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Price Momentum and Idiosyncratic Volatility

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Abstract

We find that returns to momentum investing are higher among high idiosyncratic volatility (IVol) stocks, especially high IVol losers. Higher IVol stocks also experience quicker and larger reversals. The findings are consistent with momentum profits being attributable to underreaction to firm-specific information and with IVol limiting arbitrage of the momentum effect. We also find a positive time-series relation between momentum returns and aggregate IVol. Given the long-term rise in IVol, this result helps explain the persistence of momentum profits since Jegadeesh and Titman's (1993) study.

Keywords: price momentum, idiosyncratic volatility, limits of arbitrage

JEL Classifications: G12, G14

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1. Introduction

The momentum anomaly first identified by Jegadeesh and Titman (1993) continues to puzzle financial economists. Jegadeesh and Titman (1993) find that buying stocks with recent high returns and selling stocks with recent low returns produces profits that are both statistically and economically significant. Although the magnitude and significance of the returns to momentum strategies are now well accepted, there is little agreement about the sources of momentum profits. While some argue that momentum profits represent compensation for bearing systematic risk (e.g., Conrad and Kaul, 1998; Chordia and Shivakumar, 2002), others provide evidence that supports behavioral explanations of the momentum effect (e.g., Hong, Lim and Stein, 2000; Jegadeesh and Titman, 2001).

In this paper, we examine the relation between price momentum and idiosyncratic volatility (IVol). This study is important because it contributes to our understanding of the sources of momentum profits. Using a sample of U.S. stocks over 1965–2002, we show that the momentum effect is closely related to IVol. High IVol stocks have greater momentum returns than do low IVol stocks, a relation that is driven by stocks with high IVol and low past returns (losers). High IVol stocks also display quicker and larger reversals. In a series of robustness tests, we show that the effect of IVol on price momentum is not subsumed by size, trading volume, share price, market beta, price delay or distress risk. The results are consistent with the view that momentum profits are attributable to underreaction to firm-specific information, and that IVol is an important factor in limiting the successful arbitrage of the momentum effect. Our findings are also consistent with the asymmetric-information model of Wang (1993).

We also present time-series evidence of a positive and significant relation between aggregate IVol and momentum returns. This evidence complements the cross-sectional results and further supports our view that IVol plays an important role in the momentum effect. Moreover, this finding, combined with the Campbell, Lettau, Malkiel and Xu (2001) finding of rising IVol, helps explain the persistence of the momentum effect into the 1990s and early 2000s. Schwert (2003) shows that many well-known anomalies, such as the small-firm effect and the value effect, are not observed after the periods examined by the studies that initially identify the anomalies. However, momentum profits not only persist but also increase after the period examined by Jegadeesh and Titman (1993). Our results show that the rise of IVol helps explain why the momentum effect has not disappeared following the publication of Jegadeesh and Titman's (1993) study.

There are at least two reasons why momentum profits might be related to IVol under the behavioral approach. IVol can be viewed as a proxy for firm-specific information. If momentum profits are due to initial underreaction to firm-specific information (e.g., Jegadeesh and Titman, 1993; Barberis, Shleifer and Vishny, 1998; Hong and Stein, 1999), firms with higher IVol should display greater momentum. Intuitively, stocks with more firm-specific information will, all else equal, have higher

IVol and, according to theories of underreaction, experience greater underreaction and display more price momentum.

IVol also represents an important limit of arbitrage. Behavioral biases alone are not sufficient to produce momentum profits. In an efficient market, any profitable anomaly is eliminated by rational arbitrageurs. However, momentum profits persist many years after the revelation of the effect. Therefore, we hypothesize that investors must be limited in their ability to arbitrage the momentum phenomenon for profit. Shleifer and Vishny (1997) identify volatility, especially IVol, as a limit of arbitrage. In their model, arbitrageurs are assumed to use funds provided by investors who withdraw funds if short-term performance is disappointing. Given the size of positions needed to make meaningful profits through arbitrage, arbitrageurs are also poorly diversified, which leaves them exposed to excess firm-specific risk. Therefore, arbitrageurs tend to avoid stocks with high IVol.[1] If IVol is truly a limit of arbitrage, we would expect stocks with higher IVol to also display greater momentum. Investors would eliminate the momentum effect through arbitrage for stocks with no arbitrage-limiting characteristics, allowing the momentum effect to persist and remain large for stocks with high IVol.

While a positive relation between IVol and momentum profits would be consistent with behavioral explanations, it might also be consistent with rational theories in the presence of information asymmetry. Wang (1993) develops a model with uninformed investors who trade on information in prices and dividends, which results in rational trend-chasing behavior. Under the same circumstances, informed investors act like contrarians, which eventually makes returns reverse. Thus, stocks with higher information asymmetry display greater momentum and reversal. The tests in this paper find evidence consistent with these predictions.

Our paper is related to Ang, Hodrick, Xing and Zhang (2006), who examine the relation between IVol and the cross-section of stock returns and report that high IVol is associated with "abysmally low returns." Ang, Hodrick, Xing and Zhang's (2006) main findings remain significant after controlling for momentum. While our results are consistent with theirs, significant differences exist between the papers. First, Ang, Hodrick, Xing and Zhang (2006) use a trading strategy with a holding period of only one month. The momentum effect, however, is more prevalent at the intermediate horizon (three to 12 months), raising the possibility that their study does not completely control for momentum. Second, we control for several variables previously shown to be related to the momentum effect. Ang, Hodrick, Xing and Zhang (2006) focus on the relation between IVol and stock returns and do not control for other variables in the analysis of the interaction of momentum and IVol. Finally, we examine the time-series relation between aggregate IVol and momentum returns.

[1] Ali, Hwang, and Trombley (2003) test this theory by examining the relation between IVol and the book-to-market effect. They show that the book-to-market effect is greater for firms with higher IVol. Their finding is consistent with Shleifer and Vishny's (1997) argument that risk associated with the volatility of arbitrage returns deters arbitrage activity and is an important reason why the book-to-market effect persists.

2. Related literature

The momentum effect first appears in Jegadeesh and Titman (1993), who report that buying stocks with recent high returns and selling stocks with recent low returns results in profits that are statistically and economically significant.[2] Jegadeesh and Titman (2001) find that momentum profits persist following the sample period of their previous work. Rouwenhorst (1998) reports that international equity markets also exhibit price momentum. These studies show that the momentum effect is not confined to a single market or sample period.

Explanations of the momentum effect are either risk-based or behavior-based. In Berk, Green and Naik (1999), momentum arises from the persistence in expected returns. In Johnson (2002), since the growth rate risk carries a positive price, high-growth firms tend to have high expected returns. Johnson (2002) argues that past return sorts tend to sort firms by recent growth rates. Momentum then arises because winners have higher expected returns than do losers. Wang (1993) develops a dynamic model of asymmetric information that shows that "the imperfect information of some investors can cause stock prices to be more volatile than in the case where all investors are perfectly informed" (p. 249). In his model, uninformed investors engage in rational trend-chasing behavior. Under the same circumstances, informed investors act as contrarians, a behavior which eventually brings about return reversal. Thus, stocks with higher information asymmetry display higher volatility, greater momentum and greater reversal.

Three behavioral models try to explain both the medium-horizon momentum reported by Jegadeesh and Titman (1993) and the long-horizon reversal reported by DeBondt and Thaler (1985). In Barberis, Shleifer and Vishny (1998), the conservatism bias causes investors to update their priors insufficiently when they observe new information about a firm. This leads to initial underreaction. At the same time, investors suffer from a representativeness bias, which leads to delayed overreaction. To the extent that IVol serves as a proxy for the amount of firm-specific news, stocks with higher IVol might suffer from greater underreaction than firms with lower IVol. Therefore, their model predicts greater momentum for stocks with high IVol.

In Hong and Stein (1999), there are two groups of traders: news watchers who trade only on private information, and momentum traders who trade only on past price changes. Under the assumption of gradual diffusion of firm-specific information, Hong and Stein (1999) show that investors initially underreact to news. This initial underreaction then turns into overreaction due to the activities of momentum traders. Again, if IVol is a proxy for the amount of firm-specific news, then stocks with higher IVol could be associated with greater underreaction than would firms with lower IVol. This greater initial underreaction by news watchers then leads to greater momentum.

In Daniel, Hirshleifer and Subrahmanyam (1998), informed traders suffer from overconfidence and a self-attribution bias, so they underreact to public information but

[2] Jegadeesh and Titman (1993) find evidence of momentum at the three- to 12-month horizon. At shorter horizons, there is evidence of return reversals (e.g., Subrahmanyam, 2005).

overreact to private information. In this model, difficult-to-value stocks or stocks with greater uncertainty create greater overconfidence among investors. Consequently, these stocks are subject to greater mispricing. To the extent that stocks with higher IVol have greater uncertainty and are more difficult to value, Daniel, Hirshleifer and Subrahmanyam (1998) predict that high IVol stocks will display greater momentum.

Empirical evidence on the sources of momentum profits is mixed. Jegadeesh and Titman (1993) report that momentum returns are robust to market risk. Fama and French (1996) show that their three-factor model is unable to explain the momentum effect in spite of the model's ability to explain numerous other anomalies and the cross-section of stock returns in general. Conrad and Kaul (1998) argue that the cross-sectional variation in mean returns of individual securities plays an important role in momentum profits. However, Jegadeesh and Titman (2001) show that cumulative momentum portfolio returns are negative from 13 to 60 months after portfolio formation, which is inconsistent with the hypothesis of Conrad and Kaul (1998). Chordia and Shivakumar (2002) report that the profits from momentum strategies are explained by macroeconomic variables related to business cycles, but Cooper, Gutierrez and Hameed (2004) show that these results are not robust to screening out illiquid and high trading-cost stocks.[3]

Campbell, Lettau, Malkiel and Xu (2001) offer several reasons why idiosyncratic risk might be important. First, individuals might hold undiversified portfolios due to large holdings of individual stocks, perhaps due to corporate compensation policies. Second, although some investors attempt to diversify by holding 20–30 stocks, whether this succeeds depends on the idiosyncratic risk of the stocks. Third, arbitrageurs who attempt to trade to exploit the mispricing of an individual stock face risks related to IVol, as suggested by Shleifer and Vishny (1997).

