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Idiosyncratic volatility, the VIX and stock returns

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ABSTRACT

The interplay between stock returns and idiosyncratic volatility (IVOL) has been subject to extensive empirical investigation, yielding mixed findings. Earlier empirical investigation found either a positive relationship between expected returns and idiosyncratic volatility or none at all, the latter consistent with classical asset pricing theory. Further recent empirical research suggested a negative relationship between the variables. In this study, we use data about US firms from 1990 to 2016 and show that the aggregate market volatility risk, captured by the VIX, plays a role in the relationship between IVOL and stock returns. Specifically, an increase (decline) in the VIX tends to be followed by a negative (positive) relationship between idiosyncratic volatility and future returns, even after taking into account other risk factors. We maintain that an increase in the VIX, also called the investors' fear gauge, may reflect an increase in investors' risk aversion, prompting them to balance their portfolios by increasing the diversity of their investments.

1. Introduction

The relationship between idiosyncratic volatility (IVOL) and returns has attracted a great deal of research attention, yielding, to date, mixed findings. In efficient markets, there should be no interrelation between IVOL and expected returns (Sharpe, 1964; Lintner, 1965; Fama & MacBeth, 1973). In other words, ceteris paribus, portfolios sorted based on IVOL should manifest no difference in their average excess returns (the return of the stock minus the free risk interest rate). However, the literature comes to different and ambiguous conclusions. While earlier studies report either a positive relationship between IVOL and average returns (Malkiel & Xu, 2002; Goyal & Santa-Clara, 2003) or fail to indicate any significant relationship (Tinic & West, 1986; Bali & Cakici, 2008), Ang, Hodrick, Xing, and Zhang (2009) show that stocks around the world with high IVOL tend to have low future average returns. In their study, they rule out explanations based on trading frictions, information dissemination, and higher moments. However, using EGARCH models, Fu (2009) rejects the findings of Ang et al. (2009) and demonstrates a positive relationship between IVOL and returns. In another study, Boyer, Mitton, and Vorkink (2010) report that expected idiosyncratic skewness and returns are negatively correlated. Stambaugh, Yu, and Yuan (2015) claim that part of the IVOL effect is derived from arbitrage asymmetry between holding a long position for underpriced stocks and a short position for overpriced stocks. Combining the fact that IVOL has a negative effect on the return of overpriced stocks and a positive one for underpriced stocks, with the fact that taking a short position in overpriced stocks is less common than taking a long position in underpriced stocks, results in a negative relationship between IVOL and returns.

Given the contradictory results in the literature regarding the effect of IVOL on returns, we postulate that some of the difference in returns between high and low IVOL portfolios may also be explained by the VIX. Specifically, months with a positive (negative) change in the VIX will tend to be followed by a negative (positive) relationship between IVOL and future returns. To test this contention, we sort stocks from Chicago's Center for Research in Security Prices (CRSP) on a monthly basis according to their

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idiosyncratic volatility and construct five value-weighted portfolios, with Portfolio 1 containing the lowest idiosyncratic volatility stocks and Portfolio 5 the highest. We then compute the excess returns of each portfolio in month t + 1. In line with previous works (e.g., Ang et al., 2009), we track the Portfolio "5 minus 1" (longing the highest IVOL quintile and shorting the lowest) to reflect the relationship between IVOL and future returns. The findings indicate that when the VIX increases in time t, the portfolio of interest ("5 minus 1") is negatively affected, as reflected in time t + 1. In contrast, when the VIX decreases in time t, Portfolio "5 minus 1" is positively affected in t + 1. These findings indicate that if an increase in the VIX is translated into a decrease in Portfolio "5 minus 1" in the next period, this outcome can likely occur if either Portfolio 5 performs poorly or Portfolio 1 performs well, or both.

Our work corresponds with the literature asserting that the VIX also mirrors investor sentiment. Therefore, in times of great uncertainty, during which VIX levels are higher, investors tend to be more risk-averse and, consequently, require a higher premium for IVOL. To elaborate, under these conditions, investors will choose to avoid stocks with high IVOL and prefer stocks with low IVOL, resulting in reduced returns of the high IVOL stocks relatively to the low IVOL stocks.

