Expected Idiosyncratic Skewness

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We test the prediction of recent theories that stocks with high idiosyncratic skewness should have low expected returns. Because lagged skewness alone does not adequately forecast skewness, we estimate a cross-sectional model of expected skewness that uses additional predictive variables. Consistent with recent theories, we find that expected idiosyncratic skewness and returns are negatively correlated. Specifically, the Fama-French alpha of a low-expected-skewness quintile exceeds the alpha of a high-expected-skewness quintile by 1.00% per month. Furthermore, the coefficients on expected skewness in Fama-MacBeth cross-sectional regressions are negative and significant. In addition, we find that expected skewness helps explain the phenomenon that stocks with high idiosyncratic volatility have low expected returns. (*JEL* D03, G11, G12)

Finance research has a long history of investigating the impact of return skewness on investor decision making. Arditti (1967) and Scott and Horvath (1980) show that under very general assumptions, investors demonstrate a preference for positive skewness in return distributions. Building on these results, Kraus and Litzenberger (1976) and Harvey and Siddique (2000) show that an asset's coskewness with the market portfolio should be priced in a representative agent framework. Because these studies are set in the context of fully diversified investors, they imply that a stock's idiosyncratic skewness should be irrelevant. However, others have noted that because diversification erodes skewness exposure, some investors may remain underdiversified in order to capture return skewness, and thus idiosyncratic skewness may be relevant (see Simkowitz and Beedles 1978; Conine and Tamarkin 1981).

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Recent theories—each starting from a different set of assumptions—concur that idiosyncratic skewness can be a priced component of stock returns. Mitton and Vorkink (2007), in a model incorporating heterogeneous investor preference for skewness, predict lower expected returns for stocks with idiosyncratic skewness. Barberis and Huang (2007) show that when investors have cumulative prospect theory preferences, stocks with greater idiosyncratic skewness may have lower average returns. Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007) solve an endogenous-probabilities model that produces similar asset pricing implications for skewness.

In this paper, we empirically investigate the pricing implications of idiosyncratic skewness. Despite the theoretical basis for the pricing effects of skewness preference, empirically testing the relation between idiosyncratic skewness and returns is not a straightforward exercise. The primary obstacle is that *ex ante* skewness is difficult to measure. As opposed to variances and covariances, idiosyncratic skewness is not stable over time (see Harvey and Siddique 1999), so variables other than lagged skewness are required to effectively measure expected skewness. We follow the approach of Chen, Hong, and Stein (2001) in using a number of firm-level variables to predict idiosyncratic skewness. We find that, although lagged skewness is an important predictor of future skewness, other firm characteristics are also important predictors of idiosyncratic skewness, including idiosyncratic volatility, a measure that has recently generated considerable interest in asset pricing. Other important predictive variables in our model include momentum and turnover (see Hong and Stein 2003; Chen, Hong, and Stein 2001), firm size, and industry designation. Our predictive model produces distinct variation in expected skewness across stocks as well as over time. The time-series variation in both realized and expected skewness appears to follow episodic behavior similar to the behavior of idiosyncratic volatility (see Campbell et al. 2001; Brandt et al. 2008).

Using our model of expected skewness, we find a strong negative cross-sectional relation between expected idiosyncratic skewness and average returns. We sort firms into quintiles based on their level of expected skewness. We find that the average returns for the low-expected-skewness quintile exceed the average returns of the high-expected-skewness quintile by 0.67% per month. After adjusting for risk, the differences in returns are even more pronounced. We find that the Fama-French (1993) alpha of the low-expected-skewness quintile exceeds the Fama-French alpha of the high-expected-skewness quintile by 1.00% per month. We confirm the pricing effects of idiosyncratic skewness by estimating Fama-MacBeth (1973) regressions, and find that expected skewness helps explain the cross-sectional variation in returns. The effect of idiosyncratic skewness is statistically significant and is robust in a number of alternative specifications. This finding is consistent with Zhang (2005), who finds a negative relation between total skewness and average returns when estimating skewness based on the cross-sectional returns of a group of comparable stocks. We perform additional tests to distinguish the separate effects of expected skewness and idiosyncratic volatility, and find that each has significant explanatory power for expected returns independent of the other.

We also explore whether the time-series variation in expected skewness is related to the time-series variation in the expected skewness risk premium. We find that the periods in which the cross-sectional estimate of the expected skewness premium is most significant and negative correspond to periods in which the level and dispersion of expected skewness is high and in which our model of predicted skewness fits the data well (high R^2). One interpretation of these relations is that the pricing of skewness is strongest in those periods in which there are greater opportunities for skewness-preferring investors to express their preference for securities with upside potential.

Having documented the pricing implications of idiosyncratic skewness, we turn to the question of whether skewness can help explain the phenomenon that stocks with high idiosyncratic volatility have low expected returns. The negative relation between idiosyncratic volatility and future returns, which we refer to as the "*iv* puzzle," is documented in the U.S. data in Ang et al. (2006), and is shown to be present in international markets in Ang et al. (2008). The *iv* puzzle has generated substantial interest among researchers.[1] A *negative* relation between idiosyncratic volatility and expected returns is puzzling because standard theory does not account for such a relation. On one hand, if investors fully diversify, then idiosyncratic volatility should not be priced at all. On the other hand, if investors do not fully diversify, then idiosyncratic volatility should be *positively* related to the expected returns (see Merton 1987; Malkiel and Xu 2006). However, our finding that idiosyncratic volatility is a strong predictor of idiosyncratic skewness suggests a novel reason why investors may be attracted to stocks with high idiosyncratic volatility. Investors may accept lower average returns on stocks with high idiosyncratic volatility, not because they seek higher volatility, but because they have a preference for stocks with lottery-like return properties.

We conduct tests to assess the impact of skewness preference on the *iv* puzzle. Using our model of predicted skewness, we study the relation between idiosyncratic volatility and expected returns after controlling for forecasted skewness. We construct portfolios with wide dispersion in idiosyncratic volatility but low dispersion in expected idiosyncratic skewness using the conditional-sorting methodology used by Ang et al. (2008) and others. After controlling for expected idiosyncratic skewness, the relation between idiosyncratic volatility and returns is weaker. In particular, we find that the difference between the average returns of the high-idiosyncratic-volatility portfolio and the average returns of the low-idiosyncratic-volatility portfolio is much smaller and insignificant. Moreover, the difference between the Fama-French alphas of the high-idiosyncratic-volatility portfolio and the low-idiosyncratic-volatility

[1] See, for example, Bali and Cakici (2008); Huang et al. (2006); Boehme et al. (2005); Duan, Hu, and McLean (2006); Jiang, Xu, and Yao (2008); Fu (2005); and Kapadia (2006).

portfolio is reduced from 1.30% per month to 0.48% per month. Skewness preference appears to be important in explaining the low average returns of stocks with high idiosyncratic volatility. We further attempt to disentangle the separate effects of expected skewness and idiosyncratic volatility and find that, while both characteristics have independent explanatory power for expected returns, there is also some overlapping explanatory power that could be attributed to either characteristic. Although it would be difficult to determine empirically to what this overlapping portion should be properly attributed, we argue that the negative relation between expected idiosyncratic skewness and average returns has stronger theoretical support.

The rest of the paper is organized as follows. Section 1 presents the motivation for our empirical tests, focusing on the theoretical connections for skewness preference and expected returns. Section 2 reports the results of our estimation of a skewness prediction model. Section 3 investigates the pricing implications of idiosyncratic skewness. Section 4 further distinguishes between the effects of idiosyncratic skewness and volatility and explores whether skewness preference explains the negative relation between idiosyncratic volatility and expected returns. Section 5 offers concluding remarks.

1. Motivation

To motivate our empirical investigation, we draw on a number of different papers in the asset pricing literature. Speculative behavior on the part of investors, particularly individual investors, has motivated multiple theoretical models attempting to understand the impact of this type of behavior on asset prices. For example, Mitton and Vorkink (2007) develop a model of heterogeneous preference for skewness. Essential to their model is the assumption that some investors ("lotto investors") have a preference for positive skewness while others ("traditional investors") are mean-variance optimizers seeking to maximize the Sharpe ratio of their portfolios. Stock returns have exogenous second and third moments. Lotto investors place a higher value on stocks with positive idiosyncratic skewness and choose to hold underdiversified portfolios to increase their exposure to positive skewness. Markets clear at prices such that stocks with high idiosyncratic skewness have negative alphas relative to the value-weighted market portfolio. In equilibrium, both lotto investors and traditional investors choose portfolio weights such that the marginal cost of holding additional shares is equal to the marginal benefit. Thus, in Mitton and Vorkink (2007), investors hold underdiversified portfolios in equilibrium, and total skewness (including idiosyncratic skewness) is priced. Empirically, Mitton and Vorkink (2007) find their model's predictions help to explain portfolio behavior in a dataset consisting of household accounts from a large discount brokerage.

Alternatively, Barberis and Huang (2007) develop a model with investors having cumulative prospect theory preferences in which, similar to Mitton and

Vorkink (2007), holdings are heterogeneous across agents in equilibrium. In contrast to Mitton and Vorkink (2007), agents have identical preferences, but the equilibrium obtained is one where some agents hold highly underdiversified portfolios. Cumulative prospect utility theory suggests that, through a weighting function, agents overweight the probabilities in the extremes. Barberis and Huang (2007) show that when securities have return distributions that are skewed, the equilibria that result from agents having cumulative prospect theory preferences include the pricing of the idiosyncratic skewness of a stock's return.

In addition, Brunnermeier and Parker (2005) develop a structural asset pricing model in which agents optimize over beliefs of outcomes, as opposed to taking probabilities as primitives. Agents derive felicity, analogous to utility, from increasing their beliefs about probabilities above the "true" levels on high positive payoff states as long as the costs of doing so do not offset this additional utility. This optimizing behavior of agents leads to, among other predictions, a strong preference for securities with skewed distributions (see their Proposition II). Brunnermeier, Gollier, and Parker (2007) show that optimal expectations reduce the average returns of skewed assets in general equilibrium. These theoretical predictions of a negative relation between idiosyncratic skewness and expected returns motivate our empirical investigation.[2]

Since forecasting skewness is essentially an exercise in forecasting small-probability events, this exercise is inherently difficult. Although asset pricing tests often use lagged predictors of second moments (beta and volatility) as proxies for expected levels based on the widely supported assumption that second moments are persistent, this approach appears problematic for third moments. For example, Harvey and Siddique (1999) estimate models of time-varying skewness and find that a lagged measure of skewness is, at best, a weak predictor of skewness (the autoregressive parameter for monthly skewness is about -0.4). The challenge is thus to find an appropriate way to measure expected skewness.

Zhang (2005) proposes one approach to measure expected skewness in which he estimates individual stock skewness based on the recent past cross-sectional skewness of stocks in a "peer group" (such as industry). Chen, Hong, and Stein (2001) introduce another approach in which, motivated by the model of Hong and Stein (2003), they analyze predictors of firm skewness by estimating predictive regressions across a wide cross-section of stocks.[3] Our econometric approach builds upon Chen, Hong, and Stein (2001) by constructing measures

[2] The theoretical models motivating our empirical analysis predict that total (not just idiosyncratic) skewness matters to investors. We use idiosyncratic skewness as our measure of interest for two reasons. First, by focusing on the idiosyncratic component of skewness, we highlight the distinguishing features of the theoretical models motivating our empirical analysis—that investors may hold portfolios that are not well diversified and as a result care about security-specific features of the return distribution (i.e., idiosyncratic volatility and skewness). Second, by focusing on idiosyncratic skewness, we distinguish our empirical results from existing papers that investigate the pricing of skewness (e.g., Kraus and Litzenberger 1976; Harvey and Siddique 2000). As a robustness check, we conduct asset pricing tests using total return skewness and find similar results in both statistical and economic magnitude to idiosyncratic skewness.

[3] Chen, Hong, and Stein (2001) actually estimate panel models of negative skewness motivated by the crash model of Hong and Stein (2003).

of expected skewness each month for a given firm using past returns and trading volume as well as firm characteristics. Cross-sectional regression models are then used to predict skewness. Our approach also draws upon the work of Harvey and Siddique (1999) on the time-series properties of return skewness in that our model includes lagged skewness as a predictive variable.