The importance of idiosyncratic risk also naturally arises from models of incomplete markets (e.g., Constantinides and Duffie, 1996). In incomplete markets, investors cannot perfectly diversify their risks. As a result, idiosyncratic risk matters for asset pricing. Merton (1987) also suggests that, in a market with informed and uninformed investors, firms with high IVol require higher average returns to compensate investors for holding imperfectly diversified portfolios.

Empirical evidence on the pricing of idiosyncratic risk is mixed. Douglas (1969), Lehmann (1990) and Malkiel and Xu (1997) provide evidence that idiosyncratic risk is priced in the cross -section of stocks. However, Miller and Scholes (1972) and Fama and MacBeth (1973) dispute the statistical methods used in the Douglas (1969) study. Goyal and Santa-Clara (2003) find a significant, positive time-series relation between average stock variance and the return on the market. Bali, Cakici, Yan and Zhang (2005) show that the findings of Goyal and Santa-Clara (2003) are not robust to

[3] Hong, Lim and Stein (2000); Lee and Swaminathan (2000); Grundy and Martin (2001); Griffin, Ji and Martin (2003); Cooper, Gutierrez and Hameed (2004); George and Hwang (2004); and Zhang (2006) also provide evidence consistent with behavioral explanations of the momentum effect. Sias (2007) finds that institutional investors are momentum traders. Korajczyk and Sadka (2004) and Lesmond, Shill and Zhou (2004) examine the profitability of momentum strategies after transactions costs.

the use of a value-weighted measure of average stock volatility, the use of average IVol instead of average total stock volatility, consideration of stock liquidity and extension of the sample period.

3. Data and methods

3.1. Sample

The sample includes common stocks traded on the NYSE, Amex or Nasdaq in 1965–2002. We include only issues with a share code of 10 or 11 in the CRSP U.S. Stock database, the source of all data in this study except where we state otherwise. Following Jegadeesh and Titman (2001), we exclude stocks with share prices below \$5 and market capitalizations that would place them in the lowest NYSE size decile (based on breakpoints from Kenneth French's web site) at the beginning of the holding period. Additionally, we exclude any stock listed on CRSP for less than 12 months at the time of portfolio formation. This exclusion is necessary to allow for the calculation of several variables for each stock prior to portfolio formation.

3.2. Momentum strategies

Following Jegadeesh and Titman (2001), at the beginning of each month we rank all stocks in the sample based on their past six-month returns and group the stocks into ten equally weighted portfolios based on the ranks. Each portfolio is held for six months following the portfolio formation period. (We consider alternative formation and holding periods in Section 5.2.1.) Also following Jegadeesh and Titman (2001), we use overlapping portfolios. For each month, reported returns are the equally weighted returns for the six overlapping portfolios in existence during that month. At the beginning of each month, the oldest portfolio is dropped and a new portfolio is added. The momentum return is calculated as the difference between the return of the winner decile (P10) and the return of the loser decile (P1).

3.3. Construction of variables

Similar to Ali, Hwang and Trombley (2003) and Wurgler and Zhuravskaya (2002), we calculate IVol using market model residuals estimated from the regression

$$r_{i.t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $r_{i,t}$ is the daily return on stock i; $r_{m,t}$ is the return on the portfolio of all NYSE, Amex and Nasdaq stocks; $r_{m,t-1}$ is the lagged value of $r_{m,t}$; and $\varepsilon_{i,t}$ is the regression residual. The lagged value of $r_{m,t}$ is included to account for the effects of possible non-synchronous trading (Dimson, 1979). We estimate the above regression equation for each stock on the formation date using data over the previous 12 months. We calculate IVol as the standard deviation of $\varepsilon_{i,t}$.[4]

We measure firm size using market capitalization, calculated as the number of shares outstanding multiplied by the closing stock price on the date of portfolio formation. We measure share price at market close on the portfolio formation date. We use share price as a proxy for transactions costs. *Turnover* is the total volume (shares traded) during the year preceding portfolio formation divided by shares outstanding. To account for possible double counting in Nasdaq stocks, we divide trading volume of Nasdaq stocks by two before calculating their turnover. Beta is the sum of β_{1i} and β_{2i} from Equation (1).

Delay is a proxy for the delay with which a stock's price reacts to information, and is similar to the delay measure of Hou and Moskowitz (2005). We calculate R^2 for the simple monthly market model regression and a second R^2 for the monthly market model regression with three months of lagged market returns. We subtract the ratio of the two R^2s from unity to create *Delay*. We calculate AltmanZ, a financial distress proxy, following Altman (1968). Lower values of AltmanZ represent greater risk of financial distress.

$$AltmanZ = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5, \quad (2)$$

where X_1 = working capital/total assets, X_2 = retained earnings/total assets, X_3 = earnings before interest and taxes/total assets, X_4 = market value of equity/book value of total liabilities and X_5 = sales/total assets.

3.4. Moving average-adjusted standard errors

Because we use overlapping portfolios, our average portfolio returns are serially correlated. We adjust standard errors for autocorrelation by estimating a moving average (MA) process. Throughout the paper, the reported *t*-statistics of momentum returns are calculated using adjusted standard errors obtained by estimating a MA(6) process using maximum likelihood. We use order six because our formation and holding periods are six months. The only exception is Table 10, in which the order of the MA process is the greater of K and J. By modeling the autocorrelation structure of errors as a MA process, we are likely to introduce less estimation error than we would with the Newey and West (1987) procedure.

3.5. Descriptive statistics

Table 1 reports momentum returns for 1965–2002, 1965–1989 (the original sample period of Jegadeesh and Titman, 1993) and 1990–2002. For the entire sample period, the average monthly return to the momentum portfolio is 1.26%

[4] The results are similar when we exclude $r_{m,t-1}$ from Equation (1). In Section 5.3, we examine several alternative measures of IVol and find our results to be robust.

Table 1

Monthly returns for portfolios based on price momentum

The sample includes common stocks traded on the NYSE, Amex and Nasdaq in 1965–2002 that have a CRSP share code of 10 or 11 (no foreign stocks, REITs, funds, etc.) We exclude stocks with prices below $5 at the beginning of the holding period and those with market capitalizations below the tenth percentile of NYSE stocks. Momentum portfolios are formed based on past six-month returns and held for six months. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Momentum return is calculated as the difference between returns for the past winner portfolio and the past loser portfolio. Monthly returns are reported as percentages. *t*-statistics are in parentheses.

	1965–2002		1965–1989		1990–2002	
P1 (Past losers)	0.41	(1.36)	0.55	(1.27)	0.20	(0.54)
P2	0.85	(3.26)	0.99	(2.52)	0.66	(2.48)
P3	1.02	(4.15)	1.11	(2.97)	0.92	(3.60)
P4	1.09	(4.71)	1.15	(3.36)	1.01	(4.29)
P5	1.12	(5.01)	1.18	(3.57)	1.04	(4.49)
P6	1.16	(5.27)	1.23	(3.84)	1.06	(4.27)
P7	1.19	(5.27)	1.25	(3.75)	1.11	(4.86)
P8	1.26	(5.30)	1.32	(3.80)	1.18	(4.58)
P9	1.37	(5.15)	1.40	(3.74)	1.32	(3.69)
P10 (Past winners)	1.67	(4.96)	1.63	(3.65)	1.86	(4.01)
P10 − P1	1.26	(5.96)	1.08	(4.41)	1.66	(4.54)

($t = 5.96$). For 1965–1989, the average monthly return to the momentum portfolio is 1.08% ($t = 4.41$). The average monthly momentum return for 1990–2002 is higher at 1.66% ($t = 4.54$) than the momentum return for 1965–1989, consistent with Jegadeesh and Titman (2001).

Panel A of Table 2 presents descriptive statistics for variables with a documented or possible relation to momentum returns. A strong U-shaped pattern of IVol exists across momentum deciles, with winners (P10) having a mean IVol of 14.18% per month and losers having a mean IVol of 13.59% per month, while the median momentum decile (P5) has a mean IVol of only 9.24%.

Consistent with prior literature, we find that stocks in extreme momentum deciles have smaller market capitalization and higher turnover than do stocks in median momentum deciles. For example, the winners (losers) have a mean market capitalization of $753.90 million ($593.71 million), while P5 stocks have a mean market capitalization of $1,473.90 million. Share prices generally increase from the loser portfolio to the winner portfolio. In particular, losers have substantially lower share prices. This result is to be expected; by construction, losers experience lower returns than winners during the portfolio formation period. Similar to the pattern for turnover, stocks in extreme momentum deciles tend to exhibit higher betas. Price delay is stable across deciles P1 through P9, ranging between 0.49 and 0.52. Price delay rises slightly for P10 stocks at 0.56. Altman's Z-score rises generally with prior period returns, a logical result given that the financial condition of a firm with low returns is, most likely, not as good as the financial condition of a firm with high returns.

Table 2

Descriptive statistics for portfolios based on price momentum

The sample includes common stocks traded on the NYSE, Amex and Nasdaq in 1965–2002 that have a CRSP share code of 10 or 11 (no foreign stocks, REITs, funds, etc.) We exclude stocks with prices below $5 at the beginning of the holding period and those with market capitalizations below the tenth percentile of NYSE stocks. Momentum portfolios are formed based on past six-month returns and held for six months. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. IVol is the standard deviation of the residuals from the following regression over the past 12 months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$ where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Size is the market capitalization of stocks in the portfolio. Price is the stock price. IVol, size and price are measured on the portfolio formation date. Turnover is the annualized turnover for the portfolio stocks over the year prior to portfolio formation expressed in percent. Beta is the sum of the β_{1i} and β_{2i} coefficients from the market model regression model stated above. Delay is similar to D1 in Hou and Moskowitz (2005), except we use monthly returns with three lagged returns as of the portfolio formation date. AltmanZ is Altman's Z-score from Altman (1968) and is calculated for the fiscal year containing the portfolio formation date.

