Analyst Forecast Skewness and Cross Section Stock Returns

ZHU Cai, Department of Finance, HKUST

Abstract

In the paper, we show a significant economic linkage between analyst EPS forecast skewness and cross section stock returns. The effect on stock return of our skewness measure is quite different from that based on skewness calculated from options or high frequency data. Literature shows that, using such skewness as a signal, trading profit is generated mostly from over-valued stocks with high positive skewness, which is consistent with Barberis and Huang (2008)'s lottery arguments. However, we find that for our analyst forecast skewness, trading profit mainly comes from those stocks with negative skewness. Long-short strategy purchasing stocks with low forecast skewness and shorting those with high forecast skewness earns annualized abnormal returns 11% with sharpe ratio 0.64. Our study suggests that negative skewness stocks tend to be undervalued (risk-adjusted returns for negative skewness stocks are significantly positive), while stocks with high positive skewness have fair prices (risk-adjusted returns for positive skewness stocks are not significant). Our empirical results are closely related with investors learning behavior and consistent with Veronesi (1999) theory. In the model, Veronesi shows that when investors cannot observe cash flow growth rate, they tend to overreact to bad news, push current stock price down, such behavior will lead to higher future stock returns. Our results also hold when using robust skewness defined as the gap between analyst EPS forecast mean and median.

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1 Introduction

There is a long history for studies on higher moments in returns. Researchers such as Rubinstein (1973) and Kraus and Litzenberger (1976, 1983) develop models of expected returns that incorporate skewness. In these models, the higher moments that are relevant for individual securities are co-moments with the aggregate market portfolio. Harvey and Siddique (2000) explore both skewness and co-skewness and test whether co-skewness is priced, and Dittmar (2002) tests whether a security co-skewness and co-kurtosis with the market portfolio might influence investors expected returns.

More recent, empirical work provides evidence that, besides comovement with market, higher moments of the return distribution themselves are important in pricing securities. Works of Barberis and Huang (2008) and Brunnermeier, Gollier, and Parker (2007), together with the empirical evidence presented in Mitton and Vorkink (2007) and Boyer, Mitton, and Vorkink (2010) imply that the skewness of individual securities may also influence investors portfolio decisions. Investors prefer positive skewness assets based on speculative desire, and such preference increases demand, pushes current price high and generate lower future returns. Not only for stock returns, Boyer and Vorkink (2014) also find support for such theory from option returns.

In this paper, we consider a different measure for skewness: analyst EPS forecast skewness. Such skewness proxy is different from most widely used measures in literature fundamentally, such as realized skewness from tick-by-tick data (Amaya, Christoffersen, Jcobs, and Vasquez, 2015) and risk neutral skewness from option data (Conrad, Dittmar and Ghysels, 2013). Our measure is skewness in analysts' belief, which is closely related to firm fundamentals, since analysts use fundamental data heavily to predict future earnings.

Different sources of skewness may have different effects on asset returns. Our findings are significantly distinct from common wisdom in many papers, representing by Barberis and Huang (2008). Such branch of literature shows that, using skewness from return distribution as a signal, trading profit is generated mostly from over-valued stocks with high positive skewness, due to lottery property. However, we find that for our analyst forecast skewness, trading profit mainly comes from those

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stocks with negative skewness. Long-short strategy purchasing stocks with low forecast skewness and shorting those with high forecast skewness earns annualized abnormal returns 11% with sharpe ratio 0.64. Our study suggests that negative skewness stocks tend to be undervalued (risk-adjusted returns for negative skewness stocks are significantly positive), while stocks with high positive skewness have fair prices (risk-adjusted returns for positive skewness stocks are not significant). Our empirical results are closely related with investors learning behavior and consistent with Veronesi (1999) theory. In the model, Veronesi shows that when investors cannot observe cash flow growth rate, they tend to overreact to bad news, push current stock price down, such behavior will lead to higher future stock returns.

The contribution of our paper is mainly empirical. On one hand, although many researchers study relation between analyst forecast and cross section stock returns, most of them focus on the first and second moments, for instance, mean of analyst EPS forecast (Porta, 1996), and dispersion of analyst EPS forecast (Diether, Malloy, and Scherbina, 2002). To the authors' best knowledge, no one examine the effect of third moment. Our paper fill the gap, and our findings show that third moment has different implications for stock returns. The theoretical foundation for first and second moments are based on Miller (1977), investors will overvalue stocks with high first and second moments because of short sale constraints. As a result, shorting such stocks will generate profit. Such mechanism is different from our empirical results.

On the other hand, as discussed above, although many researchers examine how skewness could affect individual stock return, all the measures are calculated from return distributions, whether under physical or risk neutral measures. No paper tries to use skewness from analysts' belief. Our paper again fill the gap. One research closely related to ours is provided by Colacito, Ghysels, Meng and Siwasarit (2015). The authors document that the first and third cross-sectional moments of the distribution of GDP growth rates made by professional forecasters can predict equity excess returns, however, our study focuses on cross-section stock returns based on different models and explanations.

The structure for the rest of this paper is as follows. Section 2 reviews the related literature. In

Section 3, we describe our data and present general framework for our empirical study. Section 4 analyzes and discusses our empirical results. Section 5 makes conclusions and provides some possible directions for future research.

2 Literature Review

Our paper is clearly related to the large literature focusing on skewness and asset returns. In such area, generally speaking, we have two branches of studies, following seminar papers of Kraus and Litzenberger (1976) and Barberis and Huang (2008).

Kraus and Litzenberger (1976) show theoretically that coskewness is a determinant of the cross-section of stock returns. Following the guidance, Harvey and Siddique (2000) explore both skewness and co-skewness and test whether co-skewness is priced, and Dittmar (2002) tests whether a security co-skewness and co-kurtosis with the market portfolio might influence investors expected returns.

Different theoretical arguments suggest that assets (idiosyncratic) skewness may explain asset returns. Brunnermeier, Gollier, and Parker (2007) develop a model of optimal (as opposed to rational) beliefs that also predicts that investors will overinvest in the most highly (right-) skewed securities, with the consequence that those securities will have lower subsequent average returns. Mitton and Vorkink (2007) introduce a rational model where investors have heterogeneous preferences for skewness and show that idiosyncratic skewness can impact prices. Barberis and Huang (2008) demonstrate that assets with greater skewness have lower returns when investors make decisions according to cumulative prospect theory. Empirically, Conrad, Dittmar and Ghysels (2013), Boyer and Vorkink (2014) and Amaya, Christoffersen, Jacobs and Vasquez (2015) find supports in cross section stock and option returns.