We find, among other results, that lagged idiosyncratic volatility is a strong positive predictor of firm skewness (see also Chen, Hong, and Stein 2001; Kapadia 2006). Idiosyncratic volatility could be a strong predictor of skewness for at least three reasons. First, idiosyncratic volatility is positively related to corporate growth options (see Cao, Simin, and Zhao 2006; Barinov 2006), and the presence of growth options implies greater skewness in returns (e.g., Andrés-Alonso, Azofra-Palenzuela, and de la Fuente-Herrero 2006). Second, higher idiosyncratic volatility may be related to technological revolutions (see Pástor and Veronesi 2007), and these revolutions may lead to industry shakeouts (Jovanovic and MacDonald 1994) which in turn imply greater skewness in returns as a few winners emerge and other firms fail. Third, simply from a mechanical standpoint, limited liability of equity implies that greater volatility leads to greater skewness (e.g., Conine and Tamarkin 1981). In the next section, we use idiosyncratic volatility, as well as other variables suggested by the literature, to estimate a model of expected skewness.

2. A Skewness Prediction Model

We develop a model of expected skewness that incorporates past returns and trading volume as well as known firm characteristics. Let the investment horizon over which investors are hoping to experience an extreme positive outcome be T months, let $S(t)$ denote the set of trading days from the first day of month $t-T+1$ through the end of month t, and let $N(t)$ denote the number of days in this set.[4] Let $\epsilon_{i,d}$ be the regression residual using the Fama and French (1993) three-factor model on day d for firm i, where the regression coefficients that define this residual are estimated using daily data for days in $S(t)$. In addition, let $iv_{i,t}$ and $is_{i,t}$ denote historical estimates of idiosyncratic volatility and skewness (respectively) for firm i using daily data for all days in $S(t)$, and let k be the number of factors in the regression. We can then define $iv_{i,t}$ and $is_{i,t}$ as

$$iv_{i,t} = \left(\frac{1}{N(t)} \sum_{d \in S(t)} \epsilon_{i,d}^2 \right)^{1/2}, \tag{1}$$

$$is_{i,t} = \frac{1}{N(t)} \frac{\sum_{d \in S(t)} \epsilon_{i,d}^3}{iv_{i,t}^3}. \tag{2}$$

[4] In our construction of skewness estimates, $N(t)$ is the number of days in the set minus a degrees of freedom adjustment of one for volatility and two for skewness. Alternative choices for the adjustment to $N(t)$ cause very little difference in the pricing results.

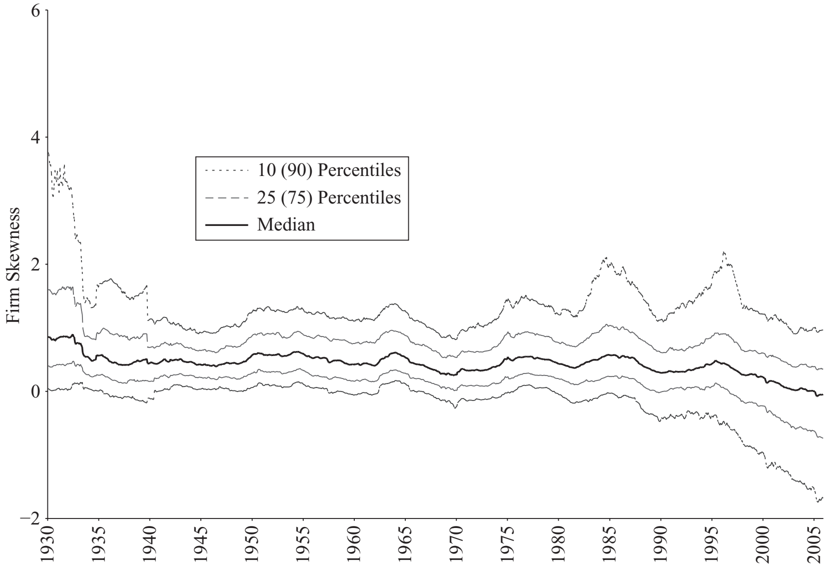

Figure 1
Cross-sectional distribution of firm-level skewness
The 10th, 25th, 50th, 75th, and 90th percentiles of the monthly cross-sectional distribution of idiosyncratic firm skewness, $is_{i,t}$, for all NYSE-listed companies from January 1930 through December 2005.

Figure 1 plots the cross-sectional distribution of $is_{i,t}$ for t equal to December 1929 through December 2005, and $T = 60$ months, using stocks that trade on the NYSE. In particular, we plot the 10th, 25th, 50th, 75th, and 90th percentiles of $is_{i,t}$ each month. All of the reported percentiles show time variation, but the 90th percentile exhibits the greatest variation, and has particularly large movements during the early 1930s, the mid-1980s, and the mid-1990s. Increases in the upper tail of the cross-section of $is_{i,t}$ also occur in the 1960s and 1970s. Because $is_{i,t}$ is the third moment scaled by $iv_{i,t}^3$ as noted in Equation (2), raw skewness increases disproportionately in these periods (relative to variance), and the U.S. equity markets appear to experience episodes of high skewness and high dispersion of skewness.[5]

For our asset pricing tests, we need measures of *expected* skewness over a horizon of T months for firm i at the end of month t, $E_t[is_{i,t+T}]$, rather than measures of historical skewness, as defined in Equation (2). These estimates of expected skewness should be feasible in that they use information available to investors at the end of month t. To model investor perceptions of expected skewness in a feasible manner, we first estimate cross-sectional regressions separately at the end of each month t in our sample,

$$is_{i,t} = \beta_{0,t} + \beta_{1,t} is_{i,t-T} + \beta_{2,t} iv_{i,t-T} + \lambda_t' \mathbf{X}_{i,t-T} + \varepsilon_{i,t}, \tag{3}$$

[5] The episodes of high skewness and high skewness dispersion may be related to what Brandt et al. (2008) label as “speculative periods” in their study of idiosyncratic volatility.

where $\mathbf{X}_{i,t-T}$ is a vector of additional firm-specific variables observable at the end of month $t-T$. Time subscripts on regression parameters are included to emphasize that we estimate these parameters using information observable at the end of month t. Equation (3) is similar to the panel estimations conducted in Chen, Hong, and Stein (2001), with the exception that we estimate the model separately each month. We then use the regression parameters from Equation (3), along with information observable at the end of each month t, to estimate expected skewness for each firm,

$$E_t[is_{i,t+T}] = \beta_{0,t} + \beta_{1,t} is_{i,t} + \beta_{2,t} iv_{i,t} + \lambda_t' \mathbf{X}_{i,t}. \tag{4}$$

This approach not only allows the relation between firm-specific variables and skewness to vary across time, but also provides feasible estimates of expected skewness each month.

The main results of our paper use this approach to estimate expected skewness using a horizon of $T = 60$ months. Ultimately, the choice of horizon is subjective. We choose to focus on horizons of multiple years based on our prior that investors typically focus on a stock's long-run upside potential (e.g., early-stage investments in Wal-Mart or Microsoft) as opposed to high returns over the short run. A horizon of $T = 60$ months implies that an investor needs 10 years of prior data to estimate the parameters of Equation (3) and generate an estimate of expected skewness as in Equation (4).[6]

The firm-specific variables $\mathbf{X}_{i,t-T}$ that we use in the cross-sectional regressions defined in Equation (3) include momentum ($mom_{i,t-T}$), turnover ($turn_{i,t-T}$), and dummy variables, which we further define below. The inclusion of $mom_{i,t-T}$, defined as the cumulative return for firm i over months $t-T-12$ through $t-T-1$, is motivated by Chen, Hong, and Stein (2001), who find that past returns are negatively correlated with forecasted skewness. The use of $turn_{i,t-T}$, defined as the average daily turnover of the firm over month $t-T$, is motivated by the model of Hong and Stein (2003), which predicts that negative skewness is most pronounced during periods of heavy trading volume.

In addition to *mom* and *turn*, we also use three sets of firm-specific dummy variables in the cross-sectional regressions defined in Equation (3), measured at the end of month $t-T$. First, to control for firm size, we include dummy variables for small and medium-size firms, where firms are grouped into three equally sized categories of small, medium, and large based on market capitalization.[7] Second, we include industry dummy variables in the regressions,

[6] We conduct robustness checks on our horizon choice and find similar results over skewness horizons ranging from six months to our base case five-year measure. In other unreported results, we estimate panel regression versions of Equation (3) and find similar results.

[7] In alternative specifications (not reported), we include a continuous variable for size, the natural log of the firm's market capitalization, rather than dummy variables for size. The continuous size variable leads to similarly significant results in our asset pricing tests. However, we find that allowing for a nonlinear size-skewness relationship, as with the size dummy variables, improves the model fit and is less impacted by the tails of the firm size distribution.

with industry classifications (as defined on Ken French's website) based on each firm's primary two-digit SIC code.[8] Third, because of the unique institutional features of the NASDAQ exchange, such as differences in turnover measurement, we include a NASDAQ dummy in our cross-sectional regressions.[9] Unlike Chen, Hong, and Stein (2001), who use only NYSE and AMEX data in their empirical tests, we include firms from NYSE, AMEX, and NASDAQ.

NASDAQ stocks only begin to report turnover on a widespread basis in January 1983. We therefore create a "baseline dataset" that includes daily returns from the beginning of February 1978 through December 2005, as well as $mom_{i,t}$, $turn_{i,t}$, and dummy variables for every stock from the end of January 1983 through December 2005. Using this dataset, we can estimate the cross-sectional regressions as in Equation (3) and obtain an estimate of expected skewness at the end of each month as in Equation (4), with $T = 60$ for each firm from January 1988 through December 2005.

Table 1 provides summary statistics for the explanatory variables used to estimate these cross-sectional regressions. Panel A reports descriptive statistics of the predictive variables and panel B reports the correlations of the variables. Both panels report statistics for idiosyncratic skewness and idiosyncratic volatility. We also include descriptive statistics for a measure of $iv_{i,t}$ for $T = 1$ since in Section 4 we use this variable for comparison with the results in Ang et al. (2006, 2008). The last two rows of each panel report statistics for momentum and turnover.

We view Equation (3) as a parsimonious model for skewness prediction, and we omit other potential variables that have been mentioned in the literature. For example, Chen, Hong, and Stein (2001) also use the book-to-market ratio and analyst coverage to predict skewness. In unreported tests, we include these variables in our regressions and find that although they add some explanatory power, they also require that we exclude a large number of observations. Given our intent to conduct cross-sectional asset pricing tests, we opt to use the full set of data with a more limited set of variables.[10]

Panel A of Table 2 reports the results of monthly estimations of Equation (3) for our baseline dataset. Each row represents a different regression specification. To summarize these monthly regressions, we report the average coefficient value, along with the percentage of months in which the estimated coefficient has the same sign as the average coefficient and is significant at the 5% level. This measure of significance should be viewed as only a general indicator of

[8] The inclusion of industry dummy variables in our skewness prediction regressions is similar in spirit to the analysis of Zhang (2005), who computes firm-specific skewness based on the cross-sectional skewness of firms in the same industry.

[9] The results are essentially unchanged if we also include a NASDAQ dummy interacted with turnover.

[10] We also estimate models (not reported) that include a measure of leverage, and find the incremental improvement in adjusted-R^2 to be relatively small. Since leverage data are not available for many firms in our sample, we opt to omit leverage from our skewness prediction model to retain a larger cross-section of firms.

