The Next Microsoft?
Skewness, Idiosyncratic Volatility, and Expected Returns[+]

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Abstract

This paper analyzes the low subsequent returns of stocks with high idiosyncratic volatility, documented by prior research. There is substantial time-series co-variation between stocks with high idiosyncratic risk. I examine an alternative measure of aggregate skewness, the cross-sectional skewness of all firms at a given point in time. Cross-sectional skewness helps explain both the common time-variation and the premium associated with firms with high idiosyncratic volatility. Sensitivity to cross-sectional skewness is also related to the underperformance of Initial Public Offerings (IPOs) and small growth stocks. IPOs only underperform if they list in times of high cross-sectional skewness. These results imply that the low returns to IPOs, small growth stocks and highly volatile stocks are a result of a preference for skewness. Finally, proxies for technological change, such as lagged patent grant growth, predict future cross-sectional skewness. This suggests an economic interpretation of cross-sectional skewness as the result of changes in industry structure brought about by shocks such as significant technological change.

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1 Introduction

Conventional asset pricing theory suggests that investors should not be compensated for bearing idiosyncratic risk. However, recent empirical evidence has questioned this fundamental premise. Recent papers find that idiosyncratic risk is correlated with expected returns both at the market and the individual stock level, although there is disagreement on the direction of the impact. For example, Goyal and Santa-Clara (2003) find that the volatility of equal-weighted portfolios is positively correlated with future market returns.[1] However, at the individual stock level, Ang, Hodrick, Xing, and Zhang (2006a; henceforth AHXZ) find that stocks with high idiosyncratic risk earn low subsequent returns. This relation is economically large with annualized alphas from the Fama and French (1993) three-factor model of approximately -14% (AHXZ pp. 285). This paper attempts to provide an explanation for this anomaly.

It is intuitively more appealing to expect higher rather than lower returns for stocks with high volatility.[2] This paper, explores the hypothesis that skewness is responsible for the low returns to highly volatile stocks. There are several reasons to investigate the effect of skewness in this context. First, the relation between idiosyncratic volatility and returns is visible only in the most volatile stocks. Stocks with exceptionally high volatility are likely to have positive skewness, given the limited liability nature of equity.[3] Second, a preference for skewness is theoretically consistent with low expected returns, unlike a preference for variance which suggests risk-seeking behavior. It is also interesting to note parallels with the literature on gambling, which initially found that agents accept gambles with high variance and low expected returns, consistent with risk seeking behavior. However Golec and Tamarkin (1998) find that this behavior is driven by a preference for skewness not variance. Although the stock market is very different from the race track, there is substantial research that investigates the relation between

[1] Bali, Cakici, Yan, and Zhang (2005) find that this relationship is weaker in an extended sample.
[2] For example, Merton (1987) describes a model where idiosyncratic volatility leads to higher expected returns in the absence of complete information.
[3] Simkowitz and Beedles (1978), Conine and Tamarkin (1981) and Duffee (1995), among others, show that individual stocks are positively skewed. Conine and Tamarkin (1981) also suggest that limited liability may cause positive skewness. Also, I find that stocks with high idiosyncratic volatility have positively skewed returns and that high volatility predicts future skewness even after controlling for past skewness (Chen, Hong and Stein, 2001, also report a similar result).

skewness and expected returns in equity markets. Prior research, for example, Kraus and Litzenberger (1976), Harvey and Siddique (2000), and Dittmar (2002), shows that co-skewness with the market is an important determinant of expected returns. Also, Barberis and Huang (2005) show that in a model where agents have utility functions based on prospect theory, idiosyncratic skewness earns a premium.

I first present new stylized facts about the AHXZ puzzle that help relate it to skewness. There is substantial co-movement between stocks with high idiosyncratic volatility, measured as in AHXZ. I form five portfolios based on size that track the excess returns of stocks with high idiosyncratic risk. Although these portfolios have no stocks in common, the average pair-wise correlation of their idiosyncratic returns is 56%. This suggests that a systematic variable drives the common time-series variation of highly volatile firms. I examine if this variable is related to time-variation in market-wide measures of skewness.

The two measures of skewness examined in this paper are cross-sectional skewness (CS-SKW) and the difference between the mean and median (Breadth) for all stocks greater than the NYSE 10% size breakpoint. The cross-sectional skewness measures capture whether the likelihood of randomly drawing a stock with exceptionally high returns is asymmetrically high in a given month. In essence, this is a measure of how likely an investor would be to randomly pick the 'next Microsoft' in a given month. An advantage of using cross-sectional measures over time-series ones is that they avoid the trade-off between time-variation and accuracy that is inherent in measuring a third-moment of the return generating process. These cross-sectional measures can also be interpreted as measures of average idiosyncratic skewness.

The cross-sectional skewness measures are persistent, thus allowing time-series predictability. More importantly, these measures seem to reflect a fundamental property of each point in time, as they are also highly correlated across mutually exclusive sets of stocks defined based on size. This persistence and common variation provide the opportunity to disentangle the effect of volatility from skewness. First, I construct a factor mimicking portfolio (IVOL) that captures the premium associated with exposure to idiosyncratic volatility. IVOL is defined as the difference in value-weighted returns between stocks with low volatility (long) and stocks with high volatility (short) after a control for size.[4] Not surprisingly, IVOL has a significantly positive time-series alpha in Fama-French three-factor regressions. I show that IVOL co-varies strongly with measures of skewness, even when these measures are defined over all stocks excluding those used in constructing the IVOL factor. Second, I show that highly volatile stocks only underperform with respect to the Fama-French three-factor model when predicted CS-SKW is high. This suggests that high predicted cross-sectional skewness causes highly volatile stocks to have greater valuations and hence lower subsequent returns. Finally, I show that if one controls for cross-section skewness by using a factor-mimicking portfolio, the alpha associated with IVOL disappears. These three tests provide strong evidence that the low returns to highly volatile stocks are the result of a premium for skewness.

If cross-sectional skewness is an important determinant of expected returns, its effects should also be visible in other contexts as well. To see if this is true, I examine the underperformance of Initial Public Offerings (IPOs), documented by prior literature (Ritter, 1991). IPOs provide an ideal setting to examine the effect of skewness for two reasons. Prior literature reports that IPO returns are positively skewed (e.g. Brav, 2000). This could be because most IPOs are young firms, with a high fraction of their value in the form of growth options. Also, IPOs provide an opportunity to conduct event time tests which provide different insights from the calendar time tests conducted for idiosyncratic volatility. Specifically, event time tests provide a reference point (the listing month) to measure skewness, and to relate it to subsequent low returns. Event-time tests show that the subsequent underperformance of IPOs is highly negatively correlated with measures of cross-sectional skewness at the time of their listing. IPOs only underperform on average if they list during times of high cross-sectional skewness. Also, in calendar time regressions, the returns of IPOs are correlated with the cross-sectional skewness mimicking factor and IVOL. Both these factors add explanatory power to the Fama-French three-factor model for IPOs.

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[4] Specifically, stocks are first sorted into quintiles based on size. Within each quintile, stocks are sorted into quintiles based on their AHXZ measure of idiosyncratic volatility. Portfolio 0 is a value-weighted portfolio of all stocks in the least volatile quintile, across all size quintiles and so on for portfolios 1 to 4. IVOL is the difference in returns between portfolio 0 and 4 (VOL = RET0 -RET4).

I find that cross-sectional skewness is also related to the abnormally low returns of small growth stocks, reported by Fama and French (1993). This is also consistent with the results on IPO underperformance, as Brav, Geczy, and Gompers (2000) find that IPO underperformance is concentrated primarily in small growth stocks. I find that stocks with high volatility load like small growth stocks even after explicit controls for size and book-to-market. Conversely, covariances with cross-sectional skewness among the 25 size and book-to-market portfolios increase monotonically as size and book-to-market decrease. That is, small growth stocks have the highest correlation with cross-sectional skewness (-76%) among all the 25 size and book-to-market portfolios.

The hypothesis that cross-sectional skewness is a systematic factor, in the Arbitrage Pricing Theory (Ross, 1976) sense, is supported by the success of its factor-mimicking portfolio in explaining the cross-section of returns. The common time-series variation in measures of cross-sectional skewness suggests there may be an underlying economic variable driving skewness across different sets of stocks. Also, industries that have experienced significant shocks are over-represented in the portfolio with highest sensitivities to cross-sectional skewness. A hypothesis that explains this is related to the creative destruction process. Consider a large economy-wide shock, such as a new technology, which has the possibility of disrupting existing industry structures. Investors realize that there will be some firms, or sets of firms, that will benefit greatly once the new structure is realized. Although they do not know which firms in particular will win out, they realize that the cross-sectional distribution of returns is likely to be skewed. Firms with high sensitivities to this underlying source of uncertainty are also likely to be over-represented in portfolios of highly volatile stocks.

To test if this sequence of events is supported by data, I examine whether proxies of technological change, like growth rates in patents or R&D investment, can forecast innovations in cross-sectional skewness. I find evidence consistent with this – both lagged growth rates of the number of patent grants and average R&D expenses (scaled by total assets) of publicly traded firms significantly predict future innovations in annual skewness.

The low returns of stocks that vary with cross-sectional skewness are distinct from co-skewness, the traditional measure of the skewness that a stock adds to the market portfolio. In particular the factor mimicking portfolios for cross-sectional skewness and co-skewness are negatively correlated. This suggests that although the common variation in returns of highly volatile stocks may be due to a systematic factor, like technological change, a possible explanation for their low returns is a preference for idiosyncratic skewness as in Barberis and Huang (2005).

There has been some recent controversy about the direction of the impact of volatility on returns. Surprisingly Fu (2005) and Spiegel and Wang (2005, henceforth SW) find exactly the opposite effect from AHXZ - stocks with high expected idiosyncratic risk earn high returns. The difference between these papers and AHXZ is the method used to compute idiosyncratic volatility. I use a bias corrected estimator, based on a simplified version of the MIDAS estimator in Ghysels, Santa-Clara, and Valkanov (2004).[5] This estimator provides the ability to mix frequencies to generate monthly conditional variance forecasts using daily returns.[6] This model strongly confirms AHXZ's results: firms predicted to be in the highest quintile based on past volatility have abnormally low returns in the following month.

The remainder of the paper is organized as follows. The next section reviews related research. Section 3 provides a brief description of the data used. Section 4 examines the common variation in stocks with high idiosyncratic risk. Section 5 introduces measures of skewness and shows that they are able to explain the common variation in the returns of highly volatile stocks. Section 6 shows that skewness is also related to IPO underperformance and the small growth portfolio. Section 7 provides a possible interpretation of these results. Finally, Section 8 concludes

2 Literature Review

This paper is related to several strands of the literature, including papers that examine idiosyncratic risk, time-series and cross-sectional skewness, co-skewness and the effect of technological innovations on asset prices. This section briefly discusses relevant papers from each of these strands.

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[5] This estimator, called MIDAS with step functions, is described in Ghysels, Sinko, and Valkanov (2006)
[6] In a sample of 150 randomly chosen stocks, the MIDAS with step function estimate has lower mean/median, squared/absolute prediction error and greater rank correlation with realized volatility than monthly return based EGARCH / GARCH models used by Fu / SW, both for in-sample and out of sample predictions.

There has been a recent renewal in academic interest in examining the effect of idiosyncratic risk on returns. Goyal and Santa-Clara (2003) find that equal-weighted idiosyncratic volatility predicts future market returns. Subsequent research by Bali, Cakici, Yan, and Zhang (2005) finds that this relationship is weaker in an extended sample. Measuring idiosyncratic volatility as the standard deviation of the residuals of a daily three-factor regression over the prior month, AHXZ find that the next month's returns of highly volatile stocks are abnormally low. In a follow-up paper (Ang, Hodrick, Xing, and Zhang, 2006b), they show that this pattern is visible internationally. Specifically they find that this effect is significant in each G7 country and is also visible across 23 developed countries. This provides out-of-sample evidence for their initial paper.[7] They also document an intriguing co-variation between portfolios sorted on idiosyncratic risk in the US and in international markets. Specifically, after controlling for US idiosyncratic risk portfolio returns, the abnormally low returns in international markets are not significant.

Fu (2005) uses a different approach to measure idiosyncratic volatility. He uses in-sample, conditional volatility from a Fama-French three-factor in mean, EGARCH in variance model on monthly returns as a proxy for idiosyncratic volatility. He finds that idiosyncratic volatility significantly predicts greater returns in Fama-Macbeth regressions on individual stocks. However, he also reports that value-weighted portfolios formed on sorts of idiosyncratic volatility do not have significant alphas.