The effect of the VIX on the IVOL-return relationship may also be explained from a different perspective. Stocks with relatively high idiosyncratic volatility may be viewed as lotteries: they have a small probability of a huge reward and a high probability of partial investment losses (Kumar, 2009). Thus, when we create portfolios according to the stocks' idiosyncratic volatility, the portfolio with the highest IVOL, say the fifth quintile file, consists mainly of lottery stocks. As investors in general do not hold well-diversified portfolios (e.g., Goetzmann & Kumar, 2008), in times of great volatility in capital markets (and thus, a high VIX), investors tend to balance and reduce the volatility of their portfolios. They can accomplish this goal by increasing the diversity of their portfolios and reducing the IVOL. In order to do so, investors can sell high IVOL stocks in favor of low IVOL stocks. Doing so will result in increasing the price of the low IVOL assets compared to the high IVOL ones, thus strengthening the negative relationship between IVOL and returns.

We provide corroborating evidence about this relationship using data from the CRSP on U.S. firms between January 1990 and December 2016. We find that high IVOL stocks have, on average, lower future returns. In addition, as hypothesized, we establish that changes in the VIX have a significantly negative effect on that relationship. In other words, an increase in the VIX is followed by an increased gap in the returns of high and low IVOL stocks. Moreover, we demonstrate that the effect of the VIX on the IVOL-return relationship is robust even after controlling for Baker and Wurgler's (2006) investor sentiment, as Stambaugh et al. (2015) suggests.

The remainder of this paper proceeds as follows. Section 2 reviews the literature, Section 3 describes the data, Section 4 outlines the method and discusses the empirical findings, and Section 5 concludes.

2. Literature review

2.1. Idiosyncratic volatility and expected returns

According to the capital asset pricing model (Sharpe, 1964; Lintner, 1965), an asset's idiosyncratic volatility, that is, the part of the total volatility of the asset's returns that cannot be explained by market returns, can be diversified away in a large portfolio. Thus, only systematic risk is rewarded. Subsequent studies (e.g., Fama & Macbeth, 1973; Fama and French, 1993) show that there are more factors that influence an asset's excess returns. Fama and French (1993) identify two additional risk factors that have explanatory power for the cross-section of returns, yielding the well-known three-factor model. These factors include the size and the value factor premiums.[1] Together with the market factor (*MKT*) provided by the excess returns of the market portfolio over the risk-free interest rate, they create the three-factor model (hereafter FF-3). The important role of these factors has been reconfirmed by other studies, such as that of Malkiel and Xu (2002).

When discussing the effect of idiosyncratic risk on expected returns, the literature comes to an ambiguous conclusion. While some studies report a positive relationship between the two, others portray the opposite picture. Merton (1987) suggests that idiosyncratic risk will be rewarded to some extent. He reports that the market portfolio is inefficient, because different individual investors invest in different available securities and therefore hold undiversified portfolios with idiosyncratic risk. If there is no insurance market to reduce the idiosyncratic risk, this risk will be rewarded. Malkiel and Xu (2002) reinforce this argument with their finding that idiosyncratic returns have a strong and positive effect on expected returns. Similarly, Goyal and Santa-Clara (2003) observe a significant positive relationship between average stock variance and expected returns. Moreover, utilizing Chicago's Center for Research in Security Prices (CRSP) data from 1962 to 1999, they show that idiosyncratic volatility explains most of the variation in average stock variance, concluding that it is idiosyncratic volatility that mainly affects the expected returns. Ang et al. (2009) use data from 23 countries to examine the correlation between idiosyncratic volatility and future returns. They calculate the idiosyncratic volatility of each stock in each month and then create value-weighted quintile portfolios based on the idiosyncratic volatility. Their results show that when taking into account all of the countries in the research, a strategy that goes long on the highest volatility quintile and shorts the quintile of stocks with the lowest idiosyncratic volatilities produces an average return of −1.31% per month. When taking into account all of the countries excluding the U.S., the same strategy will produce an alpha of −0.67%. Moreover, when reporting the differences in the raw returns between the first and fifth volatility portfolios, the results show that the strategy that goes long on the highest volatility quintile and shorts the quintile of stocks with the lowest idiosyncratic volatilities will produce a monthly raw