Table 1
Descriptive statistics of skewness prediction variables

Panel A: Descriptive statistics

	Mean	Median	Std Dev	Min	Max
$is_{i,t}$	0.851	0.549	1.635	−26.591	34.083
$iv_{i,t}$	0.036	0.030	0.023	0.002	0.606
$iv_{i,t}(1m)$	0.033	0.025	0.031	0.000	2.804
$mom_{i,t}$	0.156	0.050	0.787	−0.999	51.000
$turn_{i,t}$	0.092	0.047	0.209	0.000	46.178

Panel B: Correlations

	$is_{i,t}$	$iv_{i,t}$	$iv_{i,t}(1m)$	$mom_{i,t}$
$iv_{i,t}$	0.356			
$iv_{i,t}(1m)$	0.183	0.618		
$mom_{i,t}$	0.070	−0.127	0.032	
$turn_{i,t}$	0.018	0.175	0.115	0.154

The table reports summary statistics for the explanatory variables used to estimate monthly cross-sectional regressions to forecast firm skewness using our baseline dataset. Let $S(t)$ denote the set of trading days from the first day of month $t - T + 1$ through the end of month t, and let $N(t)$ denote the number of elements in this set less a degrees of freedom correction. Let $iv_{i,t}$ and $is_{i,t}$ denote historical estimates of idiosyncratic volatility and skewness, respectively, for firm i using daily data for all days in $S(t)$. In addition, let $\epsilon_{i,d}$ be the regression residual using the Fama-French (1993) three-factor model on day d for firm i, where the regression coefficients that define this residual are estimated using daily data for days in $S(t)$. We can then define $iv_{i,t}$ and $is_{i,t}$ as

$$iv_{i,t} = \left(\frac{1}{N(t)} \sum_{d \in S(t)} \epsilon_{i,d}^2 \right)^{1/2},$$

$$is_{i,t} = \frac{1}{N(t)} \frac{\sum_{d \in S(t)} \epsilon_{i,d}^3}{iv_{i,t}^3}.$$

We define the variables $mom_{i,t}$ and $turn_{i,t}$, respectively, as the cumulative return for firm i over months $t - 12$ through $t - 2$, and the average daily turnover of the firm over month t. We report statistics for measures of $is_{i,t}$ and $iv_{i,t}$ computed using a horizon of $T = 60$ months, as well as $mom_{i,t}$ and $turn_{i,t}$, for t from December 1983 through December 2000, the range of months over which the explanatory variables are observed in our baseline dataset. We also report summary statistics for $iv_{i,t}(1m)$, a measure of idiosyncratic volatility estimated using a horizon of $T = 1$ month over this same date range. We use all stocks that trade on NYSE, AMEX, or NASDAQ. Descriptive statistics for the variables are reported in panel A and correlations of the variables are provided in panel B.

significance for comparative purposes, given the lack of adjustment for any potential cross-sectional correlation of residuals. In panel A, we use a horizon of $T = 60$ months to define $is_{i,t}$, $is_{i,t-T}$, and $iv_{i,t-T}$. Model 1 uses only $is_{i,t-T}$ to predict $is_{i,t}$, while model 2 uses only $iv_{i,t-T}$ as a predictive variable. Both $is_{i,t-T}$ and $iv_{i,t-T}$ positively predict $is_{i,t}$, and both variables are significant in 100% of the monthly regressions. Similar results hold in model 3, which includes $iv_{i,t-T}$ and $is_{i,t-T}$ simultaneously. These regressions confirm the results of Harvey and Siddique (1999) and Chen, Hong, and Stein (2001) in that lagged idiosyncratic volatility is a stronger predictor of idiosyncratic skewness than lagged idiosyncratic skewness. The adjusted-R^2 when $iv_{i,t-T}$ is used as the only predictive variable is more than double the adjusted-R^2 when $is_{i,t-T}$ is the only predictive variable. In addition, we find that a one-standard-deviation shock in $iv_{i,t-T}$ will lead to over twice as much variation in $is_{i,t}$ as a

Table 2
Skewness predictive regressions

Panel A: Baseline dataset; Horizon $T = 60$ months

Model		$is_{i,t-T}$	$iv_{i,t-T}$	$iv_{i,t-T}$ $(1m)$	$mom_{i,t-T}$	$turn_{i,t-T}$	NASDAQ dummy	Small dummy	Medium dummy	Industry dummies	Avg. Obs.	Avg Adj.-R^2
1	Avg	0.178								no	3,244	0.041
	%sig	(1.000)										
2	Avg		20.423							no	3,244	0.089
	%sig		(1.000)									
3	Avg	0.099	18.051							no	3,244	0.091
	%sig	(0.935)	(1.000)									
4	Avg	0.084	9.903		−0.001	−0.382	−0.162	0.814	0.385	no	3,244	0.134
	%sig	(0.949)	(0.834)		(0.631)	(0.129)	(0.613)	(1.000)	(0.793)			
5	Avg									yes	3,244	0.026
	%sig											
6	Avg	0.081	8.987		−0.001	−0.333	−0.180	0.827	0.387	yes	3,244	0.152
	%sig	(0.894)	(0.770)		(0.631)	(0.120)	(0.571)	(1.000)	(0.782)			
7	Avg			11.057						no	3,244	0.049
	%sig			(0.982)								
Panel B: Robustness												
8 Full dataset; Horizon $T = 60$ months												
	Avg	0.066	7.542		−0.001	−0.194	−0.116	0.592	0.281	yes	1,723	0.097
	%sig	(0.573)	(0.558)		(0.325)	(0.045)	(0.724)	(0.783)	(0.616)			
9 Baseline dataset; Horizon $T = 6$ months												
	Avg	0.051	3.303		−0.001	−0.433	0.011	0.366	0.229	yes	3,820	0.060
	%sig	(0.646)	(0.542)		(0.478)	(0.262)	(0.054)	(0.906)	(0.868)			
10 Baseline dataset; Horizon $T = 24$ months												
	Avg	0.088	4.087		−0.002	−0.559	0.174	0.626	0.330	yes	3,722	0.093
	%sig	(0.806)	(0.547)		(0.668)	(0.221)	(0.083)	(1.000)	(0.913)			

The table reports the time-series average of coefficients from monthly cross-sectional regressions of the form

$$is_{i,t} = \beta_{0,t} + \beta_{1,t} is_{i,t-T} + \beta_{2,t} iv_{i,t-T} + \lambda_t' \mathbf{X}_{i,t-T} + \varepsilon_{i,t},$$

where $is_{i,t}$ and $iv_{i,t}$ are, respectively, idiosyncratic skewness and volatility for firm i estimated using daily excess returns relative to a Fama-French three-factor model from the beginning of month $t-T+1$ through the end of month t, and $\boldsymbol{X}_{i,t-T}$ is a vector of firm-specific variables observable at the end of month $t-T$. Variables in $\boldsymbol{X}_{i,t-T}$ include $mom_{i,t-T}$, the cumulative firm return over months *t-T-12* through *t-T-1*; $turn_{i,t-T}$, firm turnover over month *t-T*; a dummy variable indicating NASDAQ stocks; dummies for small and medium-size firms; a set of industry dummies; and $iv_{i,t-T}(1m)$, a measure of idiosyncratic volatility estimated with a horizon of $T = 1$ month. Panel A reports regressions for our baseline dataset, which includes stocks that trade on the NYSE, AMEX, or NASDAQ and in which $is_{i,t}$, $is_{i,t-T}$, and $iv_{i,t-T}$ are estimated using a horizon of $T = 60$ months for t from January 1988 through December 2005. Panel B reports robustness checks for our full dataset (December 1934 to December 2005) and for $is_{i,t}$, $is_{i,t-T,}$ and $iv_{i,t-T}$ estimated over horizons of $T = 6$ months and $T = 24$ months. The percent of coefficients that are statistically significant at the 5% level (and of the same sign as the average coefficient) is reported below the coefficient estimates.

one-standard-deviation shock in $is_{i,t-T}$. This can be determined using the coefficients of model 3 along with the standard deviations in Table 1.

Model 4 in panel A includes $iv_{i,t-T}$, $is_{i,t-T}$, as well as our other predictive variables, $mom_{i,t-T}$, $turn_{i,t-T}$, and the dummy variables for NASDAQ firms, small firms, and medium-size firms. Higher values for $mom_{i,t-T}$ and $turn_{i,t-T}$ are both associated with lower values of $is_{i,t}$, consistent with the findings of Chen, Hong, and Stein (2001). The adjusted-R^2 of the skewness predictive regression increases when the additional variables in model 4 are included. These variables have fairly consistent statistical significance, although $turn_{i,t-T}$ is significant in just 13% of the regressions. The inclusion of these additional variables reduces the predictive power of $iv_{i,t-T}$ more than $is_{i,t-T}$, but the estimated impact of a one-standard-deviation shock to $iv_{i,t-T}$ is still more than 60% greater than the estimated impact of a one-standard-deviation shock to $is_{i,t-T}$.

Model 5 in panel A reports results of regressions including only the industry dummies as explanatory variables and shows that the industry dummies alone have some ability to predict $is_{i,t}$. Including the industry dummies along with the other predictive variables (in model 6) results in the highest adjusted-R^2 of any of the regressions. Model 6 is the specification that we focus on in our subsequent tests. The last model of panel A reports results using a measure of idiosyncratic volatility estimated with a horizon of $T = 1$ month, $iv_{i,t-T}$ $(1m)$, to forecast $is_{i,t}$. These results are included for comparison with Ang et al. (2006, 2008), as discussed in Section 4.

Panel B of Table 2 reports robustness checks of the predictive regressions reported in panel A. Model 8 uses what we refer to as the "full dataset," and uses a horizon of $T = 60$ months to estimate $is_{i,t}$, $is_{i,t-T}$, and $iv_{i,t-T}$. The full dataset includes daily returns for stocks that trade on the NYSE or AMEX from the beginning of January 1925 through December 2005, and stocks that trade on NASDAQ from the beginning of January 1973 through December 2005. As mentioned above, NASDAQ stocks only begin to report turnover on a widespread basis in January 1983. Hence, when estimating the cross-sectional regressions in Equation (3) using the full dataset for t equal to January 1988 through December 2005, we are able to include $turn_{i,t-T}$ and all other explanatory variables as in model 6 of Table 2. For t equal to December 1982 through December 1987, we are able to measure $is_{i,t}$ and $is_{i,t-T}$ for all stocks in the cross-section, but we do not observe $turn_{i,t-T}$ for stocks that trade on NASDAQ. Hence, when estimating the cross-sectional regressions over this period, we omit $turn_{i,t-T}$ but include all other explanatory variables as in model 6. For t equal to December 1934 through November 1982, we can only use stocks that trade on the NYSE or AMEX, but we use our full set of explanatory variables. Relative to the results in model 6, the results using the full dataset generally have smaller estimated coefficients and less-frequent statistical significance (in part due to the smaller number of observations per year). However, the signs and relative magnitudes of the coefficients are quite similar to the results in model 6.

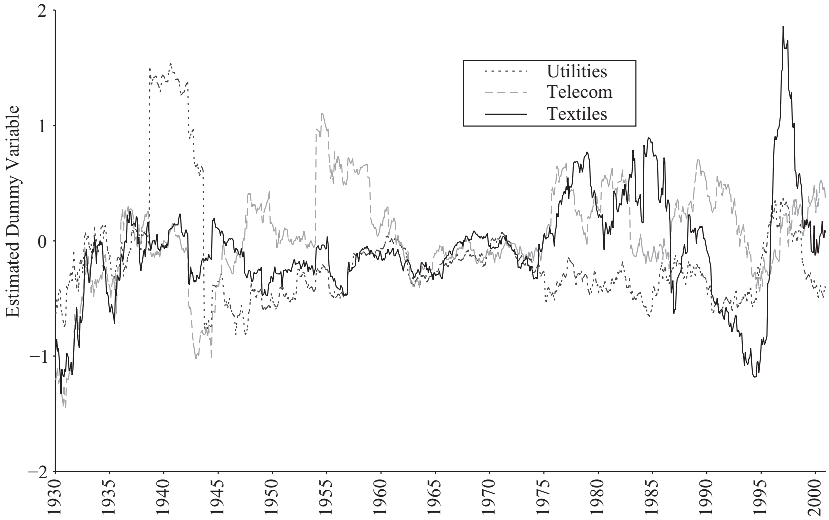

Figure 2
Predicted skewness of selected industries
The time series of estimated industry dummy variables from monthly cross-sectional estimates of our skewness prediction model described in Equation (3) and as reported in model 8 of Table 2. Dummies for utilities, telecommunications, and textiles industries following Ken French's industry designations are included.

The last two models in panel B repeat the regressions from model 6 of panel A but use measures of $is_{i,t}$, $is_{i,t-T}$, and $iv_{i,t-T}$ with horizons of six months and two years. The results are fairly similar in sign and magnitude to the results for the five-year skewness measures. We do observe that the coefficient on the NASDAQ dummy increases in value and decreases in average significance in these regressions relative to those of panel A.

In Figure 2, we report a time-series plot of some industry dummy variables (from our estimations in model 8 of Table 2) to provide some insight into their behavior. We include industry dummies for utilities, telecommunications, and textiles stocks. The plots of these three series in Figure 2 show substantial time-series variation for each of the industries; similar variation exists for industries not included. Much of the variation in these dummy plots appears to conform to expectations. For example, the sign on the utilities industry dummy is almost always negative from the 1940s forward, consistent with the belief that this heavily regulated industry offers comparatively little upside potential. The large positive spike in the utilities industry dummy during the late 1930s and early 1940s corresponds to the Natural Gas Act of 1938, which forced the splitting up of the utilities industry from a few dominant firms into many smaller companies. High positive coefficients on telecommunications stocks during the late 1950s, 1970s, and early 1990s also coincide with periods when these types of companies generated positive attention and abnormally large returns. We include the textiles industry dummy as it represents the industry with the largest time-series variation, as evidenced by the large swings in the coefficient's value from the 1970s through 2000.