Spiegel and Wang (2006) extend Fu's method to make out-of-sample predictions. That is, they re-estimate the model every month for every stock with more than five years of returns, using only prior information to predict volatility, and then roll it forward month-by-month to generate a time-series of predicted idiosyncratic volatility. They show that high idiosyncratic volatility predicts high subsequent returns, and these high returns are robust to controls for liquidity.

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[7] Between the two papers, AHXZ rule out a host of probable explanations in the US market, including size, book-to-market, momentum, leverage, liquidity (the Pastor and Stambaugh (2003) measure), volume, turnover, bid-ask spread, co-skewness, dispersion in analyst forecasts, information asymmetry (via the PIN measure), percentage of zero returns, analyst coverage, institutional ownership, delay, and individual stock skewness

There are four broad theoretical arguments that imply investors may be (or appear to be) compensated for idiosyncratic risk. Merton (1987) describes a model where investors are not well-diversified because they do not have information about all stocks. This leads to higher expected returns for high idiosyncratic volatility stocks. This is the explanation that Fu and Speigel and Wang provide for their results. Second, Miller (1977) suggests that differences of opinion, in the presence of short-sale constraints, cause optimistic views to be reflected in prices to a greater extent than negative views. If high idiosyncratic risk stocks are also short sale constrained, then a subsequent correction results in what appears to be a negative relation between idiosyncratic risk and returns.[8] A recent paper by Duan, Hu, and MacLean (2006) finds evidence in favor of a short sale constraints as a limit to arbitrage story.

An earlier Merton paper provides a different framework to think about this issue. Merton (1974) uses a model of equity as a call option on the assets of the firm to value risky debt. An increase in asset volatility results in a greater value of the option. Johnson (2004) modifies this model to show that higher parameter uncertainty will also behave in a similar manner to higher volatility, serving to raise current prices and lower expected returns. [9] This model helps explain the low returns to stocks with high analyst dispersion. Finally, there is the ever-present 'bad model' problem. Idiosyncratic risk is defined based on a specific asset pricing model – an incorrectly specified model will result in what appears to be a compensation for idiosyncratic risk, but is actually just compensation for a missing factor. [10]

The results in this paper suggest that the missing factor is related to skewness. Higher moment versions of the CAPM suggest that time-series co-skewness with the market is a risk factor. These rely on a Taylor series expansion of utility functions or parameterizing the stochastic discount factor as a linear combination of higher moments of aggregate wealth. Harvey and Siddique (2000) construct a conditional skewness factor

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[8] However, Diamond and Verrecchia (1987) show in a rational expectations model, differences in opinion will not lead to biased prices even in the presence of short-sale constraints.

[9] In fact, the Johnson model results in an identical solution to Merton (1973) except that volatility is now the sum of underlying asset volatility and parameter uncertainty.

[10] Lehmann (1990) has an interesting perspective on the 'bad model' problem and idiosyncratic risk: There is now significant evidence that we live in a multi-factor world, therefore idiosyncratic risk defined by the CAPM should be related to expected returns.

and show that it is priced, while Dittmar (2002) also considers co-kurtosis. Kumar (2005) examines the idiosyncratic and systematic (time-series) skewness preferences of institutions and finds that institutions are averse to idiosyncratic skewness, but like systematic skewness. Kumar (2005) also investigates whether institutional preferences affect expected returns. A recent paper by Barberis and Huang (2005) shows that equilibria exist in which investors with prospect theory based utility functions prefer idiosyncratic skewness.

Zhang (2005) finds that the cross-sectional skewness of similar firms (as defined by industry, size or book-to-market) predicts future total skewness of individual stocks. His results also support Barberis and Huang (2005) by showing that greater idiosyncratic skewness leads to lower subsequent returns. Unfortunately, he is unable to replicate AHXZ's results and so cannot test if they are driven by skewness. Higson, Holly, and Kattuman (2002) examine the cross-sectional skewness of growth rates of firms and its relation to the business cycle. They find that cross-sectional skewness and variances are strongly counter-cyclical and that the effects of macro-economic shocks are more pronounced for firms in the middle range of growth.

This paper is also related to the literature on technological change, industry structure, and asset prices, since skewness in returns may be an outcome of rapid technological change. Jovanovic and Macdonald (1994) describe a model in which a rise in innovation precipitates an industry shake-out. This model illustrates the typical life-cycle of an industry documented by Gort and Klepper (1982). A young industry is initially populated by a few small firms; the number of firms increases dramatically, raising output and lowering price, followed by a shakeout that results in many exits and few survivors. The shake-out is typically preceded by a technological innovation. Pastor and Veronesi (2005) derive a general equilibrium model to explain the bubble-like patterns that asset prices exhibit during technological revolutions. The model examines the effects of learning about the productivity of a new technology. Subsequent adoption of the technology leads to changes in the nature of uncertainty from idiosyncratic to systematic, resulting in falling stock prices after an initial run-up.

3 Data

I collect all available data from the Center for Research in Security Prices for U.S. listed stocks (with share code 10 or 11) from 1963-2005. Idiosyncratic volatility is computed (as in AHXZ) as the variance of residuals from a three-factor model from daily returns within a month. In particular, the residuals from the following regression on daily returns for each firm, each month, give idiosyncratic volatility:

$$R_{it} - r_f = \alpha_i + \beta_i*(R_{mt} - r_f) + \gamma_i*\text{SMB}_t + \varphi_i*\text{HML}_t + u_{it} \qquad (1)$$

Where t=1,2,…, T (the number of trading days in the month), R_m is the value-weighted return on the market, and HML and SMB are defined as in Fama and French (1993) and are from Kenneth French's website.

Idiosyncratic volatility for each firm, each month is the variance of u_{it}. Firm-months with less than 15 days of returns are excluded. For annual estimates of idiosyncratic risk, a similar procedure is adopted using daily returns within the year. In addition, I include two lags of each factor to correct for stale prices. Following the literature, I refer to a regression with the market return, SMB and HML as a three-factor regression, and when it is augmented by the momentum portfolio (UMD) as a four-factor regression. Also, all *t*- statistics in the time-series regressions in the paper are based on Newey-West standard errors (with 3 lags).

4 The common variation of stocks with high idiosyncratic volatility

This section presents a series of stylized facts that help understand the AHXZ puzzle. First, Appendix 1 examines alternate measures of expected volatility and shows that the AHXZ result is robust. In particular, using monthly realized volatility from daily returns (as AHXZ do) provides better forecasts of next months' volatility, as compared to monthly return based EGARCH estimators. Also, an alternative estimator based on MIDAS with step functions (Ghysels, Sinko, and Valkanov, 2006) that predicts future realized volatility by weighting the last five days, the last month, and the last three months' volatility also provides the same inference as AHXZ. These results show that high conditional idiosyncratic volatility results in low expected returns, consistent with AHXZ.

I then examine returns to portfolios created based on sorts on size and idiosyncratic volatility. This shows that there is substantial covariation between distinct size sorted portfolios with high idiosyncratic risk. This covariation suggests that there is an underlying factor associated with the returns of highly volatile stocks. Consequently, I define a factor, in section 4.2, that captures this co-variance and study its time-series properties.

4.1 Size and idiosyncratic volatility

Table 1 presents the results of three-factor regressions of the returns of value-weighted portfolios formed from sequential sorts, first on size and then on idiosyncratic risk (as defined by AHXZ). Except for the smallest stocks, all high idiosyncratic risk portfolios have significantly negative alphas. Panel B contains robustness checks, based on different size breakpoints (all stocks / NYSE only), equal or value-weighted portfolios, and adding a momentum factor to the three-factor regression. These robustness checks indicate that the AHXZ effect is strongest in mid-cap stocks. The smallest and largest stocks do not show as strong an effect.

To examine whether the low returns to stocks with high idiosyncratic volatility are truly idiosyncratic, I create hedged returns by calculating the difference between the returns of the most and least volatile stocks within each size quintile. This results in five portfolios, with no stocks in common, that track the excess returns of stocks with high idiosyncratic risk over time. There is substantial time-series correlation between these portfolios. Clearly, this correlation may be because of common exposure to systematic factors. I therefore regress each of these portfolios on four-factors (the market, HML, SMB, and momentum) and measure the correlation of the residuals over time. Panel C presents these correlations, which are consistently high (between 26% and 76%). All pair-wise correlations are significantly different from zero at the 1% level. This suggests that stocks with high idiosyncratic volatility are exposed to a common underlying variable that is distinct from the traditional factors.

4.2 An idiosyncratic volatility based factor

To understand whether highly volatile stocks give high returns in 'bad' times, when investors assign greater value to these returns, I create a representative portfolio for the returns to stocks with high idiosyncratic risk. As in Table 1, stocks are first sorted by size and then by idiosyncratic risk. Then value-weighted returns for stocks with the smallest idiosyncratic risk (Port 0) across size quintiles are computed to yield the size controlled idiosyncratic risk portfolio '0'. This is repeated for idiosyncratic risk quintiles 1 to 4, generating five portfolios with similar size and increasing idiosyncratic risk. Panel A in Table 2 presents summary statistics for each of these portfolios.

It is clear that the portfolio with the largest volatility has the lowest returns. The size control is effective, since all five portfolios have the same average size quintile. Idiosyncratic risk is also correlated with systematic risk, since market betas increase monotonically across volatility portfolios. This makes the low returns to highly volatility stocks anomalous, since according to the CAPM they should have higher expected returns. Another interesting finding is the loadings on SMB. Although stocks in all these portfolios have the same size, SMB loadings increase monotonically from the least to most volatile stocks. This makes the low returns of extremely volatile stocks even more anomalous. Since they co-vary with small stocks, their expected returns should be higher, and not lower than average. Increased exposure to growth serves to explain some of the low returns, but it does not go far enough, as four-factor alphas are still significantly negative. Highly volatile stocks thus behave like small growth stocks, even if they are not particularly small. When seen in this light, low returns to highly volatile stocks are not that surprising, since the inability of the Fama-French three-factor model to explain returns of the small growth portfolio is well known (Fama and French, 1993). This is explored in greater detail in section 6.3.

To create a single factor that captures the premium and the common time-series variation of highly volatile stocks, I define the size-controlled idiosyncratic risk factor (IVOL) as Portfolio 0 – Portfolio 4. This portfolio is constructed in order to have positive expected returns. However, this means that returns to highly volatile stocks, that are our object of study, are negatively correlated to this portfolio's returns. Table 2, Panel B lists the results of time-series regressions of this portfolio. The first column shows that it has a negative CAPM beta and a positive CAPM alpha, which remains after controlling for the Fama-French factors and momentum[11]. This portfolio has (insignificantly) high payoffs during recessions and is not significantly correlated with the term spread or credit spread (not reported). This, along with the evidence in AHXZ suggests that it is unlikely that conventional measures of risk can explain the low returns to highly volatile stocks. The next section examines if measures of skewness are more successful at explaining the low returns of highly volatile stocks.

5 Skewness and the returns of highly volatile stocks

The common variation in the returns of highly volatile stocks provides a way to examine if skewness is related to the AHXZ puzzle. This is especially useful, since measuring skewness accurately for individual stocks is difficult. There is a sharp trade-off between using a large history of returns to measure skewness accurately and a smaller history to capture the time-variation in skewness. However, aggregate measures that use the cross-section of returns at a given point in time provide a solution to this problem, since they are both timely and use a large sample. These cross-sectional skewness measures are also intuitive, as they represent the probability of drawing a stock with exceptionally high returns at a given point in time. Also, Zhang (2005) shows that the skewness of individual stocks is predicted better by cross-sectional measures of skewness for similar stocks than by using the stock's own history.

If skewness is responsible for the low returns to highly volatile stocks, then the returns of highly volatile stocks should be correlated with the variation in aggregate measures of skewness. Also, measures of skewness should exhibit systematic variation, in that they should be correlated over mutually exclusive sets of stocks at the same point in time. If the skewness of small stocks, for example, exhibited different time-series behavior from the skewness of large stocks, then skewness will not be able to explain the common variation in the returns of highly volatile small and large stocks. The first sub-section introduces different measures of skewness and shows that this is indeed the case. Different measures of skewness are highly correlated with each other, even when defined

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[11] In unreported results, I find that the alpha is also robust to controlling for the Pastor and Stambaugh (2003) liquidity measure

over mutually exclusive sets of stocks. The next sub-section examines if measures of skewness are related to IVOL, the factor that captures the common variation in the returns of highly volatile stocks. Finally, the third sub-section creates a factor-mimicking portfolio for cross-sectional skewness and shows that it helps to explain the premium associated with IVOL in time-series regressions.

