Published in *Journal of Empirical Finance* 39, December 2016, pp.37-53.

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

Dongcheol Kim†
Haejung Na‡

This draft: September 2016

Abstract:

Previous studies use cross-sectional forecast dispersion in examining the relation between forecast dispersion and future stock returns and report an anomalous negative dispersion-return relation. This paper examines how time-series forecast dispersion is distinct in the relation to stock returns from the negative dispersion-return relation. We find that contrary to the previously-known negative dispersion-return relation, there is a strong positive relation between time-series forecast dispersion and stock returns. We also find that time-series forecast dispersion apparently contains systematic risk components and that such risk is priced in stock returns.

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

JEL classification: G12, G14

---

† Korea University Business School, Anam-ro, Seongbuk-gu, Seoul 02841, Korea. E-mail: kimdc@korea.ac.kr. Kim was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2014-S1A5A2A01011644).
‡ Corresponding author. Department of Finance and Law, College of Business and Economics, California State University, Los Angeles. E-mail: hna5@calstatela.edu.
* We are grateful for the comments of two anonymous referees, and especially, the Editor, Daniel Ferreira. We also thank seminar and conference participants at Korea University Business School, the 2015 European Financial Management Association Conference, the 2015 Auckland Finance Meeting, the 2014 Financial Management Association Conference, the 27th Australian Finance and Banking Conference (2014), the 9th International Conference on Asia-Pacific Financial Markets (2014), and the 2013 Joint Conference with Allied Korea Finance Associations for comments on earlier drafts. The title of the earlier version was "Cross-Sectional and Intertemporal Forecast Dispersions, Risk, and Stock Returns."
** This paper was a winner of the CFA Institute Research Award at the 27th Australian Finance and Banking Conference, December 2014.

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

Abstract

Previous studies use cross-sectional forecast dispersion in examining the relation between forecast dispersion and future stock returns and report an anomalous negative dispersion-return relation. This paper examines how time-series forecast dispersion is distinct in the relation to stock returns from the negative dispersion-return relation. We find that contrary to the previously-known negative dispersion-return relation, there is a strong positive relation between time-series forecast dispersion and stock returns. We also find that time-series forecast dispersion apparently contains systematic risk components and that such risk is priced in stock returns.

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

JEL classification: G12, G14

1. Introduction

It is controversial whether analysts' earnings forecast dispersion contains non-diversifiable risk components and is thus informative in terms of pricing ability. It is critical, therefore, how we measure dispersion in analysts' forecasts. Recent studies measure dispersion from observing cross-sectional dispersion in forecasts among individual analysts at a given time. Among many, the most representative study using cross-sectional forecast dispersion is that of Diether, Malloy, and Scherbina (2002) who examine the relation between this dispersion and future stock returns. They report that there is a negative relationship between cross-sectional dispersion in analysts' forecasts and future stock returns. In other words, firms with high forecast dispersion earn lower future stock returns. This negative relationship is counter-intuitive, since, conceptually, dispersion is a measure of uncertainty (Merton, 1980) and thus, if priced, should be positively related with subsequent returns.[1] This negative relation can also be used as evidence to strongly reject the notion that cross-sectional forecast dispersion 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.[2]

---

[1] Many researchers attempt to suggest explanations for the anomalous 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. These authors interpret forecast dispersion as a proxy for differences of opinion about a stock due to asymmetric information. Johnson (2004) argues that dispersion in analysts' forecasts reflects idiosyncratic risk about cash flows which increases the option value of equity and that expected returns should decrease with idiosyncratic risk. Barron, Stanford, and Yu (2009) separate forecast 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. Avramov, Chordia, Jostova, and Philipov (2009) argue that forecast dispersion may be related to financial distress by linking the negative dispersion-return relation to the negative distress-return relation.

[2] 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. Meanwhile, Qu, Starks, and Yan (2003) argue that analyst forecast dispersion embodies a measure of information risk and find that a risk factor constructed according to this risk measure exhibits characteristics of a systematic risk factor and has a significant explanatory power of return variations.

Cross-sectional dispersion, however, may be an inappropriate proxy to investigate the issue on whether forecast dispersion contains (non-diversifiable) risk components and such risk is priced, since it could contain inherently diversifiable risk components in the following sense. Each analyst observes two signals about a firm's future earnings: one public which is common across all analysts and one private which is idiosyncratic and unique to a particular analyst. Specifically, at a given time, the idiosyncratic private information of analyst k about a firm's future earnings is represented by a signal $y_k = \mathrm{Q} + \varepsilon_k$, where Q represents the common public signal, and ε_k represents a deviation of analyst k's idiosyncratic private signal from the common public signal and is independently distributed across analysts with mean zero. Assuming that the common public signal (Q) at a time can be measured by the mean forecast (i.e., $\hat{Q} = \bar{y} = (1/K)\sum_{k=1}^{K} y_k$, where K is the number of analysts), we argue that cross-sectional forecast dispersion is the measure of deviation of idiosyncratic signals around the common public signal Q at a given time. It is more appropriate, therefore, to use dispersion in common public signals over time rather than dispersion in idiosyncratic private signals at a given time as the proxy in examining the above issue.

The purpose of this paper is therefore twofold: First, we use a measure of dispersion in public signals to examine whether analysts' forecast dispersion contains non-diversifiable risk components. We use time-series dispersion of mean forecasts over past periods as a measure of dispersion in common public signals. Second, we examine whether time-series dispersion can be used as a proxy for risk. In other words, we examine whether time-series dispersion contains non-diversifiable risk components and such risk is priced. In addition, we also examine whether cross-sectional dispersion contains idiosyncratic risk components. This is an important issue to both investors and analysts. The reason we focus on the time-series behavior of analysts' earnings forecasts, rather than that of actual earnings, is that the primary purpose of the paper is to examine whether analysts' forecasts are informative in terms of pricing ability and they play a role of information agents in capital markets.

To address the above-mentioned issue, we perform several tests. First, we examine how stock prices react to earnings signals conditionally on (cross-sectional or time-series) 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 fundamental uncertainty of the firm's future cash flows due to the 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 (cross-sectional or time-series) 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 adjusting appropriately for the systematic risk. Otherwise, the relation will still 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 forecast dispersion-based factors to macroeconomic conditions. As a final test, we conduct the Fama-MacBeth (1973) cross-sectional regression tests to examine whether risk components contained in time-series forecast dispersion are priced in stock returns.

Based on these tests, we find that there is a strong positive relation between time-series forecast dispersion and subsequent stock returns. Further, we find that time-series forecast dispersion apparently contains systematic risk components and that such risk is priced in stock returns. Meanwhile, cross-sectional dispersion is unrelated to systematic risk components but closely related to idiosyncratic volatility. We interpret these results as follows. Time-series forecast dispersion is informative in terms of pricing ability, but cross-sectional dispersion is not. Again, cross-sectional forecast dispersion is the measure of deviation of idiosyncratic signals around the common public signal at a given time, while time-series forecast dispersion is the measure of deviation of common public signals over time. Specifically, cross-sectional dispersion is the standard deviation of individual forecasts at a specific given time, while time-series dispersion is the standard deviation of collective forecasts over time. In this sense, analysts are individually non-informative, but collectively informative over time in terms of pricing ability. This may be the reason that time-series forecast dispersion contains systematic risk components, while cross-sectional forecast dispersion does not such components.