In summary, the results of this section suggest that a simple cross-sectional model including lagged idiosyncratic volatility and skewness, momentum, turnover, size, and industry dummies can help investors to forecast skewness. In the next section, we assess whether idiosyncratic skewness, as predicted by this model, can help explain the cross-section of expected returns.

3. Expected Skewness and Average Returns

The primary objective of our skewness prediction model is to allow us to test whether expected skewness contributes to our understanding of the cross-section of returns. We conduct standard asset pricing tests and find a strong negative cross-sectional relation between average returns and expected skewness, consistent with the theoretical motivation of Section 1. In this section, we first assess how average returns vary across stocks with differing levels of expected skewness. We then turn to the impact of predicted skewness in cross-sectional regressions using the methodology of Fama and MacBeth (1973).

3.1 Portfolios sorted on predicted skewness

We construct measures of expected skewness at the end of every month in our baseline dataset, $E_t[is_{i,t+T}]$, for t equal to January 1988 through November 2005, as outlined in Equations (3) and (4). The variables used in the cross-sectional regressions are given in model 6 of Table 2. We then sort stocks into quintile portfolios at the end of each month based on $E_t[is_{i,t+T}]$, and compute the value-weighted return for each portfolio over month $t+1$. Table 3 presents descriptive statistics for the five quintiles, where the first quintile represents firms with the lowest predicted skewness, and the fifth quintile represents firms with the highest predicted skewness. Column 1 of Table 3 reports the time-series average of the value-weighted portfolio returns. This column shows that mean returns decline monotonically from the first quintile to the fifth quintile. Mean returns are substantially lower in the fifth quintile (0.52%) compared to the first quintile (1.19%), a difference of 0.67% per month (t-statistic $= 2.91$), indicating large differences in average returns for firms with differing levels of predicted skewness. The largest decline in mean returns occurs between the fourth and fifth quintiles.

While predicted skewness appears to be an important determinant of returns, lagged skewness alone is *not* a good predictor of returns. In other tests (not reported), we repeat the analysis of Table 3 but sort firms into portfolios based on measures of predicted skewness that use $is_{i,t-T}$ as the only predictive variable (model 1 of Table 2). In this sorting, mean returns are only slightly lower in the fifth quintile than in the first quintile, with a difference of 0.04% per month. This result is in line with our evidence that additional variables are required to estimate expected skewness in an economically meaningful way.

Table 3
Descriptive statistics of portfolios by level of predicted skewness

	(1) Mean	(2) Standard deviation	(3) Skewness	(4) Firm skewness	(5) Firm i-vol%	(6) Size	(7) CAPM alpha	(8) FF alpha
1 (Low)	1.189	4.272	−0.604	0.167	1.888	13.596	0.143	0.140
							(2.13)	(2.29)
2	1.115	4.745	−0.789	0.375	2.087	12.950	0.005	−0.005
							(0.006)	−(0.06)
3	1.105	4.972	−0.690	0.565	2.627	11.651	0.005	−0.208
							(0.04)	−(1.63)
4	1.059	5.518	−0.195	0.809	3.406	10.470	0.054	−0.178
							(0.28)	−(1.05)
5 (High)	0.515	6.897	0.219	1.629	5.324	9.404	−0.655	−0.855
							−(2.21)	−(3.79)
1–5	0.674						0.797	0.995
	(2.91)						(2.38)	(3.78)

We construct estimates of $E_t[is_{i,t+T}]$ at the end of each month from December 1987 through November 2005 as outlined in Equations (3) and (4) of the paper, using a horizon of $T = 60$ months. The variables used in the cross-sectional regressions are given in model 6 of Table 2. We then sort stocks into quintile portfolios at the end of each month based on $E_t[is_{i,t+T}]$ and compute the value-weighted return over month $t + 1$ for each portfolio. This table reports descriptive statistics for the five quintiles, where the first quintile represents firms with the lowest predicted skewness, and the fifth quintile represents firms with the highest predicted skewness. Column 1 reports the time-series average of the value-weighted portfolio returns. Columns 2 and 3 report the time-series standard deviation and skewness of the portfolio returns. Columns 4, 5, and 6 report averages, across time, of the value-weighted cross-sectional averages of $is_{i,t}$, $iv_{i,t}(1m)$, and $ln(size_{i,t})$, respectively, within each portfolio. Columns 7 and 8 report estimated alphas and t-statistics (in parentheses) from the CAPM and the Fama-French (1993) three-factor model.

The columns in the middle of Table 3 report other descriptive statistics of the predicted-skewness quintiles. Columns 2 and 3 of Table 3 report the time-series standard deviation and skewness of the portfolio returns. Columns 4, 5, and 6 report the averages, across time, of the value-weighted cross-sectional averages of $is_{i,t}$, $iv_{i,t}(1m)$, and $ln(size_{i,t})$ within each portfolio, where $ln(size_{i,t})$ is the natural log of size for firm i at the end of month t. Average values of $iv_{i,t}(1m)$ increase monotonically from the first quintile to the fifth quintile, indicating a positive relation between $iv_{i,t}(1m)$ and $E_t[is_{i,t+T}]$, consistent with the predictive regressions of Table 2. We also find that the time-series measures of portfolio skewness (reported in column 3) increase with predicted skewness across the quintiles. We also find that firms with higher predicted skewness tend to be smaller than firms with lower predicted skewness, consistent with the results of Table 2.

Most importantly, the last two columns of Table 3 show that the differences in returns for the expected-skewness quintiles are even greater after adjusting for risk. We report alphas relative to the CAPM and relative to the Fama-French three-factor model for each of the quintiles. The difference in the Fama-French alphas is particularly pronounced, with the first quintile having an alpha of 0.14% per month and the fifth quintile having an alpha of −0.86% per month, a difference of 1.00% per month. The difference in the alphas of the first and fifth quintiles is highly statistically significant. In summary, Table 3 indicates that predicted skewness is negatively related to expected returns, even after controlling for standard measures of risk.

3.2 Fama-MacBeth regressions

To further assess the pricing effects of idiosyncratic skewness, we conduct cross-sectional regressions following the approach of Fama and MacBeth (1973). We find a strong economic and statistical relation between average returns and predicted skewness in the cross-section that persists even with the inclusion of standard cross-sectional asset pricing variables.

We construct measures of expected skewness at the end of every month in our baseline dataset, $E_t[is_{i,t+T}]$, using a horizon of $T = 60$ months for t equal to January 1988 through November 2005, as outlined in Equations (3) and (4). The variables used in the cross-sectional regressions are given in model 6 of Table 2. We sort stocks each month into one hundred portfolios based on expected skewness and construct value-weighted returns for the portfolios. We then run the following cross-sectional regression for each month t in our sample:

$$r_{p,t+1} = \gamma_{0,t} + \gamma_{1,t} E_t[is_{p,t+T}] + \phi_t' \mathbf{Z}_{p,t} + \varepsilon_{p,t}, \tag{5}$$

where $r_{p,t+1}$ is the value-weighted monthly return for portfolio p observed at the end of month $t+1$, $E_t[is_{p,t+T}]$ is the expected idiosyncratic skewness for portfolio p, and $\mathbf{Z}_{p,t}$ represents a vector of standard factor loadings, firm characteristics, and controls for our skewness-predicting instruments, all of which are observable at the end of month t. Subscripts are included in the regression coefficients to emphasize that these are estimated separately for each month t in the sample. Expected skewness for portfolio p is defined as the value-weighted average firm-level measures across all stocks in portfolio p. Portfolio loadings and characteristics are also value-weighted averages of firm-level counterparts.

We include twelve additional characteristics and factor loadings in $\mathbf{Z}_{p,t}$, which are defined as follows. Historical idiosyncratic volatility, $iv_{p,t}(1m)$, is the value-weighted average across all stocks in portfolio p, and is measured using a horizon of $T = 1$ month for comparison with Ang et al. (2006). $Size_{p,t}$ and $Book\text{-}to\text{-}Market_{p,t}$ are, respectively, the log of market capitalization and the book-to-market ratio at the end of month t. $Return_{p,t}$ is the portfolio return over month t. We define $mom_{p,t}$ as the cumulative return over months $t-12$ through $t-1$, and $turn_{p,t}$ as turnover for month t. These characteristics are included to control for the previously established connections between expected returns and these variables, given that these are instruments in our skewness prediction model of Equation (3).[11] $Beta\text{-}Market_{p,t}$, $Beta\text{-}SMB_{p,t}$, and $Beta\text{-}HML_{p,t}$ are

[11] Gervais, Kaniel, and Mingelgrin (2001) find a strong relation between firm turnover and subsequent returns. DeBondt and Thaler (1985) and Jegadeesh and Titman (1993) report momentum effects in the cross-section of returns.

the loadings on the Fama-French factors, $Beta\text{-}UMD_{p,t}$ is the loading on the Carhart (1997) momentum factor, $Beta\text{-}Liquidity_{p,t}$ is the loading on the Pástor and Stambaugh (2003) liquidity factor, and $Beta\text{-}Coskew_{p,t}$ is the loading on the squared excess market return, following Harvey and Siddique (2000). All loadings are estimated using monthly data from the end of month $t-36$ to the end of month t.[12]

In Table 4, we report the time-series averages of the γ and ϕ coefficients for our baseline sample, along with t-statistics based on Newey and West (1987) standard errors. Column 1 reports the cross-sectional pricing of expected skewness. The coefficient on expected skewness is negative and significant at the 1% level. Columns 2–4 include other factor loadings and characteristics as explanatory variables. Whether we include the factor loadings only (column 2), the characteristics only (column 3), or both factor loadings and characteristics (column 4), the coefficient on expected skewness remains significant at either the 5% or the 1% level. Including our other explanatory variables in the regression will likely lead to a decrease in the significance of expected skewness, given that the expected skewness is a linear combination of a subset of other explanatory variables. The coefficients on the other factor loadings and characteristics generally conform to expectations and are similar to those in Ang et al. (2008). Of particular interest is the fact that the coefficient on idiosyncratic volatility is negative as expected, but is not significant at standard levels. Also, in comparison with expected skewness, the t-statistics on the coskewness loadings are not as large, although the coefficients are negative as predicted. In summary, the results of Table 4 indicate that expected idiosyncratic skewness helps to explain the cross-sectional variation in expected returns beyond common instruments.

3.2.1 Robustness checks. We conduct a number of robustness checks to the results of Table 4 and report many of these in Table 5. We vary the number of portfolios, the data horizon, and the skewness measures to assess the stability of the skewness pricing results to these choices. In general, we find that the coefficient on predicted skewness remains negative and significant in these robustness checks.

We conduct cross-sectional tests with both fewer and greater numbers of portfolios relative to our base case. In columns 1 and 2 of Table 5, we repeat the analysis of Table 4 using fifty portfolios and two hundred portfolios as the test assets. The significance of γ_1 is at the 5% level in both cases. The coefficient on idiosyncratic volatility is insignificant in the case of fifty portfolios but significant in the case of two hundred portfolios. In Section 4, we further disentangle the separate effects of expected skewness and idiosyncratic volatility.

[12] The results in the paper use loadings that are estimated simultaneously, but we find similar results when each loading is estimated separately.