5.1 Different measures of skewness

Skewness for month *m* is measured using three metrics. The first, cross-sectional skewness across monthly returns of all stocks is defined as:

$$\text{CS-SKW} = \frac{\frac{1}{N_m}\sum_{i=1}^{N_m}(r_i - \bar{r})^3}{\sigma^3} \tag{2}$$

where N_m is the number of stocks, and $\bar{r}$ is the mean monthly return across all stocks in month *m*. This is my primary measure of skewness for this paper. A second measure of skewness is Breadth, which is the difference between the equal-weighted mean and median monthly return across all stocks.

$$\text{Breadth} = \text{Mean} - \text{Median} \tag{3}$$

This is an alternative measure of cross-sectional skewness that is perhaps less influenced by outliers, since it does not involve cubed terms. It is closely related to the Pearson measure of skewness, which is the difference between the mean and median scaled by standard deviation. For monthly returns, the normalization does not seem to affect the time-series much, as the correlation between breadth and the normalized series is 88.7 % (97.7% rank correlation). This measure is used to show that the primary results are robust to an alternative way of calculating skewness.

A third measure is the average time-series skewness of individual stocks computed using daily returns within each month.

$$\text{TS-SKW} = \frac{1}{N_m}\sum_{i=1}^{N_m}\frac{\frac{1}{T_m}\sum_{t=1}^{T_m}(r_{i,t} - \overline{r_{i,t}})^3}{\sigma_{i,m}{}^3} \tag{4}$$

where N_m is the number of stocks, and $r_{i,t}$ is the daily return for stock *i* on day *t* in month *m*. For all measures of skewness, stocks that are smaller than the NYSE 10% size breakpoint are excluded for two reasons. First, the returns of small firms are likely to contain some large values resulting only from microstructure effects such as bid-ask bounce. These may introduce noise into the measure. Second, their skewness is trending up over time, leading to a non-stationary series.[12] Fama and French (2004) show that newly listed stocks have become more left-skewed in their profitability and right-skewed in their growth over the last three decades. It is not surprising that this change in fundamentals is also reflected in returns of the smallest stocks. This may also be because of increasing financial market development, which Brown and Kapadia (2006) show is related to the increase in idiosyncratic volatility observed in US equity markets over the last four decades. However, since this paper is concerned with explaining the returns to highly volatile stocks, the time-trend in the cross-sectional skewness of new firms is not explored further.

Panel A of Table 3 provides summary statistics for these three measures of skewness. It is interesting to note that all three series have significant autocorrelation, so past measures can be used to predict the future. Also CS-SKW is the most persistent, with significant auto-correlations up to order 9, while auto-correlations for the other two series die out by order 2. The pair-wise correlations between these three measures are presented in Panel B. The high correlations suggest that these three measures are capturing similar phenomena. Appendix 2 studies the relationship between average time-series and cross-sectional moments in greater detail, showing that their correlation is not unexpected.

To investigate whether measures of cross-sectional skewness exhibit systematic variation over time, I define three sets of stocks – the largest 40% (Large), the next 30% (Medium), and the next 20% of stocks (Small) by NYSE size breakpoints. This categorization creates fairly equal assignment of stocks. Large increases from 484 to 741

[12] Using Ln (continuously compounded) returns instead of normal returns changes some of the properties of the CS-SKW series. In particular, there is a significantly negative time trend over the sample and CS-SKW is negative on average. However the time-series variation around the trend is highly correlated with that of CS-SKW measured from normal returns. Also, despite the time trend, the measures with and without the smallest 10% of stocks are reasonably correlated.

stocks, Medium from 408 to 746, and Small from 378 to 1003 (almost doubling with the inclusion of NASDAQ stocks in 1973) over the sample period. I refer to each of these nine series using a combination of the measure (TS-SKW, Breadth, and CS-SKW) and the suffix (1 for Small, 2 for Medium, and 3 for Large).

Panel A of Figure 1 plots a smoothed version (12 month moving average) of CS-SKW for these three sets of stocks. As is obvious from the graph, these series are highly correlated, despite having no stocks in common. Panel B of Figure 2 computes CS-SKW over all stocks excluding those in the extreme volatility quintiles (called ‘no absolutely volatile’) and excluding those in the extreme volatility quintiles within their NYSE size quintile (called ‘no relatively volatile’). The figure shows that CS-SKW of all stocks is also very similar to these two series. The only difference is during the 1997-2000 period where all stocks have a higher skew than the set excluding the most volatile stocks.

Panel C of Table 3 shows the correlation across each of these measures for each size category. The table shows two key points. First, (as also seen in Figure 1, Panel A), there is high correlation between the same measure of skewness across different size classes. This suggests that each measure is picking up something fundamental about each point in time that is correlated over different sets of stocks. Second, there is also high correlation between different measures across different size classes. In fact, there is an even stronger relation between the measures. For example, in a regression of TS-SKW1 on TS-SKW2, CS-SKW3 provides additional explanatory power:

$$\text{TS-SKW1} = \underset{[4.87]}{0.03} + \underset{[40.34]}{1.03}\ \text{TS-SKW1} + \underset{[3.55]}{0.01}\ \text{CS-SKW3}.$$

These variables are chosen to make this as difficult to possible, since TSSKW1 and TSSKW2 have the highest pair-wise correlation (91%).

5.2 Cross-sectional skewness and the returns of highly volatile stocks

This section examines the relation between measures of cross-sectional skewness and the returns of highly volatile stocks. Figure 2 shows the primary result of this paper, that the low returns to highly volatile stocks are strongly related to cross-sectional skewness. This figure plots IVOL along with the cross-sectional skewness of all stocks excluding the stocks used to construct IVOL. These two series have been orthogonalized with respect to the market to remove common dependence on market returns, and are smoothed using a 12 month moving average. There is strong negative correlation between these two series. This suggests that time-variation in skewness is related to the common time-series variation of highly volatile stocks. I have also tried other variants of this procedure, such as replacing cross-sectional skewness with breadth and calculating breadth only for stocks in the middle volatility quintile, with similar results.

Table 4, Panel A tests this relation in a time-series regression with controls for other variables, including the cross-sectional variance and the four-factors. The first specification shows that IVOL is negatively correlated with contemporaneous variance, which means that highly volatile stocks have returns that are positively correlated with variance (since IVOL shorts highly volatile stocks). The next specification shows that this reverses once we control for breadth and now breadth is negatively correlated with IVOL. Specification 3 shows that these results remain if additional controls for SMB, HML and UMD are introduced. The remaining specifications show that replacing breadth with cross-sectional skewness provides the same inference.

Panel B examines whether IVOL has high returns (and hence highly volatile stocks underperform) when average skewness is expected to be high. This reinforces the results in Panel A, by showing that higher predicted skewness serves to raise current valuations and hence predicts lower future returns. Also, since skewness is measured prior to the returns of highly volatile stocks, this shows that any concern about a mechanical contemporaneous relationship is unlikely to be true. As a pre-requisite for this I need to be able to predict realizations of SKW. I consider the class of ARMA models, allowing for asymmetric coefficients on the AR terms and choose the one with the optimal Akaike Information Criterion. The best fit model is an ARMA (1,2).

The first specification regresses IVOL on the four-factors for those months for which forecasted SKW is greater than zero. The alpha is large and significant. The second specification repeats the regression, this time only for the months in which forecasted skew is less than zero. The alpha drops to almost half and is not significant. This suggests that highly volatile stocks underperform with respect to the four-factor model only when predicted skew is high.

5.3 A factor mimicking portfolio for SKW

Figure 2 indicates that cross-sectional skewness is correlated with the returns of highly volatile stocks. However, it is not clear if this correlation is stable and predictable, or alternatively, if prior sensitivities to cross-sectional skewness predict low future returns for individual stocks. This section addresses this issue by constructing a factor mimicking portfolio for cross-sectional skewness and examining if it adds explanatory power to the Fama-French three-factor model. This differs from prior tests in that I now examine whether sensitivity to a factor, which is a return of a portfolio as opposed to a measure of skewness, can help explain the low returns of highly volatility. This factor mimicking portfolio can also be interpreted as a factor in the Arbitrage Pricing Theory sense, since it is created to exploit correlations between individual stocks through common dependence on cross-sectional skewness.

To construct the factor mimicking portfolio, I regress each stock's return over month t-36 to t-1 on the market and innovations in cross-sectional skewness of all stocks (excluding the smallest 10% based on NYSE breakpoints) from an ARMA (1, 1) model. Stocks are sorted into quintiles on the basis of their cross-sectional skewness betas. Value-weighted returns for month t are calculated for each quintile. The difference in the extreme quintile portfolio returns ('0' – '4') is SKW-FMP, the factor mimicking portfolio for skewness. The correlation between innovations in cross-sectional skewness and SKW-FMP is -56%, suggesting that the factor is a reasonably accurate projection of the cross-skewness on the space of returns.

Panel A of Table 5 presents gross returns, CAPM alphas, three-factor and four-factor alphas. There is a large difference in average returns between firms with high and low sensitivities to cross-sectional skewness. The difference is about 4.1% a year, which is between SMB (2.9%) and HML (5.2%) over the same period. The patterns in Table 5 are very similar to those in Table 2, in that stocks with high sensitivities to cross sectional skewness behave like small growth stocks. The extreme portfolio has a negative three and four-factor alpha. The magnitude of the alpha is about 3.8% per year, which is economically as well as statistically significant. This shows that sorting by prior sensitivity to cross-sectional skewness creates dispersion in returns that cannot be explained by the four-factor model.

Panel B presents a robustness check on size. Firms are first sorted into size quintiles using NYSE only size breakpoints. Within each quintile, stocks are sorted by CS-SKW betas, resulting in 25 value-weighted portfolios. Panel C indicates that within each size quintile, stocks with the highest CS-SKW betas have lower returns. Also, three-factor alphas are significant in four of the five NYSE based size quintiles. These three panels provide strong evidence that exposure to cross-sectional skewness results in low expected returns that cannot be explained by traditional factor pricing models.

To see if this factor can explain returns to highly volatile stocks, I examine returns to the IVOL factor defined earlier. Panel D reports results of time-series regressions. On introducing the SKW-FMP portfolio, the CAPM alpha drops to 0.24%, less than half its original value. On adding HML, SMB and UMD, the alpha is not significant at 0.2%. However, SKW-FMP is still highly significant. This suggests that SKW-FMP can explain a large fraction of the abnormal returns of highly volatile stocks portfolios.

Thus, this section shows that cross-sectional skewness explains both the common time-series variation of highly volatile stocks, and the premium associated with the returns to highly volatile stocks. The factor mimicking portfolio for cross-sectional skewness also has a significant premium associated with it and adds additional explanatory power to the Fama-French three-factor model. Cross-sectional skewness thus solves the AHXZ puzzle.

6 Other applications

If cross-sectional skewness is an important determinant of expected returns, its effects should be seen in other contexts as well. This section examines two known (and related) anomalies, the underperformance of IPOs and small growth stocks.

6.1 IPO underperformance

IPOs provide an interesting setting to investigate the relation between cross-sectional skewness and expected returns for several reasons. First, prior literature (e.g. Brav, 2000) has reported that IPO returns are skewed.[13] This may be because IPOs tend

[13] Since this paper has Microsoft in its title, I checked the returns of investing $1 in Microsoft at IPO. $1 invested in 1986, would yield $398 as on November 14, 2006, a simple average return of approximately 1985% a year. Interestingly, Microsoft is also in the highest quintile of stocks sorted by sensitivity to CS-SKW in its first year in the sample.

to be young firms, with a large fraction of their value in the form of growth options. Second, IPOs have been known to underperform in the long run (Ritter, 1991) consistent with the predicted direction for a skewness preference. Barberis and Huang (2005) also suggest that a skewness preference could cause the low returns to IPOs. Finally, studying IPOs provides the opportunity to perform both event-time and calendar-time tests, which provide different insights.[14] For event-time tests, the month of the IPO provides a reference point to measure skewness over. That is, if a preference for skewness drives the low returns to IPOs, firms that list when skewness in the economy is high should underperform more severely than those that list when skewness is low. The first sub-section reports results of this test. The second sub-section reports results of calendar time tests that examine whether the time-variation in returns of new lists is related to time-variation in cross-sectional skewness and also whether idiosyncratic volatility is related to underperformance.

I define an IPO as the first appearance of a firm's PERMCO on CRSP with an initial price of greater than five dollars. This method ensures that I do not miss any firms that may not be captured by other data sources (Fama and French, 2004, compare this approach with other data sources). The data begin in 1973, after the inclusion of Nasdaq listed companies on CRSP.

6.1.1 Event time tests

In event time tests, my measure of IPO underperformance is Buy and Hold Return (BHR) over matched firms. Matching is done by size at listing. Specifically,

$$\text{BHR} = \left(\prod_{t=1}^{T} (1 + r_{i,t}) - 1 \right) - \left(\prod_{t=1}^{T} (1 + r_{m,t}) - 1 \right) \tag{5}$$

where r_i is the return of the IPO firm, from listing at month t=1 to t=36 or delisting, whichever comes sooner, and r_m is the return of the matched firm based on size.

