Good Idiosyncratic Volatility, Bad Idiosyncratic Volatility, and the Cross-Section of Stock Returns

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Abstract

We decompose the idiosyncratic volatility of stock returns into "good" and "bad" volatility components, and estimate a cross-sectional model for expected good minus bad volatility. Expected good minus bad volatility not only more accurately measures conditional idiosyncratic skewness, but also yields stronger return predictability. Importantly, the return predictability remains significant when controlling for expected idiosyncratic skewness and exposure to skewness-related factors. Furthermore, our result suggest that growth options earn lower returns mainly because they lead to positively skewed returns. Although investors may dislike extreme losses more than gains, we do not find it critical to our results.

Keywords: idiosyncratic skewness, good volatility, bad volatility, cross-sectional stock returns, risk factors, growth options

JEL Code: G10, G12, G13, G17, G31

1 Introduction

Idiosyncratic skewness has been shown to be negatively associated with stock returns (e.g., Barberis and Huang (2008), Boyer et al. (2010), Conrad et al. (2013) and Amaya et al. (2015)). Stocks with positive firm-specific skewness occasionally pay large returns. They may be appealing to investors and hence earn low average returns. Although the relationship between idiosyncratic skewness and expected stock returns has been established, measuring conditional idiosyncratic skewness is still challenging because higher moments are sensitive to outliers. Moreover, recent research (e.g, Barinov (2018) and Langlois (2020)) suggest that idiosyncratic skewness *per se* is less important because stocks with high idiosyncratic skewness are less exposed to skewness-related factors. Simultaneously, there have been less thorough research on distinguishing mechanisms that make positively skewed stocks attractive to investors.

Setting against this background, we builds on estimators of idiosyncratic return volatility based on realizations of positive and negative price increments (e.g., Barndorff-Nielsen and Shephard (2002), Barndorff-Nielsen and Shephard (2010), and Patton and Sheppard (2015)). "Good" volatility is the volatility that is associated with positive asset returns, while "bad" volatility is the volatility that is associated with negative asset returns. We then estimate a cross-sectional model for expected good minus bad volatility using firm characteristics. Compared to the expected idiosyncratic skewness measure of Boyer et al. (2010), expected good minus bad volatility not only better predicts realized good minus bad volatility but also realized idiosyncratic skewness. Furthermore, the expected good minus bad volatility measure has a strong negative relationship with future stock returns, and the relationship remains robust after controlling for expected idiosyncratic skewness and other skewness-related factors proposed in the literature. Moreover, the distinction between good and bad volatility also facilitates disentangling mechanisms behind the negative relationship between idiosyncratic skewness and stock returns.

We mainly make three contributions to the literature. First, we propose expected good minus bad volatility as a better measure of the conditional asymmetry in returns than expected idiosyncratic skewness. The third moments of asset returns may be susceptible to abnormal returns.

Existing econometric methods have suggested that realized good minus bad volatility may be a valid measure of realized skewness (e.g. Feunou et al. (2016) and Bollerslev et al. (2020)). However, existing studies haven't examined the relevance of using good minus bad volatility to measure physical conditional idiosyncratic skewness at the individual stock level [1]. To capture ex-ante variation in good minus bad volatility, we run cross-sectional regressions of good minus bad volatility on lagged good minus bad volatility and a set of firm characteristics. We examine the performance of expected good minus bad volatility by comparing the root mean squared error (RMSE) to other approaches in forecasting realized good minus bad volatility and realized skewness. We offer the novel finding that expected good minus bad volatility could be a better predictor for not only realized good minus volatility but also realized idiosyncratic skewness.

Second, the expected good minus bad volatility measure has a strong negative relationship with stock returns in both portfolio sorts and Fama-MacBeth regressions. Sorting individual stocks into portfolios based on expected good minus bad volatility yields larger differences in subsequent portfolio returns than sorting by expected idiosyncratic skewness (Boyer et al. (2010)). Moreover, such differences cannot be explained by expected idiosyncratic skewness and exposure to risk factors. The relationship between expected skewness and stock returns become insignificant or even reverses direction once expected good minus bad volatility is controlled for. However, the significance of expected good minus bad volatility remains robust after controlling for the realized volatility of Ang et al. (2006), the expected idiosyncratic skewness of Boyer et al. (2010) and other control variables considered in the literature. Recent papers (Barinov (2018), Langlois (2020)) propose the aggregate volatility (FVIX) factor and predicted skewness factor (PSS), which may explain why stocks with positive idiosyncratic skewness earn low returns. When controlling for exposure to these factors, the return predictability of expected idiosyncratic skewness is insignificant. We show that the return predictability of expected good minus bad volatility remains significant. Since expected

[1] Huang and Li (2019) find a positive relationship between individual stocks' implied variance asymmetry, defined as the difference between upside and downside risk-neutral semivariances extracted from out-of-money options, and future stock returns. In contrast, we discover a strong negative relationship between conditional idiosyncratic skewness and stock returns. Option-implied risk-neutral skewness are affected by investors' risk preferences and only available for a subsample of firms with sufficient option data, which may make option-implied measures subject to more liquidity and limits to arbitrage issues. Our conditional idiosyncratic skewness measure covers a broader sample of firms and may capture different information from risk neutral skewness. Thus, the relevant economic mechanisms to explain our results also differs.

good minus bad volatility yields better forecasting performance and stronger asset pricing results, our paper highlights the benefits of using expected good minus bad volatility to measure conditional skewness in individual stock returns. The use of expected good minus bad volatility may lead to more significant portfolio returns and more effective risk hedging for real-world investors whose investment strategies are exposed to asymmetry in stock returns.

Third, we conduct a series of regressions to shed light on mechanisms behind the negative relationship between expected good minus bad volatility and stock returns. Trigeorgis and Lambertides (2014), Del Viva et al. (2017), and Bali et al. (2020) have argued that the flexibility of growth options may enhance a firm's upside value potential and reduces downside risk in bad economic states. Moreover, such asymmetry could result in returns with more large positive payoffs but less extreme negative ones, which is desirable for investors. We find that the relationship between growth option intensity (Trigeorgis and Lambertides (2014)) and stock returns becomes insignificant once expected good minus bad volatility is controlled for. Hence, our results complement those studies that suggest growth options may have lower returns than assets-in-place because assets-in-place involves high operating leverage and adjustment costs (Novy-Marx (2010, 2013)). The primary reason why growth options earn lower returns may be the skewed return profiles that growth options result in. Notably, such return asymmetry is desirable for investors.

The distinction between good and bad volatility also facilitates investigations of the relative roles that good volatility and bad volatility play in driving the cross-sectional relationship between good minus bad volatility and stock returns. Several studies has emphasized that investors may care more about downside losses more than they care about upside gains (e.g., Gul (1991) and Ang et al. (2006). If investors are more averse to downside volatility, this may make positively skewed returns attractive. We estimate components in expected good minus bad volatility that are related to good volatility and bad volatility separately. Although we find that investors may care more about downside volatility, this channel is unlikely to be the main reason behind the negative relationship between conditional idiosyncratic skewness and stock returns.

Overall, our paper provides further evidence suggesting that investors may be willing to pay more for stocks that exhibit positive idiosyncratic skewness. Thus, these stocks exhibit lower future returns. Moreover, this phenomenon cannot be explained by exposure to systematic risk factors. Our paper can also be seen as consistent with cumulative prospect theory (Barberis and Huang (2008)). Errors in the probability weighting of investors cause them to overvalue stocks that have a small probability of a large positive returns. Our results are also consistent with the optimal belief framework of Brunnermeier and Parker (2005) and the context of a market with underdiversified investors, who have preferences for skewed returns (Mitton and Vorkink (2007)).

Our paper is related to the recent literature that studies the implications of good and bad volatility for asset valuations. For example, Feunou et al. (2018) and Feunou and Okou (2019) decompose both the actual realized volatility and the option implied volatility into good and bad volatility components and study risk premium associated with good and bad volatility separately. Our methodology of constructing realized good minus bad volatility builds upon Bollerslev et al. (2020) but differs in a few ways. For example, Bollerslev et al. (2020) estimate ex-post realized good minus bad volatility using intra-day data, while we estimate conditional good minus bad volatility using cross-sectional models and daily returns. Bollerslev et al. (2020) find that the return predictability of their realized good minus bad volatility measure is very short-lived and hint that their results may be consistent with either investors rationally price bad volatility more than upside volatility or investors overreaction to extreme negative pricing movements. In contrast, our return predictability persist at longer horizons and is distinctively related to different economic mechanisms. And we conduct analysis to delineate the roles played by competing explanations such as growth options, downside risk.

Our paper also contributes to the literature that studies the relationship between expected idiosyncratic skewness and stock returns. Boyer et al. (2010) and Bali et al. (2020) estimate a cross-sectional model of expected idiosyncratic skewness, and establish a negative relationship between idiosyncratic skewness and stock returns. We complement their studies by showing that expected good minus bad volatility may have superior performance in both predicting conditional idiosyncratic skewness and future stock returns. Moreover, while Bali et al. (2020) highlight the importance of expected idiosyncratic skewness that is only related to growth options in explaining asset pricing anomalies, we conduct a set of regressions to thoroughly investigate mechanisms that affect the cross-sectional relationship between conditional idiosyncratic skewness and stock returns.

The remainder of this paper is organized as follows. Section 2 formally defines good and bad volatility and presents the cross-sectional model used to estimate expected good minus bad volatility. Section 3 shows the main empirical results. Section 4 provides evidence on mechanisms that drive the return predictability of expected good minus bad volatility. Section 5 concludes.

2 Measuring Good and Bad Volatility

In this section, we first describe the data. We then show how realized good and bad idiosyncratic volatilities are computed and construct the realized good minus bad volatility measure. Then we estimate a cross-sectional model for conditional good minus bad volatility.

2.1 Data and Measurement of Variables

Our dataset includes monthly and daily returns data on stocks traded in the NYSE, AMEX, and NASDAQ from the Center for Research in Security Prices (CRSP). The accounting variables are from COMPUSTAT's annual industrial files of income-statement and balance-sheet data. We exclude financial and utility firms with 4-digit Standard Industrial Classification (SIC) codes between 6000 and 6999 and between 4900 and 4999.

The procedures below are standard in the literature following Fama and French (1992). To ensure that the accounting variables are known before the returns they are used to explain, we match the accounting data for all fiscal year ends in calendar year $t-1$ with the returns from July of year t to June of year $t+1$. The 6-month (minimum) gap between fiscal year end and the return tests is conservative. I use a firm's market equity at the end of December of year $t-1$ to compute its book-to-market ratio for year $t-1$.