The remainder of this paper proceeds as follows. Section 2 describes the data and methodology for computing time-series forecast dispersion. Section 3 presents the characteristics of portfolios sorted by the forecast dispersion. Section 4 presents empirical evidence showing that time-series 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 1984–2014. 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.[3]

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.[4] 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.[5] 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 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 forecast dispersion, we use the standard deviation of time-series quarterly forecast errors. To obtain time-series quarterly 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),

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

[3] 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.

[4] 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.

[5] 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."

where $\overline{Q}_{i,q}$ is the mean value of analysts' quarterly earnings forecasts (available at the quarter-end month) for firm i for fiscal 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. We then define the time-series forecast error as

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

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

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

We use the standard deviation of the time-series quarterly forecast errors defined in equation (2), scaled by the stock price at the previous quarter-end, as a proxy for time-series 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 time-series 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 basic statistics of cross-sectional and time-series forecast dispersions (DISP_CS and DISP_TS) such as number of earnings forecasts, minimum, average, maximum, standard deviation, the first-order autocorrelation of each dispersion measure, and the correlation coefficient between the two dispersion measures over the entire sample period 1986–2014 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 dispersion seem to move in a similar pattern. The correlation coefficient between these two dispersion measures is 0.1859 (with p-value $<$ 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.[6] 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 of small size, high book-to-market ratio, high market beta, and low price.

[6] In addition to the monthly rebalancing, we also sort all firms every quarter to form the portfolios (i.e., quarterly rebalancing). However, we obtain quite similar results to those from monthly rebalancing. The results are available upon request.

3.2. Relationship between Analysts' Forecast Dispersion and Stock Returns

Through the whole paper, we report the results of both cross-sectional and time-series dispersions side by side and use the results of cross-sectional dispersion as the benchmark to show a distinctive feature of time-series dispersion. 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 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 2014 (348 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 1.26 percent (t-statistic of 4.62) to 0.88 percent (t-statistic of 2.34). 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 -0.38 percent, with t-statistic of -2.26. This negative relation is maintained within each DISP_TS-sorted quintile portfolio and is especially strong when time-series 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 forecast dispersion has a positive and strong monotonic relation with subsequent stock returns. In fact, this positive relation between time-series forecast dispersion and subsequent return are robust to various measures of statistical forecast errors.[7] That is, average monthly returns increase monotonically with time-series forecast dispersion from 0.99 percent (t-statistic of 3.94) to 1.60 percent (t-statistic of 3.91. The difference in average return between the largest (DISP_TS5) and smallest (DISP_TS1) quintile portfolios is positive and statistically significant at the 1-percent level; it is 0.61 percent, with t-statistic of 2.60. 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]

---

[7] We also consider various time-series models to compute time-series forecast dispersion by generating forecast errors. Specifically, we generate forecast errors by one of the following seven time-series models: (i) $\bar{Q}_{i,q+1} - E(\bar{Q}_{i,q}|I_{i,q-1})$ (one-quarter ahead forecast using an AR(1) process), (ii) $\bar{Q}_{i,q+4} - E(\bar{Q}_{i,q}|I_{i,q-1})$ (four-quarter ahead forecast using an AR(1) process), (iii) $Q_{i,q}^{\text{med}} - E(Q_{i,q}^{\text{med}}|I_{i,q-1})$ (using the median forecast, instead of the mean forecast), (iv) using an AR(2) process for $\bar{Q}_{i,q} - \bar{Q}_{i,q-4}$, (v) using an AR(4) process for $\bar{Q}_{i,q} - \bar{Q}_{i,q-4}$, (vi) using a random walk process for $\bar{Q}_{i,q} - \bar{Q}_{i,q-4}$, and (vii) $\bar{Q}_{i,q}$–Actual earnings. The results are quite similar to those reported in Table 3. In other words, all seven time-series forecast dispersions have a strong positive relation with subsequent returns, and the difference in average return between DISP_TS5 and DISP_TS1 is positive and statistically significant at the 5-percent level for all seven time-series forecast dispersions.

[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 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.

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 (314 months) are similar to those in the whole periods; these are -0.37 percent (with t-statistic of -2.29) and 0.53 percent (with t-statistic of 2.47), 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 -0.43 percent (with t-statistic of -0.44) and 1.31 percent (with t-statistic of 1.00) 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 signal, the greater the earnings information uncertainty, the smaller the price reaction for a given level of

The results are available upon request.

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 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]

[9] By using daily returns and the IBES Summary file, Kim and Kim (2003) report that average stock returns increase

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 forecast dispersion within each ES-sorted portfolio, as shown in Panel B of Table 4. In other words, the greater the time-series forecast dispersion, the greater the price return for a given level of earnings surprise. Therefore, this positive relation indicates that time-series 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

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 -0.35 percent, with t-statistic of -2.20. 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 -0.37 percent (with t-statistic of -2.04) and -0.35 percent (with t-statistic of -2.57), 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 -0.38 percent (t-statistic of -2.26), as shown in Table 3.

We similarly construct portfolios to examine whether the positive relation between time-series 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. The arbitrage returns based on *DISP_TS* are much smaller in magnitude than the original (uncontrolled) arbitrage return reported 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 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., $\widehat{\alpha}_{CS1} = \cdots = \widehat{\alpha}_{CS5} = 0$) is strongly rejected. The Gibbons, Ross, and Shanken (1989) (GRS) *F*-statistic for the joint null hypothesis is 4.778 (with p-value < 0.001). However, this joint null hypothesis is hardly rejected at the 5 percent significance level with respect to the Hansen-Jagannathan (1997) (HJ) distance which equals 0.089 (with p-value of 0.110).[12] Furthermore, the intercept estimates of these five overall *DISP_CS*-sorted quintile portfolios monotonically decrease with DISP_CS. In particular, the overall difference in the intercept estimate, $\widehat{\alpha}_{CS5} - \widehat{\alpha}_{CS1}$, is -0.36 ($t$-statistic of -2.61). This (adjusted) overall difference is almost unchanged in magnitude

---

[12] The HJ distance is defined as $\delta = \left[\underset{\theta}{\mathrm{Min}}\ g(\theta)'\, W\, g(\theta)\right]^{1/2}$, where $g(\theta) = E(m_t \boldsymbol{R}_t) - 1_N, m_t = b_0 + b_1' \boldsymbol{F_t},\ \theta = (b_0, b_1')$ 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 $H_0: \delta = 0$ is computed based on Jagannathan and Wang (1996).

and significance from the unadjusted overall difference in average raw returns which is -0.38 percent (t-statistic of -2.26), 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 such 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 except for the DISP_CS1-sorted case. A joint null hypothesis on whether all intercept estimates of the five overall DISP_TS-sorted quintile portfolios are different from zero (i.e., $\hat{\alpha}_{TS1} = \cdots = \hat{\alpha}_{TS5} = 0$) is not rejected with respect to the GRS test statistic at the 5 percent significance level which is 2.041 (with p-value of 0.072), and it is also not rejected with respect to the HJ distance which is 0.030 (with p-value of 0.590). Further, the (adjusted) overall difference in the intercept estimate, $\hat{\alpha}_{TS5} - \hat{\alpha}_{TS1}$, is statistically insignificant; it is only 0.18 percent (t-statistic of 0.97). Note that the unadjusted overall difference in average raw returns is 0.61 percent (with t-statistic of 2.60), as shown in Table 3. These results indicate that the positive relation between time-series forecast dispersion and average return is well explained by FF3 and that time-series forecast dispersion contains such 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, $\hat{\beta}_{MKT}$, $\hat{\beta}_{SMB}$, and $\hat{\beta}_{HML}$, for the 25 portfolios. All three factor loading estimates monotonically increase with time-series forecast dispersion within any DISP_CS-sorted quintile portfolios. That is, time-series 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 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 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 (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. Dispersion-Return Relations after Adjusting for Idiosyncratic Volatility

In this section, we examine how cross-sectional and time-series forecast dispersions are related to idiosyncratic volatility (IVOL). To do this, we use a factor associated with idiosyncratic volatility and examine the returns of DISP_CS- and DISP_TS-sorted portfolios after adjusting for this idiosyncratic volatility factor. We consider two idiosyncratic volatility factors. The first IVOL factor is the one that buys long the highest IVOL quintile portfolio and sells short the lowest IVOL quintile portfolio (‘High-Low’). The five IVOL quintile portfolios are formed every month by assigning all firms into one of five quintile portfolios according to their standard deviations of the residuals obtained from time-series regressions of each stock's returns on FF3 using daily returns for month t-1, if at least 10-day daily observations are available for the month, following Ang, Hong, Xing, and Zhang (2006). The second IVOL factor is the monthly series of the CBOE volatility index (VIX).