BHR are normalized to be in monthly percent terms. The results in this section are robust to calculating BHR over matched size and matched size and book- to-market reference portfolios as well. However, since Barber and Lyon (1997) show that the

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[14] See Brav, Geczy and Gompers (2000) and Ritter and Welch (2002) for a comparison of the advantages and disadvantages of each approach.

control-firm approach is more robust than the matched portfolio approach, only results for the control firm approach are presented. Table 6, Panel A provides summary statistics. The number of IPOs that meet the criteria in the 1973 to 2002 period is 10,489 and the average BHR is -0.47% per month, which is significantly different from zero. Also, median size adjusted returns at -0.70% per month, are also significantly different from zero, and are a little less than the mean, suggesting skewness.

I measure cross-sectional skewness over two sets of firms – those less than three years old and those greater than three years. Both sets are reasonably correlated with each other (rank correlation of 0.50). Also, both do not include the new lists, whose subsequent returns are our object of study. Figure 3 shows average monthly BHR for firms listed in a given month along with cross-sectional skewness of firms less than three years old. Both series are smoothed using a 12 month moving average. This figure provides visual confirmation of the hypothesis that the subsequent underperformance of firms is related to a preference for skewness. The two series are significantly negatively correlated (-0.25% rank correlation for the unsmoothed series), suggesting that IPO underperformance is inversely related to skewness at listing.

Further evidence is provided by simple tests of averages. Panel B of Table 6 shows that when the cross-sectional skewness of young firms is high (above its sample median), mean and median BHRs are significantly less than zero. However, when cross-sectional skewness is small (less than its sample median), mean BHRs are insignificantly positive. IPOs do not underperform on average if they list when cross-sectional skewness is low. Median BHRs are still negative, however they are substantially less (about one-third) than when cross-sectional skewness is high. Panel B also shows that IPO underperformance is much more severe in the 1989-2002 sub-sample as compared to the 1973-1988 sub-sample. However, for both sub-samples mean BHR are not significantly different from zero for firms that list when cross-sectional skewness is low. Panel C shows that these results are robust to alternate definitions of skewness. In particular, lagged values of cross-sectional skewness and breadth also provide similar results. Most interesting is that using cross-sectional skewness measured only over stocks that listed over three years ago provides similar inference. This reconfirms the correlation between measures of skewness over different sets of stocks.

This section thus shows that the subsequent underperformance of new lists is strongly correlated with measures of skewness at the time of their listing. This suggests that the low returns to IPOs are also the result of a premium for skewness.

6.1.2 Calendar time tests

The results in Brav, Geczy and Gompers (2000) and Ritter and Welch (2002) show that IPO underperformance is much less severe in portfolio based calendar time tests. Brav, Geczy, and Gompers find that IPO underperformance is a manifestation of the underperformance of small growth firms that is not restricted to IPOs. All IPOs do not underperform, only small growth firms (which are over-represented in the IPO sample) do. This section investigates the relation between IPO underperformance, size, idiosyncratic volatility and cross-sectional skewness in a setting similar to Brav, Geczy and Gompers (2000).

Table 7, Panel A provides summary statistics for portfolios sorted on size and age since listing. Young firms are firms for which less than three years have elapsed since listing, while old firms are all other firms. It is clear that new firms underperform, especially for the smaller size quintiles.

Panel B simultaneously sorts *all* firms first by size and then by lagged idiosyncratic volatility, showing value-weighted returns of only new lists and time-series averages of the number of them in each portfolio. The table shows that returns for the most volatile new lists are substantially lower than for other stocks. Also, new lists seem over-represented in the highly volatile stock portfolios, especially for the larger size quintiles.[15] Panel C shows that only highly volatile new lists underperform with respect to the Fama-French factors. The pattern of underperformance is similar to that of all firms, suggesting that IPO underperformance can also be seen as a manifestation of the AHXZ effect. Highly volatile new lists, especially those in the middle size quintiles severely underperform, with Fama-French alphas as low as -1.95% per month for the second size quintile. Also, these results suggest that IPO underperformance is not restricted to small

[15] These tests do not require firms to have CompuStat data. When this requirement is imposed, the average number of firms in the smallest size quintile range from 26 (smallest volatility quintile) to 45 (largest volatility quintile).

growth stocks, since highly volatile IPOs that are in the middle size quintiles also underperform.[16]

The AHXZ effect is also present if we exclude new lists. This suggests that the causality goes from highly volatile stocks underperforming to new lists underperforming rather than vice-versa.[17] Panel D reports gross returns of size sorted portfolios of old and new firms. Old firm returns are greater than new firm returns for all five size quintiles, of which the difference is significant for three.

The next tests are calendar time regressions of portfolios that are long old and short new firms, within each size quintile. All but the largest size portfolios have significant CAPM alphas. However, consistent with Brav, Geczy, and Gompers (2000), the Fama-French three-factor model provides substantial additional explanatory power. Only two of the five portfolios have positive Fama-French alphas. On adding the skewness mimicking factor (SKW-FMP), none of the portfolios have significant alphas, with the alphas of the three smallest size portfolios reducing by about one-third. Also, SKW-FMP is significant in all five regressions. These results suggest that the SKW-FMP helps explain the time-series variation on new lists. Also, on controlling for SKW-FMP none of the size sorted portfolios underperform. The results of using the IVOL portfolio instead of SKW-FMP are similar.

The evidence in this section shows that only highly volatile IPOs underperform in the long run, and this underperformance is correlated with the skewness factor constructed earlier.

6.2 Cross-sectional skewness and the Fama-French factors

Table 2 showed that despite controlling for size, highly volatile stocks load like small stocks. Table 8 investigates whether a similar phenomenon occurs for book-to-market. Stocks are first sorted into quintiles by NYSE book-to-market breakpoints and

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[16] Using sorts on NYSE based size quintiles and then on idiosyncratic volatility, I find that a large majority of new firms are in the smallest size quintile. The alpha of the most volatile portfolio is significantly negative at -1.74% (225 firms on average) in the smallest quintile, -0.75% (also significant; 50 firms on average) in the second largest and insignificantly negative in the three biggest portfolios, which have large standard errors, since the average number of firms is 26, 16 and 6 respectively.

[17] This is shown in Panel B of Table A1, which shows that even if firms with at least three years history are used, the average returns of the extreme volatility quintile are still abnormally low. Volatility is predicted using a MIDAS with step functions estimator described in Appendix 2. Similar results are obtained if firms with at least 5 years of return history are used.

then sorted on volatility within the book-to-market quintiles. The table reports results of value-weighted returns of these portfolios in Fama-French regressions. First, Panel A shows that the underperformance of highly volatile stocks is the largest among stocks with low book-to-market ratios (growth stocks). The alpha of the highest volatility portfolio decreases from -1.5% per month for the lowest book-to-market quintile to -0.73% per month, for the highest book-to-market portfolio. Panel B shows that in general, the loading on HML decreases with volatility, within a book-to-market quintile. Highly volatile stocks load like growth stocks even after controlling for book-to-market. This suggests that differences in volatility create dispersion among the covariances of stock returns (with the factors) after controlling for the characteristic (size or book-to-market). Unfortunately, the covariance with SMB makes the low returns of highly volatile stocks more difficult to explain, while the covariance with HML makes it easier.

Since, highly volatile stocks are correlated with SMB after controlling for size and with HML after controlling for growth, I examine if the underperformance of the small growth portfolio is correlated with the underperformance of highly volatile stocks and with cross-sectional skewness. S1B1 (the smallest size and book-to-market portfolio) is highly correlated with IVOL (-80%) and with SKW-FMP (-75%). Panel C shows that these correlations persist in a regression of the 25 size and book-to-market portfolios on CS-SKW after controlling for market returns. The results for using IVOL instead of CS-SKW are very similar and hence not reported. In general, the returns of small growth stocks are most correlated with both these variables. Panel D shows that the alpha of the small growth portfolio becomes insignificant after controlling for market returns and IVOL. However, on introducing SMB and HML, the alpha is significant again, though about 20% smaller than without the IVOL control. It is the relation between SMB and volatile / small growth stocks that makes the underperformance reappear.

This section thus provides evidence that the small growth portfolio shares substantial common time-series variation with the SKW-FMP portfolio. This suggests that the anomalously low returns of this portfolio are also related to a premium for skewness. There is mixed evidence for this hypothesis. In regressions of this portfolio on the market and SKW-FMP, there is no alpha. However, on including SMB and HML, the alpha reappears.

7 Interpreting Cross Sectional Skewness

This section analyzes the determinants of the time-variation and the premium associated with cross-sectional skewness. To gain a more intuitive understanding of the nature and type of firms that are exposed to cross-sectional skewness, section 7.1 examines which industries make up a significant fraction of the highest cross-sectional skewness portfolio. The industries that are over-represented in this portfolio appear to be those that have experienced significant change. Consequently, Section 7.2 explores whether the cross-sectional skewness innovations can be predicted with proxies for technological change, suggesting a technology shock based explanation for the time variation in cross-sectional skewness. This potentially explains the common variation of stocks with high skewness. Section 7.3 examines whether co-skewness with the market is responsible for the low returns to stocks with high exposures to cross-sectional skewness.

7.1 Industry effects

Table 9, Panel A examines the industry composition of the highest cross-sectional skewness portfolio, based on the Fama and French (1997) 48 industry classification scheme. The panel reports the top three industries in each decade from 1965-2005 in this portfolio, by market capitalization. The next row reports the fraction of the portfolios' market capitalization that each industry represents. However, it is possible that an industry is a high fraction of this portfolio because it has a large share of the overall market. Therefore, the third row presents the ratio of each industry's share of the highest skewness portfolio, to its share of the overall market. *Ex-ante*, there is no reason to expect that sorting on the coefficient of a firm's return on cross-sectional skewness will result in portfolios that are different from the market portfolio in terms of composition. This table shows that considerable differences exist.

A common theme that emerges from this table is that industries which have experienced significant change are over-represented in this portfolio. For example, Business Services represents 21% of this portfolio in the 1995-2005 period, which is 2.5 times its average contribution to the market as a whole. The Business Services industry contains software programming firms (like Microsoft) and internet firms (like Ebay). These segments experienced tremendous change during this period, and it is not surprising to see them over-represented in this portfolio. Also, during 1975 to1985, the most highly represented industry is oil and natural gas. This is intuitive, given the large oil shocks in the late 1970s. Computer Hardware, from 1975 to 1995 (the IBM Personal Computer was launched in 1982), and Telecommunications, from 1995 to 2005, are also consistent with this.

Although informal, this analysis suggests that firms in industries that have experienced large shocks are more likely to be in the portfolio that is most sensitive to cross-sectional skewness. Consequently, the next section examines if one such shock, significant technological change, can explain aggregate measures of cross-sectional skewness.

7.2 Cross-sectional skewness and technological change

An economy-wide shock like a new technology has the potential to disrupt existing industry structures. Gort and Klepper (1982) examine the life-cycle of 46 industries and show that technological innovations are a key determinant of industry structure. Motivated by their work, Jovanovic and Macdonald (1994) examine the US automobile tire industry from 1906 to 1973. They suggest that a technological refinement in 1916 led to a non-monotone number of firms over time. A sharp increase in the number of firms at the start of the sample is followed by a shake-out, precipitated by an increase in optimal scale brought about by the technological innovation. These results suggest that although many firms typically enter industries in order to take advantage of a technological innovation, very few firms eventually succeed.

Translating this intuition to financial markets, a possible hypothesis is that anticipation of the benefits of technological change leads to cross-sectional skewness. Firms that survive the technological shock-induced shake-out, and reap the benefits of the innovation, are likely to do exceptionally well. [18] This mechanism suggests that there should be a relation between technological innovations and cross-sectional skewness.

To test this sequence of events, I examine if proxies for technological change can predict future cross-sectional skewness. The proxies I choose are patent grants and Research and Development (R&D) expenditure by publicly listed firms. Since these data are annual, I construct an annual cross-sectional skewness measure, as the skewness of

[18] These effects are likely to be stronger in winner take all industries (like the PC operating system market) where there is competition to define the industry standard.

monthly returns of large firms over the next year. This series is not as persistent at the annual frequency as the monthly one, but I take innovations from an AR(1) model to remove the small auto-correlation (3%). Cross-sectional skewness and patent grant growth are strongly correlated (correlation of 37%) and this is confirmed in predictive regressions in Panel B of Table 9. The lagged growth in patent grants significantly predicts future cross-sectional skewness. The table also reports results of adding an additional control for lagged market returns, as a proxy for other variables like the state of the economy as a whole, which could impact both variables. Controlling for current market returns or an additional lag does not change the inference. The second proxy for technological change is lagged growth in average R&D expenditure scaled by Total Assets (R&D growth). Panel B shows that R&D growth also significantly predicts future skewness and survives the controls for lagged market returns. These results are robust to excluding the last 10 years of the sample, where the technology 'bubble' led to exceptional values for R&D expenditure.

