{ES}^{(-2)}$ and $\mathrm{ES}^{(-1)}$ ($\mathrm{ES}^{(+1)}$ and $\mathrm{ES}^{(+2)}$), according to whether firms are below or above the median negative (positive) earnings surprise. If the absolute value of ES is less than 0.005, it is regarded as belonging to the group of ES=0. Portfolios are equally weighted and rebalanced every month. 'P5-P1' indicates an arbitrage portfolio that buys long Portfolio 5 (the largest dispersion) and sells short Portfolio 1 (the smallest dispersion). Numbers in parentheses indicate t statistics.

	$\mathrm{ES} < 0$		$\mathrm{ES} = 0$	$\mathrm{ES} > 0$		Overall
	$\mathrm{ES}^{(-2)}$	$\mathrm{ES}^{(-1)}$		$\mathrm{ES}^{(+1)}$	$\mathrm{ES}^{(+2)}$	
	Panel A: Sorted by cross-sectional forecast dispersion and earnings surprise					
DISP_CS1	1.01(3.15)	0.92(3.06)	1.19(3.73)	1.16(3.91)	1.53(4.87)	1.20(4.08)
DISP_CS2	0.89(2.74)	1.05(3.51)	1.29(3.57)	1.05(3.37)	1.28(3.97)	1.10(3.60)
DISP_CS3	0.88(2.36)	0.84(2.36)	1.11(2.64)	1.17(3.26)	1.20(3.45)	1.05(3.02)
DISP_CS4	0.99(2.37)	0.75(1.9)	1.28(2.57)	1.26(3.07)	1.31(3.44)	1.08(2.79)
DISP_CS5	0.71(1.57)	0.56(1.27)	0.62(1.14)	1.12(2.58)	1.17(2.77)	0.80(1.89)
P5-P1	-0.30(-1.16)	-0.36(-1.31)	-0.57(-1.28)	-0.04(-0.15)	-0.36(-1.70)	**-0.40(-2.00)**
Overall	0.89(2.40)	0.79(2.24)	0.96(2.92)	1.15(3.37)	1.30(3.83)	
	Panel B: Sorted by time-series mean forecast dispersion and earnings surprise					
DISP_TS1	0.78(2.85)	0.79(3.02)	0.98(2.99)	0.99(3.57)	1.24(4.31)	1.04(4.00)
DISP_TS2	1.08(3.92)	0.92(3.02)	0.65(1.68)	1.15(3.83)	1.11(3.73)	1.05(3.88)
DISP_TS3	0.96(3.02)	0.87(2.56)	0.35(0.74)	1.06(3.08)	1.24(3.82)	1.06(3.56)
DISP_TS4	1.05(2.78)	0.93(2.45)	0.66(1.23)	1.46(3.68)	1.46(4.15)	1.14(3.35)
DISP_TS5	1.41(2.73)	1.48(2.83)	1.12(1.52)	1.65(3.4)	1.72(3.80)	1.63(3.68)
P5-P1	0.62(1.77)	0.69(1.74)	0.14(0.20)	0.66(2.10)	0.48(1.65)	**0.59(2.13)**
Overall	1.10(3.28)	1.03(3.01)	0.96(2.91)	1.25(3.82)	1.41(4.46)	
	Panel C: Average number of firms					Total
DISP_CS1	39	40	18	101	101	300
DISP_CS2	44	45	13	102	103	307
DISP_CS3	50	51	11	95	96	304
DISP_CS4	59	60	10	86	86	301
DISP_CS5	73	74	9	70	70	296
Total	266	269	61	454	457	1508

Table 5 Average Returns of Portfolios Sorted by Dispersion in Analysts' Earnings Forecasts And Firm Size, Book-to-market Ratio, or Market Beta

This table presents average returns (%) of portfolios that are formed every month by first sorting all firms into one of five quintile portfolios according to the magnitude of the firm characteristic variable (firm size, book-to-market ratio, or market beta), and then by sorting the firms within each quintile portfolio into one of the five portfolios according to the magnitude of cross-sectional (DISP_CS) or time-series (DISP_TS) dispersion in analysts' earnings forecasts. Portfolios are equally weighted. 'P5-P1' indicates an arbitrage portfolio that buys long Portfolio 5 (the largest dispersion) and sells short Portfolio 1 (the smallest dispersion). Numbers in parentheses indicate t-values. The sample period is from January 1986 to December 2012.