Our paper is also built on existing studies about analyst forecast and cross section stock returns. The first and second moments of analyst forecasts are widely studied in literature. Porta (1996) show that high analyst EPS forecast mean leads to lower future stock returns, due to analysts' optimism.

Da and Warachka (2011) find the disparity between long-term and short-term analyst forecasted earnings growth is a robust predictor of future returns. After adjusting for industry characteristics, stocks whose long-term earnings growth forecasts are far above or far below their implied short-term forecasts for earnings growth have negative and positive subsequent risk-adjusted returns along with downward and upward revisions in long-term forecasted earnings growth, respectively. The authors attribute such pattern to investors' inattention toward firm-level changes in long-term earnings growth.

As for the second moment of analyst forecast, Diether, Malloy, and Scherbina (2002) has established a negative relationship between stock returns and the dispersion of analysts earnings forecasts. The authors link such phenomenon to heterogeneous belief and short-sale constraints (Miller 1977). Buraschi, Trojani and Vedolin (2014) extend the literature to option market.

Our work combines these two streams of literature. On the one hand, for skewness, apart from option implied and realized stock distributions, analyst belief is another important information source, however, no previous studies examine the relationship between such skewness and future stock returns. On the other hand, although there are numerous studies about analyst forecast, no one examine the high moments for forecast, our paper again fill the gap.

3 Empirical Framework

In this section, we first give definitions of variables used in the paper. Then the general framework for our empirical study is presented.

3.1 Data Description

We use end-of-day option close price, trading volume, open interest and implied volatility surface from OptionMetrics. The analyst forecast data about EPS is obtained from I/B/E/S. Firm financial statements data is downloaded from Compustat. The definitions of variables involved in the paper are given as follows.

Implied volatility. We calculate daily implied volatility for each stock as the average of implied volatility of Δ-50 (at-the-money) put option and Δ-50 (at-the-money) call option, with time-to-maturity of 30 days,

$$IV_{day} = \frac{1}{2}PutIV_{\Delta 50} + \frac{1}{2}CallIV_{\Delta 50}.$$

The monthly implied volatility is average daily implied volatilities in that month.

Implied volatility skew. We calculate daily implied volatility skew for each stock as the spread of implied volatility of Δ-50 (at-the-money) put option and Δ-50 (at-the-money) call option, with time-to-maturity of 30 days, scaled by daily implied volatility

$$IVSKEW_{day} = \frac{PutIV_{\Delta 50} - CallIV_{\Delta 50}}{\frac{1}{2}PutIV_{\Delta 50} + \frac{1}{2}CallIV_{\Delta 50}}.$$

The monthly implied volatility skew is average daily implied volatility skews in that month.

Realized volatility. We calculate daily realized variance as square of daily returns. Then we sum daily realized variance in the month to get monthly realized variance. At last, we take square-root of monthly realized variance and scaled to get annualized monthly realized volatility, comparable with our monthly implied volatility measure,

$$RV = \sqrt{\sum RET_{daily}^2} * \sqrt{12}.$$

Volatility spread. The volatility spread is the difference between monthly implied volatility and monthly realized volatility.

Market beta and idiosyncratic volatility. At the end of each month, for each stock, we regress its daily returns on market returns, using past 252 days data,

$$RET_{stock,t} = \alpha + \beta RET_{market,t} + \epsilon_t,$$

We take β as stock's exposure on market portfolio, and calculate annualized idiosyncratic volatility from time-series of ϵ_t.

Stock bid-ask spread. Each month, for each stock, we calculate end-of-day bid-ask spread as follows

$$BASP = \frac{Ask - Bid}{\frac{1}{2}Bid + \frac{1}{2}Ask}.$$

The monthly bid-ask spread is average of daily ones.

Option/Stock trading volume ratio. Each month, for each stock, we sum all its daily option trading volumes together, including both put and call options, to get monthly option trading volume (OPVOL). Similarly, we sum all its daily stock trading volumes to get its monthly stock trading trading volume (SVOL), then we divide monthly option trading volume by monthly stock trading volume. Since one option contract gives investor the right to trade 100 underlying stocks, we scale the ratio by 100 and take logarithm,

$$OS = \log(\frac{100 * \sum OPVOL_{daily}}{\sum SVOL_{daily}}).$$

Put/Call trading volume spread. Each month, for each stock, we sum all its daily option trading volumes, for put and call options separately, and divide monthly put option trading volume by monthly call option trading volume.

Firm size. We update firm size quarterly as Logarithm of firm total assets (atq).

Market leverage ratio. First of all, we calculate total debt value as sum of current liabilities and total long-term debt. Then divide it by firm equity market value plus debt value,

$$MarLEV = \frac{dlcq + dlttq}{dlcq + dlttq + prccq * cshoq}.$$

Market-to-book ratio. We update firm market-to-book ratio as follows

$$MTB = \frac{prccq * cshoq + tdq + pstkq - txditcq}{atq},$$

where numerator is sum of traded equity market value (price times number of share outstanding), total debt value and preferred stock minus deferred taxes and investment tax credit.

Analyst forecast dispersion and skewness. Analyst forecast dispersion, and skewness is calculated closely following Garfinkel (2009). Raw dispersion and skewness are scaled by absolution value of forecast mean. Garfinkel (2009) constructs an analyst-based dispersion proxy from forecasts submitted during the month of the opinion divergence measure's calculation (to address concerns due to staleness of IBES forecasts noted by McNichols and O'Brien, 1997). This may be an appropriate approach given the short time interval (Jan-Mar 2002) considered in Garfinkel (2009). In larger samples, however, clustering of analyst forecasts plays an important role as analysts have a tendency to revise year-end forecasts following the release of quarterly earnings (see, for instance, Cooper et al., 2001). This often leads to an insufficient number of newly issued forecasts during certain months potentially rendering analyst-based divergence measure imprecise.