Table 7 presents the intercept estimates ($\hat{\alpha}_p$) of the time-series regressions of the return of DISP_TS- and DISP_CS-sorted quintile portfolios on the idiosyncratic volatility factor. The reason we use this simple time-series regression model is to examine whether the negative (positive) relation of DISP_CS (DISP_TS) with subsequent returns is affected after adjusting for the IVOL factor. Therefore, the differences in the intercept estimate between DISP_TS5 and DISP_TS1 and between DISP_CS5 and DISP_CS1, rather than the magnitude of individual intercept estimates, are of our main interest. This table shows that even after adjusting for the IVOL factor, the strong positive relation of DISP_TS with subsequent returns is still maintained, but the significant negative relation of DISP_CS with subsequent returns is no longer maintained. Specifically, DISP_TS5−DISP_TS1 (i.e., P5-P1) is still statistically positively significant; it is 0.95 percent (t-statistic of 5.04) for using the first IVOL factor (i.e., 'High-Low') and 1.31 percent (t-statistic of 2.13) for using the second IVOL factor (i.e., VIX), respectively. However, DISP_CS5−DISP_CS1 is no longer negatively statistically significant; it is -0.05 percent (t-statistic of -0.46) and 0.22 percent (t-statistic of 0.48) for using the first and second IVOL factors, respectively. In other words, DISP_TS is almost unaffected by idiosyncratic volatility, while DISP_CS is substantially affected by idiosyncratic volatility. Overall, these results indicate that cross-sectional dispersion contains components of idiosyncratic volatility.

4.5. Forecast Dispersion-Related Returns and the Macroeconomy

4.5.1. 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 forecast dispersion. The factor related to time-series 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 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).[13]

4.5.2. 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,

---

[13] The correlation coefficient between TS and CS is 0.173.

[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.

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 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.

[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.

Table 8 presents the coefficient estimates ($\times 100$) of equation (4) for future innovations in each of the seven macroeconomic variables over the whole sample period 1986:Q1 to 2014: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 for future innovations in GDP growth ($\hat{\theta}_1 = 4.76$, t-statistic of 2.02), consumption growth ($\hat{\theta}_1 = 2.89$, t-statistic of 1.99), and inflation ($\hat{\theta}_1 = 3.04$, t-statistic 1.52), while they are negatively significant for future innovations in three-month Treasury bill rate ($\hat{\theta}_1 = -1.49$, t-statistic of -2.94). 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 procyclical 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 three macroeconomic variables (GDP, consumption growth rates, and dividend yield) with an inverse relation. Specifically, the coefficients on CS ($\hat{\theta}_3$) are negatively statistically significant for future innovations in GDP growth ($\hat{\theta}_3 = -4.31$, t-statistic of -2.73), consumption growth ($\hat{\theta}_3 = -2.04$, t-statistic of -1.76), and dividend yield ($\hat{\theta}_3 = -0.49$, t-statistic of -2.56). 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 8 shows

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

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 35.02 (t-statistic of 6.90) for GDP growth rate, 18.25 (t-statistic of 6.18) for consumption growth rate, 2.48 (t-statistic of 2.48) for term spread, 5.50 (t-statistic of 2.38) for default spread, 23.88 (t-statistic of 3.94) for inflation rate, and 1.82 (t-statistic of 3.96) 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 -29.91 (t-statistic of -5.37) for GDP growth rate, -14.78 (t-statistic of -4.52) for consumption growth rate, -2.71 (t-statistic of -2.65) for term spread, -5.87 (t-statistic of -2.53) for default spread, -21.00 (t-statistic of -3.42) for inflation rate, and -2.18 (t-statistic of -3.82) 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 ($\hat{\theta}_1 =$ -6.30, t-statistic of -3.51), and the difference in the coefficient estimate on TS between expansion and contraction periods is positively statistically significant ($\hat{\theta}_2 = 4.35$, t-statistic of 2.32). 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. We interpret the above results as another evidence that time-series forecast dispersion contains systematic risk components, since it is closely related with unexpected changes (innovations) in the state variables that cause unexpected changes in the investment opportunity set in the context of the Intertemporal CAPM of Merton (1973).[17]

4.6. 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

[17] The results about the relation between TS and innovations in macroeconomic variables indicate that time-series dispersion is closely related to changes in the economic environment. Given this measure of dispersion is known ex ante, time-series dispersion would be useful as an instrumental variable to construct time-varying conditional alphas and conditional betas in the framework of Ferson and Schadt (1996) and Jha, Korkie, and Turtle (2009).

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 9 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 0.45 percent (t-statistic of 0.15) and 2.13 percent (t-statistic of 0.66), 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 -8.33 percent (t-statistic of -2.07) and -8.66 percent (t-statistic of -2.13), 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 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.

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

The results thus far show that arbitrage returns based on time-series forecast dispersion are related to future innovations in macroeconomic variables. In other words, time-series forecast dispersion may contain components of nondiversifiable risk. To examine whether such risk contained in time-series 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 (a minimum of 24 observations), 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 10 presents times-series averages ($\bar{\hat{\gamma}}_k$) of the month-by-month CSR coefficient estimates or risk premia estimates of each factor over the entire sample period January 1986 to

December 2014 (348 months). We use three sets of test assets; 25 (5×5) DISP_TS and DISP_CS-sorted equally-weighted portfolios (Panel A), 100 (10×10) size-BM equally-weighted portfolios (Panel B),[18] and individual stocks (Panel C).

The factor related to time-series 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 $\left(\bar{\bar{\gamma}}_{\mathrm{TS}}\right)$ are positive and statistically significant in all test assets considered. Specifically, when TS is alone in the model (Model 1), $\bar{\bar{\gamma}}_{\mathrm{TS}}$'s are 0.46 percent ($t$-statistic of 3.76), 0.61 percent (t-statistic of 3.04) and 0.14 percent (t-statistic of 2.25) when using 25 DISP_TS and DISP_CS-sorted portfolios, 100 size-BM portfolios, and individual stocks as test assets, respectively. Even when the Fama and French three factors are added in the model (Model 8), $\bar{\bar{\gamma}}_{\mathrm{TS}}$'s are 0.44 percent ($t$-statistic of 3.54), 0.37 percent (t-statistic of 2.43), and 0.15 percent (t-statistic of 3.27), 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 10 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. It is also noteworthy that when the betas on VIX (β_{VIX}) is in the model, the significance of the risk premium estimate of TS is unchanged.

[18] 100 size-BM portfolios 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.