Second sorting variable	First sorting variable																	
	Firm size						Book-to-market ratio						Market beta					
	small	2	3	4	large	Overall	low	2	3	4	high	Overall	low	2	3	4	high	Overall
DISP_CS1	1.40	1.42	1.21	1.03	1.01	1.21(4.08)	0.87	1.07	1.27	1.41	1.53	1.23(4.31)	1.06	1.27	1.25	1.20	1.43	1.24(3.89)
DISP_CS2	1.11	1.13	1.09	0.96	1.06	1.07(3.42)	0.87	1.05	1.12	1.19	1.44	1.14(3.86)	1.11	1.09	1.35	1.13	0.91	1.12(3.48)
DISP_CS3	0.91	1.03	0.94	1.04	1.10	1.00(2.94)	0.58	1.04	1.04	1.26	1.25	1.03(3.14)	1.02	1.12	1.17	1.09	1.20	1.12(3.25)
DISP_CS4	0.47	0.91	1.23	0.86	0.91	0.88(2.43)	0.73	0.75	1.06	1.03	1.14	0.94(2.57)	0.74	1.20	1.14	1.18	0.93	1.04(2.84)
DISP_CS5	0.40	0.84	0.93	1.02	0.90	0.82(2.07)	0.70	1.03	0.96	0.97	0.79	0.89(2.24)	0.57	0.90	0.75	1.10	0.81	0.83(2.12)
P5-P1	-1.00	-0.59	-0.28	-0.01	-0.11	**-0.40(-2.44)**	-0.17	-0.03	-0.31	-0.44	-0.74	**-0.34(-1.91)**	-0.50	-0.36	-0.50	-0.10	-0.62	**-0.42(-2.93)**
(t-value)	-4.61	-2.86	-1.30	-0.05	-0.53		-0.65	-0.14	-1.41	-2.17	-3.52		-2.93	-1.86	-2.7	-0.47	-2.91	
DISP_TS1	1.30	1.13	1.04	1.10	0.95	1.11(4.13)	1.12	1.10	1.04	1.18	1.11	1.11(4.5)	1.03	1.10	1.10	1.11	1.04	1.08(3.83)
DISP_TS2	1.13	1.09	1.10	0.94	0.86	1.03(3.63)	0.84	1.06	1.07	1.07	1.10	1.03(3.82)	0.88	1.06	1.20	1.11	1.20	1.09(3.84)
DISP_TS3	1.23	1.01	1.05	1.10	1.00	1.08(3.67)	0.99	1.05	1.29	1.10	1.20	1.13(3.73)	0.88	0.99	1.18	1.02	1.26	1.07(3.53)
DISP_TS4	1.55	1.17	1.13	1.14	0.95	1.19(3.53)	0.90	1.13	1.23	1.38	1.44	1.22(3.53)	0.89	1.03	1.20	1.21	1.61	1.19(3.58)
DISP_TS5	2.39	1.42	1.30	1.10	0.99	1.44(3.42)	1.17	1.39	1.41	1.53	2.12	1.52(3.47)	1.06	1.37	1.23	1.50	1.92	1.42(3.57)
P5-P1	1.09	0.29	0.26	0.00	0.03	**0.34(1.34)**	0.05	0.29	0.37	0.35	1.01	**0.41(1.49)**	0.03	0.26	0.13	0.40	0.88	**0.34(1.61)**
(t-value)	3.23	0.96	0.86	0.00	0.15		0.14	0.89	1.20	1.25	3.04		0.15	1.21	0.58	1.43	2.57	