[1] These two factors are generally denoted by SMB and HML, respectively. SMB refers to the returns of the portfolio that includes the smallest one-third of local firms minus the returns on the portfolio that includes the firms in the top third ranked by market capitalization. HML refers to the returns of the portfolio that includes the top third of firms with the highest book-to-market ratios minus the portfolio that includes the bottom third of firms with low book-to-market ratios.

return of −0.89%. When the U.S. stocks are removed, the difference shrinks to −0.4%. However, Fu (2009) claims that idiosyncratic volatilities are time-varying, so the one-month lagged idiosyncratic volatility may not be an appropriate proxy for the expected idiosyncratic volatility of this month. He also shows that for most stocks, idiosyncratic volatility does not follow a random walk process. Therefore, he concludes that the negative relationship between the lagged idiosyncratic volatility and average returns in Ang et al. (2009) does not imply that the relationship between idiosyncratic risk and expected returns is negative.

In order to answer the question of whether idiosyncratic risk is positively or negatively correlated with average returns, Fu (2009) uses exponential generalized autoregressive conditional heteroscedasticity (EGARCH) models and out-of-sample data to estimate expected idiosyncratic volatilities. He reports that returns are positively related to the EGARCH-estimated conditional idiosyncratic volatilities. In another related study, Cao and Xu (2010) suggest that the root of the conflict on that issue may lie in the difference between long-term idiosyncratic volatility and short-term idiosyncratic volatility. They divide idiosyncratic volatility into two components: the short-term component, which varies considerably across firms and over time, and the long-term component. They report that the short-term idiosyncratic volatility is negatively correlated with the asset's returns, while the long-term idiosyncratic volatility is positively correlated with them.

While earlier research works employ historical realized IVOL, other studies suggest using different measures of idiosyncratic volatility. For example, Diavatopoulos, Doran, and Peterson (2008) use the implied idiosyncratic volatilities derived from option prices. The authors investigate whether expected idiosyncratic risk, measured by implied volatility, is related to future returns. They find that implied idiosyncratic volatility strongly predicts realized volatility and positively predicts future stock returns, but past realized idiosyncratic volatility is unrelated to future returns at the firm level. Utilizing unexpected idiosyncratic volatility, Chua, Goh, and Zhang (2010) report that such volatility is positively related to unexpected returns. They also use unexpected idiosyncratic volatility to control for unexpected returns, and reveal that expected idiosyncratic volatility is significantly and positively related to expected returns.

2.2. *Investors' lack of diversification*

One possible explanation for the variation in the relationship between IVOL and expected stock returns is that market participants generally do not hold well-diversified portfolios. Furthermore, if investors have an aversion to volatility, high levels of market volatility will be translated into portfolio adjustments to balance their risk. In fact, the financial literature lists several factors that underlie the lack of diversification in investors' portfolios. First, investors may ignore correlations (Kroll, Levy, & Rapoport, 1988; Kroll & Levy, 1992) if they adopt availability heuristics (Tversky & Kahneman, 1973) or follow price trends (e.g., Odean, 1999). In addition, people who frame their investment decisions narrowly tend to ignore the interactions among their individual stock selection decisions and might be insensitive to correlations among the stocks in their respective portfolios (Kahneman & Lovallo, 1993; Kumar & Lim, 2008). Second, investors who are over-confident about the accuracy of their private information or their ability to interpret their private information will intentionally choose to hold focused and under-diversified portfolios (Odean, 1999). Third, investors might prefer to invest in stocks with which they are familiar (e.g., local stocks, employer stock, etc.), and this preference for the familiar could be correlated with the level of portfolio diversification (Huberman, 2001). Lastly, some investors might hold under-diversified portfolios due to information and cost reasons. It is possible that some investors possess useful, time-sensitive information about a few stocks, and they would optimally choose to hold an under-diversified portfolio containing only those stocks. Additionally, due to limitations in investors' information processing abilities, and given that searching is costly, they might choose to gather information about only a subset of assets or asset classes (Merton, 1987). In this setting, the costs associated with learning about assets or asset classes could produce under-diversification. These investors are likely to hold a layered financial portfolio consisting of a small, under-diversified stock portfolio and a relatively larger, well-diversified mutual fund portfolio.