5. Conclusions

This paper attempts to address the issue on whether time-series 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 dispersion; ii) examining the relation between time-series forecast dispersion and stock return after adjusting for several systematic risk components; iii) relating payoffs to time-series forecast dispersion-based factors to macroeconomic conditions; and iv) conducting CSR tests to examine whether risk components contained in time-series forecast dispersion are priced in stock returns.

We find that there is a strong positive relation between time-series forecast dispersion and stock returns. Further, we find that time-series forecast dispersion apparently contains systematic risk components and that such risk is priced in stock returns, while cross-sectional forecast dispersion is unrelated to systematic risk components but closely related to idiosyncratic volatility. Time-series forecast dispersion is informative in terms of pricing ability, but cross-sectional dispersion is not so. In that cross-sectional forecast dispersion is the measure of deviation of idiosyncratic signals around the common public signal at a given time, while time-series forecast dispersion is the measure of deviation of common public signals over time, we argue that analysts are *individually* non-informative, but *collectively* informative over time in terms of pricing ability.

References

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61, 259-299.

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

Altinkiliç, O., Balashov, V.S., Hansen, R.S., 2013. Are analysts' forecasts informative to the general public? *Management Science* 59, 2550-2565.

Barron, O.E., Kim, O., Lim, S.C., Stevens, D.E., 1998. Using analysts' forecasts to measure properties of analysts' information environment. *Accounting Review* 73, 421-433.

Barron, O.E., Stanford, M.H., Yu, Y., 2009. Further evidence on the relation between analysts' forecast dispersion and stock returns. *Contemporary Accounting Research* 26, 329-357.

Berkman, H., Dimitrov, V., Jain, P.C., Koch, P.D., Tice, S., 2009. Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. *Journal of Financial Economics* 92, 376-399.

Bernard, V., Thomas, J.K., 1989. Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27 (Supplement), 1-36.

Campbell, J.Y., Cochrane, J.H., 2000. Explaining the poor performance of consumption-based asset pricing models. *Journal of Finance* 55, 2863-2878.

Chen, N., 1991. Financial investment opportunities and the macroeconomy. *Journal of Finance* 51, 1681-1713.

Chordia, T., Shivakumar, L., 2002. Momentum, business cycle, and time-varying expected returns. *Journal of Finance* 57, 985-1019.

Chordia, T., Shivakumar, L., 2006. Earnings and price momentum. *Journal of Financial Economics* 80, 627-656.

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

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. *Journal of Finance* 47, 129-176.

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

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

Ferson, W.E., Schadt, R.W., 1996. Measuring fund strategy and performance in changing economic conditions. *Journal of Finance* 51, 425-461.

Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. *Accounting Review* 59, 574-605.

Gibbons, M.R., Ross, S.A., Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica* 57, 1121-1152.

Güntay, L., Dirk, H., 2010. Corporate bond credit spreads and forecast dispersion. *Journal of Banking & Finance* 34, 2328-2345.

Hansen, L.P., Jagannathan, R., 1997. Assessing specification errors in stochastic discount factor models. *Journal of Finance* 52, 557-590.

Jagannathan, R., Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. *Journal of Finance* 51, 3-54.

Jha, R., Korkie, B., Turtle, H.J., 2009. Measuring performance in a dynamic world: Conditional mean-variance fundamentals. *Journal of Banking & Finance* 33, 1851-1859.

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

Kim, D., 2006. On the information uncertainty risk and the January effect. *Journal of Business* 79, 2127-2162.

Kim, D., Kim, M., 2003. A multi-factor explanation for post-earnings-announcement drift. *Journal of Financial and Quantitative Analysis* 38, 383-398.

Liew, J., Vassalou, M., 2000. Can book-to-market, size and momentum be risk factors that predict economic growth. *Journal of Financial Economics* 57, 221-245.

Merton, R.C., 1973. An intertemporal asset pricing model. *Econometrica* 41, 867-887.

Merton, R.C., 1980. On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics* 8, 323-361.

Payne, J.L., Thomas, W.B., 2003. The implications of using stock-split adjusted I/B/E/S data in empirical research. *Accounting Review* 78, 1049-1067.

Petkova, R., 2006. Do the Fama–French factors proxy for innovations in predictive variables?

Journal of Finance 61, 581-612.

Qu, S., Starks, L., Yan, H., 2003. Risk, dispersion of analyst forecasts and stock returns. Working paper, University of Texas at Austin.

Sadka, R., Scherbina, A., 2007. Analyst disagreement, mispricing, and liquidity. *Journal of Finance* 62, 2367–2403.

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. N indicates the number of months, and "#Estimates" indicates the average number of analysts' earnings forecasts in computing cross-sectional forecasts dispersion. Min, Mean, Std, and Max indicate the minimum, mean, standard deviation, and maximum value, respectively. ρ_1 indicates the first-order autocorrelation of the cross-sectional average of DISP_TS or DISP_CS. "Correlation" is the serial correlation coefficient between the averages of DISP_TS and DISP_CS across all firms. Both DISP_TS and DISP_CS are winsorized at the 1% and 99% level. The sample period is January 1986 to December 2014.

Periods	N	#Estimates	Cross-sectional dispersion (DISP_CS)					Time-series forecast dispersion (DISP_TS)					Corre-lation
			Min	Mean	Std	Max	ρ_1	Min	Mean	Std	Max	ρ_1	
							Panel A: Whole periods						
1986-1990	60	4.77	0.0000	0.2664	0.6503	9.2374	0.5104	0.0003	0.0098	0.0108	0.0911	0.6908	0.2131
1990-1995	60	5.03	0.0000	0.2005	0.5427	9.1924	0.6421	0.0003	0.0083	0.0094	0.0906	0.8659	0.1858
1996-2000	60	5.09	0.0000	0.1735	0.5127	9.2871	0.3226	0.0003	0.0074	0.0090	0.0909	0.8879	0.1638
2001-2005	60	6.60	0.0000	0.1820	0.5230	9.3116	0.6908	0.0003	0.0083	0.0103	0.0910	0.8807	0.1666
2005-2010	60	7.34	0.0000	0.2541	0.6458	9.3095	0.9048	0.0003	0.0082	0.0111	0.0911	0.9448	0.1998
2011-2014	48	8.54	0.0000	0.2339	0.6132	9.3095	0.5456	0.0003	0.0079	0.0109	0.0909	0.9195	0.1810
Whole period	348	6.52	0.0000	0.2158	0.5828	9.3116	0.8436	0.0003	0.0082	0.0103	0.0911	0.9245	0.1859
							Panel B: Over business cycles						
							Expansionary periods						
01/86-07/90	55	4.74	0.0000	0.2683	0.6543	9.2374	0.5144	0.0003	0.0097	0.0107	0.0911	0.7050	0.2119
04/91-03/01	120	5.08	0.0000	0.1829	0.5235	9.2871	0.6623	0.0003	0.0077	0.0092	0.0909	0.9167	0.1732
12/01-12/07	73	6.79	0.0000	0.1829	0.5185	9.3116	0.6995	0.0003	0.0076	0.0099	0.091	0.9261	0.1678
07/09-12/14	66	8.43	0.0000	0.2498	0.6405	9.3095	0.8002	0.0003	0.0084	0.0113	0.0911	0.9087	0.1867
Overall	314	6.50	0.0000	0.2086	0.5697	9.3116	0.8279	0.0003	0.0081	0.0101	0.0911	0.9131	0.1824
							Recessionary periods						
08/90-03/91	8	5.12	0.0000	0.2588	0.6311	8.9970	-0.0252	0.0003	0.0108	0.012	0.0885	0.4579	0.2217
04/01-11/01	8	6.19	0.0000	0.2089	0.5759	9.1797	-0.0124	0.0003	0.0086	0.0105	0.0907	0.3389	0.1438
01/08-06/09	18	7.15	0.0000	0.3019	0.7173	9.3095	0.8693	0.0003	0.0088	0.0119	0.0909	0.7899	0.2173
Overall	34	6.69	0.0000	0.2756	0.6786	9.3095	0.8667	0.0003	0.0091	0.0116	0.0909	0.7773	0.2054

