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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, which are associated with positive and negative returns, respectively. Using firm characteristics, we estimate a cross-sectional model for the expected idiosyncratic good minus bad volatility (EIGMB). The EIGMB outperforms expected idiosyncratic skewness (EISKEW) and standard time-series models in capturing conditional idiosyncratic return asymmetry. EIGMB is negatively and significantly associated with future stock returns, even after controlling for EIKSEW and exposure to systematic-skewness-related factors. Separating the role each specific characteristic plays in driving the predictive power of EIGMB for returns, we find that return on equity and momentum are two important elements of variation in EIGMB.

1. Introduction

Finance research has emphasized the importance of idiosyncratic skewness for cross-sectional stock returns. Barberis and Huang (2008) and Brunnermeier and Parker (2005) develop models in which investors display preferences for idiosyncratic skewness, and predict that stocks with high idiosyncratic skewness earn lower average returns. Yet, simple time-series models of realized idiosyncratic skewness (see Harvey and Siddique, 1999) do not capture conditional idiosyncratic skewness well and fail to predict the cross-section of stock returns. Empirical studies, such as Boyer et al. (2010), propose to use lagged realized idiosyncratic skewness and several firm characteristics to capture expected idiosyncratic skewness, and do find a negative relation between expected idiosyncratic skewness and stock returns.

We decompose realized idiosyncratic volatility into "good" and "bad" volatility components using positive and negative returns, respectively, as in Barndorff-Nielsen and Shephard (2002) and Barndorff-Neilsen et al. (2010). In line with Feunou et al. (2016) and Bollerslev et al. (2020), we use the difference between realized idiosyncratic good and bad volatility (IGMB henceforth), as a measure of realized idiosyncratic skewness. Following Boyer et al. (2010), we then use lagged IGMB, together with several firm-level characteristics, to predict future IGMB through cross-sectional regressions, leading to an expected IGMB measure (EIGMB henceforth). While Bekaert et al. (2022a) find that an ARMA(1,1) model performs well in predicting realized idiosyncratic volatility, idiosyncratic good minus bad volatility shows limited time-series persistence. This limits the effectiveness of time-series models in forecasting IGMB. In terms of statistical accuracy, we find that EIGMB outperforms expected idiosyncratic skewness (EISKEW henceforth), and standard time-series models in capturing conditional idiosyncratic return asymmetry. Our results indicate that incorporating firm-level characteristics is important in capturing variation in IGMB.

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We then show that EIGMB exhibits a strong negative relationship with future stock returns.[2] The return spreads between portfolios with high and low EIGMB cannot be accounted for by exposure to expected idiosyncratic skewness (Boyer et al., 2010), or by recently proposed systematic-skewness-related factors: the aggregate volatility (FVIX) factor of Barinov (2018) and the predicted systematic skewness (PSS) factor of Langlois (2020).

For computing idiosyncratic returns and IGMB, our decomposition of firm-level stock returns into systematic and idiosyncratic components uses several well-established systematic factor models, including the three-factor model of Fama and French (1993), the five-factor model of Fama and French (2015), the q-factor model of Hou et al. (2015), and the principal component analysis (PCA) and risk premia PCA model of Lettau and Pelger (2020). Our analysis reveals that variation in "total" good minus bad volatility is predominantly driven by the idiosyncratic component. In addition, the return spread of sorting on EIGMB is more pronounced when we effectively control for the systematic component in firm stock returns.

Furthermore, we investigate the role each specific characteristic plays in driving the predictive power of EIGMB for future stock returns. To this end, one characteristic at a time is excluded from the predictive regression and EIGMB is re-estimated using the remaining characteristics. Then we sort stocks into value-weighted quintile portfolios based on the re-estimated EIGMB. We find that excluding return on equity (ROE) and momentum largely reduces the predictive power of EIGMB for returns, which suggests that ROE and momentum are two important elements of variation in EIGMB. High-ROE firms make more profits, which means that a smaller proportion of their firm value is derived from growth options. Trigeorgis and Lambertides (2014) and Del Viva et al. (2017) argue that the flexibility of growth options may enhance a firm's upside value potential and reduce downside risk in bad economic states. Such asymmetry could result in returns with large positive payoffs and less extreme negative ones, thereby enhancing idiosyncratic skewness and making them appealing to investors. Regarding momentum, we find that when past returns have been high, EIGMB is predicted to be lower, which is consistent with the finding of Chen et al. (2001).

We also dissect EIGMB into the expected idiosyncratic "good jump" (EIGJ) and expected idiosyncratic "bad jump" (EIBJ) components. Although we find that the regression coefficients of future returns on EIBJ are slightly larger, variation in EIGMB is primarily driven by the good jump component. Therefore, downside risk (Ang et al., 2006a) plays a limited role in the negative relationship between conditional idiosyncratic skewness and stock returns.

There is now a growing literature on the implications of good and bad volatility for asset pricing. For example, Feunou et al. (2018) and Feunou and Okou (2019) decompose the realized volatility of stock index returns into good and bad components and study the risk premium associated with good and bad volatility separately. Bekaert and Engstrom (2017) and Bekaert et al. (2015, 2022b) develop and examine a bad environment good environment model for macroeconomic fundamentals, stock returns, and variance risk premiums, which features gamma distributed shocks with time-varying shape parameters. In the model, bad (good) volatility shocks are associated with lower (higher) skewness. Segal et al. (2015) use the framework to predict output growth and examine the asset pricing implications in a long-run risk framework. However, the paper most closely related to our work is (Bollerslev et al., 2020). Our paper differs from theirs mainly in two ways. First, we examine how EIGMB over a longer horizon, for example, five years, is related to the cross-section of stock returns. The predictive power of weekly realized good minus bad volatility of Bollerslev et al. (2020) for returns is short-lived, dissipating over longer monthly horizons. Second, we study the relationship between idiosyncratic good minus bad volatility, rather than total good minus bad volatility, and the cross-section of stock returns. Our findings indicate that the idiosyncratic component is strongly associated with cross-sectional stock returns.

The remainder of this paper is organized as follows. Section 2 formally defines idiosyncratic good and bad volatility and presents the cross-sectional model used to estimate expected idiosyncratic good minus bad volatility. Section 3 investigates the relationship between EIGMB and stock returns. Section 4 analyzes the drivers of the relationship between EIGMB and future returns. Section 5 presents further analyses of the findings of this paper. Section 6 concludes.

2. Measurement of variables

2.1. Realized good and bad idiosyncratic volatility

We obtain monthly and daily return data on stocks traded in the NYSE, AMEX, and NASDAQ from CRSP and accounting variables from Compustat. We exclude financial and utility firms with Standard Industrial Classification (SIC) codes between 6000 and 6999 and between 4900 and 4999. Following Boyer et al. (2010), we calculate the residuals of the following time-series regressions using daily observations from month $t-T+1$ to t:

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

where for day d in month t, $r_{i,t,d}$ is the excess return of stock i, and $MKT_{t,d}$, $SMB_{t,d}$, and $HML_{t,d}$ are the market, size, and book-to-market factors, respectively. Regression coefficients are denoted by $\alpha_{i,t}$, $\beta_{i,t,MKT}$, $\beta_{i,t,SMB}$, and $\beta_{i,t,HML}$.

We report the results using the three-factor model specified in Eq. (1), with an estimation horizon of $T = 60$ months as the benchmark. Detailed analyses using alternative factor models and different estimation horizons are presented in Section 5.1. Our results indicate that different choices of factor models and estimation horizons do not significantly affect the main findings of the paper.

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 $t-T+1$ through the end of month t:

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

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

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

where N_m is the total number of trading days between months $t-T+1$ and t. The IV measure does not differentiate between volatility that is associated with positive or negative price changes. We further decompose IV into good and bad components following Barndorff-Nielsen and Shephard (2002):

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

[2] (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, our research uncovers a strong negative relationship between conditional idiosyncratic skewness and stock returns. Unlike option-implied risk-neutral skewness, which is affected by investors' risk preferences and available only for a subsample of firms with sufficient option data, our conditional idiosyncratic skewness measure covers a broader sample of firms and may capture different information. Additionally, option-implied measures are more susceptible to liquidity and limits to arbitrage issues. Furthermore, their approach does not separate firm-level volatility into systematic and idiosyncratic components.

Table 1
Summary statistics of main variables.

Panel A. Summary Statistics

	RET	BETA	SIZE	BM	MOM	AG	ROE	LEV	GO	MAX	TURN	IVOL	EISKEW	EIGMB
Mean	0.98	1.16	12.05	0.78	0.13	0.21	0.05	0.37	0.81	0.08	1.31	3.52	0.85	0.12
Median	−0.20	1.05	11.96	0.57	0.04	0.04	0.11	0.34	0.53	0.06	0.85	3.13	0.70	0.11
Std	17.12	0.68	2.06	0.82	0.54	0.68	0.61	0.23	1.63	0.07	1.55	1.81	0.71	0.07
Min	−72.30	−0.16	7.78	−0.85	−0.76	−0.46	−3.21	0.01	−2.75	0.01	0.04	1.11	−0.78	−0.05
Max	276.88	3.42	17.11	4.73	2.47	5.11	2.81	0.92	8.52	0.43	9.71	10.11	4.00	0.41

Panel B. Cross-sectional Correlations of Main Variables

	RET	BETA	SIZE	BM	MOM	AG	ROE	LEV	GO	MAX	TURN	IVOL	EISKEW	EIGMB
RET	1.00	−0.01	0.06	0.02	0.01	−0.02	0.01	0.02	−0.01	0.33	0.12	0.00	−0.01	−0.01
BETA		1.00	−0.17	−0.03	−0.03	0.07	−0.11	0.02	0.19	0.24	0.22	0.42	0.21	0.27
SIZE			1.00	−0.31	0.21	0.02	0.18	−0.17	−0.27	−0.38	0.18	−0.66	−0.74	−0.75
BM				1.00	−0.13	−0.11	−0.01	0.47	−0.04	0.11	−0.12	0.08	0.22	0.20
MOM					1.00	−0.04	0.05	−0.09	−0.09	−0.16	0.14	−0.08	−0.26	−0.26
AG						1.00	−0.05	−0.17	0.07	0.02	0.11	0.06	−0.03	−0.02
ROE							1.00	0.07	−0.46	−0.13	−0.02	−0.21	−0.25	−0.26
LEV								1.00	−0.12	0.09	−0.08	0.05	0.14	0.14
GO									1.00	0.24	0.07	0.37	0.36	0.39
MAX										1.00	0.23	0.53	0.40	0.43
TURN											1.00	0.08	−0.14	−0.11
IVOL												1.00	0.71	0.77
EISKEW													1.00	0.97
EIGMB														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 one-year period using the 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 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 net income to book equity; leverage (LEV) is calculated as the ratio of the book value of debt to the market value of the firm; GO is the present value of growth options; MAX is the maximum daily return observed in the previous month; turnover (TURN) is calculated as the ratio of trading volume to total shares outstanding.