2.2 Measuring Realized Good and Bad Idiosyncratic Volatility

Following Boyer et al. (2010), we first calculate the residuals of the following time-series regressions using daily observations from month t and $t+T$: [2]

$$r_{i,t,d} = \alpha_{i,t} + \beta_{i,MKT}MKT_{t,d} + \beta_{i,t,SMB}SMB_{t,d} + \beta_{i,t,HML}HML_{t,d} + \eta_{i,t,d} \tag{1}$$

where for day d in month t, $r_{i,t,d}$ is stock i's excess return, the $MKT_{t,d}$ is the market excess returns, $SMB_{t,d}$ and $HML_{t,d}$ are factors that capture size and book-to-market effects, respectively. And $\alpha_{i,t}$, $\beta_{i,MKT}$, $\beta_{i,t,SMB}$, $\beta_{i,t,SMB}$ are regression coefficients. For each stock, we calculate the idiosyncratic realized variance (IV), idiosyncratic volatility ($IVOL$) and idiosyncratic skewness ($ISKEW$) using daily residuals $\eta_{i,t,d}$ from the first day of month t through the end of month $t+T$:

$$IV_{i,t} \equiv \sum_{d=1}^{N_m} (\eta_{i,t,d})^2 \tag{2}$$

$$IVOL \equiv \sqrt{IV_{i,t}/N_m} \tag{3}$$

$$ISKEW_t \equiv \frac{\sqrt{N_m}\sum_{d=1}^{N_m} \eta_{i,t,d}^3}{RV_t^{3/2}} \tag{4}$$

where N_m is the total number of trading days between from month t and $t+T$. The realized variance measure in equation (2) does not differentiate between volatility that is associated with positive or negative price changes. In this paper, we further decompose the realized variance into "good" and "bad" components following Barndorff-Nielsen and Shephard (2002):

$$IV_{i,t}^{+} = \sum_{d=1}^{N_m} (\eta_{i,t,d})^2 \mathbf{1}_{\{\eta_{i,t,d}>0\}} \tag{5}$$

$$IV_{i,t}^{-} = \sum_{d=1}^{N_m} (\eta_{i,t,d})^2 \mathbf{1}_{\{\eta_{i,t,d}>0\}} \tag{6}$$

[2]Results are reported for $T = 60$ months. We also run analysis for T ranging from 12 months to 60 months or with more factors. Results are similar and available from the authors.

where IV_i^+ and IV_i^- are upside and downside realized variance respectively. The upside and downside realized variance measure certainly adds up to the total realized variation, $IV = IV_t^+ + IV_t^-$. Moreover, following Bollerslev et al. (2020), we define the difference between good and bad idiosyncratic volatility for firm i at month t as

$$GMB_{i,t} \equiv \frac{(IV_{i,t}^+ - IV_{i,t}^-)}{IV_{i,t}} \tag{7}$$

The difference between the upside and downside variance is normalized by the realized variance, which naturally removes the overall volatility level from the GMB_t measure, rendering $GMB_{i,t}$ to lie between -1 and 1.

The difference between realized upside and downside variance is also known as signed jump variations (Patton and Sheppard (2015), Bollerslev et al. (2020)). Feunou et al. (2013) and Feunou et al. (2016) argue that the difference between realized upside and downside variance are valid estimates for asymmetry in stock return.[3] We complement these studies in examining the relevance of good minus volatility measured over longer horizons for predicting conditional idiosyncratic skewness and stock returns.

2.3 Measuring Expected Good Minus Bad Volatility and Expected Idiosyncratic Skewness

For further asset pricing analysis, we construct measures of expected good minus bad volatility and expected idiosyncratic skewness. Following Boyer et al. (2010) and Bali et al. (2020), we run the following cross-sectional regressions with lagged regressors to obtain regression coefficients[4] and then compute estimates of expected good minus bad volatility (EGMB) and expected idiosyncratic

[3]In Appendix, we briefly outline theoretical results that support good minus bad volatility as a measure of realized skewness of stock returns under mild conditions.

[4]The regression coefficients of (8) are obtained with a rolling panel of Z from $t-T-1-l$ to $t-T-1$, which guarantees that we use no information after $t-1$ to compute Z of month t. Using l ranging from 1 to 60 months yields similar results and they are available from the authors.

skewness (EIKEW) of month t using information available to investors at the end of month $t-1$:

$$\begin{aligned} Z_t = \alpha &+ \beta Z_{t-(T+1)} + \beta_{ivol} IVOL_{t-(T+1)} + \beta_{GO} GO_{t-1} + \beta_{AG} AG_{t-1} \\ &+ \beta_{max} MAX_{t-1} + \beta_{MOM} MOM_{t-1} + \beta_{TURN} TURN_{t-1} + \beta_{ROE} ROE_{t-1} \\ &+ \beta_{SMALL} SMALL + \beta_{BIG} BIG + \beta_{EXCH} EXCH + \epsilon_t \end{aligned} \tag{8}$$

In equation (8), the variable Z_t is a M by 1 vector of either good-minus-bad volatility GBM_t or idiosyncratic skewness $ISKEW_t$ calculated from M firms' daily residuals from month t to $t+T$. The variable $IVOL_{t-(T+1)}$ is realized idiosyncratic volatility estimated using daily residuals from month $t-(T+1)$ and $t-1$. Hence, $IVOL_{t-(T+1)}$ is available to investors at the end of month $t-1$.

In line with Bali et al. (2020), we include growth options measures to capture the impact of both past (exercised) growth options via asset growth (AG) and future growth potential (GO) on the skewness of asset returns. The variable GO_{t-1} is an $M \times 1$ vector of growth-option intensity values in month $t-1$. Firms have growth options and these options have convex payoffs, which could lead to skewness in returns. Following Trigeorgis and Lambertides (2014) and Del Viva et al. (2017), this growth-option measure is defined as the percentage of firm market value (V_t) that derives from future growth opportunities. The value of future growth opportunities ($PVGO_t$) is estimated by subtracting the perpetual discounted stream of expected operating cash flows under a no-further-growth policy from the current market value of the firm V:

$$GO_{i,t} \equiv \frac{PVGO_{i,t}}{V_{i,t}} = 1 - \frac{CF_{i,t}/V_{i,t}}{k_i} \tag{9}$$

In equation (9), $V_{i,t}$ is the market value of firm i at time t, $CF_{i,t}$ is the operating cash flow of firm i at time t, and k_i is firm i's weighted-average cost of capital (WACC). Cash flow is measured as the free operating cash flow under a no-further-growth policy where capital expenditures equal depreciation.[5] To estimate the cost of equity in WACC, we use the market model with beta equal

[5]Under a no-growth policy, capital expenditures roughly equal depreciation. This leads to estimating FCF as OANCF+XINT-DPC. OANCF is the net cash flow from operating activities, XINT is interest and related expense (total), and DPC is depreciation and amortization (cash flow).

to 1, and we add a 6% market risk premium to the risk-free return for all firms. This simple setup avoids the reliance of our results on the empirical validity of the CAPM. We estimate a firm's cost of debt to be 4% less than its cost of equity. Effective tax rates τ are tax current (TXC) divided by pretax income (PI). The weighted average cost of capital WACC_t is then estimated as COST_EQUITY $\times(1-\text{LEV}_t)+$ COST_DEBT $\times\text{LEV}_t(1-\tau)$, where the leverage LEV_t is calculated as the ratio of total liabilities to the market value of the firm. The market value of the firm is the sum of market value of equity plus the value of debt approximated by total liabilities (LT). Asset growth (AG) is calculated as the percent change in firm total assets over the previous year.

We also include several variables used in the literature to predict idiosyncratic skewness. The skewness of stock returns, which may in extreme form manifested as lotteryness proxied by maximum daily return (MAX) during the previous month. MAX_{t-1} is the maximum daily return observed in month $t-1$. Motivated by Hong and Stein (2003) and Chen et al. (2001), turnover and momentum are included in forecasting regressions. Turnover ($TURN_{t-1}$) is calculated as the ratio of trading volume to shares outstanding in month $t-1$. Momentum MOM_{t-1} is the cumulative return over months $t-12$ through $t-2$. The return of equity ROE is calculated as the ratio of operating cash flow to market value of equity. Variables SMALL and BIG are 2 binary dummies for SMALL (bottom 30%) and BIG (top 30%) firms built on market capitalization observed in previous month allowing for a non-linear size-skewness relationship as in Boyer et al. (2010). Dummy variable EXCH controls for the NASDAQ exchange.

2.4 Summary Statistics and Determinants of Expected Good Minus Bad Volatility

To corroborate the impact of our main variables on determining expected good minus bad volatility and expected idiosyncratic skewness, we run a series of firm-level cross-sectional regressions based on equation (8) [6] . Panel A of Table 1 reports summary statistics for variables used in our empirical analysis [7]. The market beta is (BETA) is close to 1 (Median = 1.11). The mean

[6] To limit the influence of outliers, we winsorize the top and bottom 1% observations for each variable except size.

[7] Because estimating the cross-sectional regressions and obtain conditional skewness measures (EGMB and EISKEW) requires 10 years of prior returns and relevant accounting data, our subsequent analysis starts from July 1978 through December 2016.

book-to-market ratio (BM) is 0.76, within the range found in earlier studies (e.g., Anderson and Garcia-Feijoo (2006)). The mean monthly return (RET) is 1.27%. The average expected good minus bad volatility (EGMB) across firms has a mean of 0.13 and standard deviation of 0.06. The average expected idiosyncratic skewness is more volatile. The mean is 0.88 and the standard deviation is 0.61. Panel B of Table 1 reports average Pearson correlation coefficients among the key variables. Growth options (GO), maximum daily returns (MAX), and idiosyncratic volatility (IVOL) are positively associated with expected good minus bad volatility and expected idiosyncratic skewness. Return of equity (ROE), Size (SIZE) and momentum (MOM) are negatively correlated with expected good minus bad volatility and expected idiosyncratic skewness. Expected good minus bad volatility and expected idiosyncratic skewness is strongly correlated, with an average correlation of 0.97.

Panel A of Table 2 shows the time-series averages of cross-sectional slopes using the previously described determinants to predict good minus bad volatility. Growth options (GO), lotteryness (MAX), and idiosyncratic volatility (IVOL) are statistically significant positive drivers of good minus bad volatility. This result lends support to the idiosyncratic-skewness-enhancing impact of growth options. Higher values for momentum (MOM), profitability (ROE), investment (AG), and turnover (TURN) are all associated with lower values of GMB. On average, the cross-sectional adjusted-R^2 is 0.27. Panel B of Table 2 displays analogous results for idiosyncratic skewness. All the determinants show same predicting signs as Panel A, but with a lower average adjusted-R^2 of 0.16. These adjusted-R^2 numbers are consistent with the previous findings (e.g., Chen et al. (2001), Boyer et al. (2010), and Bali et al. (2020)).

To illuminate the temporal variation in each of the skewness measures, Figure 1 presents the 10th, 50th, and 90th percentiles of the monthly cross-sectional distributions of realized idiosyncratic skewness (ISKEW), realized good minus bad volatility (GMB), expected idiosyncratic skewness (EISKEW), and expected good minus bad volatility (EGMB), respectively. All of the reported percentiles show substantial time variations, with particularly large movements during the mid-1980s, the early 1990s, the late-1990s, and the early-2010s. Compared to the realized idiosyncratic skewness (Graph A), the realized good minus bad volatility (Graph B) tends to be more stable, with less variation in extreme percentiles, e.g., late-1990s. The conditional measures (EISKEW and EGMB) capture similar temporal variation as the realized measures (ISKEW and GMB), but have smaller dispersion between percentiles.