Table 4
Fama-MacBeth regressions

	(1)	(2)	(3)	(4)
Constant	1.527***	1.127***	5.212**	4.091**
	(5.05)	(3.36)	(2.56)	(2.16)
$E_t[is_{p,t+T}]$	−0.932***	−0.617**	−0.842***	−0.624**
	−(2.66)	−(2.28)	−(2.84)	−(2.16)
$iv_{p,t}(1m)$			−0.189	−0.223
			−(1.07)	−(1.38)
$Size_{p,t}$			−0.198**	−0.163*
			−(1.96)	−(1.72)
$Book\text{-}to\text{-}Market_{p,t}$			0.070	0.508
			(0.14)	(1.00)
$Return_{p,t}$			−0.004	−0.018
			−(0.20)	−(0.81)
$mom_{p,t}$			0.006	0.006
			(1.27)	(1.34)
$turn_{p,t}$			−1.016	−1.586
			−(0.54)	−(0.93)
$Beta\text{-}Market_{p,t}$		0.265		0.231
		(0.75)		(0.54)
$Beta\text{-}SMB_{p,t}$		0.152		−0.032
		(0.83)		−(0.14)
$Beta\text{-}HML_{p,t}$		0.048		−0.274
		(0.21)		−(1.17)
$Beta\text{-}UMD_{p,t}$		−0.024		0.183
		−(0.08)		(0.70)
$Beta\text{-}Liquidity_{p,t}$		0.636*		0.639*
		(1.71)		(1.72)
$Beta\text{-}Coskew_{p,t}$		−6.524*		−3.378
		−(1.73)		−(0.69)
Adjusted R^2	0.085	0.359	0.346	0.490

The table reports results of Fama-MacBeth (1973) regressions, the average coefficients from cross-sectional regressions,

$$r_{p,t+1} = \gamma_{0,t} + \gamma_{1,t} E_t[is_{p,t+T}] + \phi_t' \mathbf{Z}_{p,t} + \varepsilon_{p,t},$$

where $r_{p,t+1}$ is the value-weighted monthly return for portfolio p observed at the end of month $t+1$; $E_t[is_{p,t+1}]$ is expected idiosyncratic skewness for portfolio p; and $\mathbf{Z}_{p,t}$ represents a vector of portfolio loadings and characteristics observable at the end of month t. The test assets are one hundred portfolios sorted each month on $E_t[is_{p,t+1}]$. The regressions are estimated each month using our baseline dataset for t equal to December 1987 through November 2005. Expected skewness and other regressors for portfolio p are defined as the value-weighted average firm-level measures across all stocks in portfolio p. We construct measures of $E_t[is_{p,t+1}]$ as outlined in Equations (3) and (4) of the paper, using a horizon of $T = 60$. The variables used in the cross-sectional regressions to estimate $E_t[is_{p,t+1}]$ are given in model 6 of Table 2. We also include as a regressor $iv_{p,t}(1m)$, the historical idiosyncratic volatility for portfolio p. We estimate $iv_{p,t}(1m)$ as in Equation (2) of the paper, using a horizon of $T = 1$ month for comparison with Ang et al. (2006). $Size_{p,t}$ and $Book\text{-}to\text{-}Market_{p,t}$ are, respectively, the log of market capitalization and book-to-market ratio observed at the end of month t. $Return_{p,t}$ is the portfolio return over month t; $mom_{p,t}$ is the cumulative return over months $t-12$ through $t-2$; and $turn_{p,t}$ is turnover over month t. Portfolio loadings and characteristics are also value-weighted averages of firm-level counterparts using monthly data from the end of month $t-36$ to the end of month t. $Beta\text{-}Market_{p,t}$, $Beta\text{-}SMB_{p,t}$, and $Beta\text{-}HML_{p,t}$ are portfolio loadings on the three Fama-French (1993) factors; $Beta\text{-}UMD_{p,t}$ is the portfolio loading on the Carhart (1997) momentum factor; $Beta\text{-}Liquidity_{p,t}$ is the loading on the Pastor-Stambaugh (2003) liquidity factor; and $Beta\text{-}Coskew_{p,t}$ is the loading on the squared excess market return following Harvey and Siddique (2000). Average coefficients and Newey-West (1987) t-statistics (in parentheses) are reported along with average adjusted-R^2. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

We also extend the data and construct estimates of $E_t[is_{i,t+T}]$ using the full dataset (from 1934 to 2005), as in model 8 of Table 2. We then repeat the analysis of Table 4 after sorting all stocks into one hundred portfolios at the end of each month. We report time-series averages of the Fama-MacBeth cross-sectional regressions in column 3 of Table 5. Using this longer data sample, γ_1 is again negative and significant at the 5% level.

Next, we repeat the analysis of Table 4 using measures of $E_t[is_{i,t+T}]$, as outlined in Equations (3) and (4), using horizons of $T = 6$ months and $T = 24$ months. We obtain these measures of expected idiosyncratic skewness at the end of every month for our baseline dataset, from the end of January 1988 through the end of November 2005. The variables used in the cross-sectional regressions to estimate expected idiosyncratic skewness are given in models 9 and 10 of Table 2. Results for $T = 6$ are reported in column 4 and results for $T = 24$ are reported in column 5 of Table 5. In both cases, we find that the γ_1 coefficient is negative and significant at the 10% level.

In unreported tests, we also investigate the robustness of our results to two additional methodological issues. First, we investigate the importance of the horizon by constructing $is_{i,t+T}$ using monthly as opposed to daily returns. In particular, we use five and ten years of monthly returns to construct idiosyncratic skewness and use these measures in our skewness-forecasting regressions and subsequent cross-sectional asset pricing tests. We find similar relationships in the forecasting regressions, and similar significance in the asset pricing tests relative to our base case of using daily return skewness measures. Specifically, the coefficient on $E_t[is_{i,t+T}]$ is -0.435 with a t-statistic of -1.87 in the analog to column 4 of Table 4 using five years of monthly returns to construct skewness measures. Second, we conduct skewness forecasting and asset pricing tests using *total* skewness measures as opposed to *idiosyncratic* skewness measures. This check allows us to assess the dependence of our results on the Fama-French three-factor model used to construct idiosyncratic skewness measures in our base case. In addition, the theoretical models motivating our investigation suggest that investors care about the total skewness of their portfolio, not just the idiosyncratic portion of skewness. We find that using total skewness measures leads to very little change in the asset pricing results. In this case, the coefficient on $E_t[is_{i,t+T}]$ is -0.865 with a t-statistic of -2.48 in the analog to column 4 of Table 4.[13]

3.3 Time-series effects

Given the time-series features of predicted and realized skewness shown in Figures 1 and 2, a natural question is whether our cross-sectional pricing results exhibit any related temporal variations. Figure 3 plots, for each month t, the rolling average predicted skewness premium, denoted as $\overline{\gamma}_{1,t}$, from

[13] The results of both the monthly return robustness check along with the total skewness robustness check are available upon request.

Table 5
Fama-MacBeth regressions, robustness checks

	(1)	(2)	(3)	(4)	(5)
Horizon	$T = 60$	$T = 60$	$T = 60$	$T = 6$	$T = 24$
Period	88–05	88–05	34–05	88–05	88–05
Number of portfolios	50	200	100	100	100
Constant	4.602*	4.576***	2.256***	2.844*	5.322***
	(1.84)	(2.80)	(3.37)	(1.80)	(3.30)
$E_t[is_{p,t+T}]$	−0.759**	−0.564**	−0.343**	−0.447*	−0.313*
	−(2.24)	−(1.99)	−(2.02)	−(1.92)	−(1.85)
$iv_{p,t}(1m)$	−0.221	−0.349**	−0.239***	−0.297*	−0.442**
	−(1.01)	−(2.57)	−(2.61)	−(1.71)	−(2.35)
$Size_{p,t}$	−0.184	−0.177**	−0.076**	−0.087	−0.201**
	−(1.47)	−(2.15)	−(2.08)	−(1.06)	−(2.53)
$Book\text{-}to\text{-}Market_{p,t}$	0.402	0.169	–	0.414	−0.227
	(0.51)	(0.38)	–	(0.83)	−(0.43)
$Return_{p,t}$	−0.029	−0.019	−0.041***	−0.012	0.000
	−(1.14)	−(1.11)	−(3.90)	−(0.62)	(0.01)
$mom_{p,t}$	0.012**	0.006*	0.011***	−0.002	−0.002
	(1.98)	(1.70)	(4.48)	−(0.38)	−(0.49)
$turn_{p,t}$	−5.078**	−0.618	3.471	−1.163	0.514
	−(2.18)	−(0.46)	(1.28)	−(0.68)	(0.29)
$Beta\text{-}Market_{p,t}$	0.477	0.118	0.132	0.194	−0.290
	(1.07)	(0.36)	(0.71)	(0.53)	−(0.72)
$Beta\text{-}SMB_{p,t}$	0.080	−0.005	0.064	0.113	−0.052**
	(0.32)	−(0.02)	(0.57)	(0.35)	−(0.20)
$Beta\text{-}HML_{p,t}$	−0.270	−0.092	0.172	0.072	−0.009
	−(0.92)	−(0.47)	(1.62)	(0.27)	−(0.04)
$Beta\text{-}UMD_{p,t}$	−0.055	0.058	−0.093	−0.155	−0.350
	−(0.15)	(0.27)	−(0.64)	−(0.58)	−(1.04)
$Beta\text{-}Liquidity_{p,t}$	0.055	0.761**	–	0.253	0.082
	(0.12)	(2.39)	–	(0.63)	(0.20)
$Beta\ Coskew_{p,t}$	−3.308	−1.816	0.985	−2.318	1.974
	−(0.64)	−(0.45)	(0.41)	−(0.59)	(0.42)
Adjusted R^2	0.611	0.403	0.461	0.468	0.481

The table reports results of Fama-MacBeth (1973) regressions, the average coefficients from cross-sectional regressions,

$$r_{p,t+1} = \gamma_{0,t} + \gamma_{1,t} E_t[is_{p,t+T}] + \phi_t' \mathbf{Z}_{p,t} + \varepsilon_{p,t},$$

where $r_{p,t+1}$ is the value-weighted monthly return for portfolio p observed at the end of month $t+1$; $E_t[is_{p,t+1}]$ is expected idiosyncratic skewness for portfolio p; and $\mathbf{Z}_{p,t}$ represents a vector of portfolio loadings and characteristics observable at the end of month t. The test assets are portfolios sorted each month on $E_t[is_{p,t+1}]$. For column 1, we sort stocks into fifty portfolios; for column 2, we sort stocks into two hundred portfolios; for the other columns, we sort stocks into one hundred portfolios. The regressions are estimated each month using our baseline dataset for t equal to December 1987 through November 2005 for all columns except column 3, where the regressions are estimated for t equal to December 1934 through November 2005. Expected skewness and other regressors for portfolio p are defined as the value-weighted average firm-level measures across all stocks in portfolio p. We construct measures of $E_t[is_{p,t+1}]$ as outlined in Equations (3) and (4) of the paper, using a horizon of $T = 60$. The variables used in the cross-sectional regressions to estimate $E_t[is_{p,t+1}]$ are given in model 6 of Table 2. We also include as a regressor $iv_{p,t}(1m)$, the historical idiosyncratic volatility for portfolio p. We estimate $iv_{p,t}(1m)$ as in Equation (2) of the paper, using a horizon of $T = 1$ month for comparison with Ang et al. (2006). $Size_{p,t}$ and $Book\text{-}to\text{-}Market_{p,t}$ are, respectively, the log of market capitalization and book-to-market ratio observed at the end of month t. $Return_{p,t}$ is the portfolio return over month t, $mom_{p,t}$ is the cumulative return over months $t-12$ through $t-2$, and $turn_{p,t}$ is turnover over month t. Portfolio loadings and characteristics are also value-weighted averages of firm-level counterparts using monthly data from the end of month $t-36$ to the end of month t. $Beta\text{-}Market_{p,t}$, $Beta\text{-}SMB_{p,t}$, and $Beta\text{-}HML_{p,t}$ are portfolio loadings on the three Fama-French (1993) factors; $Beta\text{-}UMD_{p,t}$ is the portfolio loading on the Carhart (1997) momentum factor; $Beta\text{-}Liquidity_{p,t}$ is the loading on the Pastor-Stambaugh (2003) liquidity factor; and $Beta\text{-}Coskew_{p,t}$ is the loading on the squared excess market return following Harvey and Siddique (2000). Average coefficients and Newey-West (1987) t-statistics (in parentheses) are reported along with average adjusted-R^2. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

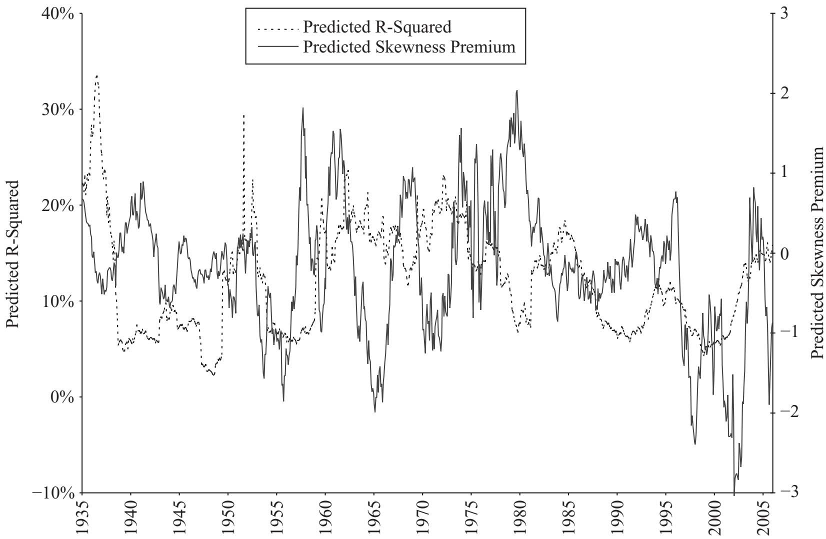

Figure 3
Predicted skewness premium and R^2
The 12-month rolling average of the predicted skewness premium γ_t from Equation (5) using our full dataset (scaled on the right axis), and the adjusted-R^2 from the cross-sectional skewness prediction regressions, $R^2_{pred,t}$, from Equation (3) using our full dataset (scaled on the left axis).