7.3 Low expected returns for stocks with high cross-sectional skewness

There are two possible reasons for the low returns to stocks with high sensitivity to cross-sectional skewness. First, these stocks may add skewness to a well-diversified portfolio. The ability to add skewness to the market portfolio, called co-skewness has been shown to be associated with low expected returns (see Harvey and Siddique, 2000; henceforth HS). Second, these stocks may provide idiosyncratic skewness, which is consistent with Barberis and Huang (2005), who show that idiosyncratic skewness commands a premium in an economy where agents have prospect-theory based preferences. This section examines if cross-sectional skewness is related to co-skewness

I compute a co-skewness factor in a manner similar to HS. Each firm's returns are regressed on the market return and the squared market return for months t-36 to t-1. Firms are then sorted according to their regression coefficients on squared market returns. The difference in value-weighted returns between the top 30% (S+) and the bottom 30% (S-) is the COSKEW factor. HS report that the difference between S+ and S- is 3.6% for their sample. In my sample, it is very close, at 3.5%. Table 10, Panel A presents results of a regression of each of these portfolios on the market and the cross-skewness factor. Portfolio 0 (or S- in HS terminology) has the most negative coefficient on SKW-FMP.

That is, it co-varies most with stocks that have high returns when cross-sectional skewness is high. The coefficient on portfolio 3 (the S+ portfolio) is also negative, but smaller in magnitude. This suggests that both stocks with negative and positive co-skewness have positive cross-sectional skewness, with stocks with negative co-skewness having the most positive cross-sectional skewness. This confirms that co-skewness and cross-skewness are capturing different phenomena. As a final check, Panel B shows that the alpha of SKW-FMP increases on adding co-skewness as an additional factor to a four-factor regression. Also after controlling for the effects of other factors, co-skewness and cross-sectional skewness are negatively correlated.

This section shows that the low returns to stocks with high sensitivities to the cross-sectional skewness factor cannot be explained by greater co-skewness with the market. This suggests that idiosyncratic skewness, as modeled by Barberis and Huang (2005) may be responsible for the low expected returns of socks with exposure to high cross-sectional skewness.

8 Conclusion

This paper examines a recent puzzle in financial economics. The returns of highly volatile stocks are abnormally low and are correlated with each other. Additionally, results show that this puzzle is related to the underperformance of the small growth portfolio in the Fama-French three-factor model. Highly volatile stocks load like small growth stocks even after explicit controls for the size and book-to-market. The common link between these two empirical results is that both highly volatile stocks and small growth stocks give high returns in times when cross-sectional skewness is high. This paper also shows that cross-sectional skewness is a fundamental measure of each time period, as it is correlated across mutually exclusive sets of stocks. Stocks with high prior sensitivities to cross-sectional skewness also have low expected returns. The alpha of the idiosyncratic risk portfolio disappears on controlling for skewness (by using a factor mimicking portfolio for cross-sectional skewness). Thus, cross-sectional skewness helps solve the AHXZ puzzle.

Another application of cross-sectional skewness is IPO underperformance. Ritter and Welch (2002), in their review of the IPO literature, conclude their section on IPO underperformance with "… we hope to see further work to tell us which sub samples are particularly prone to poor post-IPO performance…" This paper provides an answer. IPO underperformance is greatest when cross-sectional skewness of young firms is high. This provides supports for the hypothesis that the underperformance of IPOs is also caused by a skewness preference.

One possible explanation that ties these facts together is the relation between the stock market and large shocks in the economy, like technological change. Significant shocks can disrupt existing economic structures and create new winners, and thereby generate a cross-sectional skew in returns. Furthermore, stocks that are highly sensitive to such shocks are likely to both have more uncertain pay-offs and to move together over time. It is likely that such stocks are small growth stocks that are highly volatile, which are the stocks that I find co-vary strongly with cross-sectional skewness. This interpretation is further supported by the result that cross-sectional skewness innovations are predictable with proxies of technological change, like prior patent grant growth and R&D expenditure by publicly listed firms. The low returns to these stocks are not related to co-skewness, suggesting that they are caused by non-systematic skewness.

To conclude, this paper offers five key contributions. It (i) resolves the controversy between Fu and AHXZ on the direction of the impact of individual stocks volatility on returns in AHXZ's favor, and shows that (ii) highly volatile stocks move together, (iii) returns to portfolios with highly volatile stocks are correlated with cross-sectional skewness of individual stock returns, (iv) cross-sectional skewness predicts subsequent IPO underperformance and is also related to the 'small growth' anomaly, and (v) cross-sectional skewness in turn is predictable using proxies of technological change.

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Appendix 1: Forecasting individual stock volatility

Recent papers, by Fu (2005) and Spiegel and Wang (SW; 2006) find that monthly return based EGARCH estimators of conditional volatility provide different inferences from lagged realized monthly volatility from daily returns, used by AHXZ. For EGARCH estimators, higher volatility predicts positive rather than negative returns. Fu and SW suggest that this is because these are better predictors of volatility than lagged realized monthly volatility. Together, these papers provide three broad arguments to support their case. Fu shows that realized monthly volatility is not a random walk and that realized volatility is contemporaneously positively correlated with returns. Also SW argue that daily returns are likely to be contaminated with microstructure noise for smaller stocks.

Although these arguments are compelling, there are also significant advantages of using daily return based estimators. Lagged realized volatility is simple and model-free and does not have parameter estimation error. Second, Merton (1980) shows that increasing the frequency (in the absence of micro-structure effects) provides more accurate estimates of volatility. Also, the positive contemporaneous correlation of realized volatility with returns may be just a manifestation of the positive skewness of individual stocks (see Duffee, 1995). It is not clear if it can be predicted using past volatility. Finally, there are simple corrections for microstructure biases that have been shown to work reasonably well (e.g. Harris, 1990). Ultimately, the relative performance of monthly and daily return based estimators is an empirical question. This section compares the two estimators used in the literature along with other possible estimators.

Unfortunately, it is difficult to use GARCH based conditional volatility models on daily returns to provide monthly estimates volatility. The Mixed Data Sampling (MIDAS) approach used by Ghysels, Santa-Clara and Valkanov (2004) solves this problem, by allowing the ability to mix different frequencies. Ghysels at al (2004) use this approach to uncover a robust risk-return tradeoff at the market level, where GARCH models on monthly returns are not that successful. This section uses a computationally less intensive version of MIDAS, called MIDAS with step functions (Ghysels, Sinko, Valkanov, 2006), to provide monthly forecasts of volatility using daily returns.

The MIDAS with Step Functions (MIDAS-SF) model is also similar to the Heterogeneous Arrival Rate (HAR) model in Corsi (2003). The key advantage of this model is that it can be estimated by OLS, making it suitable for estimating the volatility of individual stocks. The model specification used is:

$$\sigma^2_{(t,t+22)} = \alpha + \beta_1\, \sigma^2_{(t-5,t)} + \beta_2\, \sigma^2_{(t-22,t)} + \beta_3\, \sigma^2_{(t-66,t)} + \varepsilon_t \qquad \text{(A1)}$$

This model in essence predicts the next months' volatility, using the last five days' volatility, the last months' volatility and the last three months' volatility. All realized volatility measures use the French, Schwert and Stambaugh (1987) correction for microstructure effects, by adding twice the auto-covariance of returns.[19] Harris (1990) shows that this helps correct the biases induced by discrete prices and bid-ask bounce.

Table A1 considers five different estimators for monthly realized volatility. These include MIDAS-SF, Lagged volatility, EGARCH (1,1), GARCH (1,1) and an ARMA(1,1) on monthly realized volatility (used by French, Schwert and Stambaugh, 1987). This table reports in-sample tests to predict realized monthly volatility. Also, only stocks with at least three years of returns are used.

It is clear from the table that lagged realized monthly volatility performs better across different measures than using EGARCH on monthly returns. This inference remains the same in out-of-sample tests, with or without the microstructure bias correction, excluding low priced stocks (where microstructure biases are likely to be more extreme), and also if idiosyncratic volatility rather than total volatility is predicted.[20]

Also, both the MISDAS-SF and the ARMA (1,1) that use the information in daily returns, work best in-sample (the difference between the two are not statistically significant). These results clearly show that using daily returns as in AHXZ provides better estimates of volatility than using monthly return based estimators

Panel B examines whether AHXZ's result are robust to using the MIDAS-SF estimator. Panel B estimates the following model that is a slightly modified version of MIDAS-SF that also includes the information in past realizations of market volatility:

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[19] Except for $\sigma^2_{(t-5,t)}$, which is just the average squared return of the last five days of the prior month.
[20] These results are available from the author on request.

$$\sigma^2_i(t,t+30) = \alpha + \beta\, \sigma^2_i\,(t-5,t) + \delta\, \sigma^2_i\,(t-22,t) + \gamma\, \sigma^2_i\,(t-66,t) + \beta'\, \sigma^2_m\,(t-5,t) + \delta'\, \sigma^2_m\,(t-22,t) + \gamma'\, \sigma^2_m\,(t-66,t) + \varepsilon_t \qquad \text{(A2)}$$

Where σ^2_m (t, t+x) is the variance of daily market returns from t to t+x and, σ^2_i (t,t+x) is idiosyncratic volatility from t to t+x. Idiosyncratic volatility is the variance of daily residuals computed from the Fama-French three-factor model.

Panel B clearly shows that this estimator, which also outperforms the EGARCH based estimators, provides the same inference as AHXZ. High predicted volatility is followed by low subsequent returns.

Appendix 2: Time-series and cross-sectional moments

This appendix examines the relation between average time-series variance and skewness, and cross-sectional variance and skewness. In particular the time-series measures are computed using daily returns within the month and averaged across stocks, while cross-sectional measures are computed using monthly returns.

It is easy to show that cross-sectional variance computed from monthly returns is an approximation for the average total variance of all stocks that month, computed from daily returns. The approximation depends on the extent of auto-covariance for individual stocks, which is typically small.

$$\sigma_{cs}^2 = \frac{1}{N}\sum_{i=1}^{N} R_i^2 - \overline{R}^2 \qquad \text{(A3)}$$

where R_i monthly (ln) return of stock *i*, r_i = daily return of stock *i*, and $t = 1, 2,.., T$ is the number of days within a month

$$\begin{aligned} \sigma_{cs}^2 &= \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} r_{it}\right)^2 - \overline{R}^2 \\ &= \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} r_{i,t}^2\right) + 2\sum_{p\neq q}^{T} r_{i,p} r_{i,q} - \overline{R}^2 \end{aligned} \qquad \text{(A4)}$$

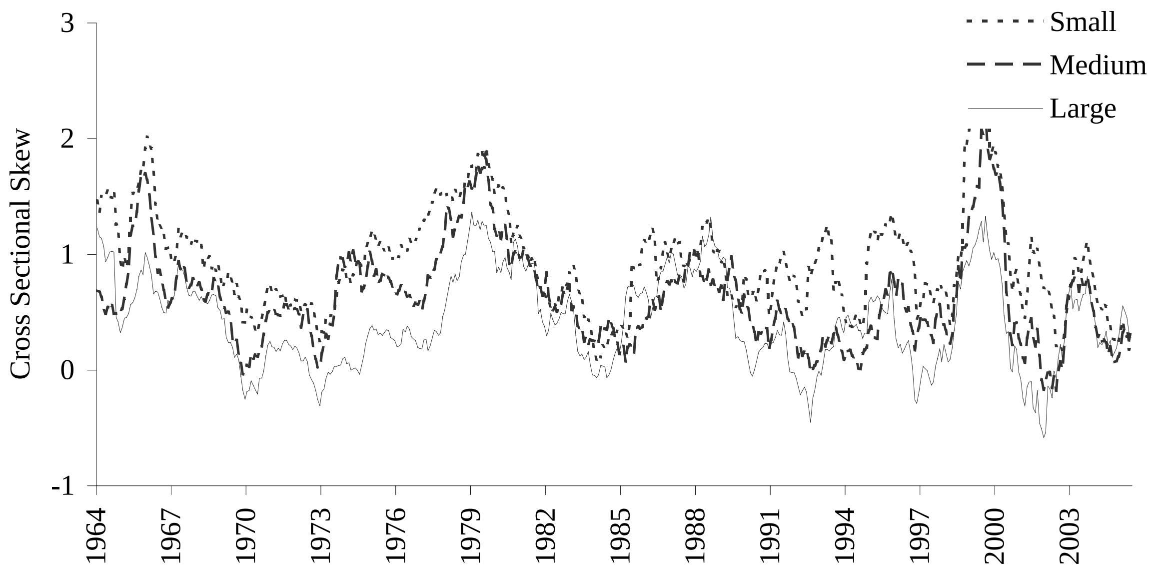
The last two terms are negligibly small as compared to the first one, which is just T times the average variance of individual stock returns. Empirically, this approximation is reasonable, with cross-sectional variance and average idiosyncratic variance correlated (over 1960-2005) at 83%. This approximation has been used in the past, for example by Brav, Brandt and Graham (2005) and also Goyal and Santa-Clara (2003).