3. Data

Our data are comprised of daily returns and market capitalization values of all firms recorded in the CRSP, covering stocks listed on the NYSE, NYSE MKT (formerly the AMEX), and NASDAQ for January 1980 to December 2016. Consistent with the previous literature, we removed ETFs, closed end funds and REITS from our sample. Additional data on market excess returns, risk free returns, size and value risk factors are from Kenneth R. French's data library.[2] Furthermore, our data include the VIX index from 1990 to December 2016, as calculated by the Chicago Board Options Exchange (CBOE). Relative to the data used in Ang, Hodrick, Xing, and Zhang (2006, 2009), which covers 1963 to 2003, our data lack old observations and include more recent observations. Our data also include the index of market-wide investor sentiment constructed by Baker and Wurgler (2006) from 1990 to September 2015.

4. Method

4.1. *Measuring idiosyncratic volatility*

We use the cross-section of stock returns to create portfolios of stocks that have different levels of IVOL. We measure IVOL using the same method as in Ang et al. (2006), namely, according to the residuals of the FF-3:

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html2

Table 1
Cross-Section (Excess) Returns Arranged by Idiosyncratic Volatility Quintiles 1980–2016.

Portfolio	1	2	3	4	5	5 minus 1	Positive months	Negative months
Panel A: Value-Weighted Portfolios								
1980–2016	0.71%	0.64%	0.66%	0.3%	−0.34%	−1.04%	176	267
1980–1989	0.7%	0.61%	0.56%	0.05%	−1.26%	−1.96%	34	86
1990–2016	0.71%	0.65%	0.7%	0.39%	0.01%	−0.7%	142	181
Panel B: Equal-Weighted Portfolios								
1980–2016	0.64%	0.84%	0.84%	0.71%	0.52%	−0.12%	194	249
1980–1989	0.69%	0.79%	0.62%	0.26%	−0.52%	−1.21%	39	81
1990–2016	0.62%	0.86%	0.92%	0.88%	0.91%	0.29%	155	168

Notes: Table 1 presents five portfolios constructed on a monthly basis according to their idiosyncratic volatility. Portfolio 1 includes the firms with the lowest idiosyncratic volatility, while Portfolio 5 includes the firms with the highest idiosyncratic volatility. For the period from 1980 to 2016, value-weighted Portfolio 1 had (on average) an excess return of 0.71% per month, while value-weighted Portfolio 5 had (on average) an excess return of −0.34% per month, which is lower by ~1.04% than Portfolio 1. For the same period, equal-weighted Portfolio 1 had (on average) an excess return of 0.64% per month, while equal-weighted Portfolio 5 had (on average) an excess return of 0.52% per month, which is lower by ~0.12% than portfolio 1. As the table illustrates, the number of months during which value-weighted Portfolio 5 outperformed value-weighted Portfolio 1 is 176, while the number of months during which value-weighted Portfolio 5 underperformed value-weighted Portfolio 1 is 267. Note that the returns in the table represent excess returns over the one-month U.S. T-bill rate.