2.5 The Accuracy of Conditional Idiosyncratic Skewness Measures

We then evaluate the accuracy of expected good minus bad volatility in measuring conditional idiosyncratic skewness. Based on theoretical results from Feunou et al. (2016), we use both realized good minus bad volatility (GMB_t) and realized idiosyncratic skewness ($ISKEW_t$) calculated using daily returns from t to $t+T$. To be specific, in each month t, we evaluate conditional skewness measures $\hat{Z}_t$, which are computed from (8) or simply equal to lagged skewness $Z_{t-(T+1)}$, in forecasting realized idiosyncratic skewness Z_t.

Panel A of Table 3 reports the average cross-sectional Pearson correlations and Spearman rank correlations between realized skewness measures and conditional forecasts. Lagged skewness values ($ISKEW_{t-(T+1)}$ and $GMB_{t-(T+1)}$) show low correlations with ex post realized values, ranging from 0.2 to 0.3. The expected measures (EISKEW and EGMB) outperform historical values in forecasting realized skewness by quite a wide margin, with average correlations about 0.45. This result highlights the usefulness of the cross-sectional regression approach to estimate conditional skewness. (e.g., Boyer et al. (2010) and Bali et al. (2020)). Furthermore, EGMB shows higher correlation with future realized values than EISKEW. For example, the correlation between $EGMB_t$ and GMB_t is 0.48, while the correlation between $EISKEW_t$ and GMB_t is 0.46. For realized idiosyncratic skewness measure $ISKEW_t$, $EGMB_t$ also yields the highest correlation.

To further examine forecasting accuracy of different conditional idiosyncratic skewness measures, we conduct analysis using root mean squared error (RMSE), a loss function commonly used in the literature [8]. Since these estimators lie in different ranges, we transform the realized values and predicted values into their cross-sectional ranks to facilitate comparisons. The RMSE at month

[8] The results are also robust to using mean absolute error (MAE) loss function.

t is defined as:

$$RMSE_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(Rank(Z_{i,t}) - Rank(\widehat{Z}_{i,t}))}, \tag{10}$$

where $Z_{i,t}$ is realized good minus bad volatility $GMB_{i,t}$ or realized idiosyncratic skewness $ISKEW_{i,t}$ for stock i and $\widehat{Z}_{i,t}$ denotes conditional forecasts (e.g. $EGMB_t$ or $GMB_{t-(T+1)}$). The $Rank(Z_{i,t})$ function gives the order (1,2,...,N_t) of variable $Z_{i,t}$ in all values Z_t sorted in ascending orders and N_t is the number of stocks available at time t. In each month t, we test for significance in RMSE differences using the modified Diebold-Mariano test proposed by Harvey et al. (1997).

The first row in Panel B of Table 3 presents the average out-of-sample RMSE of different estimators for predicting GMB_t. Among all conditional measures, the expected good minus bad volatility (EGMB) achieves the lowest RMSE, while lagged skewness as the least accurate predictor. The RMSE values are 618.16 and 713.10, respectively. We also conduct pairwise comparisons for accuracy between different measures. For example, the average RMSE of EGMB is lower than EISKEW by 11.43 and the difference between these two methods are significant at 5% level across 62% of the time. The average RMSE of EGMB is significantly lower than that of $GMB_{t-(T+1)}$ and $ISKEW_{t-(T+1)}$ almost all the time (100%, and 98%, respectively).

More importantly, it should be noted from Panel C of Table 3 that the expected good minus bad volatility $EGMB$ is also the most accurate predictor for realized idiosyncratic skewness ($ISKEW_t$) as well. Panel C of Table 3 conducts the same analysis for predicting $ISKEW_t$. Among all conditional skewness measures, EGMB still yields lowest prediction errors with average RMSE of 644.23, while lagged skewness shows the worst performance with RMSE of 726.93. As for the difference between these methods, although the leading edge of EGMB over EISKEW slightly narrows, the difference is still statistically significant 40% of the time.

To sum up, both the correlation and prediction errors analysis provide evidence that expected good minus bad volatility is the most accurate forecast of conditional idiosyncratic skewess. The finding that this good-minus-bad-volatility-based measure provides superior conditional idiosyncratic skewness forecast is novel in the literature. While Feunou et al. (2016) and Bollerslev et al. (2020) have shown the relevance of good minus bad volatility to realized skewness using high-frequency intra-day data, we highlight that the importance of good minus bad volatility for measuring conditional idiosyncratic skewness for a broader cross-section of firms.

3 Expected Good Minus Bad Volatility and Future Stock Returns

In this section, we first analyze the relationship between expected good minus bad volatility (EGMB) or expected idiosyncratic skewness (EISKEW) and future stock returns using portfolio analysis. Subsequently, we investigate the cross-sectional relationship between expected good minus bad volatility and stock returns using firm-level Fama and MacBeth (1973) regressions that simultaneously control for expected idiosyncratic skewness (EISKEW) and other firm characteristics.

3.1 Univariate Portfolio Analysis

We now examine the cross-sectional relationship between expected good minus bad volatility (EGMB) or expected idiosyncratic skewness (EISKEW) and stock returns using univariate portfolio analysis. At the end of each month, value-weighted quintile portfolios are formed by sorting stocks based on EGMB or EISKEW, where quintile 1 portfolio contains stocks with lowest EGBM or EISKEW and quintile 5 portfolio contains stocks with the highest EGMB or EISKEW. We also report the results for a self-financing long–short (5-1) portfolio that buys stocks in the top quintile and sells stocks in the bottom quintile.

Panel A of Table 4 reports, by row, the time-series average of EGMB, the one-month ahead excess returns and respective Newey-West adjusted standard errors, market shares and the risk-adjusted alphas for constructed portfolios. The average monthly return decreases monotonically from 1.09% for quintile 1 (Low) to 0.10% for quintile 5 (High). The difference in monthly returns between the highest and lowest EGMB portfolio is -0.98%, with a t-statistic of -2.93. We also control for exposure to systematic risk factors. The FF3 alpha is returns in excess of the market (MKT), size (SMB), book-to-market (HML) factors of Fama and French (1993) (FF3). FFCPS alpha is excess returns to FF3 model augmented with momentum (MOM) factor (Carhart (1997)) and liquidity factor (LIQ) of Pástor and Pietro (2003). FF5 alpha is excess returns relative the Fama and French (2015) 5-factor (FF5) model, which is FF3 model augmented with the investment factor (CMA) and profitability factor (RMW). The results in panel A show that alpha spreads between quintiles 5 and 1 adjusted by FF3, FFCPS, and FF5 models are all negative and significant: -1.31% per month for FF3 model, -0.80% for the 5-factor FFCPS model, and -0.61% for the FF5 model with robust t-statistics of -5.56, -3.61, and -2.70 respectively.

Panel B of Table 4 displays the monthly portfolio returns of sorting on EISKEW. The performance of EISKEW sorted portfolios confirms the findings of Boyer et al. (2010) and Bali et al. (2020). In particular, the average monthly return decreases monotonically from 1.06% for quintile 1 (Low) to 0.29% for quintile 5 (High). The long-short EISKEW portfolio generates an average monthly return of -0.77%, with a t-statistic of -2.57. This numbers are quantitatively very similar to the finding of Boyer et al. (2010) that the expected idiosyncratic skewness sorted long-short (5-1) portfolio earns an average of -0.67% per month from December 1987 through November 2005. Panel B of Table 4 also shows that the risk adjusted alphas of EISKEW sorted portfolios are all negative and significant, but smaller than alphas of EGMB sorted portfolios.

While both EGMB and EISKEW sorted portfolios yield statistically significant returns spreads, the magnitude of EGMB long-short portfolio (-0.98% per month) is larger than EISKEW long-short portfolio (-0.77% per month). Risk-adjusted alphas using different factor models also show this pattern. For example, the FF3 adjusted alpha of EGMB sorted portfolio is -1.28% per month, while EISKEW sorted portfolios is -1.01%. To further illuminate how important these differences are, Figure 2 depicts the cumulative profits for the strategies based on long-short portfolios of buying stocks with low conditional skewness and shorting stocks with high conditional skewness. Start with an initial investment of $W_0 = \$1$, the cumulative profits in month t is calculated as: $W_t = W_{t-1} \times (1 + r_{long-short,t} + r_{f,t})$, where $r_{long-short,t}$ denotes the monthly return of the long low EGMB/EISKEW and short high EGBM/EISKEW portfolio and r_f denotes the monthly risk-free rate. By comparison, we also show the cumulative return of MKT factor. As Figure 2 shows, the EGMB-based strategy outperforms the EISKEW strategy by quite a large margin. Specifically, the final cumulative return of EGMB strategy is \$178, which doubles the return of MKT factor and

EISKEW strategy, with returns of $69 and $80, respectively.

3.2 Constructing Expected Good Minus Bad Volatility Factor

We further examine whether an expected good minus bad volatility factor is able to explain the expected idiosyncratic skewness anomaly, and vice versa. We augment the FF5 factors (MKT, SMB, HML, CMA, RMW) with expected good minus bad volatility factor (FEGMB) or expected idiosyncratic skewness factor (FEISKEW) constructed by forming zero cost long–short portfolios associated with the 2 anomalies (EGMB or EISKEW). Following Fama and French (1993), the FEGMB factor is formed using independent bivariate sorting based on 2×3 value-weighted portfolios (i.e., median SIZE (50%, 50%) and then 25%, 50%, 75% breakpoints for EGMB). We build our factor as the difference between the average low (bottom 25%) EISKEW portfolio return minus the average high (top 25%) EGMB portfolio return. The construction of expected idiosyncratic skewness factor is analogous.

We first examine how the properties of the FEGMB and FEISKEW factors. On average, both FEGMB and FEISKEW yield positive and significant returns: 1.04% per month with a robust t-statistic of 3.09, and 0.77% per month with a t-statistic of 2.65, respectively. Table 5 presents the correlations between FEGMB, FEISKEW and the five factors of Fama and French (2015). The expected good minus bad volatility factor is strongly correlated with expected idiosyncratic skewness factor, with a correlation of 0.80. The correlation with FF5 factors are similar for these two factors. Specifically, the FEGMB and FEISKEW correlate with the size factor SMB with a negative sign. The correlation with the profitability factor RMW is strong, with a coefficient of 0.64 and 0.58 for FEGMB and FEISKEW, respectively. These results are consistent with previous literature, which argues that skewness anomalies are linked to firms' size and profitability (Langlois, 2020).