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

where $\mathbf{1}_{\{\cdot\}}$ denotes the indicator function and $IV_{i,t}^{+}$ and $IV_{i,t}^{-}$ are the upside and downside realized idiosyncratic variance respectively. The upside and downside realized idiosyncratic variance add up to the total realized idiosyncratic variance, i.e., $IV_{i,t} = IV_{i,t}^{+} + IV_{i,t}^{-}$. Moreover, following Bollerslev et al. (2020), we define the idiosyncratic good minus bad volatility as

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

The difference between the upside and downside variance is normalized by the realized variance, which removes the overall volatility level from the $IGMB_t$ measure, rendering $IGMB_{i,t}$ to lie between −1 and 1.[3]

2.2. Measuring expected idiosyncratic good minus bad volatility

We develop a model of EIGMB that uses firm characteristics together with lagged IGMB and idiosyncratic volatility.[4] Unlike idiosyncratic volatility, which is relatively persistent over time (Bekaert et al., 2022a), variation in IGMB cannot be fully predicted by lagged volatility measures. Following Boyer et al. (2010) and Bali et al. (2020), we run the following cross-sectional regressions with lagged regressors at the end of each month t to obtain regression coefficients:

$$IGMB_{i,t} = \alpha_t + \beta_{1,t} IGMB_{i,t-T} + \beta_{2,t} IVOL_{i,t-T} + \boldsymbol{\gamma}_t' \boldsymbol{X}_{i,t-T} + \epsilon_t, \tag{8}$$

where $\boldsymbol{X}_{i,t-T}$ is a set of firm-specific variables observable at the end of month $t-T$. We then use the regression parameters from Eq. (8), along with information observable at the end of each month t, to compute $EIGMB_{i,t}$:

$$EIGMB_{i,t} \equiv E_t[IGMB_{t+T}] = \alpha_t + \beta_{1,t} IGMB_{i,t} + \beta_{2,t} IVOL_{i,t} + \boldsymbol{\gamma}_t' \boldsymbol{X}_{i,t}. \tag{9}$$

This approach augments time-series predictors with other firm characteristics to capture distinct variation in EIGMB across stocks as well as over time. Compared with typical time-series approach, the regression coefficients are not firm specific, but could vary over time. Moreover, $EIGMB_{i,t}$ provides measures of conditional idiosyncratic skewness over a horizon of T months strictly using information available to investors at the end of month t. For comparison, we also compute expected idiosyncratic skewness (EISKEW) using the same approach, replacing IGMB with ISKEW in Eqs. (8) and (9).

Following Bali et al. (2020), the firm-specific variables $\boldsymbol{X}_{i,t-T}$ include asset growth (AG), future growth potential (GO), and return on equity (ROE), which are related to growth options. We also include several variables used in the literature to predict idiosyncratic skewness. The skewness of stock returns, which may in extreme form manifest itself as lotteryness, is proxied by maximum daily return (MAX) during the previous month. Motivated by Hong and Stein (2003) and Chen et al. (2001), turnover and momentum are also included in forecasting regressions. Turnover ($\mathrm{TURN}_{i,t}$) is calculated as the ratio of trading volume to shares outstanding in month t, and momentum $\mathrm{MOM}_{i,t}$ is the cumulative return over months $t-11$ through $t-1$. In addition, we also include dummy variables controlling for the size effect (SMALL and BIG), the Fama and French 30 industries (INDU), and the NASDAQ exchange (EXCH). The Appendix provides details of the construction of these variables.

[3] In the Appendix, we briefly outline theoretical results that support using good minus bad volatility as a measure of return asymmetry under mild conditions.

[4] The relationship between lagged idiosyncratic skewness measures and future stock returns is not statistically significant. The results are presented in Appendix A.

Table 2
Cross-sectional determinants of idiosyncratic good minus bad volatility and idiosyncratic skewness.

Panel A. Idiosyncratic Good Minus Bad Volatility Determinants

	Const.	IGMB	GO	ROE	MAX	IVOL	AG	MOM	TURN	SMALL	BIG	INDU	EXCH	R^2
β	0.056	0.117	0.004	−0.016	0.060	0.014	−0.004	−0.025	−0.003	0.038	−0.030	Yes	Yes	0.28
t-stats	(10.18)	(13.75)	(6.28)	(−9.84)	(5.74)	(13.13)	(−3.90)	(−14.70)	(−4.09)	(20.09)	(−16.48)			

Panel B. Idiosyncratic Skewness Determinants

	Const.	ISKEW	GO	ROE	MAX	IVOL	AG	MOM	TURN	SMALL	BIG	INDU	EXCH	R^2
β	0.264	0.087	0.042	−0.155	0.613	0.147	−0.028	−0.243	−0.050	0.442	−0.219	Yes	Yes	0.16
t-stats	(4.75)	(11.74)	(4.86)	(−10.37)	(4.33)	(7.77)	(−2.26)	(−10.79)	(−7.16)	(22.83)	(−10.88)			

This table presents the time-series averages of the slope coefficients from the monthly cross-sectional regressions of IGMB (Panel A) or ISKSW (Panel B) on firm characteristics as in Eq. (8). The corresponding (Newey and West, 1987) robust t-statistics with 6 lags are reported in parentheses. The last column reports the average adjusted R^2 values.

2.3. Summary statistics and determinants of expected idiosyncratic good minus bad volatility

Panel A of Table 1 reports summary statistics for the variables used in our empirical analysis.[5] The market beta (BETA) has a median value of 1.05. The mean book-to-market ratio (BM) is 0.78, which aligns with the range reported in earlier studies (e.g., Anderson and Garcia-Feijoo, 2006). The mean monthly excess return (RET) is 0.98%. The average EIGMB across firms has a mean of 0.12 and a standard deviation of 0.07. The EISKEW is more volatile, with a mean of 0.85 and a standard deviation is 0.70. Panel B of Table 1 reports the average Pearson correlation coefficients among key variables. Growth options (GO), maximum daily returns (MAX), and idiosyncratic volatility (IVOL) are positively associated with EIGMB and EIKEW. Return on equity (ROE), size (SIZE), and momentum (MOM) are negatively correlated with EIGMB and EISKEW. EIGMB and EISKEW are strongly correlated, with an average correlation of 0.97.

Panel A of Table 2 shows the time-series averages of slopes using the previously described determinants to predict future IGMB.[6] Growth options (GO), lotteryness (MAX), and idiosyncratic volatility (IVOL) are statistically significant positive drivers of IGMB. Higher values for momentum (MOM), profitability (ROE), investment (AG), and turnover (TURN) are all associated with lower values of EIGMB. On average, the cross-sectional adjusted-R^2 is 0.28. Panel B of Table 2 displays analogous results for ISKEW. All the determinants show the same predicting signs as in Panel A, but with a lower average adjusted-R^2 of 0.16. These adjusted-R^2 numbers are consistent with previous findings (e.g., Chen et al., 2001; Boyer et al., 2010; Bali et al., 2020).

To illuminate the temporal variation in each of the idiosyncratic skewness measures, Fig. 1 presents the 10th, 50th, and 90th percentiles of ISKEW, IGMB, EISKEW, and EIGMB. All percentiles exhibit substantial time variations, with particularly large movements during the mid-1980s, the early 1990s, the late 1990s, and the early 2010s. Compared with ISKEW, IGMB tends to be more stable, with less variation in extreme percentiles, e.g., in the late 1990s. The expected measures (EISKEW and EIGMB) display temporal variations similar to those of ISKEW and IGMB, but with smaller dispersion across firms.

2.4. Evaluating the accuracy of conditional idiosyncratic skewness measures

We assess the accuracy of different metrics $\widehat{Z}_t$ in forecasting future realized idiosyncratic skewness Z_{t+T}. The metric $\widehat{Z}_t$ includes ISKEW$_t$, IGMB$_t$, forecasts from an AR(1) model, forecasts from an ARMA(1,1) model,[7] EISKEW, and EIGMB. We use IGMB$_{t+T}$ and ISKEW$_{t+T}$ as proxies for future realized idiosyncratic skewness Z_{t+T}.