Therefore, in our paper, the analyst forecast for a given (company-fiscal period end) pair is carried forward till either the date of the consecutive estimate release for the same (company-fiscal period end) combination by the same analyst or the date which is 105 days ahead or the earnings announcement date, whichever comes sooner. The decision to carry the forecast forward for up to 105 days is based on the IBES methodology (see IBES Detailed Estimates Manual, page 19) according to which if an estimate has not been updated for 105 days, it is filtered, footnoted and excluded from the consensus calculation (IBES uses 120 days for the cutoff of estimates for Q4, but we stick to 105 days as it being a more conservative approach). This methodology helps alleviate, albeit not eliminate, the issue of forecast staleness.

We also calculate one robust version of skewness, defined as the gap between analyst forecast median and mean. Such raw measure is also scaled by absolution value of forecast mean.

3.2 Empirical Methods

Firstly, at the end of each month, we sort stocks in the whole sample [1], by skewness, into five portfolios. Then we long stocks with lowest skewness (portfolio 1) and short stocks with highest

[1] we only use common stocks, with shrcd = (10, 11).

skewness (portfolio 5) during next month. The value weighted and equal-weighted portfolio returns are calculated.

Since it is possible that our results may be driven by other established factors, after the univariate-sorting test, we further conduct Fama-Mecbeth regression and double sorting exercise, controlling for firm characteristics and other popular predictors for cross section stock returns. Fama-Mecbeth regression proceeds as follows,

$$RET_{i,t+1} = \alpha + \beta SKEW_{i,t} + \gamma_1 DISP_{i,t} + \gamma_2 MEAN_{i,t} + \rho X_{i,t} + \epsilon_{i,t},$$

where RET is monthly individual stock returns. $SKEW$ is our analyst forecast skewness. $DISP$ is analyst forecast dispersion, and $MEAN$ is analyst forecast mean. X is a vector of control variables, motivated by literature, including standard firm characteristics, such as firm size, market-to-book ratio, and market leverage ratio. X also contains volatility spread (Bali and Hovakimian, 2009), implied volatility skewness (Cremers and Weinbaum, 2010; Xing, Zhang and Zhao, 2010), option-to-stock trading volume ratio (Johnson and So, 2012), put-call option trading volume ratio (Pan and Poteshman, 2006), market beta (Chang, Christoffersen, Jacobs and Vainberg, 2011; Frazzini and Pedersen, 2014), idiosyncratic volatility (Ang, Hodrick, Xing and Zhang, 2006), past month stock return (An, Ang, Bali and Cakici, 2014) and stock liquidity measure. Since option-stock trading volume ratio, put/call trading volume ratio and implied volatility slope all share same stories in literature, we only keep implied volatility slope as control variable in cross section regression. Moreover, ex-ante skewness in Boyer, Mitton and Vorkink (2010) is added to regression as a control for skewness prediction from fundamental variables.

The double sorting procedure follows Ang, Hodrick, Xing and Zhang (2006) and Bali and Hovakimian (2009). Specifically, each month, the stocks are first sorted into deciles based on the control characteristic (e.g., size). Then, within each characteristic deciles, the stocks are further sorted into deciles based on our option strike dispersion measure. Each characteristic decile, thus, contains 10 option strike dispersion deciles. Next, strike dispersion decile 1 from each control characteristic decile are averaged into a single decile 1, strike dispersion decile 2 are averaged into a single decile 2, etc. The resulting option strike deciles contain stocks with all values of the characteristic and, hence, represent option strike dispersion decile portfolios controlling for the characteristic.

4 Empirical Results

In this section, we first examine results from univariate-sorting test. Then double sort and results of Fama-Mecbeth regression are discussed.

4.1 Summary Statistics

Table 1 provides summary statistics for whole sample. Table 2 summarizes firm characteristics for different analyst forecast skewness levels. We divide the whole samples into five groups. Implied volatility, realized volatility, variance spread and idiosyncratic volatility increase as we move from portfolios with lowest skewness to the one with highest skewness. CAPM beta is also higher for high skewness portfolios. Implied volatility smile is steeper for stocks with more negative skewness. Similarly, put and call option trading volume and option stock trading ratio decrease with skewness. The relation between analyst forecast dispersion and skewness is U-shape.

There is no significant difference for firm size, stock and option trading volumes, analyst coverage and ex-ante skewness across different skewness levels. The most significant differences across skewness levels are for market-to-book ratio, leverage ratio and pervious month stock returns. Stocks with very negative skewness have larger market-to-book ratio, low leverage ratio and experience large positive returns in previous month.

Ex-ante skewness in Boyer, Mitton and Vorkink (2010) provides a good benchmark for our analysis. The authors use a number of firm-level variables to predict skewness, including lagged idiosyncratic volatility, momentum, turnover, and dummy variables related to firm size, industry category, and trading exchange. The generated skewness could be regarded as skewness calculated from fundamentals. Such ex-ante skewness does not change much across our portfolios, yet belief skewness varies a lot, which indicates that these two kinds of skewness have different implication for future stock returns.

4.2 Univariate Portfolio Sorting Results

Both value and equally weighted long-short portfolios, sorted on analyst forecast skewness, generate significant abnormal returns, as are shown in Table 3 and Table 6. Take value-weighted portfolio for instance, we have two important findings. On the one hand, the magnitudes of abnormal returns (Alpha) decrease with skewness. The lowest skewness portfolio has most positive abnormal return, while the highest skewness portfolio has actually negative return.

On the other hand, the significant level for Alphas also decrease with skewness. Lowest skewness portfolio significantly outperforms market, after adjusting for Fama-French systematic risk factors. However, highest skewness portfolio has an insignificant risk-adjusted return.

Our empirical results distinct sharply with those in literature, based on risk-neutral or realized skewness. Common wisdom in literature suggests that we should earn significant negative returns from those stocks with high (positive) skewness. Because such stock has a small chance to earn large return, just like lottery. While having skewness preference, as argued by Barberis and Huang (2008), investors favor such stocks and buy order pressure pushes current stock price high, deviating from their fundamental value. Therefore, future returns will be low, since there is no fundamental support.

In contrast, our profit for long-short portfolio comes from low skewness stocks, inconsistent with Barberis and Huang (2008) arguments. Our results show that in our sample, there is no overprice for high skewness stocks, however, low skewness stocks are undervalued. Veronesi (1999) provides a potential explanation for our findings. In the model, Veronesi shows that when investors cannot observe cash flow growth rate, they tend to overreact to bad news, push current stock price down, such behavior will lead to higher future stock returns. Analysts basically need to estimate firm earning growth rate, based on various information sources. Therefore, such learning procedure fits into Veronesi's model.