Similarly, one can compute the skewness of each stock using daily returns within a month, and then calculate the average of this across all stocks that month. This represents the average total skewness of all stocks that month. The relation between cross-sectional skewness and average total skewness is significant, but not as strong as the relationship between the variances. It is also analytically more difficult to represent the approximation in economic terms. The relatively smaller correlation arises for two mechanical reasons (i) the functional form of skewness, since the sum of cubed returns are standardized by time-series variance for each stock and (ii) the greater relative importance of other terms that arise in the cubic expansion, like the cross-correlation terms (squared returns with lagged and future returns for each stock). On a more fundamental level, using only 22 daily returns within a month might bias the skewness calculated. Despite these effects, the contemporaneous correlation between average skewness and cross-sectional skewness is 35% (48% rank correlation).

Figure 1. Cross Sectional Skewness.

This figure plots the cross-sectional skewness of different sets of stocks. Cross-sectional skewness is measured as the skew of monthly returns of all stocks within a defined set. In Panel A, the sets are defined on the basis of NYSE size quintiles - Small (10% to 30%), Medium (30% to 60%) and Large (>60%). In Panel B, all stocks >median NYSE size are considered. The skew of all these stocks (Large), excluding all stocks in the top 20% and bottom 20% of last month's idiosyncratic volatiliy (no absolutely volatile) and excluding those in the top and bottom 20% of volatility within their size quintile (no relatively volatile) are plotted.

Panel A: Skew of Large/Medium/Small stocks



Panel B: Skew of Large stocks

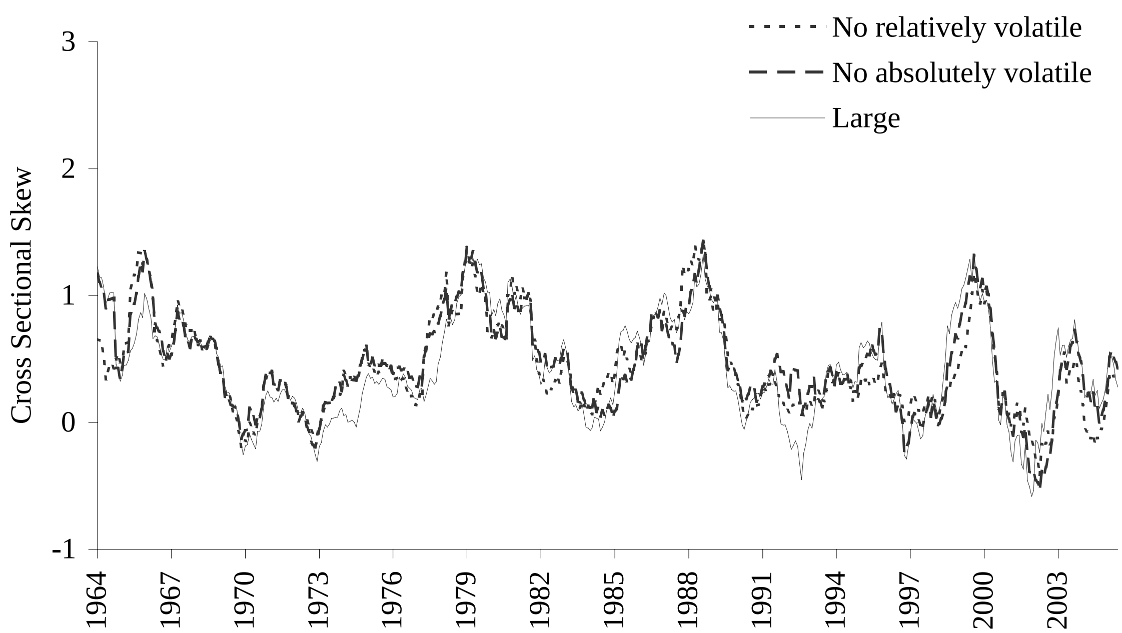


Figure 2. Cross Sectional Skewness and IVOL.

This figure plots lagged 12 month moving averages of cross-sectional skewness and returns of the IVOL factor.

IVOL construction: Stocks are first sorted into quintiles based on size. Within each quintile, stocks are sorted into quintiles based on their AHXZ measure of idiosyncratic volatility. Portfolio 0 is a value-weighted portfolio of all stocks in the least volatile quintile, across all size quintiles and so on for portfolios 1 to 4. The IVOL factor is the difference in returns between portfolio 0 and 4 (VOL = RET0 -RET4).

Skew is the skewnesss of monthly returns of all Large stocks (in the top 40% based on NYSE size breakpoints) excluding stocks used to construct IVOL above.

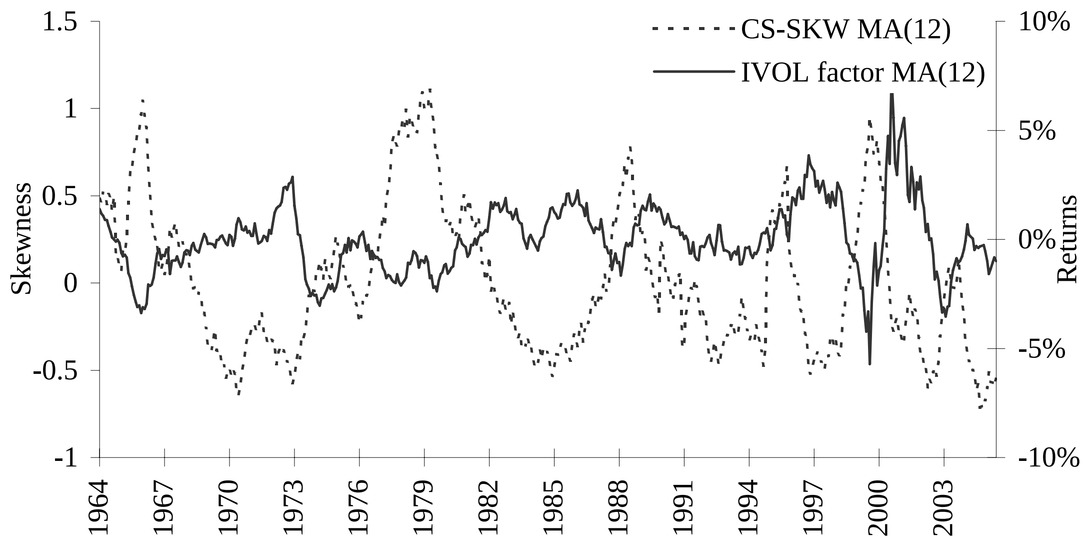


Figure 3. Initial Public Offering (IPO) under-performance and cross-sectional skewness.

This figure plots the skewness of all stocks less than three years old along with the (subsequent) underperformance of IPOs listed that month. An IPO's BHR is the excess Buy and Hold Return of the IPO over a matched firm that is similar in size. The average BHR of all firms listed in a given month is that month's measure of average IPO under-performance. YCS-SKW is the cross-sectional skewness of all firms less than three years old that are larger than NYSE 10% size breakpoint, exluding those with IPOs that month. Twelve month moving averages of both these series are plotted.

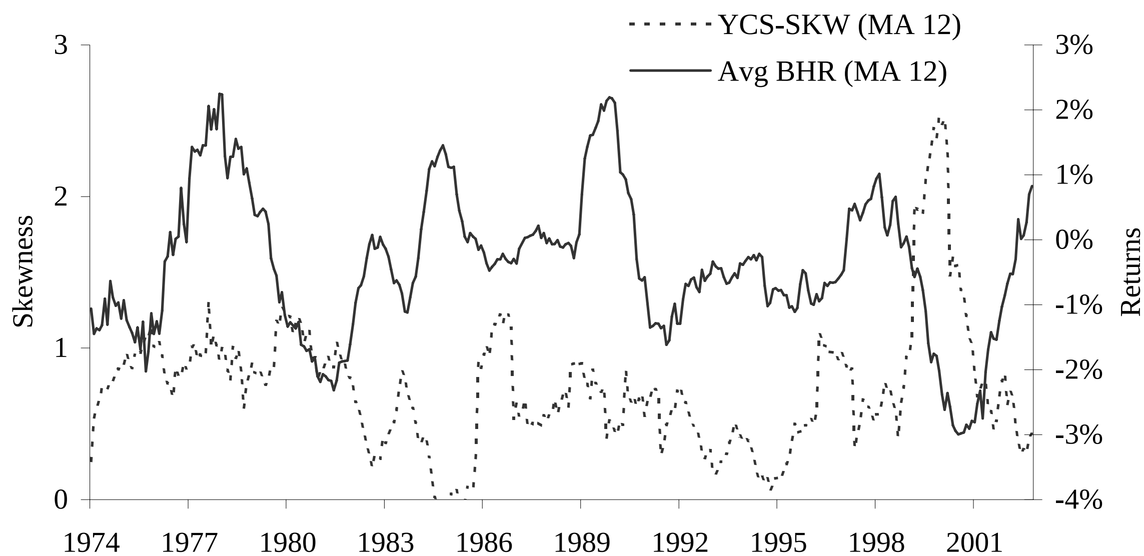


Table 1. Size and idiosyncratic volatility sorts.

Panel A contains Fama and French (1993) three-factor alphas of value-weighted portfolios formed based on size and idiosyncratic volatility. Idiosyncratic volatility is measured as in AHXZ, as the variance of residuals of a three-factor model for the prior month. All firms are first sorted by size and then on the AHXZ measure of idiosyncratic volatility. *t-* statistics reported for the alphas are based on Newey-West corrections to standard errors (three lags). Panel B reports which size portfolios have significantly (at the 10% level) negative (-), positive (+) or insignificant (0) alphas for their highest idiosyncratic volatility portfolio, based on alternative portfolio formation methods and regressors. The variations include value / equal weighting (VW / EW), forming size quintiles based on all firms / NYSE only firms, and adding an additional momentum factor (UMD). In Panel C, size and idiosyncratic volatility sorted portfolios are created as in Panel A. For each size quintile, the difference between extreme (lowest minus highest) idiosyncratic volatility quintiles is computed, leading to 5 portfolios. These five portfolios are regressed on excess market returns, HML and SMB and UMD. Panel C reports correlations of the residuals (resid) from the regressions in Panel A. All correlations are significantly different from zero at the 1% level.

Panel A: Three factor alphas

Alpha

	Size				
IVOL	Low 0	1	2	3	High 4
Low 0	0.26%	0.27%	0.22%	0.07%	0.08%
1	0.42%	0.29%	0.23%	0.19%	0.06%
2	0.42%	0.04%	0.01%	0.16%	0.01%
3	0.37%	-0.51%	-0.26%	-0.08%	0.11%
High 4	-0.23%	-1.60%	-1.37%	-0.81%	-0.23%

t-statistics

	Size				
IVOL	0	1	2	3	4
Low 0	1.75	2.22	2.23	0.86	1.36
1	2.55	2.58	2.66	2.46	1.17
2	2.12	0.37	0.13	2.31	0.10
3	1.62	-3.65	-3.00	-1.19	1.56
High 4	-0.81	-7.36	-8.48	-6.16	-1.84

Panel B: Alternative portfolio formation methods and controls for momentum

	0	1	2	3	4
NYSE size breakpoints					
EW	0	-	-	-	0
VW	-	-	-	-	0
EW + UMD	0	-	-	0	0
VW + UMD	-	-	-	0	0
All firm size breakpoints					
EW	+	-	-	-	-
VW	0	-	-	-	-
EW + UMD	+	-	-	-	-
VW + UMD	0	-	-	-	-

Panel C: Correlations

	Resid0	Resid1	Resid2	Resid3	Resid4
Resid0	100%				
Resid1	76%	100%			
Resid2	62%	80%	100%		
Resid3	40%	59%	72%	100%	
Resid4	26%	37%	48%	62%	100%

Table 2. The IVOL factor.

This table contains summary statistics for the IVOL factor. Stocks are first sorted into quintiles based on size. Within each quintile, stocks are sorted into quintiles based on their AHXZ measure of idiosyncratic volatility. Portfolio 0 is a value-weighted portfolio of all stocks in the least volatile quintile, across all size quintiles and similarly for portfolios 1 to 4. Panel A presents returns and loadings in four-factor regressions for each of these portfolios. Panel B presents statistics for the IVOL factor, defined as the difference in returns between portfolio 0 and 4 (VOL = RET0 -RET4).