Panel A of Table 3 reports the average cross-sectional Pearson correlations and Spearman rank correlations between future realized idiosyncratic skewness measures and conditional forecasts. Lagged idiosyncratic skewness (ISKEW$_t$ and IGMB$_t$) or time-series forecasts (AR(1) and ARMA(1,1)) exhibit low correlations with future realized values, ranging from 0.2 to 0.3. The expected measures (EISKEW and EIGMB) outperform lagged values in forecasting future IGMB by a large margin, with average correlations of about 0.45. Furthermore, EIGMB shows a stronger correlation with future realized values than EISKEW. For example, the correlation between EIGMB$_t$ and IGMB$_{t+T}$ is 0.465, while the correlation between EISKEW$_t$ and IGMB$_{t+T}$ is 0.438. For further comparison, we use the root mean squared error (RMSE), a loss function commonly used in the literature to quantify the forecast accuracy of different measures.[8] Since these estimators lie in different ranges (e.g., EIGMB and lagged ISKEW), we transform the realized values and predicted values into their cross-sectional ranks to facilitate comparisons. The RMSE at month t is defined as

$$RMSE_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(Rank(Z_{i,t+T}) - Rank(\widehat{Z}_{i,t}))^2}, \tag{10}$$

where the $Rank(Z_{i,t})$ function assigns the rank $(1,2,\ldots,N_t)$ to the variable $Z_{i,t}$ based on its position among all values of Z_t sorted in ascending order and N_t is the number of stocks available at time t. In each month t, we assess the difference in RMSEs using the modified Diebold–Mariano (DM) test of Harvey et al. (1997).

Panel B of Table 3 shows that EIGMB achieves the lowest RMSE in predicting IGMB$_{t+T}$. The average RMSE of EIGMB, for example, is 10.45 lower than EISKEW, and the difference is significant at the 5% level for 75% of the time. The RMSE of EIGMB is significantly lower than that of other forecasts for around 96% of the time. Moreover, Panel C of Table 3 shows that EIGMB is also the most accurate predictor for ISKEW$_{t+T}$. Although the lead of EIGMB over EISKEW slightly narrows, the difference remains statistically significant for 55% of the time.

3. Expected idiosyncratic good minus bad volatility and stock returns

In this section, we begin by analyzing the relationship between EIGMB and future stock returns using portfolio analysis. We then investigate the relationship between EIGMB and future stock returns through firm-level (Fama and MacBeth, 1973) regressions that simultaneously control for EISKEW and other firm characteristics.

3.1. Univariate portfolio analysis

At the end of each month, we sort stocks into quintile portfolios based on EIGMB. We then compute the value-weighted return for each portfolio over the subsequent month. Panel A of shows that the average monthly excess return decreases monotonically from 0.81% for quintile

[5] Because estimating EIGMB and EISKEW requires 10 years of data, our analysis spans from January 1978 through December 2020.

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

[7] The Appendix provides details on the construction of AR(1) and ARMA(1,1) forecasts. For each firm, models are fitted on a rolling basis using IGMB data of the previous 60 months.

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

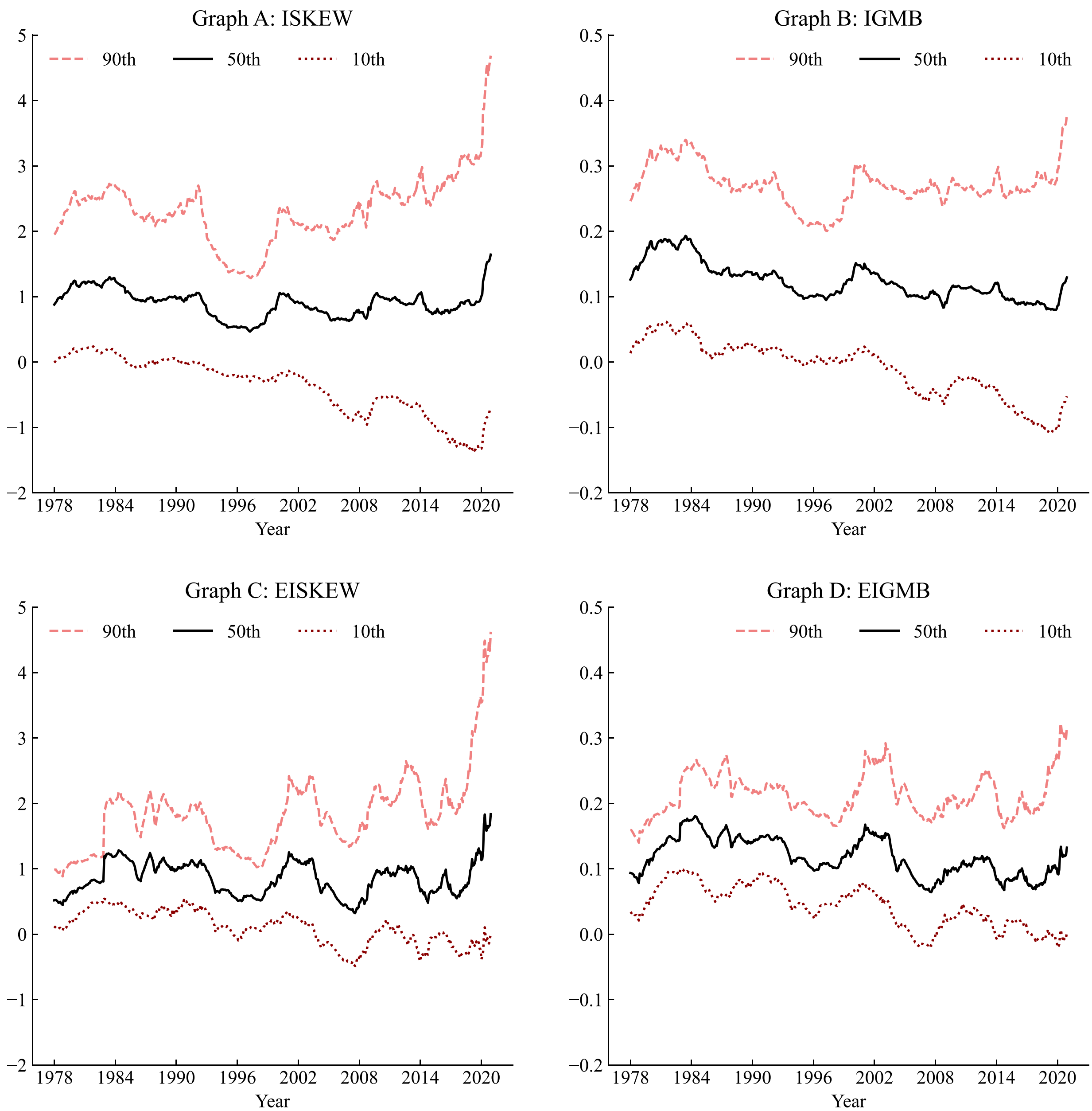

Fig. 1. Cross-Sectional Percentiles of Firm-Level Skewness Measures.
Graphs A to D display the 10th, 50th, and 90th percentiles of idiosyncratic skewness (ISKEW), idiosyncratic good minus bad volatility (IGMB), expected idiosyncratic skewness (EISKEW), and expected idiosyncratic good minus bad volatility (EIGMB), respectively.

1 (low) to −0.09% for quintile 5 (high). We also consider a long–short portfolio that buys stocks with the highest EIGMB and short stocks with the lowest EIGMB. This long–short portfolio earns an average return of −0.91%, with a t-statistic of −2.60.

We control for exposures to systematic risk factors, including the three factors of Fama and French (1993), the q-factors of Hou et al. (2015), and the five factors of Fama and French (2015). The risk-adjusted returns of the long–short portfolio based on EIGMB are significantly negative: −1.32% per month for the three-factor (FF3) model, −0.47% for the q-factor model, and −0.72% for the five-factor (FF5) model, with robust t-statistics of −5.01, −2.34, and −3.68, respectively.

Furthermore, Barinov (2018) and Langlois (2020) propose to use exposures to systematic-skewness-related factors to explain the low returns of stocks with high idiosyncratic skewness. We also control for the aggregate volatility risk factor (FVIX) of Barinov (2018) and the predicted systematic skewness (PSS) factor of Langlois (2020), finding that the predictive power of EIGMB remains.[9] The FVIX factor explains little of the return of the long–short portfolio based on EIGMB. When the PSS factor is controlled for, the risk-adjusted return of the long–short portfolio is slightly reduced to −0.51% per month, but it is still statistically significant.

We also sort stocks into quintile portfolios based on EIKEW. Panel B of shows that the differences in returns between portfolios with the

[9] The PSS factor data are collected from Langlois' website (https://hugueslanglois.com), which ends in 2017. We construct the FVIX factor following the procedures of Barinov (2018). The FVIX factor is available only after 1986, when the VXO index was introduced. As a validity check, the correlation between our FVIX factor and ΔVXO is 0.719, closely matching the correlation of 0.715 reported in Table 1 of Barinov (2018). The asset pricing tests in this section are conducted over the overlapping period of the FVIX and PSS factors, spanning from 1986 to 2017.

Table 3
Comparing conditional idiosyncratic skewness measures.