We further divide our sample into good state and bad state periods, according to NBER recession indicator. In good state, low skewness stocks increase more, while in bad state, low skewness stocks decrease less. Such findings indicate that low skewness stocks are consistently undervalued across time.

Table 9 and Table 10 compare trading strategies based on analyst forecast mean, dispersion, skewness, ex-ante skewness and robust version of analyst forecast dispersion, with different weighting schemes. Analyst forecast skewness has robust performance across different definitions and portfolio weighting schemes. Trading strategies based on average analyst forecast and dispersion are able to generate abnormal returns with equal-weighted scheme. Ex-ante skewness also only works for equal-weighted portfolios.

4.3 Double Sorting and Fama-Mecbeth Regression

In literature, there are other variables, extracted from stock and option markets, being able to predict expected cross section stock returns. Since it is possible that our results may be driven by these variables, after the univariate-sorting test, we further conduct double sorting test and Fama-Mecbeth regression, controlling for firm characteristics and other popular predictors for cross section stock returns. The cross section regression has formula

$$RET_{i,t+1} = \alpha + \beta SKEW_{i,t} + \gamma_1 DISP_{i,t} + \gamma_2 MEAN_{i,t} + \rho X_{i,t} + \epsilon_{i,t},$$

where RET is monthly individual stock returns. $SKEW_{i,t}$ is analyst EPS forecast skewness measure. X is a vector of control variables, motivated by literature. Standard firm characteristics, such as firm size, market-to-book ratio, and market leverage ratio, are includes. X also contains volatility spread (Bali and Hovakimian, 2009), implied volatility skewness (Cremers and Weinbaum, 2010; Xing, Zhang and Zhao, 2010), option-to-stock trading volume ratio (Johnson and So, 2012), put-call option trading volume ratio (Pan and Poteshman, 2006), market beta (Chang, Christoffersen, Jacobs and Vainberg, 2012; Frazzini and Pedersen, 2014), idiosyncratic volatility (Ang, Hodrick, Xing and Zhang, 2006), past month return (An, Ang, Bali and Cakici, 2014) and stock liquidity measure. We also control ex-ante skewness in Boyer, Mitton and Vorkink (2010).

The results for double-sorting long-short portfolios in Table 11 basically confirm conclusion from Fama-Mecbeth regression. Although the risk adjusted abnormal returns are lower than those in Table 3, they are still statistically significant. Among our control variables, previous month return, variance spread, and option trading activities have most severe negative effects for abnormal return of our strategy. After controlling for them, our abnormal return decreases by roughly 20%. Based on Table 2, we know that low skewness stocks experience large positive returns in previous month, therefore, our strategy may capture momentum for such stocks. Previous month option trading activities may have information about negative news, which could be also captured by our strategy.

Fama-Mecbeth regression results is illustrated in Table 12. Coefficient for our core variable: analyst EPS forecast skewness is negative and significant, indicating that high skewness leads to low future stock returns. The coefficient for ex-ante skewness is not statistically significant, which indicates that when we put our analyst forecast skewness together with ex-ante skewness, ex-ante skewness loss the power to predict cross section stock returns. The negative coefficient for previous month returns indicates short-term reversal.

4.4 Interaction between Skewness and Earning Surprise

In Veronesi (1999) model, price is a convex function of agent's belief. Therefore, in good time, a bad news will make agent revise her belief a lot, as illustrated in the paper, overreaction to bad news in good time. For individual firm, it is difficult to measure whether the firm is in its good or bad state. Here, we use earning surprise as an indicator. First of all, we define percentage earning surprise as

$$SUE = \frac{Real\ Firm\ Earning - mean(Analyst\ Earning\ Forecasts)}{Real\ Firm\ Earning}.$$

At the end of each month, we merge our sample with the latest announced earning surprise, suppose such surprise is positive, we consider the firm is in its good state, otherwise, it is in its bad state.

We further sort our sample to 3 by 3 subsamples, according to analyst forecast skewness and firm's percentage earning surprise. Within each earning surprise subsample (low, media and high SUE), stocks are sorted by analyst forecast skewness, if Veronesi (1999) theory is behind our empirical results, we should see abnormal return becomes stronger when we move from low SUE subsample to high SUE subsample.

Table 13 presents the pattern for abnormal returns. First of all, we know that for low SUE portfolio, on average, firm real earning is less than expectation. For other two portfolios, firm real earning is better than expectation. For firms in their bad state (negative earning surprise), abnormal return for skewness hedging portfolio should be weak, while for firms in their good state (positive earning surprise), abnormal return for skewness hedging portfolio should be strong. Consistent with our hypothesis, for low SUE sample, the abnormal return is insignificant, while for other two samples, abnormal returns are statistically significant, and we get largest abnormal return in high SUE sample.

5 Conclusions

In the paper, we show a significant economic linkage between analyst EPS forecast skewness and cross section stock returns. The effect on stock return of our skewness measure is quite different from that based on skewness calculated from options or high frequency data. Literature shows that, using such skewness as a signal, trading profit is generated mostly from over-valued stocks with high positive skewness, which is consistent with Barberis and Huang (2008)'s lottery arguments. However, we find that for our analyst forecast skewness, trading profit mainly comes from those stocks with negative skewness. Long-short strategy purchasing stocks with low forecast skewness and shorting those with high forecast skewness earns annualized abnormal returns 11% with sharpe ratio 0.64. Our study suggests that negative skewness stocks tend to be undervalued (risk-adjusted returns for negative skewness stocks are significantly positive), while stocks with high positive skewness have fair prices (risk-adjusted returns for positive skewness stocks are not significant). Our empirical results are closely related with investors learning behavior and consistent with Veronesi (1999) theory. In the model, Veronesi shows that when investors cannot observe cash flow growth rate, they tend to overreact to bad news, push current stock price down, such behavior will lead to higher future stock returns. Our results also hold when using robust skewness defined as the gap between analyst EPS forecast mean and median.