The last two rows in Panel A and B in Table 4 present portfolio sort results after the inclusion of FEISKEW and FEGMB. When we augment FF5 model with the FEISKEW factor, the long short $5-1$ portfolio sorted by EGMB still shows statistically significant abnormal return, i.e. -0.47% per month (t-statistics = -3.21). On the contrary, after controlling for the expected good minus bad volatility factor (FEGMB), the risk-adjusted return spreads are economically and statistically insignificant for EISKEW sorted portfolio: -0.24% per month (t-statistics = -1.20). Our results suggest that the expected good minus bad volatility factor has some power to explain the return spreads between portfolios sorted by expected idiosyncratic skewness. However, this factor is not sufficient to explain the negative relationship between expected good minus bad volatility and future stock returns.

3.3 Double-Sorted Portfolios

The results from univariate portfolio sorts in Tables 4 reveal a strong negative relation between expected good minus bad volatility and future stock returns. And such relation cannot be explained by exposure to previously documented pricing factors and the expected idiosyncratic skewness effect. By contrast, the negative relation between expected idiosyncratic skewness and future stocks become insignificant after controlling for expected good minus bad volatility factor (FEGMB). In this section, we continue our examination of the superior performance of expected good minus bad volatility using bivariate-sort portfolio analysis. Specifically, we focus on whether the negative relation between expected good minus bad volatility and future stock returns persists in bivariate portfolio analysis controlling for expected idiosyncratic skewness, and vice versa.

Panel A of Table 6 shows the results of sorting on EGMB after first sorting on EISKEW. Each month, all stocks in the sample are sorted into five quintiles based on an ascending order of EISKEW. Within each EISKEW quintile, we then sort stocks into quintiles based on EGMB and compute the value-weighted one-month-ahead return for the resulting 25 (5×5) portfolios. To focus more directly on the effect of EGMB, we also compute returns averaged across EISKEW quintiles as a way to produce quintile portfolios with large variations in EGMB, but small variations in EISKEW. These returns are reported in the last row labeled "Avg". The column labeled "5–1" reports the difference in returns between high and low EGMB portfolios within each EISKEW quintile. The column labeled "FF3 alpha" reports the average Fama–French 3-factor alphas.

The negative relationship between expected good minus bad volatility and future monthly returns can be observed in all five EISKEW sorted quintiles, especially in the high EISKEW groups (e.g. the third to fifth EISKEW quintiles). On average, the resulting FF3 alpha for the difference in returns between low and high EGMB quintile portfolios obtained by first sorting on EISKEW equals -0.75%. This economically large spread also has a highly significant t-statistic of -4.82, again underscoring that EISKEW cannot explain the return predictability of EGMB.

Panel B of Table 6 presents the results from sequential double sorts, in which we first sort on EGMB then on EISKEW. After controlling for expected good minus bad volatility, the negative relationship between EISKEW and one-month-ahead returns shown in single portfolio sorts (Table 4) diminished and even reversed. Except for the first quintile of EGMB, all the return spreads between the lowest and highest quintile portfolio sorted by EISKEW are positive. On average, the FF3 alpha for the return spread between value-weighted portfolios sorted by EISKEW equals 0.09%, with a statistically insignificant t-statistic of 0.65.

In sum, the negative relation between expected good minus bad volatility and future returns remains significant after controlling for expected idiosyncratic skewness. On the contrary, the return predictability of expected idiosyncratic skewness completely disappears, and even reverses, when controlling for the expected good minus bad volatility. Our results highlight that expected good minus bad volatility may capture more asset pricing relevant information than expected idiosyncratic skewness.

3.4 Firm-Level Fama-MacBeth Cross-Sectional Regressions

Previous sections provide evidence of a strong negative relation between expected good minus bad volatility and cross-sectional stock returns using portfolio analysis. And the relation cannot be explained by exposure to systematic risk factors and expected idiosyncratic skewness. In this section, we examine that relation using Fama and MacBeth (1973) regressions. In each month, we run cross-sectional regressions of one-month-ahead excess stock returns on expected good minus bad volatility and various control variables:

$$r_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} EGMB_{i,t} + \phi_t' X_{i,t} + \epsilon_{i,t+1}, \tag{11}$$

where $r_{i,t+1}$ is the monthly excess return for stock i observed at the end of month $t+1$, $EGMB_{i,t}$ is the expected good minus bad volatility for stock i of month t, and $X_{i,t}$ is a set of firm-specific control variables observed at time t for stock i, namely, market BETA, market capitalization (SIZE), book-to-market ratio (BM), momentum (MOM), profitability (ROE), idiosyncratic volatility of Ang et al. (2006) (IVOL) and asset growth (AG), growth options (GO), lottery preferences (MAX).

Table 7 reports the time-series averages of the γ and ϕ coefficients along with Newey and West (1987) standard error adjusted t-statistics. Row 1 reports the cross-sectional pricing of expected good minus bad volatility after controlling for the market BETA, market capitalization (SIZE) and book-to-market (BM). The coefficient on expected good minus bad volatility is negative and significant at the 1% level with robust t-statistic of -3.40. Row 2 reports similar results for expected idiosyncratic skewness, in which the coefficient is significant with t-statistic -3.49. Row 3 reports the result when both EGMB and EISKEW are both included in the regression. After controlling for the effect of EISKEW, the negative cross-sectional relation between EGMB and future stock returns remains significant with a t-statistic of -2.51. On the other hand, the EISKEW effect is completely reversed with positive coefficients.

Row 4 to 9 further control for other characteristics including idiosyncratic volatility, momentum, profitability (ROE), investment (AG), lottery preference (MAX), growth options (GO). All regression results show that coefficient on expected good minus bad volatility remains significant, while the EISKEW effect is reversed. This finding mirrors the results based on the double sorts in Section 3.3.

4 Explaining the Relationship between Good Minus Bad Volatility and Stock Returns

To gain better understanding of the findings of this paper, we further investigate economic mechanisms that may drive the cross-sectional relationship between expected good minus bad volatility and future stock returns. We first examine whether recently proposed skewness-related factors could explain the return predictability of expected good minus bad volatility. Then we relate our findings to growth option theory. Finally, we investigate whether aversion to downside volatility play important roles in the return predictability of expected good minus bad volatility.

4.1 Controlling for Skewness-Related Factors

Recent studies (Barinov (2018), Langlois (2020)) suggest that firms with high idiosyncratic skewness may offer hedges to skewness-related factors, and hence earn low return. To be specific, Barinov (2018) shows that lottery-like stocks are a hedge against increases in aggregate volatility risk thus earning low expected returns. He construct an aggregate volatility risk factor (FVIX) and shows that the maximum effect of Bali et al. (2011) and the expected skewness effect of Boyer et al. (2010) could be reduced after incorporating the FVIX factor. Langlois (2020) argues that the cross-sectional ranks of systematic and idiosyncratic skewness other than their actual values are easier to predict and proposes the predicted systematic skewness (PSS) factor. He shows that the abnormal returns of idiosyncratic skewness sorted portfolio diminished to insignificant levels after the PSS factor is included.

We investigate whether the return spread between portfolios sorted by EGMB or EISKEW can be explained by exposure to FVIX and PSS factors. Table 8 presents the risk-adjusted returns (alphas) controlling for FVIX or PSS factors[9]. Row "FF5+FVIX" in Panel A and B of Table 8 shows that the inclusion of FVIX factor besides FF5 factors has little impact on the return spreads between lowest and highest quintile portfolios sorted by EGMB or EISKEW. The spread is still economically and statistically significant: from -0.57% for FF5 model to -0.57% per month for EGMB and -0.45% of FF5 model to -0.52% for EISKEW, respectively. Thus the FVIX factor cannot explain the return predictability of expected good minus bad volatility. The last row in Panel A and B of Table 8 presents the results of augmenting the FF5 factor model with PSS factor. The risk-adjusted return spread of EGMB sorted portfolios slightly is reduced from $-.0.57\%$ of FF5 model to -0.48% and still significant with t-statistic -2.13. In contrast, the alpha of EISKEW sorted portfolio is no longer significant with t-statistics -1.34. Thus, the return predictability of

[9] The PSS factor data are collected from Langlois' website (https://hugueslanglois.com/) and we construct the FVIX factor following Barinov (2018). The FVIX factor are only available after 1986 since the VXO index was introduced. As a test of validity, the correlation between our FVIX factor and ΔVXO is 0.719, which is almost equal to the correlation of 0.715 reported in the Table 1 of Barinov (2018)

idiosyncratic skewness may be to some extent explained by the predicted systematic skewness factor, which is in line with the findings of Langlois (2020).

To sum up, recent studies (Barinov (2018) and Langlois (2020)) suggest that idiosyncratic skewness *per se* are less relevant for future returns, because stocks with high idiosyncratic skewness offer hedges to some risk factors and hence earn low returns. Our results demonstrate that the strong return predictability of expected good minus volatility remains after controlling for these skewness-related factors. Thus, our results emphasize the importance of conditional idiosyncratic skewness in portfolio construction and return diversification.

4.2 The Role of Growth Options

Various studies have investigated the importance of growth options (e.g., Berk et al. (1999), Cao et al. (2008), Grullon et al. (2012) and Trigeorgis and Lambertides (2014)) in affecting expected returns and risk characteristics. A fundamental property of growth options and real options in general (besides becoming more valuable in volatile environment) is their discretionary asymmetric nature: they are rights but not obligations whose exercise provides valuable firm flexibility. Del Viva et al. (2017) posit that actively managed firms have real options leading to convex payoffs since protective contraction put options reduce downside risk, whereas growth options preserve and enhance upside potential. As a result, this dynamic asset adaptation process creates a convex value payoff that enhances idiosyncratic skewness. Recent theories also concur (e.g, Brunnermeier and Parker (2005), Mitton and Vorkink (2007), and Barberis and Huang (2008)) that investors may have preferences for idiosyncratic skewness. Such investor preferences predict that high idiosyncratic skewness stocks have lower expected returns in equilibrium.

Row 3 of Table 7 confirms that growth option intensity (GO) exhibits a significant negative relation with subsequent stock returns, which is consistent with evidence from existing studies (e.g., Anderson and Garcia-Feijoo (2006) and Trigeorgis and Lambertides (2014)). When expected good minus bad volatility (EGMB) and growth options (GO) are included in the regression simultaneously, it is important to note from Row 5 of Table 7 that the coefficient on growth option (GO) becomes insignificant. This finding complements the empirical evidence of Bali et al. (2020). While

Bali et al. (2020) emphasize the part of expected idiosyncratic skewness that is only related to growth options (GO) in explaining several return anomalies, we show that the predictability of growth options become insignificant when expected good minus bad volatility is included in regressions. Earlier studies provide several explanations for why growth options earn lower returns. For example, Novy-Marx (2010, 2013) argue that growth options may have lower returns than assets-in-place because assets-in-place involves high operating leverage and adjustments cost). However, our empirical results underscore the positively skewed return profiles of growth options as the main reason why growth options earn lower returns.