Table 6 Estimates of the Intercept and Factor Loadings of the Fama-French Three-Factor Model

This table presents the estimates of the intercept (or Jensen's alpha) and factor loadings from the Fama-French (1993) three-factor model (FF3), $R_{pt} - R_{ft} = \alpha_p + \beta_{\mathrm{MKT},p}(R_{\mathrm{MKT},t} - R_{ft}) + \beta_{\mathrm{SMB},p}\mathrm{SMB_t} + \beta_{\mathrm{HML},p}\mathrm{HML_t} + e_{pt}$, for 25 (=5×5) portfolios sorted by the magnitude of time-series mean forecast dispersion (DISP_TS) and cross-sectional forecast dispersion (DISP_CS). Five break-points for DISP_TS and DISP_CS are independently determined. The estimation period is January 1986 to December 2012. 'P5-P1' indicates the intercept estimate from the factor model for the arbitrage portfolio that buys long Portfolio 5 (the largest dispersion) and sells short Portfolio 1 (the smallest dispersion). 'GRS' is the Gibbons, Ross, and Shanken (1989) *F*-statistic for a joint test on whether all intercept estimates of the five overall (DISP_TS- or DISP_CS-sorted) portfolios are different from zero. 'HJ-dist' is the Hansen-Jagannathan (1997) distance. Numbers in parentheses are t-statistics, and numbers in square brackets are p-values.

	DISP_CS1	DISP_CS2	DISP_CS3	DISP_CS4	DISP_CS5	P5-P1	Overall	$\alpha_{\mathrm{overall}} = 0$
			Panel A: Intercept estimates $(\hat{\alpha}_{\mathrm{p}})$					
DISP_TS1	0.14(1.39)	0.23(2.20)	0.28(2.19)	-0.07(-0.40)	-0.12(-0.46)	-0.27(-0.94)	0.19(2.42)	GRS:
DISP_TS2	0.24(2.03)	0.03(0.24)	0.28(2.48)	-0.03(-0.22)	0.09(0.35)	-0.16(-0.55)	0.07(0.90)	5.209 [0.000]
DISP_TS3	0.07(0.48)	0.07(0.49)	-0.10(-0.76)	-0.13(-1.04)	0.02(0.14)	-0.05(-0.21)	0.02(0.25)	HJ-dist:
DISP_TS4	0.57(3.17)	0.14(0.80)	0.15(0.97)	0.11(0.76)	-0.23(-1.48)	-0.80(-3.67)	0.00(0.00)	0.063
DISP_TS5	0.77(2.22)	0.67(2.13)	0.13(0.42)	0.12(0.42)	-0.32(-1.47)	-1.09(-3.28)	0.33(1.92)	[0.278]
P5-P1	0.63(1.73)	0.44(1.26)	-0.15(-0.46)	0.19(0.54)	-0.20(-0.55)		**0.14(0.67)**	
Overall	0.35(4.15)	0.22(2.71)	0.17(1.74)	0.14(1.27)	-0.15(-1.17)	**-0.50(-3.48)**		
$\alpha_{\mathrm{overall}} = 0$	GRS: 5.476[0.000]			HJ-dist: 0.155 [0.009]				
			Panel B: Factor loading estimates					
			$\hat{\beta}_{\mathrm{MKT}}$					
DISP_TS1	0.92(39.73)	0.95(39.78)	0.96(33.83)	1.03(25.93)	1.15(19.23)	0.24(3.70)	0.93(52.64)	
DISP_TS2	0.99(36.89)	1.03(39.28)	1.03(40.87)	1.04(34.93)	0.99(18.19)	0.00(-0.07)	0.98(56.60)	
DISP_TS3	1.06(32.87)	1.15(37.51)	1.18(39.48)	1.15(41.26)	1.13(29.55)	0.07(1.52)	1.07(62.72)	
DISP_TS4	1.12(27.58)	1.13(28.06)	1.22(34.26)	1.27(39.79)	1.30(36.71)	0.18(3.72)	1.19(51.57)	
DISP_TS5	1.36(17.45)	1.40(19.64)	1.47(21.86)	1.54(24.17)	1.55(31.50)	0.20(2.62)	1.39(36.06)	
P5-P1	0.44(5.43)	0.45(5.69)	0.51(6.92)	0.51(6.42)	0.40(4.88)		**0.46(9.90)**	
Overall	1.00(52.32)	1.06(58.78)	1.13(53.00)	1.23(48.45)	1.29(46.13)	**0.29(8.92)**		