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Table 1: **Summary Statistics: Stock Characteristics**

Summary statistics for various stock characteristics. RET is monthly equity returns. IV is implied volatility. RV is monthly total realized volatility. BETA is stock return loading on market portfolio. IdioVol is idiosyncratic volatility calculated from market model. IVS is implied volatility skew. SIZE is firm size. MTB is market-to-book ratio. MarLEV is market leverage ratio. SVOL and OPVOL are logarithm of monthly stock and option total trading volume. DISP is analyst forecast dispersion. SKEW is analyst forecast skewness. OS is logarithm of option and stock volume ratio. OPVOLSP is put and call option volume ratio. The sample period is from January, 1996 to December, 2011, trimmed by 1%. To avoid effect of extreme values, Data with IV and RV larger than 1 is deleted.

	RET	IV	RV	VS	IVS	SIZE	MTB	MarLEV
min	-0.3161	0.1468	0.0952	-0.1817	-0.0162	5.2637	0.1091	0.0002
mean	0.0083	0.3805	0.3068	0.0738	0.0024	8.7055	1.5440	0.2177
max	0.3280	0.8794	0.8741	0.3152	0.0424	13.6913	7.1456	0.9112
sd	0.0981	0.1320	0.1373	0.0740	0.0053	1.4307	1.0011	0.1699
	DISP	SKEW	Beta	IdioVol	OS	OPVOLSP	SVOL	OPVOL
min	0.0040	-40.9517	0.1900	0.0072	-6.3117	0.0418	14.8928	4.9127
mean	0.1094	-4.6147	1.1320	0.0196	-2.7364	0.7740	17.5056	10.1641
max	3.3888	9.6462	2.5000	0.0524	-0.3629	4.5692	20.8256	14.8170
sd	0.2502	5.8919	0.4282	0.0080	1.0957	0.5827	1.1111	1.8402

Table 2: **Group Summary Statistics**

Summary statistics in portfolios sorted by analyst forecast skewness. RET is stock returns on sorting month. IV is implied volatility. IVS is volatility skew for ATM options. RV is realized volatility. VS is spread between implied and realized volatility. SIZE is firm size. MTB is market-to-book ratio. MarLEV is market leverage ratio. DISP is analyst forecast dispersion for next-year EPS. Coverage is number of analysts following the stock. MEAN is average of analyst forecasts. SKEW is analyst forecast skewness for next year EPS. BETA is stock loading on market portfolio. IdioVol is idiosyncratic volatility from market model. SVOL and PVOL are monthly total trading volume for stocks and options. OS is ratio of option and stock trading volume. OPVOLSP is ratio between trading volume of put and call options. The sample period is from January, 1996 to December, 2011, trimmed by 1%. TSkew and ISkew are ex-ante total and idiosyncratic skewness in Boyer, Mitton and Vorkink (2010). To avoid effect of extreme values, Data with IV and RV larger than 1 is deleted.

	IV	IVS	RV	VS	SIZE	MTB	MarLEV	DISP	Coverage	MEAN
Low	0.3809	0.0031	0.3067	0.0741	8.0659	2.0718	0.1639	0.1319	9.0905	1.3676
2	0.3774	0.0030	0.3073	0.0702	8.5916	1.7387	0.2061	0.0685	10.5402	1.7117
3	0.3796	0.0027	0.3102	0.0697	8.8813	1.5094	0.2288	0.0853	12.0395	2.0039
4	0.3938	0.0025	0.3244	0.0697	9.1886	1.3239	0.2605	0.1211	13.5868	2.4367
High	0.4726	0.0029	0.3851	0.0863	8.8036	1.4125	0.3055	0.3885	14.0650	1.3629
	SKEW	Beta	IdioVol	RET	SVOL	OPVOL	OS	OPVOLSP	TSkew	ISkew
Low	-15.9296	1.0252	0.0198	0.0151	17.1513	9.3433	-3.1973	0.8071	0.6578	0.7179
2	-6.0342	1.0619	0.0195	0.0132	17.3824	9.7723	-3.0008	0.8127	0.6467	0.7083
3	-3.1360	1.0967	0.0195	0.0096	17.5188	10.1447	-2.7666	0.8191	0.6282	0.6956
4	-1.4310	1.1765	0.0202	0.0096	17.6654	10.6209	-2.4449	0.7959	0.5975	0.6754
High	1.1425	1.3522	0.0249	0.0042	17.7167	10.7091	-2.4189	0.7600	0.6649	0.7308

Table 3: **Value-Weighted Stock Portfolios Sorted by Analyst EPS Forecast Skewness**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to analyst forecast skewness. The portfolio is value-weighted. Alpha is abnormal return after adjusting of systematic risk factors. MKTRF is market factor. SMB is size factor. HML is growth factor. UMD is momentum factor. LIQ is liquidity factor. RET is annualized raw return. SR is annualized sharp ratio. The first line of each portfolio is estimated values, and the second line is standard error. The sample period is from January, 1996 to December, 2011.

	Alpha	MKTRF	SMB	HML	UMD	LIQ	RET	SR
low	0.0078	0.9625	-0.2587	-0.1624	0.0562	-0.0564	13.0695	0.7769
	(0.0014)	(0.0320)	(0.0406)	(0.0430)	(0.0257)	(0.0333)		
2	0.0043	1.0269	-0.1376	-0.2322	0.0892	-0.0827	9.3274	0.5092
	(0.0015)	(0.0343)	(0.0435)	(0.0461)	(0.0275)	(0.0357)		
3	0.0021	0.9986	-0.0211	-0.1505	-0.1271	0.0579	7.2538	0.3785
	(0.0014)	(0.0329)	(0.0417)	(0.0442)	(0.0264)	(0.0342)		
4	0.0003	1.0294	0.0395	-0.0271	-0.1468	0.0307	5.5195	0.2811
	(0.0015)	(0.0342)	(0.0433)	(0.0460)	(0.0274)	(0.0355)		
high	-0.0031	1.2488	-0.0088	-0.3679	-0.1553	0.1069	2.0491	0.0790
	(0.0024)	(0.0555)	(0.0702)	(0.0745)	(0.0444)	(0.0576)		
Hedged	0.0109	-0.2863	-0.2499	0.2055	0.2115	-0.1633	11.0205	0.6444
	(0.0030)	(0.0689)	(0.0873)	(0.0926)	(0.0552)	(0.0716)		

Table 4: **Value-Weighted Stock Portfolios Sorted by Analyst Skewness: Good State**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to analyst forecast skewness. The portfolio is value-weighted. We pick months not in recession, based on NBER business cycle indicator. Alpha is abnormal return after adjusting of systematic risk factors. MKTRF is market factor. SMB is size factor. HML is growth factor. UMD is momentum factor. LIQ is liquidity factor. RET is annualized raw return. SR is annualized sharp ratio. The first line of each portfolio is estimated values, and the second line is standard error. The sample period is from January, 1996 to December, 2011.