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 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 1986-2014. 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 ($M)	Book-to-market	Market beta	Price per share ($)
	Sorted by time-series forecast dispersion (DISP_TS)					
DISP_TS1	0.0013	0.0669	8369.63	0.41	1.0421	86.34
DISP_TS2	0.0030	0.1037	5651.52	0.50	1.1138	64.87
DISP_TS3	0.0050	0.1564	5106.09	0.56	1.1730	45.75
DISP_TS4	0.0084	0.2187	3972.04	0.63	1.2699	27.31
DISP_TS5	0.0303	0.3596	3269.82	0.75	1.4414	20.05
P5-P1	0.0290	0.2927	-5099.81	0.34	0.3993	-66.29
	Sorted by cross-sectional forecast dispersion (DISP_CS)					
DISP_CS1	0.0059	0.0150	7985.26	0.50	1.0651	65.26
DISP_CS2	0.0064	0.0382	6706.04	0.53	1.1175	50.18
DISP_CS3	0.0084	0.0691	5164.61	0.59	1.2087	62.83
DISP_CS4	0.0119	0.1384	3905.67	0.65	1.2825	42.92
DISP_CS5	0.0173	0.6846	2567.72	0.69	1.3666	22.99
P5-P1	0.0114	0.6696	-5417.54	0.19	0.3015	-42.27

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 forecast dispersion (DISP_TS) and cross-sectional forecast dispersion (DISP_CS) over the entire sample period 1986-2014. 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 2014; 348 months)							
Average return (%)							
DISP_TS1	0.96	1.03	0.98	0.99	0.77	-0.19(-0.75)	0.99(3.94)
DISP_TS2	1.04	1.00	0.95	0.96	1.08	0.04 (0.18)	1.02(3.86)
DISP_TS3	1.25	1.17	1.18	0.98	1.15	-0.10(-0.53)	1.11(3.91)
DISP_TS4	1.43	1.35	1.26	1.14	1.18	-0.25(-1.30)	1.23(3.84)
DISP_TS5	2.13	1.71	1.26	1.53	1.37	-0.76(-2.66)	1.60(3.91)
P5-P1	1.17	0.68	0.27	0.54	0.60		**0.61(2.60)**
	(4.04)	(2.51)	(1.04)	(1.92)	(1.82)		
Overall	1.26	1.21	1.11	1.03	0.88	**-0.38**	
	(4.62)	(4.3)	(3.52)	(2.98)	(2.34)	**(-2.26)**	
Standard deviation (%)							
DISP_TS1	4.56	4.79	5.10	5.84	6.81	4.59	4.64
DISP_TS2	4.81	5.07	5.45	5.46	6.22	4.11	4.90
DISP_TS3	5.12	5.41	5.58	5.80	6.10	3.48	5.22
DISP_TS4	5.70	5.81	6.29	6.51	6.71	3.56	5.94
DISP_TS5	7.70	7.48	7.87	7.99	8.23	5.28	7.55
P5-P1	5.35	4.99	4.86	5.25	6.07		4.34
Overall	5.17	5.35	6.09	6.70	7.24	3.22	

Panel B: Average returns over business cycles							
Expansionary periods (314 months)							
DISP_TS1	1.05	1.16	1.15	1.26	0.96	-0.09(-0.34)	1.13(4.64)
DISP_TS2	1.14	1.09	1.04	1.12	1.13	-0.01(-0.04)	1.13(4.48)
DISP_TS3	1.40	1.26	1.29	1.14	1.26	-0.14(-0.75)	1.25(4.67)
DISP_TS4	1.55	1.43	1.41	1.27	1.36	-0.19(-1.01)	1.36(4.54)
DISP_TS5	2.20	1.70	1.40	1.57	1.46	-0.74(-2.71)	1.66(4.39)
P5-P1	1.15	0.54	0.25	0.31	0.50		**0.53(2.47)**
	(3.79)	(1.99)	(0.97)	(1.13)	(1.56)		
Overall	1.35	1.28	1.23	1.22	0.99	**-0.37**	
	(5.06)	(4.72)	(4.04)	(3.67)	(2.73)	**(-2.29)**	
Contractionary periods (34 months)							
DISP_TS1	0.09	-0.13	-0.50	-1.47	-0.97	-1.06(-1.35)	-0.30(-0.24)
DISP_TS2	0.09	0.17	0.14	-0.50	0.58	0.49 (0.63)	-0.03(-0.02)
DISP_TS3	-0.15	0.34	0.15	-0.50	0.14	0.29 (0.38)	-0.14(-0.09)
DISP_TS4	0.36	0.57	-0.12	0.04	-0.45	-0.81(-0.86)	0.08 (0.04)
DISP_TS5	1.47	1.83	-0.02	1.17	0.55	-0.92(-0.62)	1.01 (0.44)
P5-P1	1.38	1.96	0.49	2.64	1.52		**1.31(1.00)**
	(1.39)	(1.67)	(0.38)	(1.98)	(0.94)		
Overall	0.25	0.32	0.10	-0.14	-0.19	**-0.43**	
	(0.18)	(0.21)	(0.06)	(-0.07)	(-0.09)	**(-0.44)**	

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 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 (per share) 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	1.03(3.42)	0.95(3.37)	1.21(3.88)	1.19(4.22)	1.54(5.17)	1.26(4.62)
DISP_CS2	0.89(2.93)	1.09(3.84)	1.24(3.89)	1.09(3.73)	1.37(4.51)	1.21(4.30)
DISP_CS3	1.05(2.98)	0.87(2.59)	1.15(3.15)	1.16(3.42)	1.27(3.94)	1.11(3.52)
DISP_CS4	0.89(2.30)	0.83(2.22)	0.82(2.12)	1.30(3.42)	1.27(3.55)	1.03(2.98)
DISP_CS5	0.75(1.74)	0.62(1.55)	0.51(1.27)	1.17(2.87)	1.24(3.23)	0.88(2.34)
P5-P1	-0.28(-1.17)	-0.33(-1.35)	-0.7(-3.27)	-0.02(-0.09)	-0.30(-1.59)	**-0.38(-2.26)**
Overall	0.91(2.59)	0.84(2.54)	0.98(2.90)	1.18(3.67)	1.34(4.24)	
	Panel B: Sorted by time-series forecast dispersion and earnings surprise					
DISP_TS1	0.95(3.68)	0.74(2.77)	1.08(4.27)	0.99(3.75)	1.11(4.13)	0.98(3.91)
DISP_TS2	0.99(3.63)	0.78(2.74)	1.02(3.97)	1.01(3.41)	1.26(4.57)	1.02(3.85)
DISP_TS3	1.01(3.47)	1.02(3.44)	1.19(4.30)	1.16(3.84)	1.29(4.27)	1.11(3.92)
DISP_TS4	1.04(3.01)	1.09(3.11)	1.22(3.97)	1.49(4.32)	1.33(4.01)	1.24(3.84)
DISP_TS5	1.17(2.47)	1.60(3.53)	1.91(4.76)	1.64(3.93)	1.60(3.92)	1.60(3.92)
P5-P1	0.22(0.68)	0.86(2.82)	0.84(3.35)	0.65(2.57)	0.49(1.97)	**0.62(2.63)**
Overall	1.06(3.35)	1.11(3.49)	1.38(4.76)	1.25(4.12)	1.41(4.74)	
	Panel C: Average number of firms					Total
DISP_CS1	45	45	20	115	116	341
DISP_CS2	49	50	14	117	118	348
DISP_CS3	57	58	12	107	108	342
DISP_CS4	67	67	10	95	96	335
DISP_CS5	83	83	9	77	77	329
Total	301	303	65	511	515	1695

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 2014.