Equation (5) over months $t-11$ through month t using the full dataset as in column 3 of Table 5 (scaled on the right axis). The time-series plot exhibits similar behavior as seen in Figures 1 and 2, including large negative swings in the 1950s, 1960s, 1970s, and 1990s corresponding to the speculative episodes occurring in cross-sectional skewness distributions in Figures 1 and 2. The figure also includes a plot of the adjusted-R^2 from the cross-sectional regression of Equation (3) estimated for month t (scaled on the left axis). This series appears to be negatively correlated to the plot of the predicted skewness premium. These observations suggest the possibility that the skewness premium is more pronounced during speculative periods when expected skewness is high and more easily forecasted. In an attempt to test these relations, we run the following regression:

$$\overline{\gamma}_{1,t} = \delta_0 + \delta_1 \mu_{E_t[is_{i,t+T}]} + \delta_2 \sigma_{E_t[is_{i,t+T}]} + \delta_3 R^2_{pred,t} + \varepsilon_t, \qquad (6)$$

where $\mu_{E_t[is_{i,t+T}]}$ is the cross-sectional average of predicted skewness for month t, and where $\sigma_{E_t[is_{i,t+T}]}$ is the cross-sectional standard deviation of predicted skewness for month t, and $R^2_{pred,t}$ is the adjusted-R^2 from the cross-sectional regression of Equation (3) used to estimate $E_t[is_{i,t+T}]$. Estimated coefficients of this regression along with standard errors are in Table 6. We adjust our standard errors for generated regressors following Pagan (1984) and Shanken (1992). The results of Table 6 show what Figures 1 and 3 suggest: the predicted skewness premium is most negative when dispersion in predicted skewness is

Table 6
Time-series determinants of skewness pricing

	Intercept	$\mu_{E_t[is_{i,t+T}]}$	$\sigma_{E_t[is_{i,t+T}]}$	$R^2_{pred,t}$
Est	0.589	−0.492	−1.316	−1.429
SE	(0.113)	−(0.163)	−(0.253)	−(0.611)
$N = 793$				
$R^2 = 0.146$				

The table reports coefficients from a time-series regression,

$$\bar{\gamma}_{1,t} = \delta_0 + \delta_1 \mu_{E_t[is_{i,t+T}]} + \delta_2 \sigma_{E_t[is_{i,t+T}]} + \delta_3 R^2_{pred,t} + e_t,$$

where $\bar{\gamma}_{1,t}$ is month t's twelve-month rolling average of the cross-sectional coefficient on predicted skewness from Fama-MacBeth (1973) regressions of Equation (5); $\mu_{E_t[is_{i,t+T}]}$ is month t's cross-sectional average expected idiosyncratic skewness; $\sigma_{E_t[is_{i,t+T}]}$ is month t's cross-sectional standard deviation of expected idiosyncratic skewness; and $R^2_{pred,t}$ is month t's adjusted-R^2 from the estimation of Equation (3), the cross-sectional model we use to construct measures of expected idiosyncratic skewness, $E_t[is_{i,t+1}]$. We adjust standard errors of this regression to account for generated regressors following Pagan (1984) and Shanken (1992) and to account for time-series correlation following Newey and West (1987).

high, when average predicted skewness is high, and when skewness is forecastable. The statistical significance of all three of these explanatory variables is high. Clearly, these tests are preliminary in nature and more work is required to determine the temporal variations in skewness pricing, but the results in Table 6 strongly suggest the likelihood of time variation in skewness pricing.[14]

4. Skewness, Volatility, and Expected Returns

Historically, far more research effort has been expended to understand the relation between volatility and expected returns than to understand the relation between skewness and expected returns. Because volatility and skewness are interrelated, in this section we attempt to further distinguish whether the relation between idiosyncratic skewness and returns is attributable to skewness itself or if it is at least partly attributable to idiosyncratic volatility. We begin with some additional specifications of the Fama-MacBeth regressions presented above, and conclude with an investigation of how skewness relates to the known relation between idiosyncratic volatility and expected returns.

4.1 Regressions with individual stocks

One potential concern with the Fama-MacBeth regressions presented in the previous section is that in the process of sorting stocks into portfolios based on expected skewness, we may inadvertently overstate the effect of expected skewness and understate the effect of some other characteristic (such as idiosyncratic volatility). One way to address this concern is to avoid sorting stocks into portfolios and perform the regressions at the individual stock level. Although it is more typical in the literature to perform Fama-MacBeth regressions at

[14] Our findings in this section are complementary to the aggregate finding in Kapadia (2006) that stocks with high volatility underperform only when cross-sectional skewness for the market as a whole is high.

the portfolio level, we conduct these tests at the individual stock level to get a sense of whether the aggregation into expected-skewness-sorted portfolios is unduly influencing our results. We therefore run the following cross-sectional regression for each month t in our sample:

$$r_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} E_t[is_{i,t+T}] + \phi_t' \mathbf{Z}_{i,t} + \varepsilon_{i,t}, \tag{7}$$

where $r_{i,t+1}$ is the monthly return for firm i observed at the end of month $t+1$, and all other variables are as defined in Equation (5) with the exception that they are calculated at the individual stock level.

We report the results of our estimation of Equation (7) in Table 7. Column 1 reports results with only expected skewness included in the regression. The γ_1 coefficient is negative and significant at the 5% level. In contrast, when idiosyncratic volatility is included alone in the regression (column 2), the coefficient on idiosyncratic volatility is negative but not statistically significant. In column 3, we include both expected skewness and idiosyncratic volatility and the result persists: the coefficient on expected skewness is significant but the coefficient on idiosyncratic volatility is not. Column 4 reports results with expected skewness as well as all of our factor loadings. Here the γ_1 coefficient remains negative and is significant at the 5% level. In column 5, we include all other characteristics, including idiosyncratic volatility, and in column 6 we include characteristics and factor loadings in the regression. In both of these cases, the coefficient on expected skewness is negative and significant at the 10% level. The coefficient on idiosyncratic volatility is significant at the 1% level in both cases.[15]

In summary, Table 7 shows that although the size of the coefficients is smaller than in the portfolio-based results, expected idiosyncratic skewness has significant explanatory power in the individual stock setting as well. In comparison with idiosyncratic volatility, expected skewness has greater explanatory power when control variables are not included, and idiosyncratic volatility has greater explanatory power after including control variables. Given that the expected skewness variable is a linear combination of control variables, it is not surprising that expected skewness loses some explanatory power when all control variables are included in the regression. Overall, Table 7 shows that expected skewness has explanatory power over and above the explanatory power of idiosyncratic volatility, and that the Fama-MacBeth results reported in the previous section are not unduly affected by sorting stocks on expected skewness.

4.2 Regressions with volatility-sorted portfolios

We now explore further whether sorting stocks into portfolios based on expected skewness biases our results in favor of idiosyncratic skewness and against idiosyncratic volatility. We perform Fama-MacBeth regressions in which we

[15] In unreported regressions, we also perform Fama-MacBeth regresssions at the individual stock level in which instead of using lagged *iv* as an explanatory variable we use predicted *iv*. We use the same explanatory variables for predicted *iv* as we use in our skewness prediction model. In these regressions predicted *iv* is never significant, whereas predicted skewness remains significant.

Table 7
Fama-MacBeth regressions, individual stocks

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.455***	1.257***	1.520***	1.034***	3.262***	2.919***
	(5.19)	(5.39)	(5.81)	(4.77)	(2.90)	(3.24)
$E_t[is_{i,t+T}]$	−0.669**		−0.633**	−0.384**	−0.350*	−0.297*
	−(2.05)		−(2.16)	−(1.96)	−(1.82)	−(1.77)
$iv_{i,t}(1m)$		−0.115	−0.094		−0.188***	−0.205***
		−(0.91)	−(0.79)		−(2.80)	−(3.79)
$Size_{i,t}$					−0.115*	−0.111**
					−(1.90)	−(2.19)
$Book\text{-}to\text{-}Market_{i,t}$					0.216	0.281**
					(1.28)	(2.23)
$Return_{i,t}$					−0.021***	−0.027***
					−(3.01)	−(3.68)
$mom_{i,t}$					0.007***	0.007***
					(2.72)	(3.23)
$turn_{i,t}$					1.251	0.908
					(1.24)	(1.33)
$Beta\text{-}Market_{i,t}$				0.168		0.096
				(0.79)		(0.47)
$Beta\text{-}SMB_{i,t}$				−0.021		−0.049
				−(0.15)		−(0.41)
$Beta\text{-}HML_{i,t}$				0.049		−0.041
				(0.28)		−(0.26)
$Beta\text{-}UMD_{i,t}$				−0.182		−0.181
				−(1.07)		−(1.36)
$Beta\text{-}Liquidity_{i,t}$				0.059		−0.025
				(0.30)		−(0.15)
$Beta\text{-}Coskew_{i,t}$				−1.175		0.453
				−(0.60)		(0.25)
Adjusted R^2	0.017	0.029	0.038	0.112	0.108	0.155

The table reports results of Fama-MacBeth (1973) regressions, the average coefficients from cross-sectional regressions,

$$r_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} E_t[is_{i,t+T}] + \phi_t' \mathbf{Z}_{i,t} + \varepsilon_{i,t},$$

where $r_{i,t+1}$ is the monthly return for security i observed at the end of month $t+1$, $E_t[is_{i,t+1}]$ is expected idiosyncratic skewness for security i, and $Z_{i,t}$ represents a vector of portfolio loadings and characteristics observable at the end of month t. The regressions are estimated each month using our baseline dataset for t equal to December 1987 through November 2005. We construct measures of $E_t[is_{i,t+1}]$ as outlined in Equations (3) and (4) of the paper, using a horizon of $T = 60$. The variables used in the cross-sectional regressions to estimate $E_t[is_{i,t+1}]$ are given in model 6 of panel A of Table 2. We estimate $iv_{i,t}(1m)$ as in Equation (2) of the paper using a horizon of $T = 1$ month for comparison with Ang et al. (2006). $Size_{i,t}$ and $Book\text{-}to\text{-}Market_{i,t}$ are, respectively, the log of market capitalization and book-to-market ratio observed at the end of month t. $Return_{i,t}$ is the security return over month t, $mom_{i,t}$ is the cumulative return over months $t-12$ through $t-2$, and $turn_{i,t}$ is turnover over month t. Portfolio loadings and characteristics are also value-weighted averages of firm-level counterparts using monthly data from the end of month $t-36$ to the end of month t. $Beta\text{-}Market_{i,t}$, $Beta\text{-}SMB_{i,t}$, and $Beta\text{-}HML_{i,t}$ are portfolio loadings on the three Fama-French (1993) factors; $Beta\text{-}UMD_{i,t}$, is the portfolio loading on the Carhart (1997) momentum factor; $Beta\text{-}Liquidity_{i,t}$ is the loading on the Pastor-Stambaugh (2003) liquidity factor; and $Beta\text{-}Coskew_{i,t}$ is the loading on the squared excess market return following Harvey and Siddique (2000). Average coefficients and Newey-West (1987) t-statistics (in parentheses) are reported along with average adjusted-R^2. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

sort stocks into portfolios based on idiosyncratic volatility rather than expected idiosyncratic skewness. If the sorting procedure biases the results in favor of the characteristic on which the portfolios are sorted, then these regressions should be an even more stringent test of the strength of the expected idiosyncratic skewness variable.

We perform regressions as above in Equation (5) with the exception that we sort stocks each month into one hundred portfolios based on idiosyncratic volatility instead of expected skewness. The results of the regressions are reported in Table 8. The coefficients reported in the first three columns show a similar pattern as in Table 7. When included alone in the regression the coefficient on expected skewness is negative and significant and the coefficient on idiosyncratic volatility is not significant. In column 3, when we include both variables, neither coefficient is significant. In the last three columns, we report results of regressions including the factor loadings and characteristics. In these regressions, the coefficient on expected skewness is significant at the 5% level in every case, while the coefficient on idiosyncratic volatility is significant at the 1% level. Table 8 shows that the significant explanatory power of expected idiosyncratic skewness is not dependent on the sorting procedure used, and that expected skewness has explanatory power distinct from the explanatory power of idiosyncratic volatility even when idiosyncratic volatility is used as the sorting variable when forming portfolios.