	Alpha	MKTRF	SMB	HML	UMD	LIQ	RET	SR
1ow	0.0072	0.9668	-0.2876	-0.1621	0.0738	-0.0743	15.7853	0.9895
	(0.0016)	(0.0398)	(0.0455)	(0.0514)	(0.0327)	(0.0428)		
2	0.0038	1.0140	-0.1717	-0.2946	0.1174	-0.0678	12.2720	0.6994
	(0.0017)	(0.0411)	(0.0470)	(0.0531)	(0.0339)	(0.0442)		
3	0.0032	1.0078	0.0051	-0.1596	-0.1821	0.0070	10.8069	0.6028
	(0.0016)	(0.0391)	(0.0447)	(0.0505)	(0.0322)	(0.0421)		
4	0.0003	1.0053	0.0408	-0.0685	-0.1682	0.1032	8.7213	0.4894
	(0.0016)	(0.0398)	(0.0455)	(0.0514)	(0.0328)	(0.0428)		
high	-0.0010	1.1868	0.0492	-0.3780	-0.2042	0.0798	7.0096	0.2961
	(0.0026)	(0.0641)	(0.0733)	(0.0828)	(0.0528)	(0.0690)		
hedged	0.0082	-0.2200	-0.3368	0.2159	0.2780	-0.1541	8.7757	0.5323
	(0.0032)	(0.0807)	(0.0923)	(0.1043)	(0.0665)	(0.0868)		

Table 5: **Value-Weighted Stock Portfolios Sorted by Analyst Skewness: Bad State**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to analyst forecast skewness. The portfolio is value-weighted. We pick months in recession, based on NBER business cycle indicator. Alpha is abnormal return after adjusting of systematic risk factors. MKTRF is market factor. SMB is size factor. HML is growth factor. UMD is momentum factor. LIQ is liquidity factor. RET is annualized raw return. SR is annualized sharp ratio. The first line of each portfolio is estimated values, and the second line is standard error. The sample period is from January, 1996 to December, 2011.

	Alpha	MKTRF	SMB	HML	UMD	LIQ	RET	SR
low	0.0116	0.9969	-0.0674	-0.1489	0.0849	-0.0217	-5.4189	-0.2524
	(0.0027)	(0.0521)	(0.0854)	(0.0735)	(0.0366)	(0.0419)		
1	0.0068	0.9502	-0.1167	0.1068	0.0302	0.0078	-10.7190	-0.4775
	(0.0039)	(0.0743)	(0.1218)	(0.1048)	(0.0522)	(0.0598)		
2	-0.0001	0.9928	-0.0412	0.0604	-0.0488	0.1859	-16.9350	-0.6661
	(0.0039)	(0.0734)	(0.1204)	(0.1036)	(0.0516)	(0.0591)		
3	0.0012	1.0572	0.0490	0.0148	-0.0874	-0.1032	-16.2776	-0.5646
	(0.0053)	(0.1006)	(0.1649)	(0.1419)	(0.0707)	(0.0810)		
high	-0.0036	1.5205	-0.3310	-0.4476	-0.0428	0.1526	-31.7208	-0.8539
	(0.0090)	(0.1721)	(0.2821)	(0.2427)	(0.1209)	(0.1385)		
hedged	0.0151	-0.5236	0.2636	0.2988	0.1277	-0.1743	26.3020	1.2738
	(0.0103)	(0.1969)	(0.3228)	(0.2777)	(0.1383)	(0.1584)		

Table 6: **Equal-Weighted Stock Portfolios Sorted by Analyst EPS Forecast Skewness**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to analyst forecast skewness. The portfolio is equal-weighted. Alpha is abnormal return after adjusting of systematic risk factors. MKTRF is market factor. SMB is size factor. HML is growth factor. UMD is momentum factor. LIQ is liquidity factor. RET is annualized raw return. SR is annualized sharp ratio. The first line of each portfolio is estimated values, and the second line is standard error. The sample period is from January, 1996 to December, 2011.

	Alpha	MKTRF	SMB	HML	UMD	LIQ	RET	SR
low	0.0085	1.0820	0.0808	-0.0107	-0.0764	0.0499	16.3986	0.8241
	(0.0014)	(0.0318)	(0.0402)	(0.0427)	(0.0255)	(0.0330)		
2	0.0039	1.0722	0.2159	0.0050	-0.1616	0.0593	10.9792	0.5275
	(0.0014)	(0.0310)	(0.0392)	(0.0416)	(0.0248)	(0.0321)		
3	0.0009	1.0928	0.2688	0.1157	-0.1907	0.0975	8.1327	0.3831
	(0.0012)	(0.0279)	(0.0353)	(0.0375)	(0.0223)	(0.0290)		
4	-0.0012	1.1185	0.2752	0.1997	-0.2705	0.1660	6.2714	0.2750
	(0.0015)	(0.0350)	(0.0443)	(0.0470)	(0.0280)	(0.0364)		
high	-0.0011	1.3629	0.4469	-0.3897	-0.5233	0.1262	4.7606	0.1450
	(0.0025)	(0.0583)	(0.0738)	(0.0784)	(0.0467)	(0.0606)		
Hedged	0.0096	-0.2808	-0.3661	0.3791	0.4469	-0.0763	11.6380	0.6192
	(0.0027)	(0.0625)	(0.0791)	(0.0839)	(0.0500)	(0.0648)		

Table 7: **Equal-Weighted Stock Portfolios Sorted by Analyst Skewness: Good State**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to analyst forecast skewness. The portfolio is equal-weighted. We pick months not in recession, according to NBER business cycle indictor. Alpha is abnormal return after adjusting of systematic risk factors. MKTRF is market factor. SMB is size factor. HML is growth factor. UMD is momentum factor. LIQ is liquidity factor. RET is annualized raw return. SR is annualized sharp ratio. The first line of each portfolio is estimated values, and the second line is standard error. The sample period is from January, 1996 to December, 2011.