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	1.50	1.45	1.30	1.09	1.03	1.27(4.56)	0.98	1.13	1.25	1.42	1.54	1.26(4.66)	1.13	1.19	1.20	1.07	1.47	1.21(4.11)
DISP_CS2	1.23	1.24	1.11	1.00	1.04	1.12(3.78)	0.81	1.06	1.22	1.13	1.37	1.12(3.99)	1.15	1.25	1.30	1.15	1.02	1.17(3.89)
DISP_CS3	1.20	1.08	1.07	1.07	1.20	1.12(3.45)	0.87	1.01	1.15	1.28	1.35	1.13(3.52)	1.00	1.04	1.24	1.23	1.12	1.13(3.52)
DISP_CS4	0.95	1.10	1.18	0.98	1.00	1.04(3.05)	1.02	0.85	1.13	1.10	1.27	1.07(2.98)	0.91	1.21	1.10	1.17	1.14	1.11(3.30)
DISP_CS5	0.54	0.92	1.05	1.11	1.00	0.92(2.48)	0.89	0.90	1.03	0.82	0.85	0.90(2.32)	0.69	0.94	0.88	1.00	0.82	0.87(2.41)
P5-P1	-0.96	-0.53	-0.25	0.02	-0.03	**-0.35(-2.20)**	-0.09	-0.22	-0.22	-0.60	-0.69	**-0.37(-2.04)**	-0.44	-0.25	-0.32	-0.07	-0.65	**-0.35(-2.57)**
(t-value)	-4.29	-2.69	-1.26	0.11	-0.14		-0.36	-0.96	-1.03	-3.02	-3.17		-2.69	-1.43	-1.78	-0.35	-3.21	
DISP_TS1	1.29	1.13	1.05	1.06	0.97	1.10(4.28)	1.00	1.11	1.13	1.12	1.19	1.11(4.69)	1.08	1.11	1.21	1.02	1.11	1.11(4.21)
DISP_TS2	1.19	1.12	1.16	1.02	0.89	1.08(4.07)	0.92	0.92	1.00	1.23	1.26	1.06(4.06)	0.89	1.07	1.11	1.12	1.23	1.09(3.97)
DISP_TS3	1.26	1.17	1.20	1.20	0.98	1.16(4.18)	1.05	0.95	1.24	1.19	1.20	1.12(3.99)	1.00	1.00	1.34	1.16	1.39	1.18(4.16)
DISP_TS4	1.42	1.05	1.32	1.27	1.10	1.23(3.96)	1.19	1.22	1.09	1.36	1.23	1.22(3.88)	0.97	1.14	1.26	1.35	1.42	1.23(3.95)
DISP_TS5	2.21	1.41	1.32	1.30	1.07	1.46(3.81)	1.28	1.36	1.58	1.47	1.85	1.51(3.79)	1.22	1.41	1.43	1.32	1.78	1.43(4.04)
P5-P1	0.92	0.28	0.27	0.23	0.10	**0.36(1.70)**	0.28	0.25	0.45	0.35	0.66	**0.40(1.74)**	0.14	0.30	0.22	0.31	0.67	**0.33(1.97)**
(t-value)	3.22	1.08	1.09	0.91	0.50		0.97	0.97	1.80	1.40	2.42		0.87	1.78	1.21	1.41	2.18	

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 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 2014. '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	0.06(0.70)	0.12(1.33)	0.07 (0.60)	0.06 (0.40)	-0.09(-0.42)	-0.15(-0.67)	0.10(1.48)	GRS:
DISP_TS2	0.07(0.65)	0.02(0.19)	-0.05(-0.46)	-0.06(-0.54)	0.17 (1.01)	0.11 (0.53)	0.04(0.65)	2.041
DISP_TS3	0.24(1.99)	0.13(1.09)	0.10 (1.04)	-0.12(-1.05)	0.10 (0.74)	-0.14(-0.81)	0.05(0.76)	[0.072] HJ-dist:
DISP_TS4	0.32(2.38)	0.22(1.77)	0.10 (0.71)	-0.06(-0.42)	-0.06(-0.41)	-0.38(-2.08)	0.07(0.78)	0.030
DISP_TS5	0.95(3.65)	0.52(2.33)	-0.02(-0.08)	0.20 (0.96)	-0.06(-0.32)	-1.01(-3.59)	0.27(1.75)	[0.590]
P5-P1	0.88(3.33)	0.40(1.66)	-0.09(-0.38)	0.14 (0.55)	0.03 (0.10)		**0.18(0.97)**	
Overall	0.32(4.35)	0.20(2.78)	0.09 (1.12)	0.12 (1.09)	-0.04(-0.35)	**-0.36(-2.61)**		
$\alpha_{\mathrm{overall}} = 0$		GRS: 4.778[0.000] HJ-dist: 0.089[0.110]						
			Panel B: Factor loading estimates $\hat{\beta}_{\mathrm{MKT}}$					
DISP_TS1	0.92(43.47)	0.96(45.45)	0.95(34.74)	0.98(28.49)	1.04(21.70)	0.11 (2.20)	0.92(61.62)	
DISP_TS2	0.96(41.38)	1.00(42.61)	1.05(44.11)	1.06(40.05)	0.93(23.86)	-0.03(-0.64)	0.98(66.97)	
DISP_TS3	1.00(36.47)	1.07(38.88)	1.11(48.79)	1.13(42.02)	1.10(36.84)	0.10 (2.45)	1.07(72.58)	
DISP_TS4	1.11(35.61)	1.18(41.74)	1.22(39.58)	1.26(41.86)	1.27(39.99)	0.15 (3.64)	1.19(60.05)	
DISP_TS5	1.19(19.85)	1.19(23.11)	1.41(28.19)	1.41(28.80)	1.50(35.91)	0.31 (4.81)	1.37(38.28)	
P5-P1	0.26 (4.32)	0.23 (4.07)	0.46 (8.37)	0.43 (7.11)	0.46 (7.18)		**0.45(10.68)**	
Overall	1.00(59.05)	1.05(62.32)	1.14(63.77)	1.21(49.56)	1.26(44.29)	**0.27(8.32)**		