Panel A: Time-series mean of cross-sectional averages

Portfolio	IVol %	Size $ mil	Price $	Turnover %	Beta	Delay	AltmanZ
P1	13.59	593.71	18.71	87.15	1.25	0.51	5.12
P2	11.00	998.62	24.36	60.00	1.03	0.49	5.11
P3	10.04	1,272.78	30.72	52.10	0.95	0.49	4.86
P4	9.49	1,397.89	32.64	48.21	0.90	0.49	4.92
P5	9.24	1,473.90	37.12	46.63	0.88	0.49	4.87
P6	9.25	1,506.30	36.58	46.30	0.88	0.49	5.24
P7	9.44	1,544.91	39.12	48.42	0.90	0.50	5.25
P8	9.96	1,494.06	41.12	52.39	0.95	0.50	5.59
P9	11.01	1,181.49	38.81	60.47	1.02	0.52	6.35
P10	14.18	753.90	32.85	83.24	1.17	0.56	9.31

Panel B: Correlation matrix (time-series means of monthly correlations)

	IVol	Size	Price	Turnover	Beta	Delay	AltmanZ
IVol	1.00						
Size	−0.19	1.00					
Price	−0.20	0.26	1.00				
Turnover	0.46	−0.04	−0.02	1.00			
Beta	0.48	0.02	−0.04	0.48	1.00		
Delay	0.15	−0.02	0.00	0.04	0.05	1.00	
AltmanZ	0.10	0.07	0.35	0.05	−0.07	0.02	1.00

Panel B of Table 2 reports correlations between the variables presented in Panel A. The correlation between IVol and size is negative (−0.19), consistent with the pattern we observe in Panel A of smaller firms having higher IVol. The correlation between IVol and turnover is positive and large at 0.46. Beta is identically correlated with IVol and turnover at 0.48, but displays little correlation with size or price. Delay shows little correlation with any other variable. AltmanZ is materially correlated only to price at 0.35. Firms in danger of financial distress have, most likely, suffered stock price declines, which results in this positive correlation.

4. Main results

4.1. Momentum returns and IVol

To test whether momentum profits are related to IVol, we use a method similar to that of Lee and Swaminathan (2000) and divide the sample into three portfolios by IVol (low, medium and high). We calculate momentum returns for each IVol portfolio using the past return deciles assigned earlier using all sample stocks, resulting in independent sorts on IVol and past returns. Panel A of Table 3 reports the results. Momentum returns for each IVol portfolio are positive and statistically significant. Momentum returns and their statistical significance increase across IVol portfolios, rising from 0.55% to 1.43% from the lowest to the highest IVol portfolio, with *t*-values increasing from 3.45 to 6.12. The difference in momentum returns between the high IVol portfolio and the low IVol portfolio is an economically and statistically significant 0.88% per month (10.56% per year).

A closer examination shows that this result is driven primarily by the underperformance of high IVol losers. While low IVol losers rebound to a 0.89% return in the holding period, high IVol losers continue to experience low returns at 0.17%. The monthly return difference between high IVol winners and low IVol winners is not nearly as large at 0.16% (1.60% minus 1.44%). Chan (2003) reports that stocks with news (especially bad news) experience strong momentum, whereas stocks with no news exhibit no momentum. Thus, our results are consistent with Chan's (2003) and with the argument that IVol is a proxy for firm-specific news.

Although we do not explicitly examine the relation between IVol and expected stock returns, our results are largely consistent with those of Ang, Hodrick, Xing and Zhang (2006). Specifically, in nine of our ten past performance deciles, we find the same tendency of high IVol stocks to have lower returns than those of low IVol stocks.[5]

Next, we regress momentum returns for each IVol portfolio on the Fama-French factors to determine whether the three-factor model can explain the effect of IVol on momentum profits. We perform the following time-series regressions using monthly momentum returns:

$$r_{i,t} = \alpha_i + b_i(r_{m,t} - r_{f,t}) + s_i\mathrm{SMB}_t + h_i\mathrm{HML}_t + \varepsilon_{i,t}, \tag{3}$$

where r_i is the monthly momentum return for IVol portfolio i; r_f is the risk-free rate; r_m is the return on the portfolio of all NYSE, Amex and Nasdaq firms; and ε_i

[5] Other results, not reported in detail, confirm Ang, Hodrick, Xing and Zhang's (2006) finding of a significant inverse relation between IVol and subsequent stock returns. Further, this inverse relation is stronger among past losers but is still statistically significant for past winners.

Table 3

Monthly returns for portfolios based on price momentum and IVol

The sample includes common stocks traded on the NYSE, Amex and Nasdaq in 1965–2002 that have a CRSP share code of 10 or 11 (no foreign stocks, REITs, funds, etc.) We exclude stocks with prices below \$5 at the beginning of the holding period and those with market capitalizations below the tenth percentile of NYSE stocks. Panel A presents average monthly returns on portfolios based on independent sorts of price momentum and IVol. Panel B summarizes Fama-French three-factor model regressions for monthly returns of portfolios based on price momentum and IVol. Stocks are sorted into three groups (IV1—low, IV2—medium and IV3—high) by IVol. IVol is the standard deviation of the residuals from the following regression over the past twelve months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Momentum portfolios are formed based on past six-month returns and held for six months within each group. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. In panel B row headings, r_f is the risk-free rate and r_m is the return on the CRSP equal-weighted market index; SMB and HML are defined by Fama and French (1996) and are from Kenneth French's web site. t-statistics are in parentheses.

Panel A: Momentum returns by IVol (%)

	IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
P1	0.89	(3.86)	0.72	(2.77)	0.17	(0.50)		
P2	1.06	(4.74)	1.02	(4.23)	0.55	(1.65)		
P3	1.15	(5.28)	1.13	(4.51)	0.75	(2.17)		
P4	1.17	(5.63)	1.17	(4.87)	0.81	(2.44)		
P5	1.15	(5.58)	1.20	(5.08)	0.92	(2.83)		
P6	1.18	(5.78)	1.25	(5.35)	0.95	(2.90)		
P7	1.19	(5.76)	1.26	(5.33)	1.04	(3.08)		
P8	1.23	(5.81)	1.34	(5.48)	1.15	(3.33)		
P9	1.34	(6.02)	1.48	(5.78)	1.26	(3.59)		
P10	1.44	(6.83)	1.79	(6.15)	1.60	(4.03)		
P10 − P1	0.55	(3.45)	1.07	(6.52)	1.43	(6.12)	0.88	(4.92)

Panel B: Fama-French three-factor regression results for momentum returns

	Variable	Coefficient	Std. Error	t-Stat	p-Value	Adjusted R^2
IV1 (low)	Alpha	0.65	0.21	3.04	0.00	0.01
	$R_m - R_f$	−0.10	0.08	−1.24	0.22	
	SMB	−0.06	0.10	−0.61	0.54	
	HML	−0.18	0.11	−1.71	0.09	
IV2	Alpha	1.30	0.20	6.46	0.00	0.06
	$R_m - R_f$	−0.21	0.06	−3.42	0.00	
	SMB	−0.03	0.11	−0.28	0.78	
	HML	−0.34	0.12	−2.88	0.00	
IV3 (high)	Alpha	1.62	0.26	6.18	0.00	0.03
	$R_m - R_f$	−0.19	0.07	−2.52	0.01	
	SMB	0.05	0.16	0.32	0.75	
	HML	−0.31	0.16	−1.94	0.05	
IV3 − IV1	Alpha	0.97	0.20	4.94	0.00	0.01
	$R_m - R_f$	−0.09	0.06	−1.61	0.11	
	SMB	0.11	0.10	1.05	0.29	
	HML	−0.13	0.10	−1.31	0.19	

is the error term. SMB and HML are the size and value factors defined by Fama and French (1996) and are downloaded from Kenneth French's web site. Panel B of Table 3 presents the results. The alpha for each portfolio regression is positive and significant, indicating that the Fama-French factors cannot explain momentum returns. In addition, the alpha displays a pattern across IVol portfolios similar to that of momentum returns, increasing from 0.65% for the low IVol portfolio to 1.62% for the high IVol portfolio. The relatively low adjusted R-squared values for the regressions reinforce the inability of the Fama-French model to explain momentum returns, consistent with the findings of Fama and French (1996) and Jegadeesh and Titman (2001).

We also estimate the regression using the difference in momentum returns between the high IVol portfolio and the low IVol portfolio. The alpha is positive and significant (0.97%, $t = 4.97$), which indicates that Fama-French factors cannot explain the effect of IVol on momentum profits.

4.2. Controlling for size, share price, turnover, beta, price delay and distress risk

In Panel B of Table 2, we report that IVol is positively related to turnover, market beta, price delay and Altman's Z and negatively related to size and share price. To show that IVol has incremental explanatory power beyond these variables, we sort the entire sample into three portfolios by each of these control variables. We then independently sort the entire sample into three portfolios by IVol before each stock is sorted into one of nine portfolios based on IVol and the control variable. We calculate momentum returns for each of the nine portfolios as the difference between returns for the past winners and the past losers, which we designate independently for the entire sample following Jegadeesh and Titman (1993). Finally, we calculate the difference in momentum profits between the high IVol portfolio and the low IVol portfolio and assess the statistical significance of this difference for each control variable portfolio.

4.2.1. Controlling for size

Jegadeesh and Titman (1993) and Hong, Lim and Stein (2000) find that momentum profits are higher among smaller stocks. Therefore, it is important to determine whether the effect of IVol is subsumed by size. We construct nine portfolios based on terciles formed through independent sorts on size and IVol. For each of the nine portfolios, we calculate momentum returns using the past winners and losers assigned over the entire sample, resulting in a three-way independent sort. Panel A of Table 4 presents our results. Within each size tercile, the difference in momentum returns between the high and low IVol portfolios is positive and statistically significant. Specifically, the difference in momentum returns between high and low IVol portfolios is 1.31% (t = 5.30) for small stocks, 0.88% (t = 3.47) for medium stocks

Table 4

Returns for portfolios based on price momentum, IVol, size and share price

Monthly percentage returns on portfolios based on independent sorts of price momentum, IVol and variables potentially related to the momentum effect. Stocks are sorted into three groups (IV1—low, IV2—medium and IV3—high) by IVol and three groups by the related variable. IVol is the standard deviation of the residuals from the following regression over the past 12 months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Portfolio 1 of the control variable contains stocks with the lowest values of the control variable. Momentum portfolios are formed based on past six-month returns and held for six months within each group. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Momentum return is calculated as the difference between returns for the past winner portfolio and the past loser portfolio for each IVol group. Size is defined as market capitalization on the portfolio formation date. Share price is measured on the portfolio formation date. t-statistics are in parentheses.