Panel A. Correlations

		$ISKEW_t$	$IGMB_t$	$AR(1)_t$	$ARMA(1,1)_t$	$EISKEW_t$	$EIGMB_t$
$IGMB_{t+T}$	*Pearson*	0.252	0.287	0.295	0.302	0.443	0.465
	Spearman	0.279	0.291	0.290	0.301	0.438	0.465
$ISKEW_{t+T}$	*Pearson*	0.211	0.222	0.229	0.235	0.348	0.354
	Spearman	0.254	0.257	0.255	0.266	0.398	0.415

Panel B. Prediction Errors — Future Realized Idiosyncratic Good Minus Bad Volatility

	$ISKEW_t$	$IGMB_t$	$AR(1)_t$	$ARMA(1,1)_t$	$EISKEW_t$	$EIGMB_t$
avg. RMSE	496.04	489.76	489.86	488.92	447.68	437.23
$ISKEW_t$		6.28	6.18	7.12	48.36	58.81
		(0.53)	(0.50)	(0.60)	(0.84)	(0.97)
$IGMB_t$			−0.10	0.84	42.08	52.53
			(0.01)	(0.35)	(0.80)	(0.96)
$AR(1)_t$				0.94	42.18	52.63
				(0.54)	(0.80)	(0.96)
$ARMA(1,1)_t$					41.24	51.69
					(0.80)	(0.96)
$EISKEW_t$						10.45
						(0.75)

Panel C. Prediction Errors — Future Realized Idiosyncratic Skewness

	$ISKEW_t$	$IGMB_t$	$AR(1)_t$	$ARMA(1,1)_t$	$EISKEW_t$	$EIGMB_t$
avg. RMSE	505.55	502.41	502.50	501.67	462.55	455.79
$ISKEW_t$		3.14	3.05	3.88	43.00	49.76
		(0.27)	(0.26)	(0.31)	(0.89)	(0.97)
$IGMB_t$			−0.09	0.74	39.86	46.62
			(0.0)	(0.32)	(0.87)	(0.97)
$AR(1)_t$				0.83	39.95	46.71
				(0.44)	(0.87)	(0.97)
$ARMA(1,1)_t$					39.12	45.88
					(0.87)	(0.97)
$EISKEW_t$						6.76
						(0.55)

Panel A presents the correlations between different metrics of conditional idiosyncratic skewness and future IGMB or ISKEW. Panels B and C report the prediction errors for forecasting $IGMB_{t+T}$ and $ISKEW_{t+T}$, respectively. The first row of Panel B and C reports the average RMSE. The remainder of Panel B and C shows the average differences in RMSE between the model *[name in row]* and the model *[name in column]*. The numbers in parentheses measure the proportion of periods in which the difference in RMSE is significant at the 5% level, using the adjusted Diebold–Mariano test (Harvey et al., 1997).

highest and lowest EISKEW have an average monthly return of −0.63%, with a t-statistic of −2.19. The return spread is smaller than that sorted by EIGMB, and closely match the −0.67% reported in Boyer et al. (2010). To further illuminate the performance of long–short portfolios based on EIGMB and EISKEW, we start with an initial investment of $W_0 = \$1$. The cumulative profit in month t is then 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–short portfolio based on EIGMB or EISKEW and r_f denotes the monthly risk-free rate. Fig. 2 depicts the cumulative profits of long–short portfolios based on EIGMB and EISKEW. For comparison, we also plot the cumulative return of the MKT factor. As Fig. 2 shows, the EIGMB-based strategy outperforms the EISKEW strategy by a large margin. The final cumulative return of EIGMB portfolios is \$194, which doubles the return of the MKT factor and EISKEW strategy, with returns of \$139 and \$61, respectively.

3.2. Bivariate portfolio analysis

The results from univariate portfolio sorts in reveal a strong negative relation between EIGMB and future stock returns, which cannot be explained by exposure to systematic risk factors. Using bivariate portfolio analysis, we assess the relationship between EIGMB and future stock returns, controlling for EISKEW.

Panel A of shows the results of sorting on EIGMB after first sorting on EISKEW. At the end of each month, we first sort stocks into quintile portfolios based on EISKEW. Within each EISKEW quintile portfolio, we then sort stocks into quintile portfolios based on EIGMB and compute the value-weighted returns over the next month for the resulting 25 portfolios. We find that the negative relationship between EIGMB and future stock returns can be observed within all EISKEW-sorted quintile portfolios, especially in the high-EISKEW groups (e.g., the third to fifth EISKEW quintiles). The difference in returns between portfolios with high and low EIGMB across EISKEW quintiles has an average FF3 alpha of −0.68%, with a highly significant t-statistic of −4.13.

In contrast, Panel B of presents the results of first sorting on EIGMB and then on EISKEW. Within each EIGMB quintile, the negative relationship between EISKEW and future stock returns does not hold and even reverses. On average, the FF3 alpha for the return spread between portfolios with high and low EISKEW equals −0.09%, with an insignificant t-statistic of −0.68.

3.3. Firm-level Fama–MacBeth regressions

In Table 6, we supplement the portfolio sort evidence with the results from Fama and MacBeth (1973) (FM) regressions of firm stock returns over month $t + 1$ on EIGMB and various control variables observed at the end of month t. When both EIGMB and EISKEW are included in the regression, the slope coefficient of EIGMB remains significantly negative. However, the coefficient of EISKEW reverses to positive and is statistically not significant, which is consistent with the results from the double sorts in Section 3.2. In the Appendix, we provide evidence that the change of sign is consistent with the reasoning that EIGMB provides a more accurate measure of conditional idiosyncratic skewness.

We also control for momentum (MOM), profitability (ROE), investment (AG), as well as skewness-related variables, including idiosyncratic volatility (Ang et al., 2006b; IVOL), co-skewness (Harvey and Siddique, 2000; COSKEW), and lotteryness (Bali et al., 2011; MAX). Across all specifications, the coefficient of EIGMB remains significant, confirming that its predictive power cannot be explained by previously documented factors.

Table 4
Univariate portfolio analysis.

Panel A. Univariate Portfolio Sorts Based on EIGMB						
	1	2	3	4	5	5–1
EIGMB	0.04	0.07	0.11	0.15	0.22	0.19
Ret	0.81	0.76	0.55	0.53	−0.09	−0.91
	(4.44)	(3.34)	(2.01)	(1.38)	(−0.20)	(−2.60)
% Mkt Share	65.50	23.30	8.70	2.00	0.40	
FF3	0.18	−0.00	−0.34	−0.57	−1.13	−1.32
	(3.79)	(−0.01)	(−2.74)	(−3.28)	(−4.79)	(−5.01)
q-factor	0.10	0.07	−0.03	0.03	−0.37	−0.47
	(2.33)	(0.99)	(−0.23)	(0.20)	(−1.90)	(−2.34)
FF5	0.08	−0.01	−0.22	−0.22	−0.64	−0.72
	(1.86)	(−0.22)	(−1.73)	(−1.38)	(−3.51)	(−3.68)
FF5+FVIX	0.05	0.02	−0.04	−0.13	−0.54	−0.59
	(1.01)	(0.23)	(−0.27)	(−0.63)	(−2.22)	(−2.26)
FF5+PSS	0.03	0.07	−0.03	0.02	−0.48	−0.51
	(0.68)	(1.18)	(−0.20)	(0.11)	(−2.38)	(−2.38)
Panel B. Univariate Portfolio Sorts Based on EISKEW						
	1	2	3	4	5	5–1
EISKEW	0.06	0.39	0.70	1.14	1.96	1.90
Ret	0.81	0.71	0.62	0.44	0.17	−0.63
	(4.24)	(3.31)	(2.43)	(1.29)	(0.40)	(−2.19)
% Mkt Share	59.20	25.90	11.70	2.60	0.50	
FF3	0.17	−0.03	−0.22	−0.56	−0.82	−0.99
	(3.45)	(−0.47)	(−1.73)	(−3.55)	(−3.49)	(−3.80)
q-factor	0.11	0.05	0.00	−0.03	−0.22	−0.33
	(2.20)	(0.87)	(0.01)	(−0.20)	(−1.05)	(−1.47)
FF5	0.08	−0.03	−0.15	−0.28	−0.47	−0.55
	(1.69)	(−0.48)	(−1.2)	(−1.76)	(−2.25)	(−2.42)
FF5+FVIX	0.10	−0.07	−0.01	−0.17	−0.47	−0.57
	(1.96)	(−1.08)	(−0.07)	(−0.8)	(−1.79)	(−2.03)
FF5+PSS	0.03	0.06	0.07	0.00	−0.39	−0.41
	(0.61)	(0.99)	(0.55)	(0.00)	(−1.76)	(−1.77)

This table presents univariate portfolio results from sorting stocks into quintile portfolios based on EIGMB and EISKEW. The first row displays the average EIGMB or EISKEW of individual stocks in each quintile. The row labeled "Ret" reports the average value-weighted excess returns of each quintile. The row labeled "% Mkt Share" shows the equity value of each quintile portfolio divided by total market capitalization. The remaining rows present the risk-adjusted returns (alphas) relative to different factor models, including the FF3 model, the q-factor model, the FF5 model, the FF5 model augmented with the FVIX factor, and the FF5 model augmented with the PSS factor. 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.