Panel A: Size controlled idiosyncratic volatility sorts

Portfolio	**0**	**1**	**2**	**3**	**4**
Gross Returns	0.97%	1.03%	1.01%	1.06%	0.65%
Avg size quintile	2.04	2.04	2.04	2.04	2.04
Alpha	0.05%	0.07%	0.03%	0.09%	-0.32%
	[0.9]	[1.16]	[0.61]	[1.4]	[-2.59]
Market	0.86	0.98	1.09	1.12	1.23
	[60.74]	[50.91]	[65.07]	[59.24]	[31.94]
HML	0.18	0.12	0.01	-0.18	-0.45
	[4.27]	[2.37]	[0.35]	[-4.72]	[-5.16]
SMB	-0.23	-0.14	0.00	0.28	0.65
	[-9.93]	[-4.17]	[0.11]	[8.8]	[8.72]
UMD	0.03	0.01	-0.02	-0.03	-0.06
	[0.89]	[0.24]	[-0.75]	[-1.28]	[-1.05]

Panel B: The IVOL factor

	(1)	(2)	(3)
Alpha	0.67%	0.37%	
	[3.41]	[2.56]	
Mkt	-0.73	-0.37	
	[-10.77]	[-8.21]	
HML		0.75	
		[4.95]	
SMB		-0.87	
		[-13.71]	
UMD		0.09	
		[1.54]	
Recession dummy			0.013
			[1.37]

Table 3. Different measures of skewness.

This table contains summary statistics and correlations between different measures of skewness. Panel A contains summary statistics, while Panel B reports Spearman (rank) correlation coefficients for CS-SKEW, Breadth and Average TS-SKEW. CS-SKEW is the cross-sectional skewness of monthly returns, Breadth is equal-weighted Mean-Median of monthly returns, while TS-SKEW is the time-series average skewness of daily returns averaged across all stocks. All these measures are for stocks greater than the 10% NYSE size breakpoint. All correlations are significantly different from zero at p=0.01 levels. Panel C contains Spearman correlation coefficients between different measures (CSSKEW, TSSKEW and Breadth) for firms in different size quintiles (suffix 1, 2, 3 for small, medium and large firms respectively).

Panel A: Summary statistics

Variable	Mean	Std Dev	Median	Minimum	Maximum	ρ_1	ρ_2
CS-SKW	0.863	1.018	0.742	-1.070	10.325	0.247	0.164
Brdth	0.006	0.013	0.005	-0.047	0.110	0.219	0.033
TS-SKW	0.241	0.156	0.242	-0.518	0.652	0.207	0.022

Panel B: Spearman correlations for different skewness measures

	CS-SKW	Brdth	TS-SKW
CS-SKW	1		
Brdth	0.78	1	
TS-SKW	0.48	0.65	1

Panel C: Spearman correlations of different measures of skewness for small, medium and large stocks

	TS-SKW1	TS-SKW2	TS-SKW3	CS-SKW1	CS-SKW2	CS-SKW3	Brdth1	Brdth2	Brdth3
TS-SKW1	100%								
TS-SKW2	91%	100%							
TS-SKW3	66%	79%	100%						
CS-SKW1	49%	42%	29%	100%					
CS-SKW2	42%	39%	24%	60%	100%				
CS-SKW3	45%	42%	33%	55%	58%	100%			
Brdth1	66%	61%	45%	71%	62%	61%	100%		
Brdth2	63%	60%	43%	61%	72%	67%	86%	100%	
Brdth3	52%	48%	37%	56%	61%	77%	72%	82%	100%

Table 4. Skewness and the idiosyncratic volatility factor.

Panel A regresses the idiosyncratic volatility based factor (IVOL; formed as in Table 2) on the market, cross-sectional variances (CS-VAR), Breadth or cross-sectional skewness (CS-SKW), HML, SMB and UMD. Mktrf is the excess return on the market portfolio. Panel B performs a four-factor regression of IVOL while conditioning on the predicted SKW factor. The first specification only includes months for which predicted CS-SKW is greater than zero, while the second specification only includes months for which predicted CS-SKW is less than zero.

Panel A: IVOL regressed on CS-SKW and Variance

	(1)	(2)	(3)	(4)	(5)
Intercept	0.022	0.023	0.011	0.027	0.009
	[5.47]	[10.4]	[4.41]	[5.07]	[3.2]
Mktrf	-0.661	-0.375	-0.284	-0.586	-0.343
	[-8.28]	[-7]	[-7.06]	[-7.83]	[-7.54
CS-VAR	-0.536	0.526	0.324	-0.393	0.079
	[-3.96]	[3.63]	[3.16]	[-1.23]	[0.41]
Breadth		-2.426	-1.235		
		[-8.55]	[-6.37]		
CS-SKW				-0.018	-0.007
				[-4.16]	[-3.4]
HML			0.511		0.596
			[5.13]		[4.31]
SMB			-0.610		-0.801
			[-5.35]		[-7]
UMD			0.041		0.082
			[0.69]		[0.98]

Panel B: IVOL regressed on four factors, conditioning on predicted SKW

	Predicted SKW	Predicted SKW <0
Alpha	0.51%	0.28%
	[1.97]	[1.56]
Mktrf	-0.319	-0.378
	[-4.2]	[-6.62]
HML	0.723	0.460
	[4.19]	[2.86]
SMB	-0.916	-0.712
	[-8.65]	[-7.31]
UMD	-0.018	0.257
	[-0.14]	[3.25]

Table 5. The factor mimicking portfolio for cross-sectional skewness.

This table contains results of regressions on portfolios formed on sensitivities to cross-sectional skewness. CS-SKW is the skewness of all NYSE/AMEX/NASDAQ stocks (excluding the smallest 10% of NYSE firms) measured each month. Panel A reports results of time-series factor regressions on portfolios formed on sensitivities to cross-sectional skewness. All stocks are regressed on market returns and CS-SKW for months *t-36* to *t-1*. Firms are sorted into portfolios based on CS-SKW betas (BCS). Value-weighted returns of these portfolios at time *t* are displayed below, along with time-series factor regressions. Panel B sorts all stocks on size first, using NYSE size breakpoints and then on CS-SKW Betas. Panel C reports time-series factor regressions of the IVOL factor. This factor is constructed as in Table 2 and regressed on the Fama-French three factors and momentum. The value-weighted portfolios formed on sensitivities to cross-sectional skewness are used to construct SKW-FMP as the Portfolio 0 (Lowest CS-SKW beta) - Portfolio 4 (highest CS-SKW beta).

Panel A: Time-series factor regression on portfolios formed on prior sensitivities to cross-sectional skewness

Portfolio	0	1	2	3	4
Gross Returns	1.06%	0.98%	1.05%	1.01%	0.72%
CAPM alpha	0.13%	0.06%	0.07%	-0.05%	-0.45%
t-statistic	1.85	1.25	1.24	-0.57	-2.9
CAPM Beta	0.91	0.90	1.03	1.21	1.42
FF alpha	0.08%	0.01%	0.08%	-0.04%	-0.38%
t-statistic	1.11	0.13	1.39	-0.45	-3.45
HML	0.13	0.13	-0.02	-0.08	-0.28
t-statistic	3.6	4.84	-0.33	-1.58	-5.11
SMB	-0.12	-0.12	-0.01	0.25	0.66
t-statistic	-4.52	-5.2	-0.2	6.75	14.28
4 factor alpha	0.06%	0.03%	0.11%	0.00%	-0.32%
t-statistic	0.84	0.75	1.98	-0.01	-2.68

Panel B: NYSE size breakpoints

Gross Returns

	NYSE size quintiles				
BCS	0	1	2	3	4
0	1.24%	1.39%	1.29%	1.23%	0.97%
1	1.44%	1.41%	1.34%	1.19%	0.96%
2	1.37%	1.36%	1.28%	1.23%	1.03%
3	1.29%	1.30%	1.22%	1.18%	0.85%
4	0.82%	0.88%	0.96%	0.96%	0.86%

Time-series average number of stocks

	NYSE size quintiles				
BCS	0	1	2	3	4
0	525	121	85	69	61
1	525	122	86	70	62
2	525	122	86	70	62
3	525	122	86	70	62
4	525	121	85	69	61

Panel C: Time series regressions on 0- 4 (Low Beta CS-SKW - High Beta CSKEW) portfolios formed within size quintiles

Size quintile	**0**	**1**	**2**	**3**	**4**
0-4 CAPM Regressions					
Alpha	0.53%	0.71%	0.53%	0.47%	0.24%
	[3.67]	[4.51]	[3.25]	[2.9]	[1.52]
0-4 FF 3 Factor regressions					
Alpha	0.38%	0.47%	0.29%	0.27%	0.04%
	[2.96]	[3.85]	[2.13]	[1.93]	[0.24]
BMkt	-0.08	-0.22	-0.20	-0.22	-0.11
	[-1.75]	[-4.78]	[-4.78]	[-4.38]	[-1.91]
BHML	0.33	0.51	0.50	0.42	0.41
	[4.68]	[6.69]	[6.63]	[5.72]	[4.93]
BSMB	-0.32	-0.30	-0.31	-0.30	-0.23
	[-6.24]	[-4.99]	[-5.2]	[-4.7]	[-3.06]
0-4 Four Factor regressions					
Alpha	0.25%	0.39%	0.32%	0.31%	0.10%
	[1.62]	[2.88]	[2.11]	[1.99]	[0.62]

Panel D: IVOL regressed on the four factors and skewness mimicking factor

	(1)		(2)		(3)	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
Alpha	0.67%	[3.41]	0.24%	[1.80]	0.20%	[1.41]
Mktrf	-0.73	[-10.77]	-0.31	[-6.24]	-0.25	[-6.47]
SKW-FMP			0.86	[9.68]	0.55	[10.36]
HML					0.40	[4.63]
SMB					-0.43	[-4.43]
UMD					0.05	[0.86]

Table 6. Initial Public Offering (IPO) under-performance and skewness.

This table relates IPO under-performance to skewness at the time of listing. IPO under-performance is the excess Buy and Hold Return (BHR) of IPO firms for their first three years (or until delisting) over firms matched on size. BHR are in monthly percent terms. Panel A presents summary statistics. Panel B presents mean and median BHRs when cross-sectional skewness of young firms (YCS-SKW) is less than or greater than its sample median. Young firms are firms that listed in the three years, excluding the current month. Panel C presents robustness checks, including using lagged cross-sectional skewness, lagged breadth (Mean - Median return) of young firms and cross-sectional skewness of old (> three years since listing) firms. The *p* values for means (*t*- test) and medians (signed rank test) test whether they are equal to zero.

Panel A: Summary Statistics

	Mean	Median	N	Std Dev	Skewness
IPO returns	0.91%	-0.20%	10,489	5.7%	7.64
Matched firm returns	1.38%	0.63%	10,499	5.3%	6.87
Excess BHR	-0.47%	-0.70%	10,489	7.7%	0.81

Panel B: BHR conditioning on cross-sectional skewness of young firms

	YCS-SKW<Median			**YCS-SKW>Median**		
	BHR	*p* value	N	BHR	*p* value	N
Full sample: 1973-2002						
Mean	0.05%	0.64	5452	-1.03%	< 0.01	5037
Median	-0.30%	< 0.01		-1.04%	< 0.01	
Sub sample: 1973-1988						
Mean	0.17%	0.22	1958	-0.59%	< 0.01	1963
Median	-0.07%	0.54		-0.61%	< 0.01	
Sub sample: 1989-2002						
Mean	-0.02%	0.88	3494	-1.31%	< 0.01	3074
Median	-0.48%	< 0.01		-1.29%	< 0.01	

Panel C: Robustness (Full Sample: 1973-2002)

	Skew < Median			**Skew > Median**		
	BHR	*p* value	N	BHR	*p* value	N
BHR conditioning on lagged cross-sectional skewness of young firms						
Mean	-0.14%	0.23	5358	-0.82%	< 0.01	5131
Median	-0.45%	< 0.01		-0.96%	< 0.01	
BHR conditioning on lagged breadth of young firms						
Mean	-0.10%	0.37	5360	-0.86%	< 0.01	5129
Median	-0.42%	< 0.01		-0.92%	< 0.01	
BHR conditioning on cross-sectional skewness of old firms						
Mean	-0.13%	0.24	5628	-0.86%	< 0.01	4861
Median	-0.43%	< 0.01		-0.99%	< 0.01	

Table 7. New lists, volatility, and skewness in calendar time.