Panel A: Momentum returns (%) by size and IVol

		IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
S1	P1	1.13	(4.38)	0.81	(3.12)	0.20	(0.59)		
	P5	1.29	(5.60)	1.43	(5.11)	1.04	(3.17)		
	P10	1.29	(5.00)	2.13	(6.53)	1.67	(4.20)		
	P10 − P1	0.16	(0.51)	1.32	(6.11)	1.47	(6.28)	1.31	(5.30)
S2	P1	0.79	(2.95)	0.74	(2.71)	0.12	(0.39)		
	P5	1.26	(5.86)	1.25	(5.21)	0.82	(2.45)		
	P10	1.41	(5.10)	1.79	(5.93)	1.62	(4.25)		
	P10 − P1	0.62	(2.63)	1.05	(5.99)	1.50	(6.11)	0.88	(3.47)
S3	P1	0.97	(4.41)	0.65	(2.34)	0.27	(0.72)		
	P5	1.03	(5.01)	0.98	(4.32)	0.83	(2.21)		
	P10	1.51	(6.63)	1.52	(4.68)	1.38	(2.94)		
	P10 − P1	0.54	(2.68)	0.87	(3.80)	1.11	(3.29)	0.57	(1.64)

Panel B: Momentum returns (%) by share price and IVol

		IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
PR1	P1	1.08	(4.10)	0.76	(3.06)	0.21	(0.60)		
	P5	1.18	(5.87)	1.37	(5.51)	1.02	(3.23)		
	P10	0.97	(2.34)	1.72	(5.74)	1.41	(3.47)		
	P10 − P1	−0.11	(−0.90)	0.96	(4.89)	1.20	(4.61)	1.31	(3.53)
PR2	P1	0.84	(3.26)	0.73	(2.48)	0.20	(0.60)		
	P5	1.21	(5.70)	1.22	(5.05)	0.80	(2.34)		
	P10	1.25	(5.35)	1.88	(6.16)	1.71	(4.55)		
	P10 − P1	0.41	(1.52)	1.15	(5.93)	1.51	(6.76)	1.10	(4.83)
PR3	P1	0.98	(4.50)	0.73	(2.79)	0.11	(0.23)		
	P5	1.07	(5.12)	1.01	(3.99)	0.78	(2.07)		
	P10	1.54	(7.08)	1.74	(5.70)	1.78	(4.16)		
	P10 − P1	0.56	(3.26)	1.01	(5.24)	1.67	(4.73)	1.11	(3.62)

and 0.57% ($t = 1.64$) for large stocks, indicating that IVol affects momentum returns even after controlling for size.

4.2.2. Controlling for share price

Panel B of Table 4 presents momentum returns for portfolios formed on IVol and share price. Share price is viewed as inversely related to transactions costs (see, for example, Stoll, 2000). Shleifer and Vishny (1997) argue that transactions costs limit arbitrage. Since IVol is also a theorized limit of arbitrage, it is important to determine whether the IVol effect is robust to other limits of arbitrage. We perform independent sorts on IVol, share price and past returns. Within each share price portfolio, the difference in momentum returns between high and low IVol portfolios is positive and significant, indicating that sorting stocks by price does not eliminate the positive effect of IVol on momentum returns. The differences are positive (ranging from 1.11 to 1.31% per month) and statistically significant (t-values ranging from 3.53 to 4.83).

4.2.3. Controlling for turnover

Lee and Swaminathan (2000) report a relation between momentum returns and turnover; firms with high turnover tend to experience higher momentum returns. Panel A of Table 5 presents momentum returns for portfolios formed based on IVol and turnover. We perform independent sorts on IVol, turnover and past returns. In each of the three turnover portfolios, the difference in momentum returns between high and low IVol portfolios is positive. This difference, however, is not statistically significant for high turnover stocks. This result is likely attributable to the positive correlation between volume and volatility reported in the literature (see Karpoff, 1987). Indeed, the correlation between turnover and IVol in our sample is 0.46. In spite of this high correlation, the difference in momentum returns between high and low IVol portfolios is positive and statistically significant in each of the two lower turnover portfolios. More specifically, the difference in momentum returns between high and low IVol portfolios for the lowest turnover portfolio is 0.48% per month ($t = 2.09$). For medium turnover stocks, the difference in momentum returns between high and low IVol portfolios is 0.85% ($t = 2.73$). In summary, although the effect of IVol on momentum profits appears to be related to the trading volume effect identified by Lee and Swaminathan (2000), IVol provides additional explanatory power.

4.2.4. Controlling for beta

Panel B of Table 5 presents momentum returns for portfolios formed based on IVol and market beta. High beta stocks also tend to have high IVol (see Table 2). To show that our results are not driven by beta, we perform independent sorts on IVol, beta and past returns. Within each beta portfolio, the difference in momentum returns between high and low IVol portfolios is positive, economically significant and marginally statistically significant, indicating that sorting stocks by beta does not eliminate the positive effect of IVol on momentum returns. These differences are economically significant, ranging from 0.47% per month for the lowest beta stocks to 0.99% per month for the highest beta stocks. The difference is marginally statistically significant for low-beta stocks and high-beta stocks, and is highly statistically significant for the middle beta portfolio.

Table 5

Returns for portfolios based on price momentum, IVol, turnover and beta

Monthly percentage returns on portfolios based on independent sorts of price momentum, IVol and variables potentially related to the momentum effect. Stocks are sorted into three groups (IV1—low, IV2—medium and IV3—high) by IVol and three groups by the related variable. IVol is the standard deviation of the residuals from the following regression over the past 12 months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Portfolio 1 of the control variable contains stocks with the lowest values of the control variable. Momentum portfolios are formed based on past six-month returns and held for six months within each group. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Momentum return is calculated as the difference between returns for the past winner portfolio and the past loser portfolio for each IVol group. Turnover is the average annual turnover for the portfolio stocks over the year before portfolio formation. Annual turnover is calculated as annual volume divided by shares outstanding. Beta is the sum of the β_{1i} and β_{2i} coefficients from the market model regression model stated above. t-statistics are in parentheses.

		IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
Panel A: Momentum returns (%) by percent of turnover and IVol									
T1	P1	0.94	(3.33)	0.94	(4.34)	0.62	(1.67)		
	P5	1.17	(5.53)	1.28	(5.70)	1.34	(4.09)		
	P10	1.49	(6.54)	1.64	(5.31)	1.65	(4.42)		
	P10 − P1	0.55	(2.32)	0.70	(2.83)	1.03	(3.58)	0.48	(2.09)
T2	P1	0.98	(3.66)	0.82	(3.56)	0.44	(1.25)		
	P5	1.10	(5.08)	1.25	(5.30)	1.16	(4.05)		
	P10	1.44	(5.35)	1.91	(6.46)	1.75	(4.62)		
	P10 − P1	0.46	(1.98)	1.09	(5.75)	1.31	(4.89)	0.85	(2.73)
T3	P1	0.47	(1.55)	0.51	(1.63)	0.05	(0.15)		
	P5	1.09	(4.48)	1.10	(4.00)	0.66	(1.86)		
	P10	1.87	(7.43)	1.73	(5.32)	1.53	(3.67)		
	P10 − P1	1.40	(4.61)	1.22	(5.62)	1.48	(6.03)	0.08	(0.44)
Panel B: Momentum returns (%) by beta									
B1	P1	0.79	(3.14)	0.75	(3.05)	0.23	(0.74)		
	P5	1.13	(5.50)	1.17	(5.29)	0.97	(3.83)		
	P10	1.32	(6.59)	1.59	(6.20)	1.23	(3.89)		
	P10 − P1	0.53	(2.39)	0.84	(4.64)	1.00	(3.73)	0.47	(1.62)
B2	P1	0.91	(3.27)	0.68	(2.68)	0.25	(0.85)		
	P5	1.15	(5.13)	1.20	(5.24)	1.00	(3.54)		
	P10	1.75	(5.65)	1.91	(6.58)	1.75	(5.36)		
	P10 − P1	0.84	(2.72)	1.23	(6.84)	1.50	(5.96)	0.66	(3.17)
B3	P1	1.06	(3.52)	0.62	(2.04)	0.20	(0.53)		
	P5	0.90	(3.12)	1.20	(3.77)	0.97	(2.54)		
	P10	1.62	(4.51)	1.83	(5.24)	1.75	(3.87)		
	P10 − P1	0.56	(1.84)	1.21	(5.51)	1.55	(5.83)	0.99	(1.67)

4.2.5. Controlling for price delay

Panel A of Table 6 presents returns for portfolios formed on IVol and price delay. Hou and Moskowitz (2005) show that IVol is priced among firms whose stock prices are slow to respond to information, and that momentum increases with delay for all except the highest delayed firms. To show that our results are not driven by

Table 6

Returns for portfolios based on price momentum, IVol, price delay and Altman's Z

Monthly percentage returns of portfolios based on independent sorts of price momentum, IVol and variables potentially related to the momentum effect. Stocks are sorted into three groups (IV1—low, IV2—medium and IV3—high) by IVol and three groups by the related variable. IVol is the standard deviation of the residuals from the following regression over the past 12 months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Portfolio 1 of the control variable contains stocks with the lowest values of the control variable. Momentum portfolios are formed based on past six-month returns and held for six months within each group. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Momentum return is the difference between returns for the past winner portfolio and the past loser portfolio for each IVol group. The price delay is similar to D1 in Hou and Moskowitz (2005), except we use monthly returns with three lagged returns. Price delay is measured on the portfolio formation date. We calculate Altman's Z-score following Altman (1968) for the fiscal year containing the portfolio formation date. t-statistics are in parentheses.

		IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
Panel A: Momentum returns (%) by price delay and IVol									
PD1	P1	0.98	(3.03)	0.84	(2.47)	0.32	(0.68)		
	P5	1.12	(5.58)	1.22	(4.69)	0.95	(2.57)		
	P10	1.62	(6.16)	1.80	(6.03)	1.90	(4.52)		
	P10 − P1	0.64	(1.94)	0.96	(3.96)	1.58	(5.73)	0.94	(3.33)
PD2	P1	0.67	(2.39)	0.79	(2.48)	0.32	(0.78)		
	P5	1.22	(6.68)	1.18	(4.89)	0.95	(2.73)		
	P10	1.38	(5.51)	1.95	(7.04)	1.51	(3.83)		
	P10 − P1	0.71	(2.82)	1.16	(5.46)	1.19	(4.69)	0.48	(2.61)
PD3	P1	1.02	(3.16)	0.64	(2.13)	0.30	(0.77)		
	P5	1.09	(6.52)	1.25	(5.37)	0.75	(2.28)		
	P10	1.27	(5.39)	1.61	(6.14)	1.27	(3.39)		
	P10 − P1	0.25	(0.62)	0.97	(4.52)	0.97	(3.64)	0.72	(2.34)
Panel B: Momentum returns (%) by Altman's Z-score and IVol									
Z1	P1	1.55	(1.61)	−0.22	(−0.58)	−1.02	(−2.11)		
	P5	0.87	(4.68)	0.48	(1.65)	−0.18	(−0.42)		
	P10	0.95	(2.99)	0.90	(2.81)	0.00	(−0.01)		
	P10 − P1	−0.60	(−0.76)	1.12	(3.77)	1.02	(2.70)	1.61	(2.06)
Z2	P1	0.89	(3.00)	0.86	(2.64)	0.54	(1.24)		
	P5	1.05	(5.04)	1.06	(4.00)	0.53	(1.48)		
	P10	0.87	(3.06)	1.25	(4.18)	1.13	(2.80)		
	P10 − P1	−0.02	(−0.12)	0.39	(1.49)	0.59	(2.22)	0.61	(2.17)
Z3	P1	1.08	(3.77)	1.29	(4.06)	1.48	(3.32)		
	P5	1.35	(6.77)	1.52	(5.89)	1.35	(3.65)		
	P10	1.60	(6.36)	2.20	(7.16)	2.39	(5.18)		
	P10 − P1	0.52	(2.40)	0.91	(3.76)	0.91	(2.49)	0.39	(1.76)

price delay, we perform independent sorts by IVol, price delay and past returns. Within each price-delay portfolio, the difference in momentum returns between high and low IVol portfolios is positive and statistically significant, indicating that sorting stocks by price delay does not eliminate the positive effect of IVol on momentum returns.

The lowest and highest delay portfolios display the highest difference in momentum returns between high and low IVol portfolios, at 0.94% per month and 0.72% per month respectively. The middle delay portfolio stocks display a difference of 0.48% per month.

4.2.6. Controlling for financial distress risk

Panel B of Table 6 presents returns for portfolios formed on IVol and Altman's Z. Chen and Chollete (2006) show that the IVol effect on returns found by Ang, Hodrick, Xing and Zhang (2006) exists only among stocks with high risk of financial distress. To show that our results are not driven by financial distress risk, we perform independent sorts by IVol, Altman's Z and past returns. Within each distress risk portfolio, the difference in momentum returns between high and low IVol portfolios is positive and statistically significant, indicating that sorting stocks by price distress risk does not eliminate the positive effect of IVol on momentum returns. The IVol effect is greatest among stocks with the highest distress risk (lowest Altman's Z), at 1.61% per month, and decreases to 0.39% per month among stocks with the lowest distress risk.

4.2.7. Summary

Overall, we conclude that the effect of IVol on momentum is not subsumed by size, price, turnover, beta, price delay or financial distress risk.[6] The results using risk-adjusted returns, not reported in detail, are qualitatively similar to those in Tables 4–6. In particular, even though the IVol effect on momentum profits appears to be related to the trading volume effect in Lee and Swaminathan (2000), IVol provides additional explanatory power.

4.3. Long-horizon momentum returns and IVol

In this section, we examine long-horizon momentum returns during the five years following portfolio formation for portfolios formed on IVol. Figure 1 provides a graphic depiction of our results. The middle line in each chart shows the mean cumulative momentum return, while the two outer lines give the 95% confidence interval for the mean return. Within each IVol portfolio, we observe a pattern similar to the findings of Jegadeesh and Titman (2001), with the cumulative momentum profits increasing in the first year and decreasing thereafter. As pointed out by Jegadeesh and Titman (2001), this finding is inconsistent with Conrad and Kaul's (1998) hypothesis that momentum profits are due to differences in unconditional expected returns.

[6] In other tests not reported in detail, we find that the effect of IVol on momentum is not subsumed by the percent of zero return days, number of institutional owners, percentage institutional ownership, quoted spread or analyst coverage.

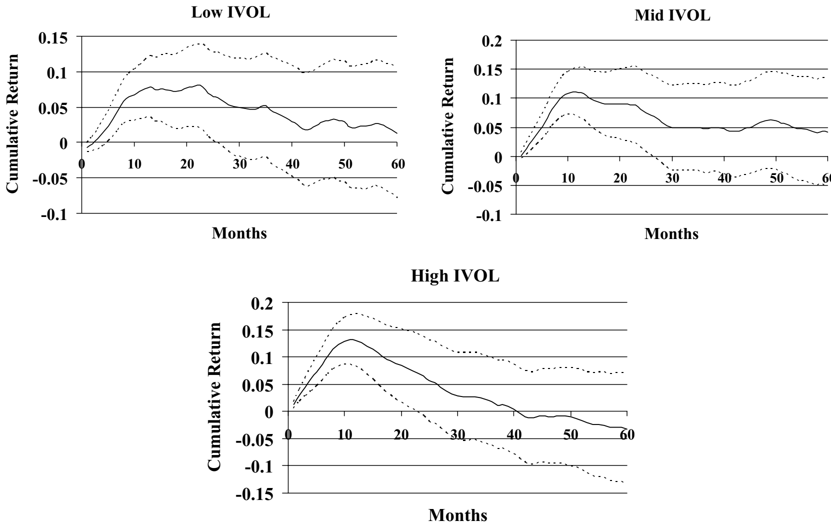

Figure 1

Long-horizon momentum returns and IVol

Cumulative momentum returns for the five years following portfolio formation for portfolios based on independent sorts of price momentum and IVol. Stocks are sorted into three groups by IVol, defined as the standard deviation of daily residuals over the previous 12 months from the market model $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i; $r_{m,t}$ is the return on the portfolio of all NYSE, Amex and Nasdaq firms; and $r_{m,t-1}$ is the lagged value of $r_{m,t}$. Momentum portfolios are formed based on past six-month returns. Momentum return is the difference between returns for the past winner portfolio and the past loser portfolio for each IVol group. The middle line shows the mean cumulative momentum return, while the two outer lines give the 95% confidence interval for the mean return.

Comparing across IVol portfolios, we find that the high IVol portfolio displays larger momentum profits in the first year, and quicker and larger reversals after the first year.

Table 7 presents the difference in momentum returns between the high IVol portfolio and the low IVol portfolio. This difference is positive at 0.51% per month (about 6% per year) in the first year, but then becomes negative for each of years two through five. These results suggest that the magnitude and persistence of price momentum are both related to IVol. Specifically, the momentum effect and the price reversal effect are both driven by shorting high IVol losers. The return on this subset of stocks is not significantly different from zero in year 1, but outperforms all other groups of stocks in the momentum portfolio in years two through five with a positive and significant return of 1.27% per month ($t = 3.78$).

Our finding that high IVol stocks display both higher momentum and quicker and larger reversals is consistent with behavioral theories. As pointed out by Bhojraj and Swaminathan (2006), a key prediction of recent behavioral theories is that a large

Table 7

Long-horizon returns for portfolios based on price momentum and IVol

Average monthly percentage returns for the five years following portfolio formation on portfolios based on independent sorts of price momentum and IVol. Stocks are sorted by IVol (IV1—low, IV2—medium and IV3—high). IVol is the standard deviation of the residuals from the following regression over the past 12 months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Momentum portfolios are formed based on past six-month returns. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Momentum return is the difference between returns for the past winner portfolio and the past loser portfolio for each IVol group. *t*-statistics are in parentheses.

Year		All		IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
1	P1	0.45	(1.56)	0.81	(3.57)	0.71	(2.70)	0.27	(0.80)		
	P5	1.14	(5.11)	1.15	(5.54)	1.21	(5.23)	0.99	(3.08)		
	P10	1.50	(4.64)	1.45	(6.98)	1.66	(5.93)	1.42	(3.72)		
	P10 − P1	1.05	(6.25)	0.64	(4.54)	0.95	(5.94)	1.15	(6.15)	0.51	(3.16)
2	P1	1.11	(4.12)	1.13	(5.96)	1.15	(4.74)	1.12	(3.34)		
	P5	1.15	(5.05)	1.15	(5.44)	1.22	(5.01)	1.01	(3.23)		
	P10	0.75	(2.40)	0.97	(3.82)	0.94	(3.39)	0.61	(1.76)		
	P10 − P1	−0.36	(−2.59)	−0.16	(−1.06)	−0.21	(−1.42)	−0.51	(−3.88)	−0.35	(−2.35)
3	P1	1.34	(4.57)	1.21	(6.04)	1.38	(5.05)	1.35	(3.72)		
	P5	1.24	(5.19)	1.21	(5.54)	1.30	(5.14)	1.28	(3.76)		
	P10	0.96	(3.10)	1.04	(4.01)	1.03	(3.73)	0.90	(2.60)		
	P10 − P1	−0.38	(−2.46)	−0.17	(−1.21)	−0.35	(−2.24)	−0.45	(−3.05)	−0.28	(−2.22)
4	P1	1.26	(4.38)	1.21	(6.61)	1.21	(4.52)	1.33	(3.73)		
	P5	1.20	(5.19)	1.17	(5.47)	1.24	(4.96)	1.21	(3.91)		
	P10	1.08	(3.54)	1.07	(4.67)	1.16	(4.51)	1.03	(2.93)		
	P10 − P1	−0.18	(−1.47)	−0.14	(−1.20)	−0.05	(−0.38)	−0.30	(−2.59)	−0.16	(−1.50)
5	P1	1.23	(4.62)	1.03	(4.64)	1.20	(4.57)	1.28	(4.04)		
	P5	1.20	(5.15)	1.17	(5.35)	1.23	(4.89)	1.20	(3.96)		
	P10	1.07	(3.12)	0.96	(3.89)	1.13	(4.02)	1.08	(2.83)		
	P10 − P1	−0.16	(−0.83)	−0.07	(−0.61)	−0.07	(−0.38)	−0.20	(−1.20)	−0.13	(−0.87)
2–5	P1	1.23	(4.65)	1.11	(5.79)	1.24	(4.96)	1.27	(3.78)		
	P5	1.19	(5.25)	1.16	(5.52)	1.25	(5.15)	1.18	(3.85)		
	P10	0.96	(3.24)	1.06	(4.82)	1.07	(4.12)	0.91	(2.66)		
	P10 − P1	−0.27	(−2.88)	−0.05	(−0.63)	−0.17	(−1.75)	−0.36	(−3.93)	−0.31	(−3.60)

momentum effect should be accompanied by a large reversal effect. Hirshleifer (2001) argues that, "in the recent models of how mistaken beliefs cause momentum and reversals . . . the misperceptions that drive momentum are also the drivers of long-term reversal. . . . those sets of assets with the largest momentum effects should also have the largest reversal effects" (p. 1575). Our results are consistent with this prediction, and hence provide additional support for the behavioral explanations of the momentum effect. Our finding that high IVol stocks display both higher momentum and quicker and larger reversals is also consistent with the rational model of Wang (1993).