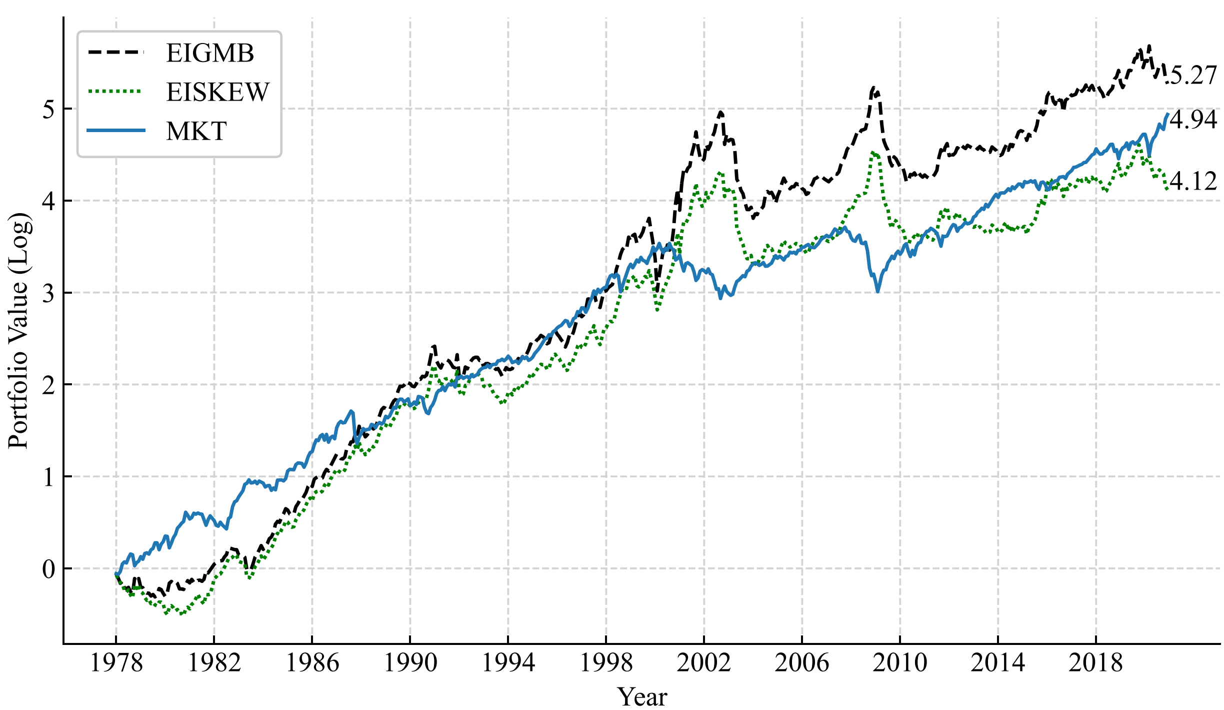

Fig. 2. Cumulative Portfolio Gains.
This figure shows the log cumulative monthly portfolio value for the MKT factor and value-weighted long–short portfolio based on the expected idiosyncratic good minus bad volatility (EIGMB) and expected idiosyncratic skewness (EISKEW) from Jan 1978 to December 2020. The final log portfolio value is 5.27 for EIGMB strategy, 4.12 for EISKEW strategy, and 4.94 for MKT factor, respectively. All portfolios are rebalanced and reinvested monthly, as described in the main text.

Table 5
Bivariate dependent-sort portfolio analysis.

Panel A. Sorted by EIGMB Controlling for EISKEW

EISKEW	EIGMB quintiles					5–1	FF3 alpha
	1	2	3	4	5		
1	0.91	0.75	0.81	0.84	0.90	−0.01	−0.17
	(3.98)	(3.78)	(4.3)	(4.18)	(3.61)	(−0.06)	(−0.86)
2	0.80	0.72	0.89	0.84	0.53	−0.27	−0.41
	(4.18)	(3.25)	(3.44)	(3.05)	(1.75)	(−1.20)	(−1.96)
3	0.71	0.74	0.66	0.53	0.51	−0.20	−0.58
	(3.04)	(2.60)	(2.10)	(1.54)	(1.21)	(−0.61)	(−2.16)
4	0.55	0.83	0.69	0.34	−0.09	−0.65	−0.91
	(1.85)	(2.36)	(1.71)	(0.82)	(−0.21)	(−2.19)	(−3.78)
5	0.64	0.19	0.42	−0.14	−0.81	−1.46	−1.32
	(1.66)	(0.42)	(0.97)	(−0.27)	(−1.46)	(−3.88)	(−3.49)
Avg	0.72	0.65	0.69	0.48	0.21	−0.52	−0.68
	(3.09)	(2.45)	(2.41)	(1.51)	(0.56)	(−2.50)	(−4.13)

Panel B. Sorted by EISKEW Controlling for EIGMB

EIGMB	EISKEW quintiles					5–1	FF3 alpha
	1	2	3	4	5		
1	1.04	0.68	0.75	0.83	0.72	−0.32	−0.42
	(4.21)	(3.24)	(3.98)	(4.46)	(3.65)	(−1.81)	(−2.22)
2	0.91	0.78	0.70	0.79	0.69	−0.21	−0.21
	(3.65)	(3.02)	(3.04)	(3.35)	(2.87)	(−1.14)	(−1.08)
3	0.51	0.70	0.69	0.64	0.55	0.04	−0.03
	(1.62)	(2.33)	(2.39)	(2.13)	(1.86)	(0.22)	(−0.17)
4	0.49	0.52	0.40	0.84	0.65	0.16	0.20
	(1.06)	(1.36)	(1.11)	(2.32)	(1.67)	(0.50)	(0.74)
5	−0.23	0.27	0.05	0.03	−0.42	−0.20	−0.01
	(−0.46)	(0.58)	(0.11)	(0.06)	(−0.94)	(−0.66)	(−0.02)
Avg	0.54	0.59	0.52	0.63	0.44	−0.10	−0.09
	(1.70)	(2.02)	(1.85)	(2.22)	(1.59)	(−0.70)	(−0.68)

This table presents the results of bivariate dependent-sorts. In Panel A, we first sort stocks into quintile portfolios based on EISKEW. Within each EISKEW quintile, stocks are further sorted into quintile portfolios based on EIGMB. In Panel B, we first stocks into quantile portfolios based on EIGMB and then on EISKEW. The column labeled "5–1" reports the difference in returns between quintile 5 and quintile 1. The column labeled "FF3 alpha" reports the average FF3 model adjusted alphas. The corresponding (Newey and West, 1987) robust *t*-statistics with 6 lags are reported in parentheses. The row "Avg" presents the average return differences between portfolios with high and low EIKSEW (EIGMB) across EIGMB (EISKEW) portfolios.

Table 6
Fama–Macbeth regressions of stock returns on EIGMB and control variables.

	BETA	SIZE	BM	EIGMB	EISKEW	GO	MOM	ROE	AG	$IVOL_{1m}$	COSKEW	MAX
1	0.027	−0.281	0.129	−6.115								
	(0.20)	(−8.43)	(2.14)	(−4.47)								
2	−0.002	−0.261	0.137		−0.585							
	(−0.02)	(−7.57)	(2.24)		(−4.72)							
3	−0.021	−0.147	0.124			−0.095						
	(−0.15)	(−3.73)	(2.13)			(−2.21)						
4	0.034	−0.291	0.135	−7.486	0.040							
	(0.28)	(−8.65)	(2.33)	(−2.04)	(0.12)							
5	0.046	−0.299	0.112	−7.140		−0.048						
	(0.35)	(−9.03)	(1.97)	(−5.59)		(−1.24)						
6	0.033	−0.293	0.137	−6.209		−0.008	0.346	0.145	−0.455			
	(0.28)	(−9.31)	(2.52)	(−4.71)		(−0.22)	(2.15)	(2.73)	(−6.14)			
7	0.098	−0.302	0.145	−5.787		0.013	0.352	0.171	−0.466	−11.444		
	(0.87)	(−9.80)	(2.66)	(−5.01)		(0.36)	(2.24)	(3.23)	(−6.34)	(−3.97)		
8	0.020	−0.294	0.139	−5.855		−0.007	0.370	0.145	−0.461		−0.378	
	(0.17)	(−9.39)	(2.57)	(−4.50)		(−0.18)	(2.41)	(2.79)	(−6.30)		(−3.24)	
9	0.110	−0.295	0.145	−4.859		0.011	0.317	0.174	−0.462			−4.394
	(0.96)	(−9.46)	(2.64)	(−4.02)		(0.29)	(1.98)	(3.25)	(−6.21)			(−6.50)
10	0.084	−0.274	0.150	−5.102		0.008	0.378	0.173	−0.470	9.322	−0.367	−6.833
	(0.74)	(−9.12)	(2.78)	(−4.48)		(0.23)	(2.52)	(3.30)	(−6.56)	(2.01)	(−3.22)	(−6.57)

This table reports the slope coefficients and (Newey and West, 1987) *t*-statistics with 6 lags (in parentheses) from FM regressions of firm-level stock returns on EIGMB and control variables. $IVOL_{1m}$ is the idiosyncratic volatility, estimated with a horizon of 1 month as in Ang et al. (2006b); COSKEW is the co-skewness as in Harvey and Siddique (2000).

Table 7
Long–short portfolios based on EIGMB and EISKEW across subperiods.

	High			Low		
	EIGMB	EISKEW	Diff	EIGMB	EISKEW	Diff
Ret	0.51	0.17	0.34	1.41	1.24	0.17
	(1.32)	(0.43)	(2.50)	(2.55)	(2.65)	(0.96)
FF3	0.86	0.52	0.34	1.72	1.62	0.10
	(3.19)	(1.75)	(2.62)	(4.53)	(4.58)	(0.74)
q-factor	0.32	−0.01	0.33	0.60	0.73	−0.13
	(1.22)	(−0.04)	(2.50)	(1.99)	(2.28)	(−0.87)
FF5	0.43	0.12	0.31	0.85	0.99	−0.14
	(1.85)	(0.44)	(2.29)	(2.96)	(2.93)	(−1.18)

We classify months into periods of high (low) relative forecast accuracy when the DM statistic is above (below) its time-series median. This table reports the excess returns and factor-model adjusted alphas for long–short portfolios that buy stocks in the lowest quintile of EIGMB (or EISKEW) and sell those in the highest quintile across subperiods. The column labeled "Diff" reports the difference in returns between the long–short portfolios based on EIGMB and EISKEW. The corresponding (Newey and West, 1987) robust t-statistics with 6 lags are reported in parentheses.