4.3 Skewness and the idiosyncratic volatility puzzle

Having documented pricing effects of idiosyncratic skewness, we now assess whether idiosyncratic skewness can help explain the negative relation between idiosyncratic volatility and expected returns, as documented by Ang et al. (2006). In doing so, we also hope to further disentangle the separate effects of idiosyncratic skewness and idiosyncratic volatility on expected returns. Perhaps because a negative relation between risk and return is difficult to reconcile with standard assumptions regarding investor utility, other explanations for the *iv* puzzle tend to focus on market imperfections that could induce such a relation, such as short-sale constraints or a lack of information disclosure (Boehme et al. 2005; Duan, Hu, and McLean 2006; Jiang, Xu, and Yao 2008). In contrast, an explanation for the *iv* puzzle based on skewness preference does not focus on the existence of market imperfections. If investors have a preference for positive skewness, they may accept lower average returns on stocks with high idiosyncratic volatility if those stocks also offer highly skewed returns.

Ang et al. (2008) address the potential impact of idiosyncratic skewness on the negative relation between idiosyncratic volatility and returns. They find that skewness has a strong negative cross-sectional correlation with expected returns. In terms of statistical significance, they show that the negative relation between lagged skewness and returns is even stronger than the negative relation between lagged idiosyncratic volatility and returns. At the same time, these authors show that the *iv* puzzle persists even after controlling for lagged skewness. However, Ang et al. (2008) only use lagged skewness as their measure of expected skewness. Since other variables are also important predictors of skewness, these authors may underestimate the true impact of skewness

Table 8
Fama-MacBeth regressions, idiosyncratic volatility-sorted portfolios

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.736***	1.182***	1.472***	1.721***	6.933***	4.219***
	(4.86)	(4.95)	(4.30)	(4.01)	(3.69)	(2.66)
$E_t[is_{p,t+T}]$	−1.262*		−0.780	−1.171**	−1.387**	−1.177**
	−(1.83)		−(1.31)	−(2.55)	−(2.53)	−(2.38)
$iv_{p,t}(1m)$		−0.119	−0.113		−0.334***	−0.300***
		−(0.93)	−(0.84)		−(3.68)	−(3.12)
$Size_{p,t}$					−0.275***	−0.133
					−(2.94)	−(1.60)
$Book\text{-}to\text{-}Market_{p,t}$					−0.467	0.063
					−(0.90)	(0.12)
$Return_{p,t}$					−0.005	−0.009
					−(0.40)	−(0.62)
$mom_{p,t}$					0.002	0.003
					(0.44)	(0.90)
$turn_{p,t}$					1.620	2.624**
					(1.04)	(2.06)
$Beta\text{-}Market_{p,t}$				−0.050		−0.373
				−(0.14)		−(1.00)
$Beta\text{-}SMB_{p,t}$				0.154		0.091
				(0.69)		(0.34)
$Beta\text{-}HML_{p,t}$				0.302		0.085
				(1.44)		(0.34)
$Beta\text{-}UMD_{p,t}$				−0.371		−0.270
				−(1.09)		−(0.96)
$Beta\text{-}Liquidity_{p,t}$				0.477		0.667
				(1.08)		(1.63)
$Beta\text{-}Coskew_{p,t}$				−3.700		−0.554
				−(0.83)		−(0.12)
Adjusted R^2	0.066	0.114	0.159	0.342	0.323	0.448

The table reports results of Fama-MacBeth (1973) regressions, the average coefficients from cross-sectional regressions,

$$r_{p,t+1} = \gamma_{0,t} + \gamma_{1,t} E_t[is_{p,t+T}] + \phi_t' \mathbf{Z}_{p,t} + \varepsilon_{p,t},$$

where $r_{p,t+1}$ is the value-weighted monthly return for portfolio p observed at the end of month $t+1$; $E_t[is_{p,t+1}]$ is expected idiosyncratic skewness for portfolio p; and $Z_{p,t}$ represents a vector of portfolio loadings and characteristics observable at the end of month t. The test assets are one hundred portfolios sorted each month on $iv_{p,t}$. The regressions are estimated each month using our baseline dataset for t equal to December 1987 through November 2005. Expected skewness and other regressors for portfolio p are defined as the value-weighted average firm-level measures across all stocks in portfolio p. We construct measures of $E_t[is_{p,t+1}]$ as outlined in Equations (3) and (4) of the paper, using a horizon of $T = 60$. The variables used in the cross-sectional regressions to estimate $E_t[is_{p,t+1}]$ are given in model 6 of Table 2. We also include as a regressor $iv_{p,t}(1m)$, the historical idiosyncratic volatility for portfolio p. We estimate $iv_{p,t}(1m)$ as in Equation (2) of the paper, using a horizon of $T = 1$ month for comparison with Ang et al. (2006). $Size_{p,t}$ and $Book\text{-}to\text{-}Market_{p,t}$ are, respectively, the log of market capitalization and book-to-market ratio observed at the end of month t. $Return_{p,t}$ is the portfolio return over month t; $mom_{p,t}$ is the cumulative return over months $t-12$ through $t-2$; and $turn_{p,t}$ is turnover over month t. Portfolio loadings and characteristics are also value-weighted averages of firm-level counterparts using monthly data from the end of month $t-36$ to the end of month t. $Beta\text{-}Market_{p,t}$, $Beta\text{-}SMB_{p,t}$, and $Beta\text{-}HML_{p,t}$ are portfolio loadings from the Fama-French (1992) three-factor model; $Beta\text{-}UMD_{p,t}$ is the portfolio loading on the Carhart (1997) momentum factor; $Beta\text{-}Liquidity_{p,t}$ is the loading on the Pastor-Stambaugh (2003) liquidity factor; and $Beta\text{-}Coskew_{p,t}$ is the loading on the squared excess market return following Harvey and Siddique (2000). Average coefficients and Newey-West (1987) t-statistics (in parentheses) are reported along with average adjusted-R^2. Significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Table 9
Descriptive statistics of portfolios by level of idiosyncratic volatility

	(1) Mean	(2) Std Dev	(3) Skewness	(4) Firm skewness	(5) Firm i-vol%	(6) Size	(7) CAPM alpha	(8) FF alpha
1 (Low)	1.207	3.782	−0.676	0.659	0.899	12.812	0.266	0.116
							(2.79)	(1.74)
2	1.143	4.667	−0.741	0.485	1.602	12.568	0.042	−0.051
							(0.54)	−(0.67)
3	1.117	5.792	−0.786	0.557	2.325	11.814	−0.134	−0.084
							−(1.13)	−(0.75)
4	0.759	7.178	−0.599	0.727	3.424	11.007	−0.618	−0.417
							−(2.93)	−(2.65)
5 (High)	0.119	8.380	−0.089	1.116	7.083	9.872	−1.265	−1.184
							−(3.78)	−(4.44)
1–5	1.087						1.531	1.300
	(2.50)						(3.79)	(4.32)

The table reports descriptive statistics for portfolios formed on the basis of idiosyncratic volatility. We construct estimates of $iv_{i,t}(1m)$ at the end of each month from December 1987 through November 2005 as outlined in Equation (1) of the paper. We then sort stocks into quintile portfolios at the end of each month based on $iv_{i,t}(1m)$ and compute the value-weighted return over month $t+1$ for each portfolio. We report descriptive statistics for each of the five quintiles, where the first quintile represents firms with the lowest levels of $iv_{i,t}(1m)$, and the fifth quintile represents firms with the highest levels of $iv_{i,t}(1m)$. Column 1 reports the time-series average of the value-weighted portfolio returns. Columns 2 and 3 report the time-series standard deviation and skewness of the portfolio returns. Columns 4, 5, and 6 report averages, across time, of the value-weighted cross-sectional averages of $is_{i,t}$, $iv_{i,t}(1m)$, and $ln(size_{i,t})$ within each portfolio. Columns 7 and 8 report estimated alphas and Newey-West (1987) t-statistics (in parentheses) from the CAPM and the Fama-French (1993) three-factor model.

preference on the *iv* puzzle.[16] To study the impact of predicted skewness on the *iv* puzzle, we begin with the key results of Ang et al. (2006), and then assess how those results change when we control for predicted skewness. Finally, in order to further distinguish the independent effects of idiosyncratic volatility and skewness, we also do the reverse experiment to determine to what degree idiosyncratic volatility seems to explain our results on the relation between expected idiosyncratic skewness and returns.

4.3.1 Idiosyncratic volatility and expected returns. We begin by repeating the analysis of Ang et al. (2006) using our baseline dataset. We construct "*iv* portfolios" by sorting stocks at the end of each month on $iv_{i,t}(1m)$, defined as in Tables 1 and 2, into quintile portfolios. We then calculate the value-weighted return over month $t+1$ for each portfolio. In Table 9, we provide summary statistics for the portfolio returns. We find the characteristics of these portfolios to be similar to those reported in Ang et al. (2006). The first two and last two columns of Table 9 are directly comparable to panel B of Table 6 of Ang et al. (2006). These columns indicate that average returns (over month $t+1$), return standard deviations, as well as pricing errors of the CAPM and Fama-French three-factor model are comparable to Ang et al. (2006). In particular, column 1

[16] In a similar vein, Fu (2005) argues that lagged idiosyncratic volatility is not a good measure of expected idiosyncratic volatility, and that the *iv* puzzle does not persist when using more sophisticated estimates of expected volatility.

of Table 9 illustrates the poor average performance of the high-*iv* quintile portfolio. Whereas the low-*iv* quintile has mean returns of 1.21% per month, the high-*iv* quintile has mean returns of 0.12% per month. In addition, the last two columns show large pricing errors of the CAPM and the Fama-French model. The difference in the Fama-French alphas between the first and fifth quintiles is 1.30% per month. Table 9 shows, similar to Ang et al. (2006), that the *iv* puzzle is most pronounced in the high-*iv* quintile, where mean returns and alphas are disproportionately low relative to the other four quintiles.

We also include two skewness variables in Table 9. The first skewness variable, in column 3, is the time-series skewness estimate of the respective quintile portfolio returns. While this statistic is negative across all portfolios, quintiles of higher idiosyncratic volatility exhibit less negative levels of skewness in their returns. The other skewness variable, firm skewness (in column 4), is the average across time of the value-weighted cross-sectional average of $is_{i,t}$ for each portfolio, estimated as described in Equation (2) using a horizon of $T = 60$ months.[17] The pattern of increasing firm skewness in quintiles with higher volatility again illustrates a strong contemporaneous relation between idiosyncratic volatility and idiosyncratic skewness. These two measures of skewness suggest that lagged idiosyncratic volatility is related to the skewness of portfolio returns.[18] Consistent with the results for the mean returns, the largest increase in skewness occurs between the fourth and fifth quintiles. Columns 5 and 6 report the averages, across time, of the value-weighted cross-sectional averages of $iv_{i,t}(1m)$ and $ln(size_{i,t})$ within each portfolio. The relations between idiosyncratic volatility, idiosyncratic skewness, and size are consistent with skewness-preferring investors taking speculative positions in small firms with highly skewed returns and accepting lower average returns in their positions for a chance of hitting an investment "home run."

4.3.2 Conditional sorting. We next directly address the question of whether predicted skewness can help explain the *iv* puzzle. Following the methodology in Ang et al. (2006, 2008), we conduct a double-sorting exercise to control for expected skewness. At the end of each month in our baseline dataset from January 1988 through November 2005, we first sort firms into five $E_t[is_{i,t+T}]$ quintiles, where we measure $E_t[is_{i,t+T}]$ as in Equations (3) and (4) using a horizon of $T = 60$ months. The variables we use in the cross-sectional regression of Equation (3) are those used in model 6 of Table 2. Then, for each $E_t[is_{i,t+T}]$ quintile, we sort firms into five "iv^c portfolios," using $iv_{i,t}(1m)$ as above, where the superscript c denotes conditional sorting. Within each of these twenty-five

[17] We use a horizon of $T = 1$ to compute $iv_{i,t}(1m)$ to be consistent with the results of Ang et al. (2006, 2008). We use a horizon of $T = 60$ to compute $is_{i,t}$, consistent with earlier work in our paper. Our results are qualitatively robust to using other horizons of T in measuring both $is_{i,t}$ and $iv_{i,t}$.