5. Robustness tests

5.1. Alternative sample periods

To test whether our results are robust to different sample periods, we bifurcate our sample period. The first bifurcation cuts the sample between 1965 to 1989

Table 8

Returns for portfolios based on price momentum and IVol: Subperiods

Average monthly percentage returns of portfolios based on returns for two bifurcations of the sample period. Stocks are sorted by IVol (IV1—low, IV2—medium and IV3—high). IVol is the standard deviation of the residuals from the following regression over the past 12 months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$ where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Momentum portfolios are formed based on past six-month returns and held for six months within each group. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Momentum return is the difference between returns for the past winner portfolio and the past loser portfolio for each IVol group. t-statistics are in parentheses.

Period		IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
1965–1989	P1	1.03	(3.32)	0.81	(2.15)	0.32	(0.68)		
	P5	1.17	(4.06)	1.31	(3.83)	1.06	(2.27)		
	P10	1.48	(4.96)	1.74	(4.25)	1.52	(2.91)		
	P10 − P1	0.45	(2.14)	0.93	(4.58)	1.20	(4.72)	0.75	(4.73)
1990–2002	P1	0.67	(2.32)	0.63	(2.34)	−0.06	(−0.14)		
	P5	1.12	(4.27)	1.04	(3.88)	0.71	(1.67)		
	P10	1.40	(5.34)	1.93	(5.32)	1.67	(2.23)		
	P10 − P1	0.73	(3.67)	1.30	(6.09)	1.73	(4.32)	1.00	(3.00)
1965–1983	P1	1.00	(2.57)	0.81	(1.65)	0.49	(0.81)		
	P5	0.99	(2.80)	1.28	(2.85)	1.19	(1.97)		
	P10	1.44	(4.06)	1.77	(3.50)	1.67	(2.55)		
	P10 − P1	0.44	(2.28)	0.96	(4.25)	1.18	(3.70)	0.74	(3.97)
1984–2002	P1	0.79	(3.13)	0.67	(3.19)	−0.11	(−0.34)		
	P5	1.32	(5.64)	1.16	(5.58)	0.71	(2.45)		
	P10	1.45	(5.72)	1.84	(6.14)	1.56	(3.11)		
	P10 − P1	0.67	(2.70)	1.17	(5.75)	1.67	(5.24)	1.00	(3.57)

and 1990 to 2002. The first period matches that of Jegadeesh and Titman (1993). Table 8 presents our results. For each subperiod, both momentum returns and statistical significance increase with IVol. From 1965 to 1989, the low IVol portfolio displays momentum returns of 0.45% per month (t = 2.14), while the high IVol portfolio displays momentum returns of 1.20% per month (t = 4.72). From 1990 to 2002, the low IVol portfolio displays momentum returns of 0.73% per month (t = 3.67), while the high IVol portfolio displays momentum returns of 1.73% per month (t = 4.32). For both subperiods, the difference in momentum returns between the highest IVol and the lowest IVol portfolio is large and statistically significant at the 1% level, a result driven by the return on the subset of high IVol losers.

We repeat the exercise, bifurcating the original sample period into two periods of equal length. The results are similar along all dimensions examined. The difference in momentum returns between the high IVol portfolio and the low IVol portfolio for each subperiod is large and significant, with a value of 0.74% per month in 1965–1983 and a value of 1.00% per month in 1984–2002. Both results are statistically significant at the 1% level. In summary, the positive and significant difference between the momentum returns of high and low IVol portfolios in Table 3 is robust to different sample periods and is driven by high IVol losers.

5.2. Alternative momentum strategies

5.2.1. Alternative formation and holding periods

All results presented previously are based on a six-month formation period and a six-month holding period. To examine whether our results are robust to alternative formation and holding periods, we consider 15 alternative momentum strategies that combine four different formation periods (3, 6, 9, 12 months) with four different holding periods (3, 6, 9, 12 months), following Jegadeesh and Titman (1993). Table 9 presents the results. Overall, the effect of IVol on momentum returns is robust to different portfolio formation and holding periods. For all 15 strategies, the difference in momentum returns between the high IVol portfolio and the low IVol portfolio is positive, and for 12 of these strategies, the difference is statistically significant. For example, when the formation period is three months and the holding period is six months, the difference in momentum returns between the high IVol portfolio and the low IVol portfolio is 1.36% per month ($t = 5.61$). For strategies with a formation period of nine months in combination with a 12-month holding period, or a formation period of 12 months in combination with a nine- or 12-month holding period, the difference between the momentum returns on the high IVol portfolio and on the low IVol portfolio is still positive but statistically insignificant. This result indicates that the effect of IVol on momentum returns is generally decreasing in both formation period length and holding period length.

5.2.2. Skipping a month between the formation period and holding period

Following Jegadeesh and Titman (2001), we also repeat the analysis, skipping a month between the formation and holding periods to help eliminate concerns about microstructure effects. We use a six-month formation period and a six-month holding period. We present the results in bold in Table 9. The effect of IVol on momentum returns is slightly reduced in both magnitude and statistical significance compared to the same strategy without skipping a month (see Table 3). However, the difference in momentum returns between the high and the low IVol portfolios is still economically large and statistically significant (0.61%, $t = 3.43$), indicating that the IVol effect is not an artifact of microstructure effects.

5.3. Alternative specifications of IVol

5.3.1. Pre-formation period IVol

In our previous tests, we estimate IVol using daily stock returns over the 12 months prior to the beginning of the portfolio-holding period. However, this

Table 9

Returns for portfolios based on price momentum and IVol: Alternative momentum strategies

Average monthly percentage returns of portfolios based on independent sorts of returns and IVol for the full sample. J is the number of months in the ranking period. K is the number of months in the holding period. For $J = K = 6$ (presented in bold), the strategy is modified by skipping a month between the ranking and holding periods. For each strategy, we sort stocks into three groups (IV1—low, IV2—medium and IV3—high) by IVol. IVol is the standard deviation of the residuals from the following regression over the past 12 months: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. Momentum portfolios are formed based on past J month returns and held for K months within each group. P1 through P10 represent momentum portfolios, with P1 containing past losers and P10 containing past winners. Momentum return is the difference between returns for the past winner portfolio and the past loser portfolio for each IVol group. t-statistics are in parentheses.

		$K = 3$				$K = 6$				$K = 9$				$K = 12$			
J		IV1	IV2	IV3		IV1	IV2	IV3		IV1	IV2	IV3		IV1	IV2	IV3	
3	P1	1.15	1.04	0.38		1.13	0.88	0.16		0.93	0.76	0.00		0.82	0.68	−0.04	
		(4.07)	(3.26)	(1.03)		(3.86)	(2.74)	(0.42)		(3.40)	(3.08)	(0.01)		(3.67)	(2.88)	(−0.12)	
	P5	1.24	1.27	0.82		1.18	1.21	0.85		1.16	1.19	0.82		1.14	1.18	0.85	
		(6.07)	(4.88)	(2.26)		(5.66)	(4.67)	(2.34)		(6.27)	(5.73)	(2.68)		(5.18)	(5.08)	(2.50)	
	P10	1.12	1.49	1.35		1.25	1.74	1.64		1.67	1.99	1.78		1.69	2.01	1.73	
		(5.31)	(5.35)	(3.41)		(5.31)	(6.01)	(4.10)		(7.15)	(8.44)	(4.54)		(7.00)	(8.39)	(4.22)	
	P10 − P1	−0.03	0.45	0.97	1.00	0.12	0.86	1.48	1.36	0.74	1.23	1.78	1.04	0.87	1.33	1.77	0.90
		(0.02)	(2.83)	(4.21)	(4.17)	(0.55)	(4.55)	(5.97)	(5.61)	(3.81)	(8.32)	(6.46)	(3.72)	(4.36)	(9.88)	(5.44)	(3.53)
6	P1	1.07	0.87	0.34		**0.69**	**0.56**	**0.09**		0.84	0.58	0.06		0.90	0.63	0.16	
		(4.56)	(3.37)	(1.00)		**(2.92)**	**(2.16)**	**(0.28)**		(3.47)	(2.46)	(0.20)		(4.68)	(2.58)	(0.45)	
	P5	1.21	1.27	0.94		**1.12**	**1.20**	**0.96**		1.15	1.19	0.91		1.14	1.21	0.90	
		(5.91)	(5.49)	(2.83)		**(5.43)**	**(5.10)**	**(2.99)**		(6.10)	(5.98)	(3.10)		(5.28)	(5.29)	(2.72)	
	P10	1.18	1.48	1.33		**1.60**	**1.87**	**1.61**		1.77	1.93	1.68		1.69	1.90	1.56	
		(5.53)	(5.64)	(3.45)		**(7.71)**	**(6.34)**	**(4.08)**		(8.41)	(8.09)	(4.44)		(7.26)	(8.26)	(3.98)	
	P10 − P1	0.11	0.61	0.99	0.88	**0.91**	**1.31**	**1.52**	**0.61**	0.93	1.35	1.62	0.69	0.79	1.27	1.40	0.61
		(1.00)	(5.07)	(5.08)	(4.90)	**(5.95)**	**(7.80)**	**(6.99)**	**(3.43)**	(5.03)	(9.23)	(7.17)	(3.62)	(3.10)	(9.85)	(5.57)	(2.29)

(*continued*)

Table 9 (*continued*)

Returns for portfolios based on price momentum and IVol: Alternative momentum strategies