4.3 Dissecting Good Minus Bad Volatility

In this section, we dissect good minus bad volatility into 'good' and 'bad' components to study whether the negative relationship between expected good minus bad volatility and future returns is caused by investors' strongly aversion to extreme negative returns. We decompose the good minus bad volatility as follows:

$$GMB_{i,t} \equiv \frac{(IV_{i,t}^{+} - IV_{i,t}^{-})}{IV_{i,t}} = \frac{(IV_{i,t}^{+} - BV_{i,t}/2)}{IV_{i,t}} + \frac{(BV_{i,t}/2 - IV_{i,t}^{-})}{IV_{i,t}},$$

where $BV_{i,t}$ is the realized bipower variation (see Barndorff-Nielsen and Shephard (2006) or appendix.) We thus define the "good jump" component and "bad jump" component as[10]:

$$GJ_{i,t} \equiv \frac{(IV_{i,t}^{+} - BV_{i,t}/2)}{IV_{i,t}} \tag{12}$$

$$BJ_{i,t} \equiv \frac{(BV_{i,t}/2 - IV_{i,t}^{-})}{IV_{i,t}} \tag{13}$$

After extracting these two components, we follow the same methods in Section 2 to compute expected good jump (EGJ) and expected bad jump (EBJ) using Equation (8). The average expected good jump (EGJ) across firms has a mean of 0.131 and standard deviation of 0.051. The magnitude of average expected bad jump (EBJ) is relatively smaller. The mean is -0.006 and the standard

[10] In Appendix, we briefly outline theoretical results that support the decomposition of expected minus bad volatility.

deviation is 0.028. This suggests that the return asymmetry at the firm level is mostly driven by the good volatility, which are associated with positive returns.

To test the return predictability of expected good and bad jump, we conduct a series of Fama and MacBeth (1973) regressions like Section 3.4 and Table 9 presents the results. Row 1 of Table 9 reports the cross-sectional regression coefficients of expected good jump after controlling for the standard Fama-French 3 factors. The coefficient on expected good jump is negative and significant at the 1% level (the t-statistic is -3.33). Row 2 reports similar results for expected bad jump, in which we also observe marginal significant predictability with a t-statistic of -1.93. The coefficient of expected bad jump is slightly higher than that of expected good jump though. When we consider these two components together, Row 3 shows they remain both negative and significant, which means both good jump and bad jump are important components of EGMB. Row 4 to 7 analyze the relationship between growth options and stock returns, after controlling for expected good (bad) jump. Row 4 and 5 demonstrate the results when expected bad jump is included in the regression. The coefficient of growth options is reduced from -0.121 to -0.084 but still significant, with t-statistics of -2.20 and -1.85, respectively. However, as Row 6 demonstrates, when we only control for expected good jump, the pricing ability of GO diminished to -0.059 with an insignificant t-statistic -1.30. When both expected good jump and expected bad jump are included in the regression, the GO coefficient further declines. Row 8 to Row 12 further control for other characteristics, such as idiosyncratic volatility (IVOL), momentum (MOM), profitability (ROE), investment (AG), and lottery preference (MAX). The coefficients of expected good jump and expected bad jump remain negative and significant, thus they can not be explained by previously documented factors.

To sum up, both the good and bad jump components are important determinants of expected good minus bad volatility. Moreover, the predictability of growth options are diminished to a larger extent with the inclusion of expected good jump component than the inclusion of the bad jump component. This empirical result emphasizes that growth options play more roles in enhancing a firm's upside return potentials than reducing downside losses. In the meantime, while Bollerslev et al. (2020) hints that the return predictability of weekly realized good minus bad volatility may arise as investors overreact to extreme negative returns, we do not find much empirical support for this hypothesis. Even though the regression coefficient is slightly higher for expected bad jump, the overall impact of expected bad component on returns is much smaller. Hence, we do not find much support to the theory of downside risk (e.g, Gul (1991) and Ang et al. (2006)) in our analysis.

5 Conclusion

We decompose realized idiosyncratic volatility into good and bad idiosyncratic volatility and estimate a cross-sectional model for expected good minus bad volatility. The expected good minus bad volatility not only measures conditional idiosyncratic skewness more accurately than expected idiosyncratic skewness and lagged skewness measures, but also yields superior cross-sectional return predictability. Portfolios sorted by good minus bad volatility yields larger average returns than portfolios sorted by idiosyncratic skewness, and the gain in returns is economically considerable. Once the expected good minus volatility is included, the return predictability between expected idiosyncratic skewness and stock returns vanishes or even change sign. The return predictability of expected good minus bad volatility is also robust to potential risk factors and control variables. Of particular interest, the aggregate volatility risk factor (Barinov, 2018) and predicted skewness factor (Langlois, 2020) cannot explain the return spreads between portfolios sorted by expected good minus bad volatility, while they may reduce unexplained return spreads between portfolios sorted by expected idiosyncratic skewness to insignificant levels. We interpret our results as highlighting the context of a market with underdiversified investors, who have a preference for occasionally large positive gains. In fact, it may be the preference for skewed payoffs that lead to underdiversification in equilibrium (Mitton and Vorkink, 2007).

Further empirical tests suggest that expected good minus bad volatility may play an important role in explaining the negative relationship between growth option and cross-sectional stock returns. When expected good minus bad volatility is included in the regression, growth option intensity, i.e., the proportion of firm's value that derives from future growth opportunities, no longer predicts future stock returns. Our finding lends support to real option theory, which posits that flexibility of growth options may enhance firm's upside value potential and reduces downside risk in bad economic states. Such asymmetric effect of growth options could result in positively skewed returns, which are attractive to investors with a preference for skewness.

The distinction between good minus bad volatility also allows us to separately study the contribution of good volatility and bad volatility in driving the cross-sectional relation between expected good minus bad volatility and future stock returns. Although investors may display strong aversion to extreme negative returns, we don't find strong evidence for such preference, at least for idiosyncratic returns.

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Tables and Figures

Table 1: Summary Statistics of Main Variables

Panel A. Summary Statistics

	RET	BETA	SIZE	BM	MOM	AG	ROE	LEV	GO	MAX	TURN	IVOL	EISKEW	EGMB
Mean	1.27	1.15	11.78	0.76	0.13	0.24	0.06	0.36	0.80	0.08	0.12	3.65	0.88	0.13
Median	0.02	1.11	11.67	0.56	0.04	0.05	0.11	0.33	0.55	0.06	0.08	3.29	0.76	0.12
Std	17.61	0.28	2.03	0.81	0.56	0.72	0.58	0.24	1.51	0.07	0.13	1.81	0.61	0.06
Min	-74.60	0.59	7.66	-0.80	-0.76	-0.46	-2.92	0.01	-2.66	0.01	0.00	1.12	-0.39	-0.01
Max	300.11	1.78	16.98	4.67	2.48	4.89	2.60	0.92	7.80	0.42	0.76	9.91	3.41	0.36

Panel B. Cross Correlations of Main Variables

	RET	BETA	SIZE	BM	MOM	AG	ROE	LEV	GO	MAX	TURN	IVOL	EISKEW	EGMB
R	1.0	-0.01	-0.01	0.02	0.02	-0.02	0.01	0.02	-0.01	-0.02	-0.01	-0.01	-0.00	-0.01
BETA		1.00	0.08	-0.11	0.00	0.09	-0.04	-0.07	0.08	0.08	0.26	0.15	-0.04	0.01
SIZE			1.00	-0.29	0.21	0.02	0.17	-0.15	-0.26	-0.36	0.22	-0.64	-0.79	-0.79
BM				1.00	-0.12	-0.12	-0.00	0.47	-0.05	0.09	-0.14	0.05	0.21	0.19
MOM					1.00	-0.05	0.05	-0.08	-0.09	-0.15	0.16	-0.08	-0.26	-0.26
AG						1.00	-0.05	-0.17	0.09	0.03	0.12	0.06	-0.03	-0.02
ROE							1.00	0.07	-0.46	-0.13	-0.01	-0.20	-0.27	-0.28
LEV								1.00	-0.13	0.06	-0.11	0.02	0.12	0.11
GO									1.00	0.24	0.04	0.36	0.35	0.37
MAX										1.00	0.19	0.52	0.43	0.48
TURN											1.00	0.04	-0.20	-0.15
IVOL												1.00	0.73	0.78
EISKEW													1.00	0.97
EGMB														1.00

This table reports summary statistics (Panel A) and correlations (Panel B) for the main variables used in our empirical analyses. RET is the monthly excess return in percentage points; market risk (BETA) is estimated over a 3-year period using the Sharpe-Lintner capital asset pricing model (CAPM) model; SIZE is measured as the natural logarithm of the market value of equity. BM is book-to-market ratio; MOM is momentum, measured as the compound gross return from month t-12 to t-2; AG is asset growth, calculated as the percent change in firm total assets over the previous year; ROE is calculated as the ratio of operating cash flow to shareholders' equity; leverage (LEV) is calculated as the ratio of the book value of debt to the market value of the firm; GO is the growth-option value calculated as per equation (9); MAX is the maximum daily return observed in the previous month; turnover (TURN), calculated as the ratio of trading volume to total shares outstanding; IVOL is the idiosyncratic volatility; EISKEW and EGMB are expected idiosyncratic skewness and expected good minus bad volatility, respectively, estimated from equation (8) over a horizon of 60 months.

Table 2: Cross-Sectional Determinants of Good minus Bad Volatility and Idiosyncratic Skewness

Panel A. Good minus Bad Volatility Determinants

	Constant	GMB	GO	ROE	MAX	IVOL	AG	MOM	TURN	SMALL	BIG	R^2
coefficient	0.072	0.152	0.001	-0.011	0.047	0.012	-0.004	-0.02	-0.022	0.034	-0.035	0.27
t-stats	(31.46)	(29.64)	(2.76)	(-13.82)	(10.15)	(28.26)	(-6.05)	(-26.61)	(-4.19)	(28.44)	(-41.22)	

Panel B. Idiosyncratic Skewness Determinants

	Constant	ISKEW	GO	ROE	MAX	IVOL	AG	MOM	TURN	SMALL	BIG	R^2
coefficient	0.442	0.121	0.009	-0.102	0.343	0.099	-0.028	-0.176	-0.496	0.427	-0.29	0.16
t-stats	(20.59)	(24.91)	(2.08)	(-12.1)	(5.55)	(19.79)	(-3.64)	(-19.86)	(-8.96)	(30.3)	(-31.08)	

This table presents the time-series average of the slope coefficients from the monthly cross-sectional regressions of good minus bad volatility (Panel A) or idiosyncratic skewness (Panel B) as in equation (8) from July 1978 to December 2016. The corresponding Newey and West (1987) robust t-statistics are reported in parentheses. The dependent variable (GMB or ISKEW) is estimated over a period of 5 years (T = 60 months). GO is the growth-option value calculated as per equation (9); ROE proxies for profitability, calculated as the ratio of operating cash flow to shareholders' equity; MAX is the maximum daily return observed in the previous month; Asset growth (AG), calculated as the percent change in firm total assets over the previous year. BM is book-to-market ratio; MOM is momentum, measured as the compound gross return from month t-12 to t-2; turnover (TURN), calculated as the ratio of trading volume to total shares outstanding; lagged good minus bad volatility (GMB), calculated in the preceding nonoverlapping 5 years; SMALL and BIG, 2 binary dummies built on the bottom 30% and top 30% of lagged market capitalization. The last column reports the average adjusted R^2 values.