	Alpha	MKTRF	SMB	HML	UMD	LIQ	RET	SR
low	0.0079	1.0956	0.0673	0.0337	-0.0603	0.0212	19.3106	1.0738
	(0.0015)	(0.0382)	(0.0437)	(0.0493)	(0.0315)	(0.0411)		
2	0.0032	1.0931	0.1985	0.0360	-0.1451	0.0168	13.1270	0.7048
	(0.0015)	(0.0369)	(0.0421)	(0.0476)	(0.0303)	(0.0396)		
3	0.0007	1.0954	0.2788	0.1619	-0.1772	0.0498	10.9661	0.5927
	(0.0013)	(0.0327)	(0.0373)	(0.0422)	(0.0269)	(0.0351)		
4	-0.0013	1.1239	0.2947	0.2654	-0.2498	0.1268	9.4297	0.4780
	(0.0017)	(0.0414)	(0.0473)	(0.0535)	(0.0341)	(0.0445)		
high	-0.0007	1.3787	0.4890	-0.3140	-0.5629	0.0695	7.4171	0.2495
	(0.0028)	(0.0692)	(0.0791)	(0.0893)	(0.0570)	(0.0744)		
hedged	0.0086	-0.2831	-0.4217	0.3477	0.5026	-0.0483	11.8934	0.6630
	(0.0030)	(0.0739)	(0.0845)	(0.0955)	(0.0609)	(0.0795)		

Table 8: **Equal-Weighted Stock Portfolios Sorted by Analyst Skewness: Bad State**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to analyst forecast skewness. The portfolio is equal-weighted. We pick months in recession, according to NBER business cycle indicator. Alpha is abnormal return after adjusting of systematic risk factors. MKTRF is market factor. SMB is size factor. HML is growth factor. UMD is momentum factor. LIQ is liquidity factor. RET is annualized raw return. SR is annualized sharp ratio. The first line of each portfolio is estimated values, and the second line is standard error. The sample period is from January, 1996 to December, 2011.

	Alpha	MKTRF	SMB	HML	UMD	LIQ	RET	SR
low	0.0112	1.1559	0.2472	-0.2352	-0.0427	0.0327	-3.4257	-0.1152
	(0.0037)	(0.0707)	(0.1159)	(0.0997)	(0.0497)	(0.0569)		
2	0.0084	1.1084	0.3566	-0.0600	-0.1404	0.1151	-3.6420	-0.1131
	(0.0042)	(0.0790)	(0.1295)	(0.1114)	(0.0555)	(0.0636)		
3	0.0042	1.2080	0.2018	-0.0832	-0.1820	0.1432	-11.1564	-0.3229
	(0.0038)	(0.0726)	(0.1191)	(0.1025)	(0.0510)	(0.0585)		
4	-0.0003	1.2150	0.1392	-0.1278	-0.3019	0.1650	-15.2298	-0.4046
	(0.0045)	(0.0865)	(0.1419)	(0.1220)	(0.0608)	(0.0696)		
high	0.0012	1.5325	0.4073	-0.7159	-0.4041	0.1138	-13.3246	-0.2692
	(0.0085)	(0.1610)	(0.2640)	(0.2271)	(0.1131)	(0.1296)		
hedged	0.0100	-0.3766	-0.1600	0.4806	0.3613	-0.0811	9.8990	0.4079
	(0.0097)	(0.1850)	(0.3034)	(0.2610)	(0.1300)	(0.1489)		

Table 9: **Value-Weighted Stock Portfolios Sorted by Various Return Predictors**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to various return predictors. Due to limits of space, we only report t-statistics for abnormal returns. AMEAN represents analyst forecast average. ADISP represents analyst forecast dispersion. ASKEW is analyst forecast skewness. ISkew and TSkew are ex-ante idiosyncratic and total skewness in Boyer, Mitton and Vorkink (2010). The sample period is from January, 1996 to December, 2011.

		$\alpha(\%)$	MKT	SMB	HML	UMD	LIQ	Sharp	t_α
AMEAN	low	0.54	1.54	0.48	-0.44	-0.21	-0.10	0.38	2.17
	high	-0.01	0.89	-0.22	0.17	-0.00	0.08	0.33	-0.10
	hedge	-0.54	-0.65	-0.70	0.61	0.21	0.17	-0.32	-1.88
ADISP	low	0.47	0.85	-0.35	0.07	0.05	-0.02	0.63	4.14
	high	-0.25	1.40	0.38	-0.02	-0.21	-0.08	0.13	-1.18
	hedged	-0.72	0.55	0.72	-0.10	-0.26	-0.05	-0.25	-2.51
ASKEW	low	0.83	0.90	-0.24	0.03	0.07	-0.02	0.90	5.90
	high	-0.10	1.22	0.06	-0.23	-0.24	0.08	0.16	-0.48
	hedged	-0.93	0.32	0.29	-0.26	-0.31	0.10	-0.53	-3.00
ISkew	low	0.61	1.05	-0.03	-0.24	0.10	0.04	0.65	3.50
	high	0.05	1.09	-0.01	0.16	-0.27	-0.06	0.20	0.21
	hedged	-0.56	0.04	0.01	0.40	-0.36	-0.10	-0.44	-1.65
TSkew	low	0.65	1.03	0.02	-0.14	0.16	0.01	0.71	3.55
	high	0.08	1.03	0.01	0.01	-0.32	0.02	0.21	0.28
	hedged	-0.58	0.00	-0.01	0.15	-0.48	0.01	-0.44	-1.53
RSkew	low	0.48	0.81	-0.31	0.11	0.05	-0.02	0.67	4.01
	high	-0.18	1.34	0.28	0.01	-0.19	-0.08	0.15	-0.90
	hedged	-0.65	0.53	0.58	-0.10	-0.24	-0.06	-0.26	-2.41

Table 10: **Equal-Weighted Stock Portfolios Sorted by Various Return Predictors**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 5 groups, according to various return predictors. Due to limits of space, we only report t-statistics for abnormal returns. AMEAN represents analyst forecast average. ADISP represents analyst forecast dispersion. ASKEW is analyst forecast skewness. ISkew and TSkew are ex-ante idiosyncratic and total skewness in Boyer, Mitton and Vorkink (2010). RSkew is robust skewness for analyst forecasts. The sample period is from January, 1996 to December, 2011.