4. Drivers of the relationship between expected idiosyncratic good minus bad volatility and stock returns

In this section, we focus on the drivers of the cross-sectional relationship between EIGMB and future stock returns. First, we investigate whether the predictive power of EIGMB for returns is related to its accuracy as a measure of conditional idiosyncratic skewness. Second, we break down EIGMB to identify the key characteristics driving the predictive power of EIGMB. Finally, we investigate whether the predictive power of EIGMB arises from good or bad jumps.

4.1. The role of forecast accuracy

The Diebold–Mariano (DM) statistics in Section 2.4 assesses, on a month-by-month basis, the differences in forecast errors between EIGMB and EISKEW in predicting future realized idiosyncratic skewness. A higher DM statistic indicates that EIGMB is more accurate than EISKEW. We classify months into periods of high (low) relative forecast accuracy when the DM statistic is above (below) its time-series median.

Table 7 shows value-weighted returns and factor-model adjusted alphas for long–short portfolios that buy stocks in the lowest quintile of EIGMB (or EISKEW) and sell those in the highest quintile during these subperiods. In periods of relatively high forecast accuracy, the alphas of the long–short portfolios sorted by EIGMB are about 0.31% higher than those sorted by EISKEW. This difference is substantial and highly significant. In contrast, in periods when the forecast accuracy of EIGMB and EISKEW is similar, differences in average returns between long–short portfolios sorted by EIGMB and EISKEW are small and statistically not significant. These results suggest a positive link between the predictive power of the EIGMB and its accuracy in forecasting future realized idiosyncratic skewness.

4.2. Dissecting expected idiosyncratic good minus bad volatility

To shed light on the role each specific characteristic plays in driving the predictive power of EIGMB for returns, we exclude one characteristic at a time from Eqs. (8) and (9) and re-estimate EIGMB using the remaining characteristics. Then we sort stocks into value-weighted quintile portfolios based on these re-estimated EIGMB.[10]

Table 9 presents the average returns and FF5 alphas of long–short portfolios sorted by EIGMB while omitting different characteristics. Excluding one characteristic at a time produces highly significant FF5 alphas, ranging from −0.53% to −0.80% per month, suggesting that no single predictor fully drives the predictive power of EIGMB. Even though additional characteristics beyond time-series predictors are introduced to forecast future IGMB, Table 9 shows that lagged realized IGMB and IVOL still capture part of the variation in EIGMB.

We also find that return on equity (ROE) and momentum are two important elements of variation in EIGMB that contribute to the excess returns of EIGMB-sorted portfolios. We find that removing variation in EIGMB that is related only to ROE or momentum largely reduces the risk-adjusted returns of portfolio sorted by EIGMB. High-ROE firms make more profits, meaning that a smaller proportion of their firm value is derived from growth options. Trigeorgis and Lambertides (2014) and Del Viva et al. (2017) argue that the flexibility of growth options may enhance a firm's upside value potential and reduce downside risk in bad economic states. Such asymmetry could result in returns with large positive payoffs and less extreme negative ones, enhancing the idiosyncratic skewness of firm stock returns. In terms of momentum, we find that when past returns have been high, EIGMB is predicted to be lower, which is consistent with the finding of Chen et al. (2001) that past returns are negatively related to the negative skewness of firm stock returns.

However, removing certain predictors, such as GO and AG, does not reduce the predictive power of EIGMB. GO measures the proportion of a firm's value derived from growth options, which involves projecting future profits and applying proper discount rates. Our calculations show that variation in EIGMB that is related only to GO is weakly associated with stock returns. Similarly, variation in EIGMB associated with asset growth (AG), which proxies for the exercise of growth opportunities, also does not predict excess returns.

In addition, using turnover as a proxy for differences of opinions (Hong and Stein, 2003), we find that turnover is negatively related to EIGMB and removing turnover only moderately reduces the predictive power of EIGMB.

4.3. Good jumps and bad jumps

We decompose idiosyncratic good minus bad volatility into good and bad components to study whether the negative relationship between EIGMB and future returns arises from good or bad jumps. The decomposition is as follows:

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

where $BV_{i,t}$ is the realized bipower variation (see Barndorff-Nielsen and Shephard, 2006 or the Appendix). We thus define the idiosyncratic good jump component and idiosyncratic bad jump component as[11]

$$IGJ_{i,t} \equiv \frac{(IV^{+}_{i,t} - BV_{i,t}/2)}{IV_{i,t}}, \tag{11}$$

$$IBJ_{i,t} \equiv \frac{(BV_{i,t}/2 - IV^{-}_{i,t})}{IV_{i,t}}. \tag{12}$$

[10] We thank an anonymous referee for suggesting this approach.

[11] In the Appendix, we briefly outline theoretical results that support the decomposition of idiosyncratic good minus bad volatility into good and bad jumps.

Table 8
Cross-sectional regression of future returns on EIGJ, EIBJ and control variables.

	BETA	SIZE	BM	EIGJ	EIBJ	GO	MOM	ROE	AG	IVOL_{1m}	COSKEW	MAX
1	−0.003	−0.237	0.120	−6.041								
	(−0.02)	(−6.59)	(2.03)	(−3.65)								
2	0.033	−0.196	0.163		−9.099							
	(0.25)	(−5.10)	(2.74)		(−3.23)							
3	0.055	−0.276	0.143	−5.665	−7.935							
	(0.42)	(−7.95)	(2.51)	(−3.64)	(−3.04)							
4	−0.021	−0.147	0.124			−0.095						
	(−0.15)	(−3.73)	(2.13)			(−2.21)						
5	0.012	−0.249	0.104	−6.857		−0.061						
	(0.09)	(−7.05)	(1.83)	(−4.59)		(−1.59)						
6	0.051	−0.206	0.141		−10.428	−0.078						
	(0.39)	(−5.54)	(2.52)		(−3.99)	(−1.98)						
7	0.073	−0.290	0.126	−6.594	−8.705	−0.058						
	(0.57)	(−8.42)	(2.29)	(−4.55)	(−3.42)	(−1.52)						
8	0.052	−0.287	0.156	−5.343	−8.134	−0.021	0.346	0.147	−0.478			
	(0.45)	(−8.75)	(2.99)	(−3.62)	(−3.06)	(−0.55)	(2.14)	(2.83)	(−6.32)			
9	0.105	−0.299	0.166	−4.727	−7.687	−0.002	0.360	0.174	−0.487	−11.711		
	(0.94)	(−9.62)	(3.18)	(−3.19)	(−3.15)	(−0.04)	(2.28)	(3.34)	(−6.52)	(−4.00)		
10	0.040	−0.287	0.157	−4.881	−8.082	−0.020	0.372	0.149	−0.483		−0.394	
	(0.35)	(−8.81)	(3.05)	(−3.35)	(−3.06)	(−0.53)	(2.41)	(2.91)	(−6.47)		(−3.43)	
11	0.113	−0.295	0.164	−4.548	−5.132	−0.002	0.325	0.175	−0.476			−4.459
	(1.00)	(−9.23)	(3.11)	(−3.05)	(−2.09)	(−0.04)	(2.02)	(3.35)	(−6.31)			(−6.68)
12	0.089	−0.270	0.169	−4.085	−6.607	−0.006	0.390	0.176	−0.487	9.052	−0.383	−6.803
	(0.79)	(−8.91)	(3.27)	(−2.77)	(−2.75)	(−0.18)	(2.58)	(3.41)	(−6.69)	(1.92)	(−3.45)	(−6.57)

This table reports the slope coefficients and (Newey and West, 1987) t-statistics with 6 lags (in parentheses) from FM regressions of firm-level stock returns on EIGJ, EIBJ, and control variables.

Table 9
Univariate portfolio sorts based on EIGMB excluding certain characteristics.

		EIGMB excluding predictor										
	EIGMB	IGMB	IVOL	GO	AG	MAX	MOM	TURN	ROE	SIZE	EXCH	INDU
5 − 1	−0.91	−0.82	−0.72	−0.96	−0.93	−0.88	−0.72	−0.86	−0.72	−0.83	−0.95	−0.87
	(−2.60)	(−2.18)	(−2.11)	(−2.86)	(−2.76)	(−2.54)	(−2.06)	(−2.48)	(−2.15)	(−2.51)	(−2.76)	(−2.53)
FF5	−0.72	−0.64	−0.53	−0.80	−0.80	−0.74	−0.54	−0.75	−0.56	−0.67	−0.79	−0.65
	(−3.68)	(−3.11)	(−2.58)	(−3.88)	(−3.76)	(−3.56)	(−2.75)	(−3.50)	(−2.45)	(−3.36)	(−3.73)	(−3.29)

This table reports the average value-weighted returns and FF5 alphas of long–short (5 − 1) portfolios sorted on EIGMB excluding certain characteristics. We exclude one characteristic (name in column) at a time from Eqs. (8) and (9) and re-estimate EIGMB using remaining characteristics. We then sort stocks into quintile portfolios based on re-estimated EIGMB. For comparison, the first column reports the performance of the original EIGMB sorted portfolio. The corresponding (Newey and West, 1987) robust t-statistics with 6 lags are reported in parentheses.

Using the same methods as in Section 2.2, we compute the expected idiosyncratic good jump (EIGJ) and expected idiosyncratic bad jump (EIBJ). Fig. 3 presents the time-series percentiles of EIGJ, and EIBJ. Over the sample period, the median of EIGJ ranges from 0.1 to 0.2, while the median of EIBJ is close to zero. The averages of the standard deviations of EIGJ and EIBJ are 0.053 and 0.031, respectively. This suggests that variation in EIGMB is primarily driven by EIGJ.