				$\hat{\beta}_{SMB}$			
DISP_TS1	0.06(1.69)	0.14(4.16)	0.32(7.84)	0.47(8.31)	0.29(3.45)	0.24(2.63)	0.22(8.61)
DISP_TS2	0.13(3.32)	0.22(5.87)	0.33(9.06)	0.36(8.44)	0.69(8.96)	0.57(6.19)	0.31(12.46)
DISP_TS3	0.35(7.54)	0.33(7.50)	0.42(9.91)	0.50(12.55)	0.65(11.83)	0.30(4.35)	0.42(17.16)
DISP_TS4	0.58(9.98)	0.49(8.47)	0.50(9.79)	0.63(13.87)	0.72(14.17)	0.14(1.99)	0.58(17.42)
DISP_TS5	0.89(7.99)	1.02(10.09)	0.81(8.41)	0.86(9.50)	1.03(14.59)	0.14(1.31)	0.99(17.86)
P5-P1	0.83(7.17)	0.88(7.85)	0.49(4.66)	0.39(3.47)	0.73(6.24)		**0.77(11.52)**
Overall	0.39(14.1)	0.39(15.01)	0.53(17.28)	0.68(18.54)	0.87(21.56)	**0.48(10.31)**	
				$\hat{\beta}_{HML}$			
DISP_TS1	0.13(3.62)	0.08(2.11)	-0.02(-0.54)	-0.17(-2.80)	-0.27(-2.89)	-0.39(-4.03)	0.03(1.21)
DISP_TS2	0.33(7.95)	0.27(6.67)	0.23(5.86)	0.11(2.36)	-0.06(-0.75)	-0.39(-3.97)	0.23(8.53)
DISP_TS3	0.40(8.19)	0.34(7.19)	0.37(8.05)	0.34(7.98)	0.15(2.63)	-0.25(-3.36)	0.33(12.50)
DISP_TS4	0.52(8.27)	0.48(7.75)	0.33(5.96)	0.40(8.24)	0.45(8.28)	-0.06(-0.85)	0.41(11.70)
DISP_TS5	0.35(2.91)	0.25(2.32)	0.31(3.02)	0.52(5.26)	0.59(7.82)	0.24(2.12)	0.53(8.89)
P5-P1	0.22(1.76)	0.18(1.45)	0.34(2.97)	0.69(5.65)	0.86(6.79)		**0.50(6.90)**
Overall	0.14(4.58)	0.16(5.75)	0.12(3.62)	0.18(4.73)	0.22(5.13)	**0.08(1.72)**	

Table 7 Analysts' Forecasts Dispersion-Related Factors and Macroeconomic Conditions

This table presents the coefficient estimates (×100) of the following regression model,

$$u^{K}_{q+1,q+4} = \theta_0 + \theta_1 \mathrm{TS}_{q-3,q} + \theta_2 \mathrm{TS}_{q-3,q}\mathrm{D}_q + \theta_3 \mathrm{CS}_{q-3,q} + \theta_4 \mathrm{CS}_{q-3,q}\mathrm{D}_q + \theta_{C1}\Lambda_{q-3,q} + \theta_{C2}\Lambda_{q-3,q}\mathrm{D}_q + \varepsilon_q,$$