				$\hat{\beta}_{SMB}$			
DISP_TS1	0.17(5.45)	0.21(6.94)	0.34(8.81)	0.55(11.09)	0.40 (5.88)	0.24(3.19)	0.32(15.02)
DISP_TS2	0.31(9.28)	0.33(9.78)	0.43(12.66)	0.40(10.70)	0.77(13.80)	0.46(7.09)	0.43(20.54)
DISP_TS3	0.31(7.95)	0.33(8.38)	0.45(13.74)	0.47(12.27)	0.62(14.39)	0.30(5.26)	0.45(21.18)
DISP_TS4	0.36(8.02)	0.31(7.68)	0.48(10.81)	0.55(12.73)	0.68(14.99)	0.32(5.33)	0.56(19.73)
DISP_TS5	0.79(9.21)	0.90(12.25)	0.62 (8.64)	0.77(10.96)	0.92(15.47)	0.14(1.46)	0.89(17.28)
P5-P1	0.62 (7.13)	0.69 (8.73)	0.27 (3.49)	0.22 (2.57)	0.52 (5.68)		**0.57(9.39)**
Overall	0.45(18.65)	0.43(17.67)	0.52(20.39)	0.70(19.86)	0.87(21.23)	**0.42(9.10)**	
				$\hat{\beta}_{HML}$			
DISP_TS1	0.07(2.36)	0.04(1.31)	0.01(0.23)	-0.10(-1.89)	-0.46(-6.51)	-0.54(-6.97)	0.00 (0.06)
DISP_TS2	0.26(7.44)	0.16(4.64)	0.08(2.27)	0.16 (4.14)	-0.15(-2.51)	-0.40(-5.93)	0.17 (7.74)
DISP_TS3	0.30(7.23)	0.24(5.95)	0.23(6.92)	0.29 (7.17)	0.08 (1.80)	-0.22(-3.60)	0.27(12.22)
DISP_TS4	0.40(8.62)	0.35(8.46)	0.30(6.54)	0.31 (6.97)	0.40 (8.56)	0.00 (0.03)	0.36(12.35)
DISP_TS5	0.31(3.54)	0.33(4.3)	0.22(3.01)	0.36 (4.92)	0.49 (7.84)	0.17 (1.79)	0.40 (7.49)
P5-P1	0.24(2.65)	0.29(3.5)	0.21(2.64)	0.46 (5.06)	0.95 (9.96)		**0.40 (6.37)**
Overall	0.07(2.55)	0.10(3.93)	0.06(2.11)	0.09 (2.40)	0.10 (2.25)	**0.03 (0.66)**	

Table 7 Dispersion-Return Relations after Adjusting for Idiosyncratic Volatility

This table presents the intercept estimates ($\hat{\alpha}_p$) from the time-series regression of portfolio returns (R_{pt}) on the idiosyncratic volatility factor (IVOL_t) for each set of five quintile portfolios sorted by time-series dispersion (DISP_TS) and cross-sectional dispersion (DISP_CS). Two IVOL factors are used. The first one is the portfolio return of the highest IVOL quintile portfolio return minus the lowest IVOL quintile portfolio return ('High-Low'), and the second one is the monthly series of the CEOE volatility index (VIX). The five IVOL quintile portfolios are formed every month by assigning all firms into one of five quintile portfolios according to their standard deviations of the residuals obtained from time-series regressions of each stock's returns on the Fama and French three factors using daily returns for month t-1, if at least 10-day daily observations are available for the month, following Ang, Hong, Xing, and Zhang (2006). Numbers in parentheses are t-statistics. The estimation period is January 1986 to December 2014.

Portfolio	IVOL factor: 'High−Low'		IVOL factor: VIX	
	Portfolios sorted by		Portfolios sorted by	
	DISP_TS	DISP_CS	DISP_TS	DISP_CS
1 (small)	1.00 (4.63)	1.34 (5.83)	3.83 (6.03)	3.94 (5.59)
2	1.06 (4.69)	1.30 (5.52)	4.03 (6.01)	4.12 (5.66)
3	1.18 (4.93)	1.33 (5.36)	4.31 (6.03)	4.22 (5.25)
4	1.38 (5.15)	1.35 (5.32)	4.49 (5.47)	4.17 (4.60)
5 (large)	1.95 (6.35)	1.29 (4.99)	5.14 (4.89)	4.16 (4.21)
P5-P1	**0.95 (5.04)**	**-0.05 (-0.46)**	**1.31 (2.13)**	**0.22 (0.48)**

Table 8 Analysts' Forecasts Dispersion-Related Factors and Macroeconomic Conditions

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

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

where the dependent variable, $u_{q+1,q+4}^{K}$, 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	4.76 (2.02)	35.02 (6.90)	2.89 (1.99)	18.25 (6.18)	-0.10 (-0.43)	2.48 (2.48)
TS*D		-29.91 (-5.37)		-14.78 (-4.52)		-2.71(-2.65)
CS	-4.31(-2.73)	-6.01 (-1.13)	-2.04 (-1.76)	-8.17 (-2.84)	0.11 (0.41)	-3.35(-2.74)
CS*D		1.01 (0.18)		5.44 (1.76)		3.65 (2.91)
Constant	-1.02(-3.06)	-5.92 (-3.56)	-0.72 (-2.90)	-4.20 (-4.70)	0.02 (0.46)	-1.17(-3.10)
FF3	YES	YES	YES	YES	YES	YES
FF3*D	NO	YES	NO	YES	NO	YES
Adj R^2	0.135	0.280	0.242	0.374	-0.012	0.091
	Innovations in default spread		Innovations in inflation rate		Innovations in 3-month Treasury bill rate	
TS	-0.20(-0.63)	5.50 (2.38)	3.04 (1.52)	23.88 (3.94)	-1.49(-2.94)	-6.30(-3.51)
TS*D		-5.87(-2.53)		-21.00(-3.42)		4.35(2.32)
CS	0.29 (1.32)	0.52 (0.24)	0.43 (0.33)	4.92 (1.00)	-0.44(-0.88)	1.18(1.09)
CS*D		-0.23(-0.11)		-5.01 (-0.97)		-1.39(-1.12)
Constant	0.02 (0.50)	-0.54(-0.76)	0.04 (0.19)	-4.00 (-2.36)	0.01(0.09)	0.70(1.44)
FF3	YES	YES	YES	YES	YES	YES
FF3*D	NO	YES	NO	YES	NO	YES
Adj R^2	-0.005	0.088	0.052	0.147	0.042	0.055
	Innovations in dividend yield					
TS	-0.08(-0.32)	1.82 (3.96)				
TS∗D		-2.18 (-3.82)				
CS	-0.49(-2.56)	-0.26 (-0.46)				
CS∗D		-0.08 (-0.14)				
Constant	-0.01(-0.39)	-0.40 (-2.50)				
FF3	YES	YES				
FF3∗D	NO	YES				
Adj R^2	0.040	0.140				

Table 9 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 $q-1$. '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 forecast dispersion (DISP_TS)		Cross-sectional forecast dispersion (DISP_CS)	
	P5-P1	% < 0	P5 - P1	% > 0
	Panel A: Raw returns			
	1.58	36.21	-1.16	38.46
	(2.96)	[0.004]	(-2.26)	[0.016]
	Panel B: Adjusted returns			
With business cycle dummy	0.45	46.10	-8.33	31.65
	(0.15)	[0.456]	(-2.07)	[0.003]
Without business cycle dummy	2.13	42.61	-8.66	36.52
	(0.66)	[0.135]	(-2.13)	[0.005]

Table 10 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 five year returns (a minimum of 24 months). Test assets are 25 (5×5) DISP_TS and DISP_CS-sorted equally-weighted portfolios (Panel A), 100 (10×10) size-BM equally-weighted portfolios (Panel B) 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 C). TS and CS are factors related to time-series and cross-sectional forecast dispersions, respectively, MKT, SMB, and HML are the Fama and French (1993) three factors, and VIX is the monthly series of the CBOE volatility index. $\overline{\text{Adj}}\ R^2$ 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 2014.