Table 8 presents the results of month-by-month FM regressions of firm stock returns on EIGJ and EIBJ. The slope coefficients of EIGJ and EIBJ are both negative and significant. Although the regression coefficient of EIBJ is slightly higher than that of EIBJ, the overall impact of EIBJ on returns is limited due to the relatively smaller variation in EIBJ. Therefore, downside risk, as proposed by Gul (1991) and Ang et al. (2006a), does not play a large role in driving the predictive power of EIGMB. Furthermore, in the Appendix, we conduct portfolio sorts to investigate the predictive power of each component. We find that the predictive power of each component alone is significantly weaker than that of EIGMB, which suggests that both EIGJ and EIBJ are important components of EIGMB.

5. Further analysis

In this section, we explore whether the predictive power of EIGMB for returns is influenced by the choice of factor models and estimation horizons used to decompose stock returns into systematic and idiosyncratic components. We also examine how our results relate to the predictive power of growth options (GO) for returns. Additionally, we investigate whether our findings are linked to good and bad macroeconomic uncertainty and whether sentiment affects the relationship between EIGMB and cross-sectional stock returns.

5.1. Different factor models and window lengths for constructing EIGMB

Following Boyer et al. (2010), we estimate EIGMB using a five-year window and the three-factor model of Fama and French (1993) as the benchmark. To demonstrate that our analysis is robust to different window lengths, we also report results of $T = 12$, 24, 36, 48, and 72 months when constructing EIGMB using Eq. (1).

Panel A of presents value-weighted returns and alphas of EIGMB quintile-sorted portfolios for different estimation windows. As the estimation horizon increases from 12 to 72 months, the return difference between the highest and lowest EIGMB portfolios ranges from −0.72% to −0.93%, with significant alphas after adjusting for FF5 model. Longer estimation windows, such as 60 or 72 months, generally yield more significant return spreads. Shorter windows, such as 12 months, however, are associated with weaker predictive power for future returns. Although using shorter windows might better capture the time variation in EIGMB, such potential gain seems to be outweighed by the statistical uncertainty of measuring EIGMB over short horizons. Therefore, we opt for an estimation horizon of 60 months, as used by Boyer et al. (2010).

We also consider a few systematic factors, including the q-factors of Hou et al. (2015), the five factors of Fama and French (2015), and factors extracted using principal component analysis (PCA) and Lettau

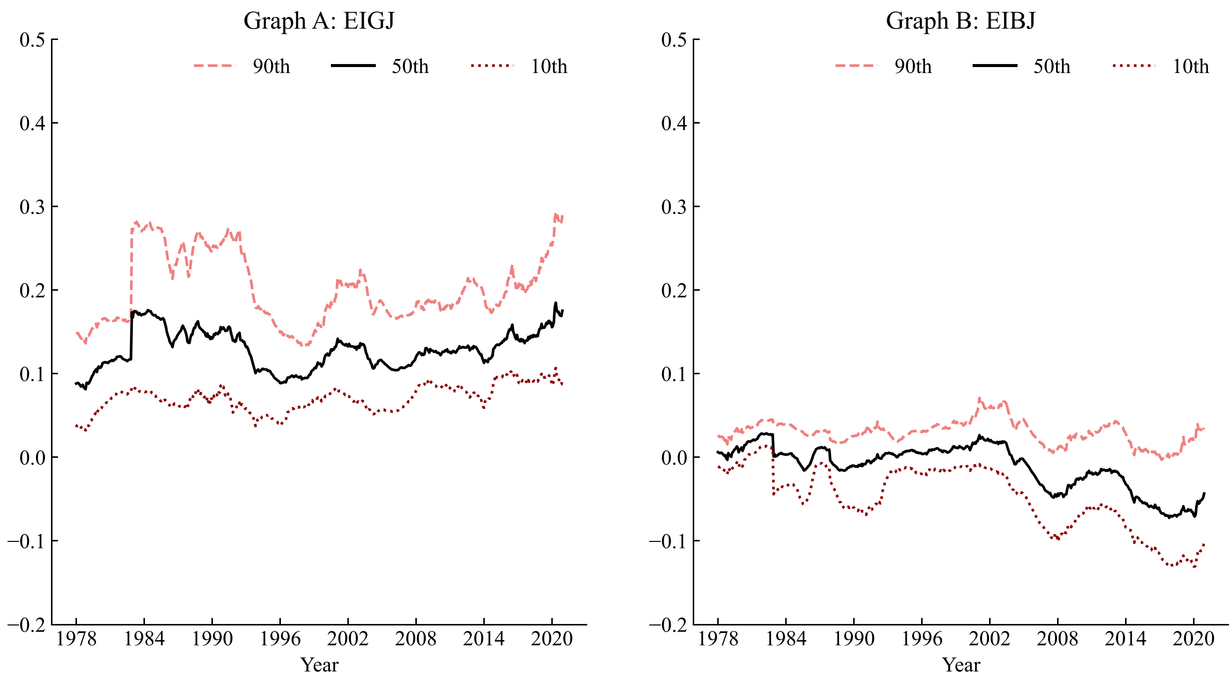

Fig. 3. Expected Idiosyncratic Good and Bad Jumps.
Graphs A and B display the 10th, 50th, and 90th percentiles of expected idiosyncratic good jump (EIGJ) and expected idiosyncratic bad jump (EIBJ).

Table 10
Univariate portfolio sorts: Different methods of estimating idiosyncratic volatility.

Panel A. Different Estimation Horizons						
	12 months	24 months	36 months	48 months	60 months	72 months
5−1 return	−0.72	−0.78	−0.82	−0.85	−0.91	−0.93
	(−2.09)	(−2.15)	(−2.22)	(−2.38)	(−2.60)	(−2.74)
FF5 alpha	−0.47	−0.54	−0.58	−0.63	−0.72	−0.75
	(−2.23)	(−2.64)	(−2.74)	(−3.25)	(−3.68)	(−3.52)
Panel B. Different Factor Models						
	Total	FF3	q−factor	FF5	PCA5	RPPCA5
R^2		14.41	14.42	14.48	15.82	15.83
5−1 return	−0.84	−0.91	−0.89	−0.91	−0.94	−0.94
	(−2.37)	(−2.60)	(−2.57)	(−2.61)	(−2.72)	(−2.71)
FF5 alpha	−0.62	−0.72	−0.70	−0.73	−0.76	−0.76
	(−3.13)	(−3.68)	(−3.60)	(−3.67)	(−3.69)	(−3.68)

Panel A presents average excess returns and risk-adjusted alphas from sorting on EIGMB using different estimation horizons. Panel B reports results from calculating idiosyncratic volatility as per Eq. (1) with different systematic factors. The row "R^2" presents the average R^2 (in percentage terms) from regressing firm stock returns against different systematic factors. "Total" stands for using the raw excess returns without adjusting for systematic risk factors. The last two rows in Panel B present average returns and risk-adjusted alphas for long–short portfolios sorted by EIGMB controlling for different systematic factors.

and Pelger's (2020) risk premia principle component analysis (RPPCA) to calculate idiosyncratic volatility.[12] As in Section 2.2, we then compute EIGMB and expected good minus bad volatility (EGMB) using total firm volatility.

Panel B of presents the return spreads between the highest and lowest quintile portfolios across different volatility measures. When we sort on EGMB instead of EIGMB, the difference in average returns between the extreme quintile portfolios is 0.84%. Sorting on EIGMB yields larger return spreads. For example, the FF3 model generates an average return difference of 0.91%, and the PCA-based models produce the largest return difference of 0.94%. If a cross-sectional relationship between EIGMB and stock returns exists, better accounting for the systematic components should reduce measurement errors in EIGMB and increase the returns spreads between EIGMB-sorted portfolios. Overall, this argument is consistent with the magnitude of the average R^2 of time-series regressions in the manner of Eq. (1) reported in Panel B of . Of these five models, the PCA-based models produce the largest R^2 of approximately 15.83%, while the FF3 model yields an R^2 of 14.41%. Therefore, using distinct factor models to estimate idiosyncratic volatility reinforces our finding that EIGMB matters for cross-sectional stock returns.

5.2. *Growth options and stock returns*

We next examine how EIGMB relates to the findings of Del Viva et al. (2017) regarding GO and stocks returns. Following their approach, GO is computed as the percentage of firm market value that derives from future growth opportunities. Table 6 confirms that GO exhibits a significant negative relation with subsequent stock returns.

[12] Thanks to an anonymous referee for suggesting the PCA approach. We draw on the large cross-section of characteristics from Gu et al. (2020) and, following Lettau and Pelger (2020), extract five factors by running PCA and RPPCA from single-sorted decile anomaly portfolios.

Table 11
Cross-sectional regressions of stock returns on GO and exposure to macroeconomic uncertainty.

	BETA	SIZE	BM	GO	β_{bv}	β_{gv}	EIGMB
1	−0.051	−0.136	0.130	−0.094			
	(−0.37)	(−3.44)	(2.20)	(−2.16)			
2	−0.053	−0.148	0.079	−0.103	−0.019		
	(−0.39)	(−3.73)	(1.29)	(−2.42)	(−2.52)		
3	−0.067	−0.146	0.079	−0.102		0.021	
	(−0.49)	(−3.68)	(1.32)	(−2.40)		(2.33)	
4	−0.055	−0.159	0.050	−0.106	−0.025	−0.008	
	(−0.41)	(−4.03)	(0.83)	(−2.49)	(−1.77)	(−0.47)	
5	0.002	−0.295	0.042	−0.063	−0.029	−0.013	−6.445
	(0.02)	(−8.91)	(0.70)	(−1.66)	(−2.13)	(−0.79)	(−5.02)

This table reports the slope coefficients and (Newey and West, 1987) t-statistics with 6 lags (in parentheses) from FM regressions of firm-level stock returns on GO, betas for bad and good macroeconomic uncertainty and control variables that are previously defined.