where the dependent variable, $u^{K}_{q+1,q+4}$, is the continuously compounded growth rate of innovation in a macroeconomic variable K over quarters q+1 through q+4. The innovations are obtained from the VAR(1) model that includes seven macroeconomic variables; GDP growth rate, consumption growth rate, inflation rate, term spread, default spread, dividend yield, and 3-month T-bill rate. $\mathrm{TS}_{q-3,q}$ and $\mathrm{CS}_{q-3,q}$ are the continuously compounded values over quarters q-3 through q of the factors related to time-series and cross-sectional forecast dispersions, respectively. D_q is a business cycle dummy variable that equals 1 for expansion periods and 0 for contraction periods. $\Lambda_{q-3,q}$ is a vector of control risk factors which are continuously compounded over quarters q-3 through q. The Fama and French (1993) three factors, MKT, SMB, and HML, are used as the control risk factors. Numbers in parentheses indicate t-statistics based on the autocorrelation-consistent Newey-West standard errors.

Explanatory variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	Innovations in GDP growth rate		Innovations in consumption growth rate		Innovations in term spread	
TS	4.03(2.37)	29.12(3.02)	2.61(2.15)	16.24(2.35)	0.02(0.13)	1.09(1.44)
TS*D		-26.12(-2.69)		-13.83(-1.97)		-1.20(-1.56)
CS	-8.31(-3.27)	-19.14(-0.76)	-5.08(-2.84)	-8.31(-0.46)	0.45(1.48)	-0.51(-0.42)
CS*D		9.68(0.38)		1.99 (0.11)		1.07(0.83)
Constant	-0.89(-2.61)	-6.01(-1.52)	-0.63(-2.63)	-3.48(-1.17)	0.02(0.44)	-0.13(-0.62)
FF3	YES	YES	YES	YES	YES	YES
FF3*D	NO	YES	NO	YES	NO	YES
Adj R^2	0.121	0.219	0.144	0.183	0.007	-0.022
	Innovations in default spread		Innovations in inflation rate		Innovations in 3-month Treasury bill rate	
TS	-0.08(-0.39)	5.94(2.83)	3.13(2.63)	12.26(2.40)	-0.71(-1.70)	-8.10(-5.06)
TS*D		-6.20(-2.95)		-10.32(-1.98)		7.68 (4.54)
CS	0.51(1.75)	-0.64(-0.20)	0.77(0.52)	-10.55(-0.80)	-1.01(-1.17)	7.35 (2.81)
CS*D		0.88(0.28)		11.15(0.83)		-8.38(-3.03)
Constant	0.01(0.27)	-0.51(-0.87)	-0.07(-0.29)	-4.68(-2.38)	-0.06(-0.61)	1.51(2.79)
FF3	YES	YES	YES	YES	YES	YES
FF3*D	NO	YES	NO	YES	NO	YES
Adj R^2	-0.008	0.339	0.092	0.242	-0.002	0.044
	Innovations in dividend yield					
TS	-0.16(-1.07)	0.24(1.56)				
TS∗D		-0.48(-1.83)				
CS	-0.11(-0.72)	0.70 (1.29)				
CS∗D		-0.78(-1.35)				
Constant	0.01(0.80)	0.19(2.67)				
FF3	YES	YES				
FF3∗D	NO	YES				
Adj R^2	-0.030	-0.063				

Table 8 Analysts' Forecast Dispersion-Based Payoffs Adjusted for Macroeconomic Variables