Table 3: Comparing Conditional Idiosyncratic Skewness Measures

Panel A. Ex Post Correlations

		$ISKEW_{t-T+1}$	GMB_{t-T+1}	$EISKEW_t$	$EGMB_t$
GMB_t	*Pearson*	0.266	0.311	0.444	0.464
	Spearman	0.307	0.320	0.455	0.474
$ISKEW_t$	*Pearson*	0.221	0.234	0.351	0.352
	Spearman	0.279	0.283	0.419	0.429

Panel B. Prediction Errors - Realized Good Minus Bad Volatility

	$ISKEW_{t-T+1}$	GMB_{t-T+1}	$EISKEW_t$	$EGMB_t$
avg. RMSE	713.1	706.19	629.59	618.16
$ISKEW_{t-T+1}$		6.91	83.51	94.94
		(0.49)	(0.88)	(0.98)
GMB_{t-T+1}			76.60	88.03
			(0.87)	(0.97)
$EISKEW_t$				11.43
				(0.62)

Panel C. Prediction Errors - Realized Idiosyncratic Skewness

	$ISKEW_{t-T+1}$	GMB_{t-T+1}	$EISKEW_t$	$EGMB_t$
avg. RMSE	726.93	725.42	649.89	644.23
$ISKEW_{t-T+1}$		1.51	77.04	82.70
		(0.23)	(0.9)	(1.0)
GMB_{t-T+1}			75.53	81.19
			(0.9)	(1.0)
$EISKEW_t$				5.66
				(0.4)

This table presents the out-of-sample correlation and prediction errors of different measurements. In each month t, we predict the ex post GMB_t or $ISKEW_t$ using daily returns from t to $t+T-1$ by 4 methods: lagged realized skewness measures, i.e., i) $ISKEW_{t-T+1}$ and ii) GMB_{t-T+1} using daily returns from $t-T$ to $t-1$; iii) $EISKEW_t$ and iv) $EGMB_t$ measured as Equation (8) using cross-sectional determinants in $t-1$. Panel A reports the average cross-sectional correlations between GMB_t or $ISKEW_t$ and the 4 prediction methods. "Pearson" and "Spearman" denote the Pearson correlation and Spearman rank correlation, respectively. Panel B and Panel C report the prediction error for predicting GMB_t or $ISKEW_t$. The first row of Panel B reports the average RMSE over our sample period. The remainder of Panel B present the average differences in RMSE between the model *[name in row]* and the model *[name in column]*. The values of the numbers in parentheses indicate the share of time periods for which the difference is significant at 5%(e.g. 0.6 indicates that the difference is significant 60% of the time). We test the significance using the adjusted Diebold-Mariano test(Harvey et al., 1997).

Table 4: Univariate Portfolio Analysis

Panel A. Univariate Portfolio Sorts based on EGMB

	1	2	3	4	5	5-1
EGMB	0.05	0.08	0.12	0.16	0.22	0.17
Ret	1.09	1.00	0.95	0.52	0.10	-0.98
	(5.47)	(3.84)	(2.85)	(1.29)	(0.23)	(-2.93)
Std	4.22	5.46	6.78	8.00	8.74	6.76
% Mkt Share	76.50	17.90	3.80	1.50	0.40	
FF3	0.14	-0.10	-0.26	-0.78	-1.17	-1.31
	(3.69)	(-0.96)	(-2.13)	(-4.52)	(-5.31)	(-5.56)
FFCPS	0.09	0.02	-0.06	-0.39	-0.71	-0.80
	(2.53)	(0.2)	(-0.62)	(-2.59)	(-3.27)	(-3.61)
FF5	0.03	0.02	0.02	-0.29	-0.58	-0.61
	(0.89)	(0.2)	(0.24)	(-1.75)	(-2.71)	(-2.7)
FF5+FEISKEW	0.03	0.03	0.06	-0.22	-0.45	-0.47
	(0.79)	(0.36)	(0.66)	(-1.52)	(-3.17)	(-3.21)
FF5+FEGMB	0.02	0.05	0.08	-0.15	-0.32	-0.34
	(0.59)	(0.5)	(0.86)	(-1.01)	(-2.12)	(-2.13)

Panel B. Univariate Portfolio Sorts based on EISKEW

	1	2	3	4	5	5-1
EISKEW	0.20	0.47	0.76	1.16	1.82	1.63
Ret	1.06	1.02	0.94	0.74	0.29	-0.77
	(5.15)	(3.9)	(2.91)	(2.0)	(0.71)	(-2.57)
Std	4.34	5.47	6.55	7.27	8.06	6.09
% Mkt Share	73.90	19.90	4.20	1.60	0.40	
FF3	0.11	-0.08	-0.25	-0.57	-0.96	-1.07
	(2.53)	(-0.69)	(-1.95)	(-4.26)	(-4.56)	(-4.71)
FFCPS	0.05	0.10	-0.02	-0.19	-0.54	-0.60
	(1.24)	(1.01)	(-0.15)	(-1.6)	(-2.47)	(-2.59)
FF5	0.00	0.07	0.01	-0.25	-0.50	-0.50
	(0.02)	(0.61)	(0.1)	(-1.68)	(-2.13)	(-1.99)
FF5+FEISKEW	-0.01	0.09	0.05	-0.18	-0.35	-0.35
	(-0.18)	(0.83)	(0.42)	(-1.51)	(-2.16)	(-2.02)
FF5+FEGMB	-0.01	0.10	0.07	-0.12	-0.25	-0.24
	(-0.22)	(0.9)	(0.55)	(-0.95)	(-1.34)	(-1.2)

This table presents the average returns and portfolio characteristics of univariate portfolio analyses. Monthly value-weighted portfolios are formed by sorting all stocks into five quantiles based on the given sort variable, over the July 1978 to Dec 2016 period. The first row presents the average EGMB or EISKEW of individual stocks in each quantile. The row labeled "Ret" and "Std" reports the mean and standard deviation of 1-month ahead excess returns of each portfolio. The row labeld "% Mkt Share" reports the percentage of total market capitalization. The last 5 rows show the risk-adjusted returns (alphas) to 5 different factor models: i) "FF3" is with respect to the market (MKT), size (SMB), book-to-market (HML) factors of Fama and French (1993) ii) "FFCPS" is with respect to "FF3" model augmented with momentum(MOM), and liquidity risk (LIQ) factors of Carhart (1997) , and Pástor and Pietro (2003); iii) "FF5" is "FF3" model augmented with investment (CMA), and profitability (RMW) factors of Fama and French (2015); iv) and v) "FF5" model augmented with expected idiosyncratic skewness factor (FEISKEW) or expected good minus bad volatility factor (FEGMB). The column labeled "5–1" reports the difference in returns between portfolio 5 and portfolio 1. The corresponding Newey and West (1987) robust *t*-statistics with 6 lags are reported in parentheses. Panel A displays the results sorted by expected good minus bad volatility EGMB and Panel B by expected idiosyncratic skewness EISKEW.

Table 5: Correlations of Expected Good minus Bad Volatility and Expected Idiosyncratic Skewness Factors with the Five Factors of Fama and French (2015)

	FEGMB	FEISKEW	Mkt-RF	SMB	HML	RMW	CMA
FEGMB	1.00	0.80	-0.28	-0.41	0.29	0.64	0.21
FEISKEW	0.80	1.00	-0.22	-0.36	0.20	0.58	0.16
Mkt-RF	-0.28	-0.22	1.00	0.24	-0.28	-0.31	-0.39
SMB	-0.41	-0.36	0.24	1.00	-0.15	-0.41	-0.08
HML	0.29	0.20	-0.28	-0.15	1.00	0.22	0.69
RMW	0.64	0.58	-0.31	-0.41	0.22	1.00	0.12
CMA	0.21	0.16	-0.39	-0.08	0.69	0.12	1.00

The table reports pairwise correlations of Expected Good minus Bad Volatility and Expected Idiosyncratic Skewness Factors with the Five Factors of Fama and French (2015). The expected good minus bad volatility factor (FEGMB) or expected idiosyncratic skewness factor (FEISKEW) is constructed by forming zero cost long–short portfolios associated with the 2 anomalies (EGMB or EISKEW). Mkt-RF is the excess market return, SMB is the size factor, HML is the book-to-market factor, RMW is the profitability factor, and CMA is the investment factor.

Table 6: Bivariate Dependent-Sort Portfolio Analysis

Panel A. Sorted by EGMB Controlling for EISKEW

	1	2	3	4	5	5-1	FF3 alpha
1	1.23	1.05	1.07	1.11	0.98	-0.25	-0.37
	(4.71)	(5.08)	(5.14)	(4.98)	(3.77)	(-1.58)	(-2.23)
2	1.08	1.03	0.92	1.18	0.80	-0.29	-0.36
	(4.86)	(4.04)	(3.33)	(3.77)	(2.21)	(-1.24)	(-1.6)
3	1.22	1.09	0.91	0.96	0.60	-0.62	-0.82
	(4.67)	(3.55)	(2.92)	(2.65)	(1.4)	(-2.11)	(-3.48)
4	1.10	0.76	0.76	0.64	-0.08	-1.18	-1.35
	(3.62)	(1.93)	(2.01)	(1.51)	(-0.16)	(-3.6)	(-4.7)
5	0.65	0.47	0.43	0.32	-0.27	-0.92	-0.87
	(1.73)	(1.14)	(0.92)	(0.58)	(-0.48)	(-2.6)	(-2.66)
avg	1.06	0.88	0.82	0.84	0.41	-0.65	-0.75
	(4.23)	(3.04)	(2.69)	(2.43)	(1.04)	(-3.24)	(-4.82)

Panel B. Sorted by EISKEW Controlling for EGMB

	1	2	3	4	5	5-1	FF3 alpha
1	1.26	1.00	1.07	1.15	1.00	-0.25	-0.38
	(4.42)	(4.45)	(5.46)	(5.86)	(4.33)	(-1.14)	(-1.55)
2	1.02	1.04	0.83	1.02	1.17	0.15	0.10
	(3.72)	(3.86)	(2.95)	(4.0)	(4.57)	(0.69)	(0.49)
3	0.82	1.05	1.14	0.85	1.13	0.32	0.30
	(2.28)	(3.26)	(3.55)	(2.57)	(3.8)	(1.27)	(1.23)
4	0.48	0.68	0.75	0.90	0.72	0.24	0.35
	(1.04)	(1.74)	(1.89)	(2.32)	(2.03)	(0.8)	(1.38)
5	-0.08	0.30	0.42	0.51	-0.19	-0.11	0.06
	(-0.17)	(0.62)	(0.84)	(1.03)	(-0.39)	(-0.42)	(0.24)
avg	0.70	0.82	0.84	0.89	0.77	0.07	0.09
	(2.06)	(2.61)	(2.7)	(2.9)	(2.66)	(0.44)	(0.65)

This table presents the results of bivariate dependent-sort portfolio analyses of the relation between expected good minus bad volatility EGMB and future stock returns after controlling for the expected idiosyncratic skewness EISKEW, and vice versa. In Panel A, for each month, all stocks in the sample are first sorted into 5 quintiles based on an ascending sort of EISKEW. Within each quintile, the stocks are then sorted into 5 quintiles according to EGMB. For each 5×5 grouping, we form a value-weighted portfolio and reports the one-month-ahead excess return. The row "Avg" stands for average EGMB quantile portfolios across the 5 EISKEW portfolios. In Panel B, we reverse the order to first sort on EGMB and then on EISKEW. The column labeled "5–1" reports the difference in the returns between portfolio 5 and portfolio 1. The column labeled "FF3 alpha" reports the average Fama–French 3-factor alphas. The corresponding Newey and West (1987) robust t-statistics are reported in parentheses.