Earlier studies provide several explanations for why growth options earn lower returns. For example, (Novy-Marx, 2010, 2013) suggests that growth options tend to have lower returns than assets-in-place because the latter are associated with higher operating leverage and adjustment costs, which increase their risk and expected returns. Del Viva et al. (2017) posit that actively managed firms have real options leading to convex payoffs since protective put options reduce downside risk, whereas growth options preserve and enhance upside potential. As a result, this dynamic asset adaptation process creates a convex payoff that enhances idiosyncratic skewness.

When both EIGMB and GO are included in the regression, the coefficient for GO becomes insignificant. This finding supports the argument of Del Viva et al. (2017) that growth options are negatively related to stock returns because investors favor the positively skewed profile of growth options.

Table 8 further examines which component of EIGMB drives this result. When EIGJ is included in the regression, the coefficient of GO diminishes and becomes insignificant. However, when controlling only for EIBJ, the coefficient of GO is reduced but remains significant with a t-statistic of −1.98. Therefore, the predictive power of GO mainly relates to the idiosyncratic skewness coming from positive jumps.

5.3. Good and bad macroeconomic uncertainty

We investigate whether good and bad macroeconomic uncertainty are useful for explaining the relationship between growth options (GO) and cross-sectional stock returns. Following the empirical procedures of Segal et al. (2015), we construct measures of expected consumption growth (CG_t) and good and bad macroeconomic uncertainty (V_g and V_b).[13]

To measure the risk exposure of each stock to good and bad uncertainty, we first estimate "pre-ranking" betas using data from the previous five years:

$$r_{i,t} = \alpha_i + \beta_{i,cg} CG_t + \beta_{i,gv} V_{g,t} + \beta_{i,bv} V_{b,t} + \epsilon_{i,t}, \tag{13}$$

where $r_{i,t}$ is the annual excess returns for stock i in year t, and the expected consumption growth CG_t is included as a control. Then, we independently sort stocks into five portfolios according to size, five portfolios according to good uncertainty beta, and five portfolios according to bad uncertainty beta. In this way, 125 value-weighted portfolios are formed from the intersection of the three independent sorts. Lastly, following Fama and French (1992), we estimate the uncertainty betas of these portfolios as per Eq. (13) over the full sample and use them as the betas of individuals stocks in these portfolios.

Table 11 shows the time-series averages of the slopes from month-by-month FM regressions of firm-level stock returns on good and bad macroeconomic uncertainty betas and other variables. As in Segal et al. (2015), the slope coefficient of bad (good) macroeconomic uncertainty is negative (positive). However, controlling for good and bad macroeconomic uncertainty betas has minimal impact on the coefficient of GO. By contrast, when EIGMB is included in the regression, the slope coefficient for GO becomes insignificant. Therefore, exposure to macroeconomic uncertainty does not capture the role of EIGMB in explaining the return patterns of growth options.

5.4. Skewness and market sentiment

We investigate the role of market sentiment in driving the relationship between EIGMB and future stock returns. Stambaugh et al. (2012) suggest that in the presence of short-selling constraints, long–short strategies that exploit anomalies are more profitable following high levels of sentiment. Moreover, the short leg of the strategy is more profitable following high sentiment, whereas the long leg is not. We estimate the following time-series regression:

$$R_{i,t} = a + b_i * S_{t-1} + \mu_t \tag{14}$$

where $R_{i,t}$ is excess return or risk-adjusted return in month t of the high-EIGMB portfolio, the low-EIGMB portfolio or the difference, i.e., the long–short portfolio; S_{t-1} is the level of the investor-sentiment index of Baker and Wurgler (2006) in month $t-1$; and μ_t is the residual term. Panel A of Table 12 reports that the slope coefficient is significantly negative for the long–short portfolio, showing that the EIGMB anomaly is stronger following periods of high market sentiment. While the slope coefficient is significantly negative for the high-EIGMB portfolio, it is negative but insignificant for the low-EIGMB portfolio. This indicates that the short leg of the long–short portfolio is more profitable following high sentiment, whereas the long leg is not. Panel B of Table 12 further controls for the FF5 factors, and the results remain qualitatively similar. Overall, our findings are consistent with the setting of Stambaugh et al. (2012) in which stocks with high EIGMB are overpriced.

6. Conclusion

We decompose idiosyncratic volatility into good and bad components and estimate a cross-sectional model for EIGMB. EIGMB outperforms EISKEW and standard time-series models in capturing conditional idiosyncratic return asymmetry. Meanwhile, EIGMB exhibits a strong negative relationship with future stock returns, even after controlling for EIKSEW and exposure to systematic-skewness-related factors.

Langlois (2020) argues that idiosyncratic skewness *per se* is less relevant for predicting future returns compared with systematic skewness. We find that the idiosyncratic component predominantly drives variation in total good minus bad volatility. Moreover, the return spread of EIGMB-sorted portfolios is more pronounced when the systematic component of firm stock returns is effectively controlled for.

We investigate the role each specific characteristic plays in driving the predictive power of EIGMB for future stock returns, finding

[13] The Appendix describes our construction in detail.

Table 12
Investor sentiment and performance of EIGMB portfolios.

	1	5	5–1
Excess Returns	−0.30	−2.63	−2.33
	(−1.29)	(−4.01)	(−4.39)
Risk-Adjusted Returns	0.23	−1.00	−1.23
	(4.03)	(−2.80)	(−3.27)

This table reports slope coefficients and t-statistics for the sentiment index. We use the FF5 model to adjust for risk.

that return on equity and momentum are two important elements of variation in EIGMB. Our decomposition of EIGMB into good jump (EIGJ) and bad jump (EIGJ) components also reveals that the good jump component primarily drives variation in EIGMB. Even though the regression coefficient of EIBJ in predicting future returns is slightly larger than that of EIGJ, downside risk plays a limited role in the predictive power of EIGMB for returns.

CRediT authorship contribution statement

Yunting Liu: Writing – review & editing, Methodology, Investigation, Conceptualization. **Yandi Zhu:** Writing – original draft, Validation, Software, Formal analysis.

Appendix A. Brief theoretical analysis of the decomposition

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 follows a jump diffusion process. We mainly rely on Barndorff-Neilsen et al. (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 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,

$$RV_t = \sum_{i=1}^{n} r^2_{t-1+i/n} \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1\le\tau\le t} J_\tau^2.$$

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:

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

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

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

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

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, and 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.

$$RSK_t \equiv \sum_{i=1}^{n} r^3_{t-1+i/n} \xrightarrow{p} \sum_{t-1\le\tau\le t} J_\tau^3 \quad \text{as } n\to\infty \tag{A.2}$$

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 the sign of the average jumps matters: firms with more positive jumps on average will have positive skewness.

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

$$BV_t \equiv \sum_{i=2}^{n} |r_{t-1+i/n}||r_{t-1+i/n-1/n}| \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 ds \quad \text{as } n\to\infty. \tag{A.3}$$

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

Appendix B. Variable definitions

- **Market Beta (BETA)**. The market beta of individual stocks is estimated over a one-year period using the capital asset pricing model (CAPM) model.
- **Size (SIZE)**. The log value of stock's market capitalization.
- **Book-to-market ratio (BM)**. Book equity is total shareholders' equity (Compustat item SEQ) plus deferred taxes (Compustat item TXDB) minus the book value of preferred stocks. A stock's BM is the ratio of book equity to market capitalization.
- **Asset growth (AG)**. The percent change in firm's total assets (Compustat item AT) over the previous year.
- **Growth options (GO)**. Following Trigeorgis and Lambertides (2014) and Del Viva et al. (2017), this growth-option measure is defined as the percentage of firm market value ($V_{i,t}$) that derives from future growth opportunities ($PVGO_{i,t}$):

$$GO_{i,t} \equiv \frac{PVGO_{i,t}}{V_{i,t}} = 1 - \frac{CF_{i,t}/V_{i,t}}{k_{i,t}}. \tag{B.1}$$

where $CF_{i,t}$ denotes operating cash flow and $k_{i,t}$ is firm i's weighted-average cost of capital (WACC). $CF_{i,t}$ is measured as the

free operating cash flow under a no-further-growth policy where capital expenditures equal depreciation.[14] To estimate WACC, we use the market model with a beta of 1, adding a 6% market risk premium to the risk-free return for all firms. This simple setup avoids relying on the empirical validity of CAPM. We estimate a firm's cost of debt as 4% less than its cost of equity. Effective tax rates τ are current taxes (Compustat item TXC) divided by pretax income (Compustat item PI). The WACC is then estimated as COST_EQUITY $\times(1-\mathrm{LEV}_t)+$ COST_DEBT $\times\mathrm{LEV}_t(1-\tau)$, where the leverage LEV_t is calculated as the ratio of total liabilities (Compustat item LT) to the market value of the firm (the sum of market capitalization and total liabilities).
- **Return on equity (ROE)**. The ratio of income before extraordinary items (Compustat item IBQ) to book equity.
- **Maximum daily return (MAX)**. The maximum daily return observed in the previous month.
- **Turnover (TURN)**. The ratio of trading volume to total shares outstanding.
- **Momentum (MOM)**. Momentum returns are the cumulative compounded stock returns over previous 11 months skipping the most recent month.
- **Size dummies (SMALL and BIG)**. Binary dummies for SMALL (bottom 30%) and BIG (top 30%) firms built on market capitalization observed in the previous month.
- **Exchange dummy (EXCH)**. A binary indicator equals one if a stock is listed on National Association of Securities Dealers Automated Quotations (NASDAQ) exchange.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbankfin.2024.107343.

Data availability

The authors do not have permission to share data.

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[14] Under a no-growth policy, capital expenditures roughly equal depreciation. This leads to estimating CF 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).