This table presents analysts' forecasts dispersion-based quarterly arbitrage returns after adjusting for the predicted returns from a set of macroeconomic variables. Adjusted returns are measured as the unexplained portion (intercept plus residual) of the following time-series regression model: $R_{i,q} = \lambda_{i,0} + \lambda_{i,1}X_{q-1} + \lambda_{i,2}D_{q-1} + \varepsilon_{i,q}$, where $R_{i,q}$ is raw return of firm i at quarter q, X_{q-1} is a vector containing seven macroeconomic variables (GDP growth rate, consumption growth rate, inflation rate, term spread, default spread, dividend yield, and three-month Treasury bill yield), and D_{q-1} is a business cycle dummy that equals one in expansionary periods and zero otherwise. The parameters are estimated each quarter for each firm by using the previous 20 quarters data from $q-20$ to $q-1$ (a minimum of eight quarters). 'P5-P1' indicates an arbitrage portfolio that buys long Portfolio 5 (the largest dispersion) and sells short Portfolio 1 (the smallest dispersion). '% < 0' indicates the percentage of P5-P1 that are negative, and '% > 0' indicates the percentage of P5-P1 that are positive. Numbers in parentheses indicate t-statistics, and numbers in square brackets indicate p-values from the sign test measuring deviations from 50 percent.

	Time-series mean forecast dispersion (DISP_TS)		Cross-sectional forecast dispersion (DISP_CS)	
	P5-P1	% < 0	P5 - P1	% > 0
	Panel A: Raw returns			
	1.03	58.49	-1.13	62.26
	(2.41)	[0.098]	(-1.71)	[0.015]
	Panel B: Adjusted returns			
With business cycle dummy	6.91	54.65	-9.91	60.47
	(0.98)	[0.451]	(-1.93)	[0.066]
Without business cycle dummy	4.20	51.16	-10.82	59.30
	(0.60)	[0.914]	(-2.21)	[0.105]

Table 9 Time-Series Averages of the Cross-Sectional Regression Coefficient Estimates

This table presents times-series averages of the month-by-month cross-sectional regression coefficient estimates of excess returns of test assets on their factor loadings, following Fama and MacBeth (1973). The factor loadings of the test asset are predictive betas which are estimated from time-series regressions of raw returns of the test asset on the factors by month-by-month rolling over past two year returns (a minimum of 12 months). Test assets are 100 size-BM equally weighted portfolios (Panel A) which are formed by sorting all NYSE, AMEX, and NASDAQ firms at the end of every June based on the intersection of 10 firm size break-points and 10 book-to-market break-points and individual stocks (Panel B). TS and CS are factors related to time-series and cross-sectional forecast dispersions, respectively, and MKT, SMB, and HML are the Fama and French (1993) three factors. $\overline{\text{Adj}}\ R^2$ is the time-series average of month-by-month cross-sectional regression's adjusted R^2. Numbers in parentheses indicate t-statistic. The sample period is January 1986 to December 2012.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
					Panel A: Using 10×10 size-BM portfolios				
β_{TS}	0.54(2.36)		0.6(3.07)	0.63(2.72)		0.65(3.21)	0.52(2.39)		0.43(1.96)
β_{CS}		-0.03(-0.16)	-0.09(-0.56)		-0.01(-0.06)	-0.02(-0.15)		-0.12(-1.18)	-0.08(-0.76)
β_{MKT}				-0.62(-2.1)	-0.61(-2.41)	-0.68(-2.62)	-1.06(-2.81)	-1.03(-2.71)	-0.97(-2.62)
β_{SMB}							0.15(0.46)	0.28(1.03)	0.18(0.53)
β_{HML}							-0.04(-0.08)	-0.02(-0.05)	0.01(0.03)
Intercept	0.89(3.04)	1.26(4.4)	0.96(3.48)	1.44(4.81)	1.81(6.33)	1.53(5.72)	1.69(6.61)	1.72(6.55)	1.67(6.79)
$\overline{\text{Adj}}\ R^2$	0.061	0.079	0.120	0.137	0.136	0.174	0.200	0.199	0.220
					Panel B: Using individual stocks				
β_{TS}	0.13(2.08)		0.13(2.26)	0.11(2.14)		0.11(2.29)	0.16(2.71)		0.16(2.75)
β_{CS}		-0.01(-0.18)	-0.01(-0.19)		-0.03(-0.75)	-0.04(-0.89)		0.01(0.31)	0.05(0.91)
β_{MKT}				0.15(1.25)	0.2(1.65)	0.21(1.87)	0.16(1.7)	0.02(0.28)	0.15(1.68)
β_{SMB}							-0.04(-0.53)	-0.06(-0.46)	-0.08(-1.11)
β_{HML}							-0.03(-0.61)	-0.04(-0.33)	-0.02(-0.41)
Intercept	1.11(3.76)	1.19(3.95)	1.12(3.91)	0.93(4.13)	0.97(4.24)	0.93(4.17)	0.93(4.16)	0.98(4.31)	0.92(4.21)
$\overline{\text{Adj}}\ R^2$	0.005	0.006	0.010	0.016	0.016	0.019	0.020	0.020	0.023