Table 7: Cross-Sectional Regressions of Future Returns on EGMB and Control Variables

	BETA	SIZE	BM	EGMB	EISKEW	GO	IVOL	MOM	ROE	AG	MAX
1	-0.067	-0.257***	0.216***	-6.153***							
	(-0.25)	(-6.84)	(3.05)	(-3.4)							
2	-0.117	-0.232***	0.227***		-0.532***						
	(-0.42)	(-6.0)	(3.1)		(-3.49)						
3	-0.116	-0.12***	0.232***			-0.121**					
	(-0.42)	(-2.72)	(3.3)			(-2.2)					
4	-0.026	-0.256***	0.21***	-12.636**	0.599						
	(-0.11)	(-6.78)	(3.08)	(-2.51)	(1.28)						
5	-0.042	-0.278***	0.194***	-7.277***		-0.05					
	(-0.16)	(-7.39)	(2.9)	(-4.34)		(-1.13)					
6	0.078	-0.286***	0.186***	-14.26***	0.615	-0.027	-0.014***				
	(0.33)	(-7.9)	(2.88)	(-3.18)	(1.41)	(-0.7)	(-2.68)				
7	0.052	-0.28***	0.227***	-16.515***	0.964**	-0.017	-0.015***	0.412**			
	(0.24)	(-7.97)	(3.69)	(-3.56)	(2.16)	(-0.45)	(-2.88)	(2.24)			
8	0.055	-0.277***	0.226***	-17.323***	1.064**	0.001	-0.015***	0.428**	0.153**		
	(0.26)	(-7.78)	(3.67)	(-3.61)	(2.3)	(0.02)	(-2.97)	(2.32)	(2.35)		
9	0.105	-0.29***	0.198***	-18.552***	1.11**	0.002	-0.014***	0.409**	0.138**	-0.415***	
	(0.49)	(-8.25)	(3.25)	(-3.8)	(2.37)	(0.06)	(-2.91)	(2.23)	(2.11)	(-5.89)	
10	0.11	-0.291***	0.201***	-15.476***	0.822*	0.004	-0.011**	0.388**	0.149**	-0.421***	-2.069***
	(0.52)	(-8.28)	(3.32)	(-3.37)	(1.82)	(0.11)	(-2.2)	(2.12)	(2.33)	(-5.99)	(-3.03)
11	0.11	-0.291***	0.201***	-15.476***	0.822*	0.004	-0.011**	0.388**	0.149**	-0.421***	-2.069***
	(0.52)	(-8.28)	(3.32)	(-3.37)	(1.82)	(0.11)	(-2.2)	(2.12)	(2.33)	(-5.99)	(-3.03)

This table reports the estimated coefficients and Newey and West (1987) t-statistics (in parentheses) from Fama and MacBeth (1973) cross-sectional regressions. The reported coefficient is the time-series average of month-by-month regression slopes over 462 months (July 1978 through December 2016). BETA is the firm's market beta; SIZE is the natural logarithm of the market value of equity; BM is book-to-market ratio; EGMB and EISKEW are expected good minus bad volatility and expected idiosyncratic skewness, respectively, estimated from equation (8) over a horizon of 60 months. IVOL is the idiosyncratic volatility, estimated with a horizon of 1 month for comparison with Ang et al. (2006); MOM is momentum, measured as the compound gross return from month $t-12$ to $t-2$; ROE proxies for profitability, calculated as the ratio of operating cash flow to shareholders' equity; AG is asset growth, calculated as the percent change in firm total assets over the previous year; MAX is the maximum daily return observed in the previous month; GO is the growth-option value calculated as per equation (9). Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Table 8: Controlling for Skewness-Related Factors

Panel A. Univariate portfolio sorts based on EGMB

	1	2	3	4	5	5-1
Ret	1.09	1.00	0.95	0.52	0.10	-0.98
	(5.47)	(3.84)	(2.85)	(1.29)	(0.23)	(-2.93)
FF5	0.03	0.02	0.02	-0.29	-0.58	-0.61
	(0.99)	(0.21)	(0.23)	(-1.94)	(-2.92)	(-2.99)
FF5+FVIX	0.04	0.04	0.07	-0.28	-0.57	-0.61
	(1.02)	(0.39)	(0.57)	(-1.61)	(-2.53)	(-2.64)
FF5+PSS	0.02	0.07	0.12	-0.20	-0.50	-0.52
	(0.56)	(0.79)	(1.17)	(-1.46)	(-2.32)	(-2.38)

Panel B. Univariate portfolio sorts based on EISKEW

	1	2	3	4	5	5-1
Ret	1.06	1.02	0.94	0.74	0.29	-0.77
	(5.15)	(3.9)	(2.91)	(2.0)	(0.71)	(-2.57)
FF5	0.00	0.07	0.01	-0.25	-0.50	-0.50
	(0.02)	(0.71)	(0.11)	(-1.82)	(-2.22)	(-2.15)
FF5+FVIX	0.04	0.06	0.00	-0.25	-0.48	-0.52
	(0.96)	(0.5)	(0.0)	(-1.53)	(-1.94)	(-2.06)
FF5+PSS	-0.02	0.16	0.13	-0.12	-0.39	-0.37
	(-0.56)	(1.75)	(1.21)	(-0.89)	(-1.6)	(-1.51)

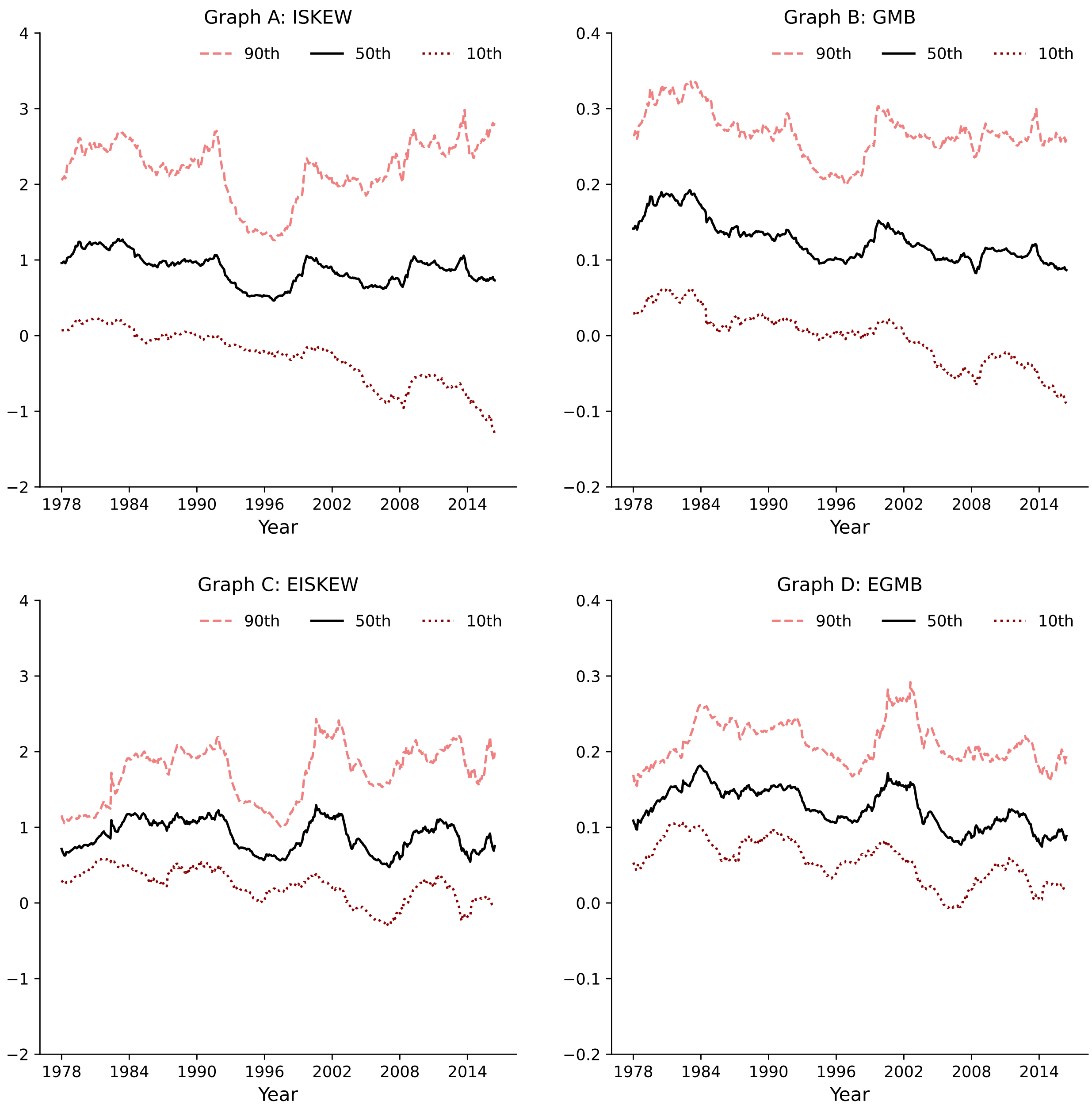
This table presents further univariate portfolio analyses after the inclusion of other skewness-related factors. Monthly value-weighted portfolios are formed by sorting all stocks into five quantiles based on the given sort variable, over the July 1978 to Dec 2016 period. The row labeled "Ret" reports the average 1-month ahead excess returns of each portfolio. The last 3 rows show the risk-adjusted returns (alphas) to 3 different factor models: i) "FF5" is Fama and French (2015) market (MKT), size (SMB), book-to-market (HML), investment (CMA), and profitability (RMW) 5 factor model; ii) "FF5+FVIX" is FF5 model augmented with the aggregate volatility risk factor (FVIX, Barinov (2018)). iii) "FF5+PSS" is FF5 model augmented with the predicted systematic skewness factor (PSS, Langlois (2020)). The column labeled "5–1" reports the difference in returns between portfolio 5 and portfolio 1. The corresponding Newey and West (1987) robust t-statistics are reported in parentheses. Panel A displays the results sorted by expected good minus bad volatility EGMB and Panel B by expected idiosyncratic skewness EISKEW.