[18] Return skewness is comprised of idiosyncratic skewness and other coskewness components. Table 2 shows that idiosyncratic volatility forecasts idiosyncratic skewness, but without further analysis we do not know if idiosyncratic volatility forecasts other coskewness terms.

Table 10
Descriptive statistics of conditionally sorted portfolios

	(1) Mean	(2) Std Dev	(3) Skewness	(4) Firm skewness	(5) Firm i-vol%	(6) Size	(7) CAPM alpha	(8) FF alpha
Panel A: Conditionally IV-sorted portfolios								
1 (Low)	1.150	3.792	−0.493	0.841	1.039	12.114	0.219	0.105
							(2.101)	(1.276)
2	1.245	4.210	−0.774	0.660	1.871	12.003	0.235	0.105
							(2.373)	(1.243)
3	1.061	4.973	−0.665	0.631	2.603	11.687	−0.070	−0.095
							−(0.692)	−(0.933)
4	1.012	5.818	−0.737	0.649	3.568	11.355	−0.122	−0.026
							−(0.948)	−(0.207)
5 (High)	0.781	6.901	−0.677	0.765	6.252	10.911	−0.541	−0.373
							−(2.507)	−(2.031)
1–5	0.369						0.760	0.478
	(1.159)						(2.691)	(2.216)
UCMC	0.718						0.772	0.822
	(2.980)						(3.173)	(3.549)
Panel B: Conditionally skew-sorted portfolios								
1 (Low)	1.229	4.264	−0.549	0.215	2.832	13.053	0.213	0.212
							(2.098)	(2.170)
2	1.173	4.264	−0.548	0.466	2.926	12.443	0.149	0.089
							(1.631)	(1.065)
3	1.098	4.360	−0.808	0.654	2.983	11.798	0.061	0.063
							(0.642)	(0.695)
4	1.240	4.290	−0.505	0.912	3.216	10.927	0.281	0.040
							(1.912)	(0.288)
5 (High)	0.979	5.316	−0.551	2.041	3.489	9.848	−0.044	−0.342
							−(0.206)	−(1.616)
1–5	0.250						0.258	0.554
	(1.031)						(1.049)	(2.340)
UCMC	0.395						0.510	0.403
	(1.230)						(1.583)	(1.412)

The table reports descriptive statistics for portfolios formed on the basis of both expected skewness and idiosyncratic volatility. We construct estimates of $E_t[is_{i,t+T}]$ at the end of each month from December 1988 through November 2005 as outlined in Equations (3) and (4) of the paper, using a horizon of $T = 60$. We construct $iv_{p,t}$ as in Equation (2) of the paper using a horizon of $T = 1$ month for comparison with Ang et al. (2006). In panel A, we sort stocks into quintile portfolios at the end of each month based on $E_t[is_{i,t+T}]$. We sort stocks within each $E_t[is_{i,t+T}]$ quintile into $iv_{i,t}$ quintiles and compute the value-weighted return for these twenty-five portfolios over month $t+1$. We then value weight the portfolios across each of the five $E_t[is_{i,t+T}]$ quintiles, thereby controlling for the effects of expected idiosyncratic skewness. In panel B, we reverse the roles of $E_t[is_{i,t+T}]$ and $iv_{i,t}$, thereby creating a set of $E_t[is_{i,t+T}]$-sorted portfolios controlling for the effects of $iv_{i,t}$. This panel reports descriptive statistics for the five conditionally sorted quintiles, where the first quintile represents firms with the lowest levels of $iv_{i,t}$ in panel A and $E_t[is_{i,t+T}]$ in panel B, and the fifth quintile represents firms with the highest levels. Column 1 reports the time-series average of the value-weighted portfolio returns. Columns 2 and 3 report the time-series standard deviation and skewness of the portfolio returns. Columns 4, 5, and 6 report averages, across time, of the value-weighted cross-sectional averages of $is_{i,t+T}$, $iv_{i,t}$, and $\ln(size_{it})$ within each portfolio. Columns 7 and 8 report estimated alphas and Newey-West (1987) t-statistics (in parentheses) from the CAPM and the Fama-French (1993) three-factor model.

bins, we calculate the value-weighted return over month $t+1$. We then value weight the returns across each of the five $E_t[is_{i,t+T}]$ quintiles, thereby controlling for the effect of expected skewness. The results of this exercise are reported in panel A of Table 10.

Panel A of Table 10 suggests that skewness preference may play a substantial role in the differing returns of the *iv* portfolios. Column 1 shows that the spread of average returns across the conditionally sorted iv^c portfolios is much smaller than in the unconditionally sorted iv quintiles. The return premium between the first and fifth portfolios is only 0.37% per month and is no longer significant, down from the 1.09% spread found in Table 9. The iv puzzle of Ang et al. (2006) is substantially reduced when we control for expected idiosyncratic skewness.

Columns 2 and 3 of panel A of Table 10 report the time-series standard deviation and skewness of the conditionally sorted portfolio returns. Columns 4, 5, and 6 report the averages, across time, of the value-weighted cross-sectional averages of $is_{i,t}$, $iv_{i,t}(1m)$, and $ln(size_{i,t})$ within each portfolio. We find relatively small variations in portfolio skewness across the five iv^c quintile portfolios, indicating that our model of expected skewness predicts skewness reasonably well. The average firm skewness measures also show relatively small differences relative to the variation found in the unconditionally sorted iv portfolios in Table 9. In fact, firm skewness is now slightly lower in the high-iv^c quintile relative to the low-iv^c quintile. However, we still find a wide spread in idiosyncratic volatility across the portfolios. The spread is comparable to that of the portfolios unconditionally sorted on idiosyncratic volatility reported in Table 9, although volatility is lower in the fifth quintile compared with Table 9.

Finally, in columns 7 and 8 of panel A of Table 10, we control for risk to see if material pricing differences are found across the quintile portfolios. We report alphas relative to the CAPM and relative to the Fama-French three-factor model for each of the conditionally sorted portfolios. The high-iv^c portfolio has a CAPM intercept estimate of -0.54%, which is significant with a t-statistic of 2.5, indicating that on a CAPM risk-adjusted basis, the iv puzzle still persists. However, this point estimate is less than half the magnitude of the estimate for the unconditionally sorted high-iv quintile in Table 9. Similarly, the high-iv^c portfolio results in panel A of Table 10 indicate a Fama-French intercept of -0.37% on the high-iv^c portfolio, which is small relative to the -1.18% intercept for the unconditionally sorted high-iv quintile in Table 9. The evidence indicates that idiosyncratic volatility generates much smaller differences in pricing errors relative to the CAPM and Fama-French models after controlling for idiosyncratic skewness.

In the bottom row of panel A of Table 10, we report results from constructing a difference-in-differences portfolio, UCMC (unconditional minus conditional), to better assess the improvements associated with forecasting skewness. In particular, we take a long position in the zero-investment iv-sorted long/short portfolio and a short position in the zero-investment iv^c-sorted long/short portfolio. (The iv-sorted long/short portfolio is constructed by taking a long position in the low-iv quintile portfolio and shorting the high-iv quintile portfolio, and the iv^c-sorted long/short portfolio is constructed by taking a long position in the low-iv^c quintile portfolio and shorting the high-iv^c quintile portfolio.) The resulting difference-in-differences portfolio should allow us to formally test the ability of expected skewness to explain the iv puzzle. The results are strongly supportive of the explanatory power of predicted skewness. The CAPM alpha on the UCMC portfolio is 0.77% with a t-statistic of 3.2 and the Fama-French three-factor model has an intercept of 0.82% with a t-statistic of 3.5.

In panel B of Table 10, we repeat the analysis of panel A, except that we reverse the roles of expected skewness and idiosyncratic volatility. Thus, we control for the effect of *iv* in the expected skewness-sorted portfolios to see if *iv* helps explain the differing returns of the expected skewness quintile portfolios as reported in Table 3. The results in panel B show that controlling for *iv* does reduce the magnitude of the difference in returns between the low- and high-skewness quintiles. Compared to Table 3, the differences in returns and CAPM alphas between the low and high portfolios are no longer significant. However, the difference between the Fama-French alphas on the low and high portfolios remains significant, with a t-statistic of 2.3. The magnitude of the difference indicates that the Fama-French alpha of the low-skewness quintile exceeds the alpha of the high-skewness quintile by 0.55% per month, even after controlling for *iv*. The final row of panel B reports the results of a UCMC portfolio constructed as described for panel A, but with the roles of expected skewness and idiosyncratic volatility reversed. In contrast to the results in panel A, the alphas on this UCMC portfolio are not significant at standard levels. Thus, although controlling for *iv* has some impact on the results in Table 3, the insignificant UCMC portfolio alphas suggest that the changes induced by idiosyncratic volatility are not statistically significant. By this measure at least, expected idiosyncratic skewness appears to explain the negative relation between idiosyncratic volatility and returns better than idiosyncratic volatility explains the negative relation between expected skewness and returns.

4.3.3 Discussion. The results in Table 10 suggest that idiosyncratic skewness is important in explaining the low average returns of stocks with high idiosyncratic volatility. At the same time, these results show that, looking at things from the other direction, idiosyncratic volatility explains part of our finding that expected idiosyncratic skewness is negatively correlated with returns. In either case, the significant explanatory power of one of the variables remains after controlling for the other.[19] In addition, there is some "overlapping" explanatory power that could be attributed to either variable. Empirically, it may be difficult to determine whether this overlapping explanatory power should be properly attributed to volatility or skewness. From a theoretical perspective, however, the skewness explanation appears to have the upper hand, given that there are already established theoretical explanations for the negative relation between idiosyncratic skewness and expected returns (i.e., Barberis and Huang 2007; Brunnermeier and Parker 2005; Mitton and Vorkink 2007). The *iv* puzzle, by

[19] We find consistent results in other tests (not reported) in which we independently sort stocks on expected skewness and idiosyncratic volatility, thus forming twenty-five portfolios reflecting stocks' ranking in skewness and volatility. These results show that, although the changes are not always monotonic across quintiles, alphas are generally lower for the higher-skewness quintiles (across a given *iv* portfolio) and alphas are generally lower for the higher-*iv* portfolios (across a given skewness portfolio).

contrast, is an interesting anomaly for which a complete explanation is still being sought.

To the extent that expected skewness explains the *iv* puzzle, this explanation is not mutually exclusive of other explanations of the *iv* puzzle based on market imperfections. To the contrary, we view the skewness-preference explanation as complementary to explanations that focus on short-sale constraints or differences of opinion. High valuations driven by underdiversified, skewness-preferring investors are more likely to persist when the costs of short selling are high. Similarly, large dispersion of opinion may imply greater heterogeneity in skewness preference, with underdiversified investors valuing the upside potential of a stock more than similarly informed well-diversified investors with less preference for skewness. Multiple factors may contribute to the *iv* puzzle, but skewness preference adds a critical element of explaining why some investors place high value on stocks with high past idiosyncratic risk in the first place.

5. Conclusion

Although a number of theories point toward a pricing premium for stocks with idiosyncratic skewness, empirical testing of the relation between idiosyncratic skewness and returns has been slow in coming. We attempt to fill this void by estimating a model of predicted skewness and then using predicted skewness to explain the cross-section of returns. We find that lagged idiosyncratic volatility is a stronger predictor of skewness than is lagged idiosyncratic skewness. We thus rely on idiosyncratic volatility and a small number of other variables to predict idiosyncratic skewness. We find significant pricing effects of predicted skewness, especially in relation to the Fama-French three-factor model. Sorting stocks on predicted skewness, the Fama-French alpha of the low-skewness quintile exceeds the alpha of the high-skewness quintile by 1.00% per month. Investors appear to pay a premium for stocks that are expected to have more highly skewed returns.

In our analysis, we also shed light on the negative relation between idiosyncratic volatility and expected returns. Why do investors pay a premium for stocks that have a greater level of idiosyncratic risk? Our results suggest that investors might pay a premium for these stocks because a high level of idiosyncratic volatility is a good indicator of stocks that offer a high level of future skewness exposure. Unwanted risk (volatility) signals desired opportunities (skewness), and skewness-preferring investors may be willing to accept a stock with higher idiosyncratic volatility and lower expected returns in return for a chance at an extreme winner. We find that forecasted skewness helps explain the negative relation between idiosyncratic volatility and expected returns. While market imperfections such as short-sale constraints and informational problems may also play a role in the phenomenon, our results suggest that a starting point for understanding the negative relation between idiosyncratic volatility and expected returns lies in the preferences of investors.

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