		K = 3				K = 6				K = 9				K = 12			
J		IV1	IV2	IV3		IV1	IV2	IV3		IV1	IV2	IV3		IV1	IV2	IV3	
9	P1	0.99	0.83	0.34		0.78	0.64	0.17		0.73	0.64	0.19		0.81	0.71	0.32	
		(5.09)	(3.75)	(1.10)		(4.02)	(2.82)	(0.54)		(3.46)	(2.85)	(0.63)		(3.76)	(3.00)	(0.85)	
	P5	1.18	1.26	0.96		1.15	1.22	0.97		1.15	1.20	0.96		1.16	1.21	0.95	
		(6.38)	(6.22)	(3.22)		(6.24)	(6.20)	(3.35)		(6.13)	(6.03)	(3.30)		(5.50)	(5.51)	(2.86)	
	P10	1.29	1.55	1.32		1.51	1.80	1.54		1.65	1.82	1.51		1.65	1.76	1.38	
		(7.05)	(7.04)	(3.63)		(8.34)	(7.50)	(4.24)		(8.50)	(7.81)	(4.15)		(7.23)	(7.56)	(3.72)	
	P10 − P1	0.30	0.72	0.98	0.68	0.73	1.16	1.37	0.64	0.92	1.18	1.32	0.40	0.84	1.05	1.06	0.22
		(3.03)	(8.92)	(5.64)	(4.83)	(6.43)	(8.54)	(7.22)	(4.63)	(6.42)	(10.35)	(8.17)	(2.26)	(3.90)	(12.50)	(6.55)	(1.14)
12	P1	0.93	0.78	0.33		0.82	0.71	0.27		0.82	0.75	0.33		0.89	0.81	0.46	
		(4.43)	(3.36)	(0.93)		(3.96)	(2.95)	(0.74)		(3.69)	(3.22)	(0.90)		(4.02)	(3.56)	(1.28)	
	P5	1.17	1.25	1.00		1.15	1.21	1.00		1.15	1.20	0.98		1.15	1.21	0.99	
		(5.71)	(5.46)	(3.12)		(5.52)	(5.59)	(3.16)		(5.63)	(5.56)	(2.94)		(5.63)	(5.49)	(2.97)	
	P10	1.28	1.52	1.30		1.46	1.66	1.42		1.53	1.66	1.35		1.52	1.62	1.22	
		(6.67)	(6.52)	(3.47)		(7.80)	(6.89)	(3.89)		(7.53)	(7.17)	(3.71)		(6.97)	(6.77)	(3.40)	
	P10 − P1	0.35	0.74	0.97	0.62	0.64	0.95	1.15	0.51	0.71	0.91	1.02	0.31	0.63	0.81	0.76	0.13
		(4.12)	(9.18)	(5.34)	(3.86)	(5.42)	(8.39)	(5.72)	(3.81)	(4.62)	(11.77)	(6.05)	(1.52)	(3.16)	(10.74)	(7.46)	(0.53)

estimation period overlaps with our portfolio formation period by six months. To ensure that our results are not driven by this overlap, we re-estimate the market model IVol by using daily returns over the 12-month period prior to the start of the formation period. Panel A of Table 10 presents the results. The effect of IVol on momentum returns is slightly reduced, but still economically large and statistically significant.

Table 10

Returns for portfolios based on price momentum and IVol: Alternative specifications of IVol

Average monthly percentage returns of portfolios based on independent sorts of returns and alternative specifications of IVol for the full 1965–2002 sample. Momentum portfolios are formed based on past six-month returns and held for six months within each group. P1 through P10 are momentum portfolios, with P1 containing past losers and P10 containing past winners. We sort stocks into three groups (IV1 — low, IV2 — medium and IV3 – high) by IVol. Momentum return is calculated as the difference between returns for the past winner portfolio and the past loser portfolio in each IVol group. In Panel A, IVol is the standard deviation of the residuals from the market model regression over the 12 months before the portfolio formation period: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t} + \beta_{2i} r_{m,t-1} + \varepsilon_{i,t}$, where $r_{i,t}$ is the daily return on security i and $r_{m,t}$ is the value-weighted CRSP index return. In Panel B, IVol is total volatility, the standard deviation of stock returns. In Panel C, IVol is the residual standard deviation of the daily Fama and French (1996) three-factor model (Equation (4) in the text). In Panel D, IVol is the residual standard deviation of the daily Fama-French model with an added volatility term (Equation (5) in the text). t-statistics are in parentheses.

	IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
Panel A: Momentum returns by pre-formation period IVol (%)								
P1	0.74	(2.91)	0.61	(2.23)	0.23	(0.65)		
P2	1.03	(4.53)	0.95	(3.99)	0.63	(1.89)		
P3	1.13	(5.22)	1.11	(4.45)	0.81	(2.38)		
P4	1.16	(5.63)	1.14	(4.87)	0.90	(2.73)		
P5	1.13	(5.48)	1.17	(5.05)	1.01	(3.10)		
P6	1.16	(5.73)	1.21	(5.13)	1.04	(3.26)		
P7	1.17	(5.66)	1.25	(5.28)	1.10	(3.35)		
P8	1.22	(5.85)	1.31	(5.35)	1.20	(3.55)		
P9	1.30	(5.86)	1.45	(5.75)	1.32	(3.77)		
P10	1.42	(6.66)	1.77	(5.79)	1.64	(4.09)		
P10 − P1	0.68	(4.36)	1.16	(6.21)	1.41	(6.16)	0.73	(4.38)
Panel B: Momentum returns by total volatility (%)								
P1	0.93	(4.15)	0.74	(2.86)	0.17	(0.50)		
P2	1.08	(4.75)	1.02	(4.26)	0.56	(1.67)		
P3	1.16	(5.39)	1.14	(4.53)	0.74	(2.12)		
P4	1.18	(5.83)	1.17	(4.83)	0.80	(2.37)		
P5	1.16	(5.68)	1.20	(5.02)	0.91	(2.72)		
P6	1.19	(5.80)	1.24	(5.33)	0.94	(2.84)		
P7	1.20	(5.79)	1.25	(5.32)	1.03	(3.00)		
P8	1.24	(5.80)	1.35	(5.58)	1.12	(3.16)		
P9	1.33	(6.01)	1.49	(5.87)	1.26	(3.52)		
P10	1.42	(6.93)	1.80	(6.23)	1.59	(3.90)		
P10 − P1	0.49	(3.21)	1.06	(6.81)	1.42	(5.97)	0.93	(5.37)

(*continued*)

Table 10 (*continued*)

Returns for portfolios based on price momentum and IVol: Alternative specifications of IVol

	IV1 (low)		IV2		IV3 (high)		IV3 − IV1	
Panel C: Momentum returns by Fama-French three-factor IVol (%)								
P1	0.92	(3.94)	0.71	(2.73)	0.17	(0.51)		
P2	1.07	(4.73)	1.01	(4.22)	0.55	(1.64)		
P3	1.15	(5.31)	1.13	(4.52)	0.75	(2.20)		
P4	1.17	(5.66)	1.17	(4.87)	0.81	(2.44)		
P5	1.15	(5.58)	1.20	(5.08)	0.92	(2.84)		
P6	1.18	(5.75)	1.25	(5.38)	0.96	(2.93)		
P7	1.19	(5.75)	1.26	(5.32)	1.03	(3.10)		
P8	1.23	(5.80)	1.34	(5.51)	1.14	(3.32)		
P9	1.33	(5.99)	1.48	(5.77)	1.27	(3.64)		
P10	1.41	(6.62)	1.81	(6.22)	1.60	(4.01)		
P10 − P1	0.49	(2.91)	1.10	(6.77)	1.43	(6.07)	0.94	(5.32)
Panel D: Momentum returns by Fama-French three-factor IVol with market volatility factor (%)								
P1	0.91	(3.90)	0.71	(2.75)	0.17	(0.50)		
P2	1.07	(4.73)	1.01	(4.20)	0.55	(1.65)		
P3	1.15	(5.34)	1.13	(4.51)	0.75	(2.18)		
P4	1.16	(5.66)	1.17	(4.87)	0.81	(2.44)		
P5	1.15	(5.58)	1.20	(5.07)	0.92	(2.84)		
P6	1.18	(5.75)	1.25	(5.39)	0.96	(2.93)		
P7	1.18	(5.74)	1.27	(5.32)	1.03	(3.10)		
P8	1.23	(5.80)	1.35	(5.49)	1.14	(3.33)		
P9	1.33	(5.98)	1.48	(5.77)	1.27	(3.65)		
P10	1.42	(6.69)	1.81	(6.19)	1.60	(4.01)		
P10 − P1	0.51	(3.02)	1.10	(6.70)	1.43	(6.09)	0.92	(5.31)

The difference in momentum returns between the high IVol portfolio and low IVol portfolio is 0.73% per month ($t = 4.38$).

5.3.2. Total volatility

In all previous tests, we calculate IVol as the standard deviation of the residuals of the market model regression. We now repeat our analysis using two alternative proxies for IVol: total volatility and Fama-French IVol. Total volatility is calculated as the standard deviation of returns over the 12-month period prior to portfolio formation. Total volatility contains an element of systematic volatility, but it has the benefit of being model-free.

Panel B of Table 10 presents the results for total volatility. Momentum returns for each total volatility portfolio are quite close to those in Table 3. The difference in momentum returns between the highest total volatility portfolio and the lowest total volatility portfolio is also very similar at 0.93% per month (0.88% in Table 3). The t-value of 5.37 represents statistical significance at the 0.1% level.

5.3.3. Fama-French IVol

Fama-French IVol is calculated as the standard deviation of the residuals of the Fama-French three-factor model regression of daily returns over the 12 months prior to portfolio formation. We produce the residuals using the regression:

$$r_{i,t} - r_{f,t} = \alpha_i + b_{1i}(r_{m,t} - r_{f,t}) + b_{2i}(r_{m,t-1} - r_{f,t-1}) + s_{1i}\mathrm{SMB}_t + s_{2i}\mathrm{SMB}_{t-1} + h_{1i}\mathrm{HML}_t + h_{2i}\mathrm{HML}_{t-1} + \varepsilon_{i,t}, \quad (4)$$

where r_i is the daily return on security i; r_f is the risk-free rate; r_m is the return on the portfolio of all NYSE, Amex and Nasdaq firms; and ε_i is the desired regression residual. SMB and HML are defined by Fama and French (1996) and come from Kenneth French's web site. Following Bollen and Busse (2001), we include the lagged values of the three factors in the regression as additional independent variables to accommodate nonsynchronous trading.

Panel C of Table 10 presents the results. Once again, momentum returns for each IVol portfolio are quite close to those shown in Table 3. The difference in momentum returns between the highest IVol portfolio and the lowest IVol portfolio is very similar, at 0.94% per month. The t-value of the difference is similar to the previous specification at 5.32.