$$r^i = \alpha^i + \beta^i_{MKT} MKT + \beta^i_{SMB} SMB + \beta^i_{HML} HML + \varepsilon^i \tag{1}$$

where r^i is the daily excess return of stock i over the one-month U.S. T-bill rate, and α^i is the intercept. MKT is computed as the value-weighted excess return of the market portfolio over the one-month U.S. T-bill rate. SMB is the return of the smallest one-third of local firms minus the return on the firms in the top third, ranked by market capitalization. HML is the return of the portfolio that goes long on the top third of local firms with the highest book-to-market ratios and shorts the bottom third of local firms with the lowest book-to-market ratios. The coefficients β^i_{MKT}, β^i_{SMB}, and β^i_{HML} are the respective coefficients of three factors listed above. Following Ang et al. (2006), we define the IVOL of stock i in month t as the standard deviation of the residuals' ε^i after estimating Eq. (1), using the daily excess returns in month t. We run this regression every month *t* for each stock *i* in the sample to determine the IVOL.

4.2. *Constructing portfolios according to idiosyncratic volatility*

To compute the difference in excess returns between high- and low-IVOL stocks for each month t, we sort the firms into quintile value-weighted portfolios ranked by their IVOL as measured in Eq. (1).[3] Portfolio 1 contains firms with the lowest IVOL in month t, while Portfolio 5 contains firms with the highest IVOL in month t. Subsequently, we compute the excess returns of each portfolio in month t + 1. The quintile portfolios are rebalanced every month. Our procedure is aligned with that discussed in Ang et al. (2006) where L = 1, M = 0, N = 1.[4]

For robustness purposes, we replicate the process described above also with equal-weighted portfolios. Table 1 lists the average excess returns for each value-weighted and equal-weighted portfolio across different sample periods. Table 2 details the descriptive statistics of the value-weighted portfolios between 1980 and 2016. Figs. 1 and 2 illustrate the monthly and annual excess returns of the value-weighted Portfolio 5 over Portfolio 1, respectively, between 1990 and 2016. Fig. 3 depicts the average monthly excess returns of the value-weighted and equal-weighted portfolios arranged according to their IVOL in the period 1990–2016. We split the data into two sub-periods (1980–1989 and 1990–2016), because VIX data are available only from 1990.

Portfolio "5 minus 1" represents a strategy that is longs on the highest IVOL quintile and shorts on the lowest volatility quintile. As reported in Table 1, the value-weighted portfolio with the highest IVOL (Portfolio 5) has, on average, a lower monthly excess return of 1.96% and 0.7% than the portfolio with the lowest IVOL (Portfolio 1), for 1980–1989 and 1990–2016, respectively. These results are similar to those reported in Ang et al. (2009); their sample period ranges from 1963 to 2003. However, for equal-weighted portfolios, the picture is a bit different: the equal-weighted portfolio with the highest IVOL has, on average, a lower monthly excess return of 1.21% than the portfolio with the lowest IVOL for 1980–1989, but a higher monthly excess return of 0.29% for 1990–2016. In addition, between 1990 and 2016, the number of months with a positive difference (i.e., the number of times Portfolio 5 outperformed Portfolio 1) is 142 in the case of value-weighted portfolios, while the number of months with a negative difference (i.e., times when Portfolio 5 underperformed Portfolio 1) is 181. In the case of the equal-weighted portfolios, the number of positive differences in that period is 155, compared to 168 negative differences. According to the sign test (not reported here, but available upon request), the difference between the number of positive and negative months is not statistically significant in the case of the equal-weighted portfolios. This result may imply that in the case of equal-weighted portfolios, the direction of the effect of IVOL on the stocks' returns varies over time.

[3] In cases where the number of firms is not a multiple of 5, we add the extra firms to the portfolio with the lowest idiosyncratic volatility.

[4] In Ang et al. (2006), "L" denotes the estimation period, "M" the waiting period and "N" is the holding period. If L = 1, M = 0, N = 1, the idiosyncratic volatility is based on a period of one month, there is no waiting period, and the excess return is based on a period of one month.

Table 2
Descriptive Statistics of Quintile Value-Weighted Portfolios Arranged by Idiosyncratic Volatility 1980–2016.