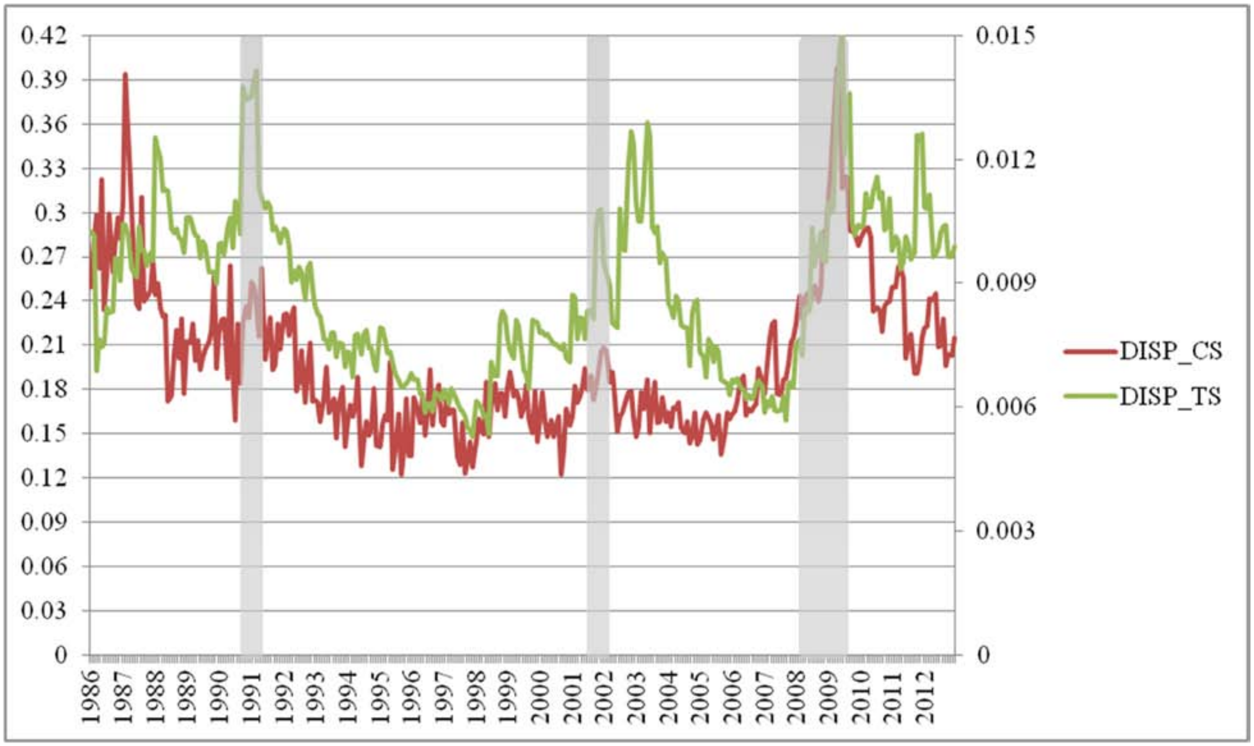

Figure 1. Time-series Pattern of Mean Cross-sectional and Time-series Dispersion

'DISP_CS' refers to cross-sectional dispersion in analysts' earnings forecasts, and 'DISP_TS' refers to time-series mean forecast dispersion. Gray bars indicate the NBER recession periods.