5.3.4. IVol from the Fama-French model adding a market volatility factor

IVol from the Fama-French model adding a market volatility factor is calculated as the standard deviation of the residuals of the regression:

$$r_{i,t} - r_{f,t} = \alpha_i + b_{1i}(r_{m,t} - r_{f,t}) + b_{2i}(r_{m,t-1} - r_{f,t-1}) + s_{1i}\mathrm{SMB}_t + s_{2i}\mathrm{SMB}_{t-1} + h_{1i}\mathrm{HML}_t + h_{2i}\mathrm{HML}_{t-1} + v_{1i}r_{m,t}^2 + v_{2i}r_{m,t-1}^2 + \varepsilon_{i,t}, \quad (5)$$

where the three factors are as defined above, and squared market return is the market volatility proxy. Panel D of Table 10 presents the results. Again, momentum returns for each IVol portfolio are quite close to those shown in Table 3. The difference in momentum returns between the highest IVol portfolio and the lowest IVol portfolio is very similar, at 0.92% per month. The t-value of the difference is equivalent to the two previous volatility specifications at 5.31.

6. Time-series relation between aggregate IVol and momentum profits

6.1. Regression analysis

The previous two sections focus on relation between momentum profits and IVol in the cross section. In this section, we explore the time-series relation between momentum profits and aggregate IVol.

Ex ante, neither theory nor empirical evidence suggests a horizon at which IVol should affect momentum returns. We conduct the analysis at an annual frequency for two reasons. First, higher frequency (e.g., monthly or quarterly) momentum returns likely contain considerable noise. As a result, the explanatory power of IVol might be subdued by the large month-to-month or quarter-to-quarter variations in momentum returns. Second, the number of non-overlapping observations for lower frequency (e.g., multi-year) momentum returns is small. For example, if we were to examine the relation between IVol and momentum returns at a three-year horizon, we would have only 12 non-overlapping observations, and our test would have little power.

We control for lagged three-year market returns because Cooper, Gutierrez and Hameed (2004) report that momentum profits are related to them. We also control for the lagged momentum return in our regressions to account for possible autocorrelation. To see if the results are robust to macroeconomic influences, we control for default spread, dividend yield and term spread. Lettau and Ludvigson (2001) show that fluctuations in the aggregate consumption-wealth ratio help predict stock returns, so we include the ratio as another control.

We estimate the following regresion:

$$\begin{aligned}\mathrm{MomRet}_t = {} & a + b_1\mathrm{AggIVol}_{t-1} + b_2\mathrm{MktVol}_{t-1} + b_3\mathrm{TotVol}_{t-1} \\ & + b_3\mathrm{MomRet}_{t-1} + b_4\mathrm{3YMktRet}_{t-1} + b_5\mathrm{DP}_{t-1} + b_6\mathrm{Term}_{t-1} \\ & + b_7\mathrm{Def}_{t-1} + b_8\mathrm{TB3M}_{t-1} + b_9\mathrm{CAY}_{t-1} + e_t, \qquad (6)\end{aligned}$$

where MomRet_t is the cumulative return to the momentum strategy over each year. We calculate momentum profits for each month as the return difference between past winners and past losers. We cumulate the momentum profits across all months for each year. $\mathrm{AggIVol}_{t-1}$ is the average aggregate IVol over the past year. We estimate the IVol for each firm each month according to Equation (4).[7] We then calculate the aggregate IVol by taking a value-weighted average of the IVol across all sample firms. Finally, we compute the average aggregate IVol across all months in a year. MktVol_{t-1} is market volatility over the past year, TotVol_{t-1} is the average total stock volatility over the past year, $\mathrm{3YMktRet}_{t-1}$ is the three-year market return, DP_{t-1} is the lagged dividend yield, Term_{t-1} is the lagged term spread, Def_{t-1} is the lagged default spread, $\mathrm{TB3M}_{t-1}$ is the lagged three-month T-bill rate and CAY_{t-1} is the lagged consumption-wealth ratio. The T-bill rates, Treasury bond yields and Baa corporate

[7] The results are unchanged if we use the market model to estimate IVol.

Table 11

Time-series regressions of annual momentum returns on aggregate IVol

The dependent variable is the cumulative momentum return (the difference between past winners and past losers) across the months of each year (MomRet_t). The independent variables are lagged values of MomRet, aggregate IVol (AggIVol_{t-1}) defined below, market volatility (MktVol_{t-1}), average total stock volatility (TotVol_{t-1}), three-year CRSP value-weighted market return (3YMktRet_{t-1}), dividend yield on the S&P 500 index (DP_{t-1}), term spread, the difference between ten-year T-bond yields and three-month T-bill rates (Term_{t-1}), default spread, the difference between Baa corporate bond yields and ten-year T-bond yields (Def_{t-1}), three-month T-bill rate(TB3M_{t-1}) and consumption-wealth ratio (CAY_{t-1}). AggIVol_{t-1} is the value-weighted average across sample stocks of the standard deviation of residuals from the Fama-French three-factor model using daily returns over the 12 months before portfolio formation. *t*-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.143	−0.239	−0.167	−0.192	0.032	0.029
	(−1.32)	(−1.19)	(−0.80)	(−1.03)	(0.17)	(0.12)
AggIVol_{t-1}	0.775	1.553	1.207	1.968	2.161	2.162
	(1.77)	(2.58)	(1.88)	(3.09)	(3.48)	(3.41)
MktVol_{t-1}				−2.920		−0.059
				(−2.77)		(−0.03)
TotVol_{t-1}					−2.148	−2.115
					(−3.30)	(−1.55)
MomRet_{t-1}	−0.467	−0.502	−0.461	−0.622	−0.430	−0.434
	(−2.64)	(−2.42)	(−2.23)	(−3.20)	(−2.42)	(−1.93)
3YMktRet_{t-1}	0.404	0.329	0.280	0.205	0.100	0.102
	(3.34)	(2.48)	(1.84)	(1.47)	(0.71)	(0.67)
DP_{t-1}		0.032	0.013	0.002	−0.041	−0.041
		(1.22)	(0.30)	(0.06)	(−1.01)	(−0.86)
Term_{t-1}		0.004	0.025	0.010	0.036	0.035
		(0.17)	(0.80)	(0.35)	(1.30)	(1.08)
Def_{t-1}		−0.097	−0.103	−0.028	−0.041	−0.040
		(−2.05)	(−2.16)	(−0.56)	(−0.91)	(−0.81)
TB3M_{t-1}			0.012	0.020	0.032	0.032
			(0.61)	(1.11)	(1.78)	(1.67)
CAY_{t-1}			−2.795	−2.238	−2.132	−2.131
			(−1.57)	(−1.39)	(−1.38)	(−1.36)
Adjusted R^2	0.29	0.36	0.37	0.49	0.54	0.52

bond yields come from the Federal Reserve Bank of St. Louis' web site. The S&P 500 dividend yield is from Robert Shiller's web site. The default spread is the difference between Baa corporate bond yields and ten-year T-bond yields. We calculate term spread as the difference between ten-year T-bond yields and three-month T-bill rates. The consumption-wealth ratio data come from Martin Lettau's web site.

Table 11 presents the results. Consistent with Cooper, Gutierrez and Hameed (2004), we find strong evidence that momentum profits are positively related to lagged three-year market returns. The coefficients on lagged momentum returns are negative in all regressions, indicating that momentum returns are negatively autocorrelated at the annual frequency. All the regressions show a positive and significant relation between lagged IVol and momentum returns.[8] The coefficient on AggIVol_{t-1} ranges from 0.775 to 2.162, depending on control variables. The t-statistics range from 1.77 to 3.48, indicating statistical significance at conventional levels.

The last three regressions in Table 11 control for market volatility and total volatility. We continue to find a significant and positive relation between momentum profits and aggregate IVol. In contrast to the coefficient on aggregate IVol, the coefficients on market volatility and total volatility are negative. This difference in sign is driven, in part, by the positive correlations of market and total volatilities with IVol. Overall, we find that IVol has a significant positive impact on momentum profits.

In summary, we present evidence of a positive time-series relation between IVol and momentum returns. The result is robust to various control variables and alternative methods despite the small number of non-overlapping observations. It complements the cross-sectional results and provides further support for our view that IVol plays an important role in explaining the momentum effect.

6.2. *Implications for the persistence of momentum effect*

Schwert (2003) finds that many well-known anomalies, such as the small-firm effect and the value effect, are not observed after the sample periods examined by the studies that initially identify these anomalies. The momentum anomaly proves to be an exception. Momentum profits not only persist, but also increase after the period examined by Jegadeesh and Titman (1993). In Table 1 we report that the average momentum return is 1.07% for 1965–1989 and 1.61% for 1990–2002.

We contend that IVol is an important reason why momentum profits persist and even increase over time. The results we present in Table 11 indicate a positive time-series relation between IVol and momentum returns. Campbell, Lettau, Malkiel and Xu (2001) also show that firm-level volatility displays an upward trend over 1962–1997.[9] Taken together, the above results suggest that the increase in momentum profits after the publication of Jegadeesh and Titman (1993) is likely driven by the long-term rise in IVol.

7. Conclusions

This paper examines the relation between price momentum and IVol, a variable not previously investigated in the momentum literature. We find that stocks with higher IVol display greater momentum than do stocks with lower IVol. This relation is statistically significant, large and robust to consideration of firm size, transactions costs, turnover, price delay, distress risk, different sample periods, different formation

[8] The results are qualitatively similar when we use lagged aggregate IVol.

[9] In a test not reported in detail, we confirm that this trend of increasing IVol continues into the late 1990s and early 2000s.

and holding periods and alternative specifications of IVol. Further, the relation is primarily driven by high IVol losers.

Our findings are consistent with the view that momentum profits result from underreaction to firm-specific information, for which IVol can be viewed as a proxy. The results are also consistent with the hypothesis that IVol represents an important limit of arbitrage. Momentum returns are highest among stocks with the highest IVol, consistent with the momentum effect being more easily arbitraged away for stocks with less idiosyncratic risk. Our results also support the asymmetric-information model of Wang (1993).

We also find time-series evidence of a positive relation between aggregate IVol and momentum returns. This finding complements the cross-sectional results, supports our view that IVol plays an important role in the momentum effect, and helps explain the persistence and increase of momentum profits in the 1990s and early 2000s. While most well-known anomalies disappear after the sample periods examined by the original studies, momentum profits increase after the sample period of their discovery by Jegadeesh and Titman (1993). We contend that the long-term rise in firm-specific volatility reported by Campbell, Lettau, Malkiel and Xu (2001), combined with our finding of a positive time-series relation between IVol and momentum returns, provides at least a partial explanation for this phenomenon.

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