This table reports time-series factor regressions of newly listed stocks (first appearance on CRSP of the firm < = 36 months ago). Panel A provides gross returns of portfolios sorted on size (last month's market capitalization) for new and old firms. Panels B and C sort all firms by size and prior idiosyncratic volatility, and report gross returns and results from three factor regressions for all new firms. Panel D sorts new and old (>36 months since listing) firms by market capitalization and calculates returns of a portfolio long old stocks and short new stocks. Panel D reports results of calendar time regressions of this portfolio on the market, the three-factor model, and the three-factor model augmented with the skewness mimicking portfolio (SKW-FMP).

Panel A: Gross Returns

Size quintile	**0**	**1**	**2**	**3**	**4**
New firm returns	1.38%	0.74%	0.75%	1.02%	0.91%
Average number of firms	187	218	201	153	64
Old firm retuns	1.87%	1.28%	1.29%	1.29%	0.98%
Average number of firms	808	777	795	843	931

Panel B: Value-weighted portfolios of new lists by size and volatility quintiles

Gross Returns

Volatility \ Size	**0**	**1**	**2**	**3**	**4**
0	1.26%	0.98%	1.22%	1.33%	1.52%
1	1.21%	1.62%	1.44%	1.66%	1.02%
2	1.60%	1.17%	1.20%	1.25%	1.29%
3	2.02%	0.77%	0.74%	1.07%	1.24%
4	1.26%	-0.59%	-0.32%	0.28%	0.47%

Average number of firms

Volatility \ Size	**0**	**1**	**2**	**3**	**4**
0	63	74	59	38	13
1	58	70	59	41	13
2	60	69	64	49	18
3	62	71	70	60	26
4	62	76	80	75	45

Panel C: Fama-French 3 factor regressions

Alphas

Volatility \ Size	0	1	2	3	4
0	0.20%	-0.10%	0.08%	0.16%	0.44%
1	0.00%	0.30%	0.10%	0.41%	-0.04%
2	0.25%	-0.17%	-0.04%	0.06%	0.28%
3	0.74%	-0.62%	-0.46%	-0.10%	0.32%
4	-0.24%	-1.95%	-1.53%	-0.71%	-0.21%

t statistics for alphas

Volatility \ Size	0	1	2	3	4
0	0.75	-0.50	0.47	0.99	1.89
1	0.01	1.44	0.63	1.91	-0.19
2	0.68	-0.74	-0.19	0.34	1.18
3	1.65	-2.08	-2.52	-0.59	1.23
4	-0.51	-5.27	-5.33	-3.13	-0.69

Panel D: Calendar time regressions for Old minus New firm portfolios, within each size quintile.

Size quintile	**0**	**1**	**2**	**3**	**4**
Returns	0.50%	0.55%	0.54%	0.27%	0.07%
t statistic	2.78	3.68	3.82	1.56	0.33
CAPM alpha	0.54%	0.59%	0.63%	0.42%	0.24%
t statistic	3.03	3.47	3.95	2.22	1.15
3 Factor alpha	0.21%	0.33%	0.28%	0.00%	-0.01%
t statistic	1.05	1.89	2.27	-0.05	-0.03
3 Factor + SKW-FMP alpha	0.14%	0.24%	0.18%	-0.09%	-0.09%
t statistic	0.64	1.33	1.58	-0.73	-0.53
SKW-FMP loading	0.167	0.206	0.216	0.181	0.196
t statistic	2.99	3.59	5.12	3.29	2.50

Table 8. IVOL, SKW, and the small growth portfolio.

Panel A and B examines value-weighted portfolios formed from sequential sorts, first on book-to-market and then on lagged idiosyncratic volatility. Panel A presents alphas from Fama-French three-factor regressions, while Panel B presents the loading on the HML factor. Panel C examines the 25 size and book-to-market portfolios formed as in Fama and French (1993). It reports the coefficient on CS-SKW from regressions of each portfolio on the market and CS-SKW. Panel D reports results of time series regressions of the small growth portfolio on the Fama-French factors, CS-SKW and IVOL.

Panel A: B/M size breakpoints - three factor alpha

Coefficient

	NYSE B/M quintile				
IVOL	0	1	2	3	4
0	0.21%	0.09%	-0.12%	-0.05%	0.01%
1	0.23%	-0.15%	-0.04%	0.04%	0.09%
2	0.17%	-0.08%	-0.22%	0.05%	-0.16%
3	-0.48%	-0.49%	-0.51%	-0.23%	-0.46%
4	-1.52%	-1.14%	-0.74%	-1.05%	-0.73%

t-statistic

	NYSE B/M quintile				
IVOL	0	1	2	3	4
0	2.78	1.12	-1.44	-0.61	0.11
1	2.47	-1.65	-0.42	0.46	0.52
2	1.22	-0.70	-1.50	0.34	-0.88
3	-2.93	-3.11	-3.81	-1.53	-2.19
4	-6.22	-6.49	-4.04	-5.05	-2.40

Panel B: B/M size breakpoints - HML loading

	NYSE B/M quintile				
IVOL	0	1	2	3	4
0	-0.25	0.24	0.47	0.65	0.74
1	-0.61	0.09	0.36	0.49	0.63
2	-0.85	-0.06	0.25	0.42	0.63
3	-0.91	-0.20	-0.03	0.10	0.44
4	-0.85	-0.64	-0.09	0.05	0.39

	NYSE B/M quintile				
IVOL	0	1	2	3	4
0	-3.43	3.45	7.28	12.35	12.73
1	-16.62	1.48	5.35	8.55	5.77
2	-7.42	-1.09	3.26	4.34	4.58
3	-6.03	-2.06	-0.26	0.74	2.49
4	-4.66	-4.28	-0.57	0.27	1.70

Panel C: 25 Size, B/M portfolios on CS-SKW

	Book to market				
Size	1	2	3	4	5
1	-0.76	-0.59	-0.36	-0.27	-0.27
2	-0.57	-0.28	-0.15	-0.09	-0.14
3	-0.48	-0.12	0.01	0.06	0.01
4	-0.32	0.03	0.11	0.10	0.12
5	0.08	0.19	0.20	0.28	0.19

	Book to market				
Size	1	2	3	4	5
1	-11.89	-6.30	-4.82	-4.45	-4.57
2	-9.66	-4.49	-2.82	-1.73	-2.43
3	-11.59	-2.32	0.20	1.13	0.18
4	-7.67	0.54	1.95	2.08	1.94
5	3.74	7.92	6.62	6.78	3.86

Panel D: Regressions of the small growth portfolio on the Fama-French factors, SKW and IVOL

	(1)		(2)		(3)		(4)		(5)	
	Coeff.	***t-stat***	**Coeff.**	***t-stat***	**Coeff.**	***t-stat***	**Coeff.**	***t-stat***	**Coeff.**	***t-stat***
Alpha	-0.45%	-1.89	-0.47%	-4.46	-0.02%	0.002	0.06%	0.30	-0.41%	-4.08
Market	1.46	26.87	1.07	38.00	1.04	18.05	0.91	17.75	1.02	33.00
HML			-0.33	-6.25					-0.24	-4.90
SMB			1.38	32.71					1.25	19.89
SKW-FMP					-0.83	-9.96				
IVOL							-0.76	-11.89	-0.15	-3.05

Table 9. Interpreting cross-sectional skewness.

Panel A examines the industry composition of the portfolio of stocks with highest cross-sectional skewness betas over the prior 36 months. The first row reports the fraction of the portfolio's market capitalization that the industry represents. The Fama-French 48 industry classification scheme is used. The second row (relative representation) is the ratio of the previous row to the fraction of the overall market that this industry represents. Panel B reports regressions of annual measures of cross-sectional skewness for all Large and Medium stocks (> NYSE 30% size breakpoint). This is the skewness of all monthly returns of these stocks over the calendar year *y*. The explanatory variables include lagged patent grant growth (Log ($Patents_{t-1}$ / $Patents_{t-2}$)), Log($R\&D_{t-1}$ / $R\&D_{t-2}$) , where R&D =Average R&D Expense/Total Assets across all publicly listed firms.

Panel A: Industry effects

	1	2	3
1966-75			
Industry	Consumer Goods	Oil and Gas	Trading
Fraction of highest CS-SKW Beta portfolio	7.8%	7.3%	6.7%
Relative representation	0.88	0.55	3.93
1976-85			
Industry	Oil and Gas	Computer Hardware	Trading
Fraction of highest CS-SKW Beta portfolio	25.7%	5.3%	5.3%
Relative representation	1.82	0.86	0.93
1986-95			
Industry	Business Services	Trading	Computer Hardware
Fraction of highest CS-SKW Beta portfolio	11.2%	7.9%	7.9%
Relative representation	3.53	0.68	1.93
1995-2005			
Industry	Business Services	Electronic Equipment	Communication
Fraction of highest CS-SKW Beta portfolio	21.1%	10.0%	8.8%
Relative representation	2.57	1.99	1.64

Panel B: Cross-sectional skewness and technological innovation.

	(1)	**(2)**	**(3)**	**(4)**
Constant	-0.09	-0.064	-0.019	-0.03833
	[-1.56]	[-1.1]	[-0.3]	[-0.55]
Lag Patent Grant Growth	3.94	3.39		
	[2.13]	[1.73]		
Lag R&D growth			1.91	1.85
			[2.34]	[2.15]
Lag market returns		-5.74		4.74
		[-1.18]		[1.07]

Table 10. Co-skewness and Cross-sectional skewness.

Panel A presents gross returns and results of a time-series regression of portfolios formed on co-skewness betas on the market and the cross-skewness factor. The portfolios are formed in a manner similar to Harvey and Siddique (2000). In particular, stocks are first regressed on market and squared market returns from periods *t* -36 to *t* -1. Value-weighted portfolios are formed based on ranks of the coefficients on squared market returns (co-skew beta). Portfolio 1 contains the smallest 30%, 2 the middle 40% and 3 the largest 30% co-skew betas. Panel B reports results of a regression of the factor mimicking portfolio for cross-sectional-skewness on the four factor model and the co-skewness factor, which is the difference between co-skew portfolio 0 and portfolio 2.

Panel A: Co-skew Beta portfolios

	Co-skew Beta grouping		
	0	**1**	**2**
Gross Returns	1.24%	1.02%	0.89%
Alpha	0.32%	0.03%	-0.09%
	3.26	0.68	-1.27
Mkt Beta	1.041	0.986	1.052
	36.05	86.56	50.67
CSKEW Beta	-0.193	0.108	-0.051
	-4.68	4.93	-2.69

Panel B: Cross-sectional skewness factor regressed on co-skewness and additional controls

	Coefficient	***t-statistic***
Alpha	0.43%	2.65
Mkt	-0.21	-4.19
Coskew	-0.19	-2.71
HML	0.44	5.41
SMB	-0.75	-12.86
UMD	0.08	1.24

Table A1. Performance of volatility models.

Panel A reports statistics on the performance of various models for forecasting volatility. These statistics include Mean Absolute Error (MAE), Mean Squared Error (MSE), Spearman's rank correlation coefficient (Correlation) of predicted volatility with realized volatility and an aymptotic standard error for the correlation coefficient. All performance measures are with respect to realized monthly volatility, each month. Panel B estimates predicted volatility from a MIDAS-SF model that uses past realizations of both market (Mktvol) and individual stock idiosyncratic volatility (Ivol). In particular, the following model is estimated for stocks with atleast three years of returns:

$$\text{Ivol}(t,t+30) = \alpha + \beta\ \text{Ivol}(t-5,t) + \delta\ \text{IVvol}(t-22,t) + \gamma\ \text{Ivol}(t-66,t)$$
$$+ \beta'\ \text{MktVol}(t-5,t) + \delta'\text{Mktvol}(t-22,t) + \gamma'\ \text{Mktvol}(t-66,t) + \varepsilon_t$$

Panel B sorts stocks, into value-weighted portfolios using predicted values of volatility using this model. Panel B reports gross returns and four factor alphas for these portfolios.

Panel A: In-sample performance (Total volatility)

Model	N	MAE	MSE	Correlation	SE(Rho)
MIDAS-SF Stock	12474	0.1212%	0.0024%	75.7%	0.58%
MIDAS-SF market	12474	0.1440%	0.0030%	68.5%	0.65%
Lagged volatility	12474	0.337%	0.0038%	72.5%	0.62%
EGARCH(1,1)	12331	0.1646%	0.0057%	61.0%	0.71%
GARCH (1,1)	12474	0.1609%	0.0050%	63.3%	0.69%
ARMA(1,1)	12474	0.1217%	0.0025%	76.2%	0.58%

Panel B: Value-weighted portfolios sorted on predicted idiosyncratic volatility

	0	1	2	3	4
Gross returns	0.98%	1.05%	1.05%	0.93%	0.67%
Average number of stocks	670	670	670	670	670
3 factor alpha	0.04%	0.04%	0.03%	-0.14%	-0.46%
t	0.84	0.65	0.32	-1.37	-2.86