Table 9: Cross-Sectional Regression of Future Returns on EGJ, EBJ and Control Variables

	BETA	SIZE	BM	EGJ	EBJ	GO	IVOL	MOM	ROE	AG	MAX
1	-0.075	-0.219***	0.208***	-7.252***							
	(-0.28)	(-5.49)	(2.91)	(-3.33)							
2	-0.071	-0.175***	0.246***		-8.648*						
	(-0.27)	(-4.14)	(3.48)		(-1.93)						
3	-0.039	-0.243***	0.219***	-6.262***	-6.811*						
	(-0.15)	(-6.08)	(3.15)	(-3.55)	(-1.77)						
4	-0.116	-0.12***	0.232***			-0.121**					
	(-0.42)	(-2.72)	(3.3)			(-2.2)					
5	-0.042	-0.2***	0.214***		-11.168***	-0.084*					
	(-0.16)	(-4.82)	(3.2)		(-2.8)	(-1.85)					
6	-0.052	-0.233***	0.189***	-8.465***		-0.059					
	(-0.2)	(-5.95)	(2.79)	(-4.46)		(-1.3)					
7	-0.007	-0.266***	0.195***	-7.274***	-8.583**	-0.054					
	(-0.03)	(-6.67)	(2.95)	(-4.63)	(-2.39)	(-1.24)					
8	0.057	-0.277***	0.192***	-6.982***	-9.865***	-0.035	-0.014**				
	(0.23)	(-7.4)	(2.94)	(-4.77)	(-3.11)	(-0.87)	(-2.48)				
9	0.002	-0.268***	0.242***	-5.891***	-7.245**	-0.027	-0.015***	0.418**			
	(0.01)	(-7.4)	(3.89)	(-4.02)	(-2.07)	(-0.72)	(-2.88)	(2.28)			
10	0.006	-0.267***	0.242***	-5.677***	-7.086**	-0.003	-0.015***	0.425**	0.155**		
	(0.02)	(-7.3)	(3.89)	(-3.77)	(-1.98)	(-0.07)	(-2.97)	(2.32)	(2.46)		
11	0.051	-0.28***	0.216***	-5.752***	-9.43***	-0.002	-0.015***	0.406**	0.132**	-0.41***	
	(0.23)	(-7.85)	(3.51)	(-3.74)	(-2.7)	(-0.04)	(-2.87)	(2.22)	(2.09)	(-5.55)	
12	0.068	-0.278***	0.217***	-5.315***	-8.033***	0.006	-0.011**	0.386**	0.145**	-0.406***	-2.244***
	(0.3)	(-7.89)	(3.54)	(-3.38)	(-2.63)	(0.14)	(-2.23)	(2.11)	(2.35)	(-5.47)	(-3.3)

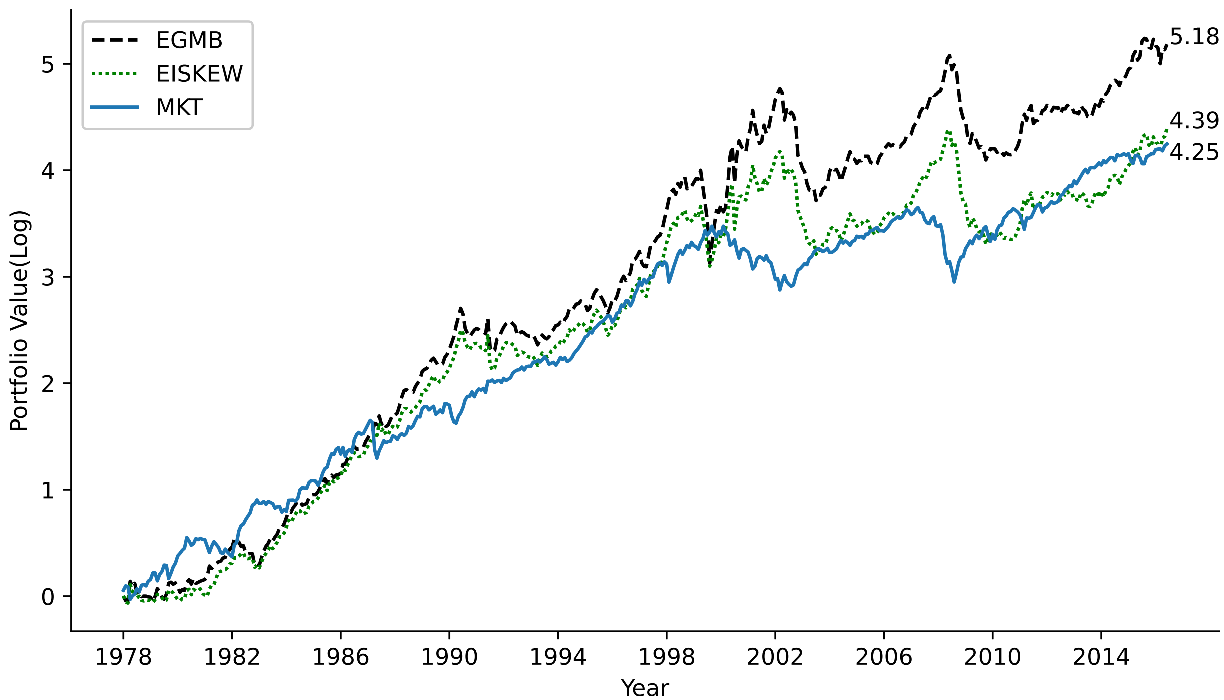
This table reports the estimated coefficients and Newey and West (1987) t-statistics (in parentheses) from Fama and MacBeth (1973) cross-sectional regressions. The reported coefficient is the time-series average of month-by-month regression slopes over 462 months (July 1978 through December 2016). BETA is the firm's market beta; SIZE is the natural logarithm of the market value of equity; BM is book-to-market ratio; EGJ and EBJ are expected good jump and expected bad jump, respectively, estimated from equation (8) over a horizon of 60 months. IVOL is the idiosyncratic volatility, estimated with a horizon of 1 month for comparison with Ang et al. (2006); MOM is momentum, measured as the compound gross return from month t-12 to t-2; ROE proxies for profitability, calculated as the ratio of operating cash flow to shareholders' equity; AG is asset growth, calculated as the percent change in firm total assets over the previous year; MAX is the maximum daily return observed in the previous month; GO is the growth-option value calculated as per equation (9). Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Figure 1: Cross-sectional Distribution of Firm-level Skewness Measures



Graphs A to D display the 10th, 50th, and 90th percentiles of the monthly cross-sectional distribution of idiosyncratic skewness (ISKEW), good minus bad volatility (GMB), expected idiosyncratic skewness (EISKEW), and expected good minus bad volatility (EGMB), respectively.

Figure 2: Cumulative Portfolio Gains



This Figure shows the log cumulative portfolio value for the MKT factor and value-weighted long–short portfolio based on the expected good minus bad volatility (EGMB) and expected idiosyncratic skewness (EISKEW) from July 1978 to December 2016. The final log portfolio value is 5.18 for EGMB strategy, 4.39 for EISKEW strategy, and 4.25 for MKT factor, respectively. All the portfolios are rebalanced and accumulated on a monthly basis, as described in the main text.

Appendix

We briefly outline the key theoretical results that allow us to estimate volatilities from positive and negative price increments under the assumption that the underlying continuous-time price process follow a jump diffusion process. We mainly rely on Barndorff-Nielsen and Shephard (2010).

To set out the notation, let p_T denote the natural logarithmic price of a security at time T, which is assumed to follow the generic jump diffusion process,

$$p_T = \int_0^T \mu_\tau d\tau + \int_0^T \sigma_\tau dW_\tau + J_T$$

where μ and σ denote the drift and diffusive volatility processes, respectively, W is a standard Brownian motion, and J is a pure jump process. We will denote the natural logarithmic discrete-time return over the time-interval of length $1/n$ as $r_{t+i/n} = p_{t+i/n} - p_{t+(i-1)/n}$.

Andersen et al. (2003) show that the following general results as the sampling frequency N goes to infinity for realized variance from time $t-1$ to t

$$RV_t = \sum_{i=1}^{n} r_{t-1+i/n}^2 \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1 \leq \tau \leq t} J_\tau^2$$

That is, the realized variance converges to the quadratic variation comprised of the separate components due to "continuous" and "jump" price increments.

Barndorff-Nielsen and Shephard (2002) decompose the total realized variation into separate components associated with the positive and negative high-frequency returns,

$$RV_t^+ = \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbf{1}_{\{r_{t-1+i/n} > 0\}}, \quad RV_t^- = \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbf{1}_{\{r_{t-1+i/n} < 0\}} \tag{14}$$

The upside and downside realized variance measures obviously add up to the total daily realized variation, $RV_t = RV_t^+ + RV_t^-$. Moreover, it is possible to show that

$$RV_t^+ \to \frac{1}{2}\int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1\leq\tau\leq t} J_\tau^2 \mathbf{1}_{(J_\tau>0)}$$
$$RV_t^- \to \frac{1}{2}\int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1\leq\tau\leq t} J_\tau^2 \mathbf{1}_{(J_\tau<0)}$$

such that the separately defined positive and negative semi-variance measures converge to one-half of the integrated variance plus the sum of squared positive and negative jumps, respectively.

These limiting results imply that the difference between the semi-variance measures removes the variation due to the continuous component and thus only reflects the variation stemming from jumps. The difference between positive and negative semi-variance is also known as the signed jump variation. Feunou et al. (2016) provide theoretical argument that the difference between positive and negative semivariances can be perceived as a measure of realized skewness. It is positive when there are more jumps in the positive return realizations, which it is negative when there are more jumps in the negative return territory.

From Barndorff-Nielsen and Shephard (2006), it can also be shown that the realized skewness measure converges to the jump component raised to the third power.

$$RSK_t \equiv \sum_{i=1}^{n} r_{t-1+i/n}^3 \xrightarrow{p} \sum_{t-1\leq\tau\leq t} J_\tau^3 \quad \text{as } n \to \infty \tag{15}$$

This result is important in two respects: First, it shows that the realized third moment in the limit separates the jump contribution from the continuous contribution and it just captures the jump part. It does not capture skewness arising from correlation between return and variance innovations (the "leverage" effect). For returns sampled at daily and higher frequencies, such leverage effect are empirically very weak. Second, it shows that

And bipower variations BV_t, which unlike realized variance, converges to the continuous part of the process: the integrated variance

$$BV_t \equiv \sum_{i=2}^{n} |r_{t-1+i/n}||r_{t-1+i/n-1/n}| \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 ds \quad \text{as } n \to \infty \tag{16}$$

Therefore, using bipower variation make it possible to separate the positive jump component and negative component from the positive realized variance RV^+ and negative realized variance RV^-.