Explan. variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
					Panel A: Using (5×5) DISP_TS × DISP_CS portfolios						
β_{TS}	0.46(3.76)		0.52 (4.17)		0.40 (3.36)		0.46 (3.71)	0.44 (3.54)		0.52 (3.68)	0.63 (4.07)
β_{CS}		-0.06(-0.45)	-0.07(-0.44)			-0.13(-0.99)	-0.11(-0.72)		-0.29(-1.69)	-0.14(-0.61)	-0.22(-1.82)
β_{MKT}				0.93 (3.01)	-0.03(-0.10)	0.69 (2.35)	0.15 (0.56)	0.29 (0.95)	0.70 (2.21)	0.21 (0.71)	
β_{SMB}				0.02 (0.07)				-0.30(-1.37)	0.45 (1.50)	0.03 (0.11)	
β_{HML}				0.37 (2.09)				0.10 (0.52)	-0.03(-0.15)	-0.02(-0.10)	
β_{VIX}											-1.11(-2.36)
Intcpt	0.88(2.97)	0.91 (3.77)	0.94 (3.89)	-0.26(-0.77)	0.90 (2.50)	0.28 (0.87)	0.83 (2.62)	0.61 (1.85)	0.24 (0.67)	0.90 (2.50)	0.50 (2.24)
$\overline{\text{Adj}}\ R^2$	0.106	0.142	0.230	0.181	0.132	0.184	0.251	0.236	0.252	0.296	0.266
					Panel B: using (10×10) size × BM portfolios						
β_{TS}	0.61(3.04)		0.64 (3.39)		0.48 (2.76)		0.97 (3.60)	0.37 (2.43)		0.43 (3.24)	0.58 (2.32)
β_{CS}		-0.07(-0.47)	-0.18(-1.47)			-0.07(-0.39)	-0.37(-1.47)		-0.18(-1.19)	-0.20(-1.35)	-0.41(-1.55)
β_{MKT}				-0.69(-3.07)	-0.56(-2.39)	-0.81(-3.37)	-0.97(-2.96)	-0.45(-2.11)	-0.70(-3.00)	-0.40(-1.76)	
β_{SMB}				0.23 (1.89)				-0.06(-0.54)	0.11 (0.97)	-0.08(-0.55)	
β_{HML}				0.18 (1.05)				0.13 (1.08)	-0.05(-0.48)	0.00 (0.01)	
β_{VIX}											0.14 (0.40)
Intcpt	0.43(1.54)	1.19 (3.98)	0.41 (1.53)	0.17 (5.66)	1.07 (3.28)	1.86 (5.61)	1.15 (4.69)	1.09 (3.83)	1.77 (5.71)	1.31(5.37)	0.86 (3.41)
$\overline{\text{Adj}}\ R^2$	0.086	0.044	0.117	0.192	0.140	0.153	0.196	0.220	0.220	0.250	0.184

Explan. variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
						Panel C: Using all individual stocks					
β_{TS}	0.14(2.25)		0.14 (2.31)		0.11(3.14)		0.10 (2.00)	0.15 (3.27)		0.14 (2.92)	0.17 (2.97)
β_{CS}		0.00(-0.11)	-0.01(-0.76)			-0.04(-0.82)	-0.00(-0.21)		-0.01(-0.23)	-0.00(-0.08)	-0.02(-0.25)
β_{MKT}				0.14(1.91)	0.06(0.55)	0.22 (2.07)	0.06 (0.72)	0.05 (0.67)	0.19 (2.22)	0.06 (0.67)	
β_{SMB}				0.01(0.27)				-0.05(-1.31)	0.05 (1.19)	-0.04(-0.82)	
β_{HML}				0.01(0.31)				0.02 (0.62)	-0.01(-0.41)	0.05 (0.78)	
β_{VIX}											-0.58(-2.98)
Intcpt	1.02(4.02)	1.19 (4.05)	1.01 (4.02)	1.01(4.23)	0.98(4.59)	1.01 (4.78)	1.00 (4.18)	0.99 (4.18)	0.98 (4.69)	0.97 (4.65)	0.90 (4.28)
$\overline{\text{Adj}}\ R^2$	0.007	0.002	0.009	0.011	0.014	0.016	0.011	0.013	0.019	0.020	0.019

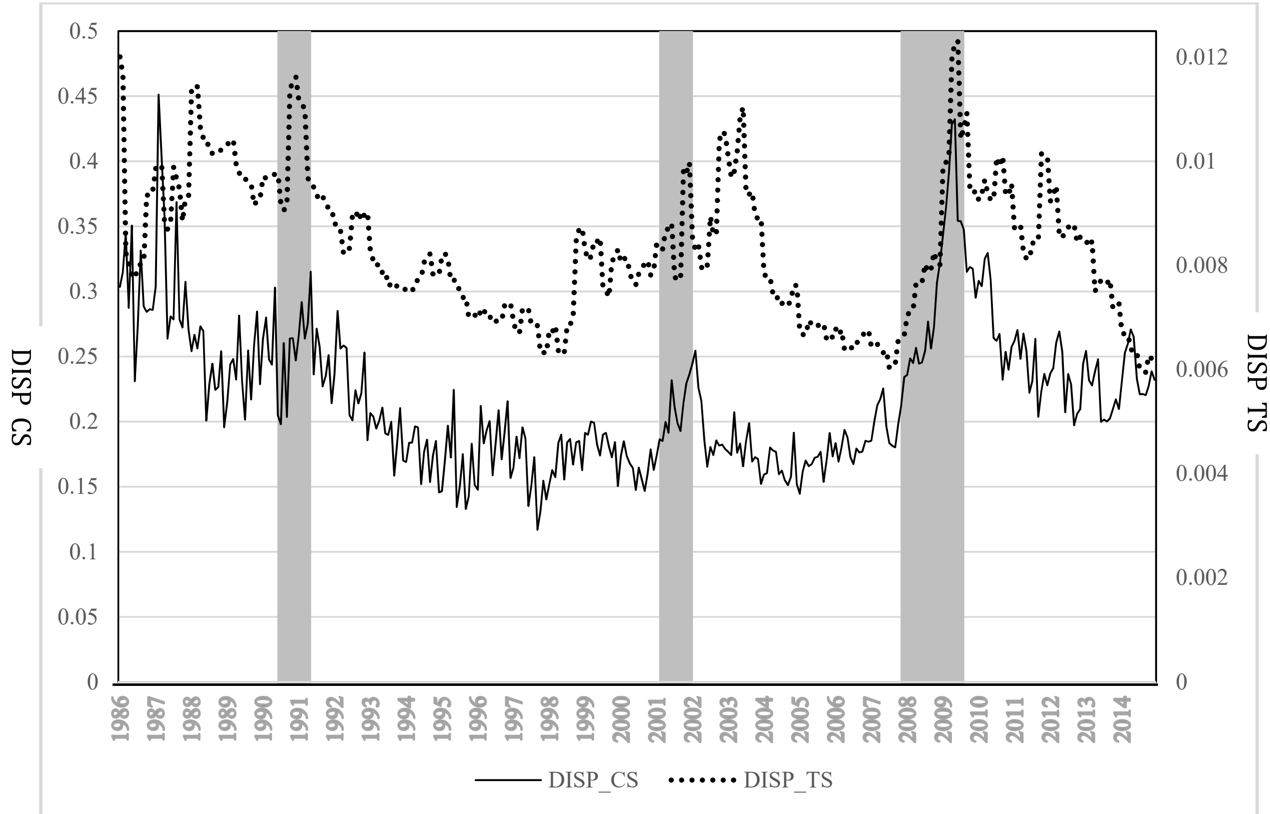

Figure 1 Time-series pattern of cross-sectional and time-series forecast dispersions

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