		α(%)	MKT	SMB	HML	UMD	LIQ	Sharp	t_α
AMEAN	low	0.18	1.42	0.82	-0.30	-0.57	0.04	0.25	0.77
	high	-0.20	1.01	0.04	0.42	-0.08	0.14	0.28	-1.67
	hedged	-0.37	-0.42	-0.79	0.72	0.50	0.10	-0.16	-1.36
ADISP	low	0.45	0.93	0.04	0.29	-0.01	0.04	0.69	3.43
	high	-0.08	1.32	0.79	0.03	-0.48	0.07	0.22	-0.43
	hedge	-0.54	0.40	0.75	-0.26	-0.47	0.02	-0.22	-2.21
ASkew	low	0.72	1.05	0.28	0.17	-0.07	0.02	0.78	5.65
	high	-0.29	1.35	0.69	-0.21	-0.58	0.09	0.10	-1.30
	hedged	-1.00	0.30	0.41	-0.38	-0.52	0.07	-0.62	-3.98
ISkew	low	0.57	1.08	0.39	0.26	-0.01	0.16	0.76	3.46
	high	-0.16	1.20	0.54	-0.03	-0.60	0.03	0.11	-0.75
	hedged	-0.74	0.13	0.15	-0.29	-0.60	-0.13	-0.67	-2.53
TSkew	low	0.57	1.09	0.40	0.33	0.02	0.15	0.77	3.35
	high	-0.21	1.20	0.57	-0.09	-0.62	0.05	0.09	-0.92
	hedged	-0.78	0.11	0.18	-0.42	-0.63	-0.10	-0.67	-2.52
RSkew	low	0.41	0.92	0.09	0.30	-0.03	0.04	0.66	3.16
	high	-0.14	1.33	0.73	0.02	-0.47	0.06	0.19	-0.72
	hedged	-0.55	0.42	0.65	-0.28	-0.44	0.02	-0.24	-2.31

Table 11: **Statistics for Double Sorted Long-Short Strategy Performance**

Double sort, based on analyst forecast skewness and control variables listed below. VS is volatility spread. IdioVol is idiosyncratic volatility from market model. SIZE is log firm market value. MTB is market-to-book ratio. MarLEV is market leverage ratio. RET is lagged monthly underlying return. IVSKEW is implied volatility skew. SVOL and OPVOL are monthly total trading volumes for stocks and options. OS is ratio of option trading volume to stock trading volume. BETA is stock loading on market portfolio. OPVOLSP is ratio of put and call option trading volume. ANAM is mean of analyst forecasts. ANAD is analyst forecast dispersion. IdioSkew and TotalSkew are ex-ante idiosyncratic and total skewness in Boyer, Mitton and Vorkink (2010). The sample period is from January, 1996 to December, 2011. The time window is month.

Controls	Alpha	Tvalue	SharpRatio	Skewness	Kurtosis
BETA	9.35	3.24	0.59	-0.48	1.86
IdioVol	9.68	2.69	0.50	-0.17	1.66
IVSKEW	11.74	3.33	0.52	-0.10	1.07
MarLEV	9.67	3.00	0.50	-0.12	2.29
RET	8.91	2.36	0.37	-0.26	0.75
MTB	10.24	2.67	0.44	0.20	2.58
OPVOL	8.65	2.40	0.32	-0.70	2.34
OPVOLSP	9.43	2.41	0.32	-0.33	1.73
OS	10.29	3.55	0.52	-0.63	2.76
SIZE	10.61	3.44	0.53	-0.29	1.42
SVOL	9.91	2.80	0.41	-0.18	1.32
VS	8.47	2.12	0.37	-0.09	2.40
ANAM	8.22	2.68	0.44	-0.23	2.71
ANAD	9.45	2.59	0.66	-0.20	0.95
IdioSkew	12.22	3.93	0.74	-0.43	2.15
TotalSkew	9.68	3.02	0.57	-0.19	0.64

Table 12: **Stock Return and Analyst EPS Forecast Skewness**

Fama-Macbeth cross-section regression. Effect of analyst EPS forecast skewness on stock returns.

$$RET_{i,t+1} = \alpha + \beta SKEW_{i,t} + \gamma_1 DISP_{i,t} + \gamma_2 MEAN_{i,t} + \rho X_{i,t} + \epsilon_{i,t},$$

where $X_{i,t}$ is a vector of control variables. DISP is analyst forecast dispersion. MEAN is analyst forecast average. VS is volatility spread. IdioVol is idiosyncratic volatility from market model. SIZE is log firm market value. MTB is market-to-book ratio. MarLEV is market leverage ratio. RET is lagged monthly underlying return. IVSKEW is implied volatility skew. SLIQ is stock bid-ask spread. ExanteSkew is ex-ante idiosyncatic/total skewness in Boyer, Mitton and Vorkink (2010). Coverage is number of analysts following the stock. Beta is CAPM market beta. The sample period is from January, 1996 to December, 2011. The time window is month. Neway-West adjustment with 12 lags is used to calculate robust standard errors.

SKEW	DISP	MEAN	VS	IdioVol	RET	SIZE
-0.0004***	0.0080	-0.0009**	0.0007	-0.3055·	-0.0205**	-0.0005
(0.0001)	(0.0075)	(0.0003)	(0.0086)	(0.1623)	(0.0077)	(0.0011)
MTB	MarLEV	IVSKEW	SLIQ	ExanteSkew	Coverage	Beta
-0.0014	-0.0008	-0.1098	-0.0968	-0.0062·	0.0001	0.0024
(0.0010)	(0.0055)	(0.0875)	(0.9844)	(0.0034)	(0.0001)	(0.0035)

Table 13: **Interaction between Analyst Forecast Skewness and Earning Surprise**

We sort the whole sample based on percentage earning surprise,

$$SUE = \frac{Real\ Firm\ Earning - mean(Analyst\ Earning\ Forecasts)}{Real\ Firm\ Earning}.$$

into 3 portfolios, low SUE, media SUE and high SUE. Then, within each portfolio, we further sort stocks by analyst forecast skewness, into 3 subsamples, low skewness, media skewness and high skewness. We conduct Fama-French regression for long-short portfolios. The table reports average earning surprise, average analyst forecast skewness, abnormal returns for long-short portfolios and t statistics for abnormal returns. Sample period ranges from January, 1996 to December, 2011.

	SUE	SKEW	$\alpha(\%)$	t_α
Low SUE	-0.1690	-8.3774	0.52	1.81
Media SUE	0.0468	-12.2812	0.54	2.16
High SUE	0.3231	-8.4739	0.68	2.46