Portfolio	1	2	3	4	5
Panel A: 1980–2016					
Mean	0.71%	0.64%	0.66%	0.3%	−0.34%
Stdev.	3.6%	4.5%	5.66%	7.17%	8.72%
Max	12.1%	12.78%	16.41%	22.62%	35.77%
Min	−19.24%	−24.95%	−28.91%	−32.2%	−35.25%
Skewness	−0.76	−0.73	−0.73	−0.58	−0.2
Kurtosis	2.87	2.92	2.28	2.16	2.51
Panel B: 1980–1989					
Mean	0.7%	0.61%	0.56%	0.05%	−1.26%
Stdev.	4.1%	5.1%	5.65%	6.48%	6.42%
Max	12.1%	12.8%	13.3%	14.9%	11.5%
Min	−19.2%	−24.9%	−28.9%	−32.2%	−30.1%
Skewness	−0.95	−0.92	−1.09	−1.16	−1.02
Kurtosis	4.34	4.35	5.51	5.02	3.52
Panel C: 1990–2016					
Mean	0.71%	0.65%	0.7%	0.39%	0.01%
Stdev.	3.42%	4.26%	5.67%	7.42%	9.42%
Max	10%	12.13%	16.41%	22.62%	35.77%
Min	−13.72%	−19.52%	−20.75%	−26.67%	−35.25%
Skewness	−0.63	−0.59	−0.6	−0.45	−0.16
Kurtosis	1.67	1.67	1.18	1.5	2.03

Notes: The table presents the descriptive statistics of the five value-weighted portfolios sorted according to their idiosyncratic volatility, for different periods.

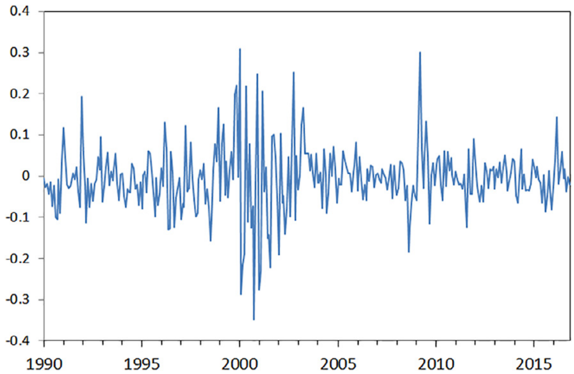

Fig. 1. Monthly Excess Returns of Value-Weighted Portfolio 5 minus 1 for 1990–2016. *Notes:* The figure depicts the monthly excess returns of the value-weighted Portfolio 5 over the value-weighted Portfolio 1 in the period 1990–2016. Idiosyncratic volatility is calculated as the standard deviation of the residuals resulting from estimating Eq. (1) – the Fama and French (1993) three-factor model. On average, Portfolio 5 underperformed Portfolio 1 by approximately 0.7% per month. When we exclude the three negative outlier months in which Portfolio 5 underperformed Portfolio 1 significantly, the results remain qualitatively unchanged. In this case, on average, Portfolio 5 underperformed Portfolio 1 by 0.42% per month.

4.3. The VIX, idiosyncratic volatility and returns

In this section, we attempt to capture the effect of the VIX on the excess returns of high IVOL stocks. We define the excess returns of Portfolio 5 over Portfolio 1 as follows:

$$Y_t = R_{5,t} - R_{1,t} \tag{2}$$

where $R_{i,t}$ is the excess return of portfolio i in month t. In other words, Y_t denotes the monthly excess returns of Portfolio 5 over Portfolio 1. Recall that the portfolios are built based on the IVOL measured in month $t-1$.

As previously discussed, we hypothesize that the VIX can affect the nature of the relationship between IVOL and stock returns. Thus, we link Y_{t+1} to the rate of change in the VIX using the following regression:

$$Y_{t+1} = c + \beta_1 \ln\left(\frac{VIX_t}{VIX_{t-1}}\right) + u_t \tag{3}$$

where Y_{t+1} is the excess return of Portfolio 5 over Portfolio 1 in month t + 1, the expression $ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$ is the rate of change in the VIX

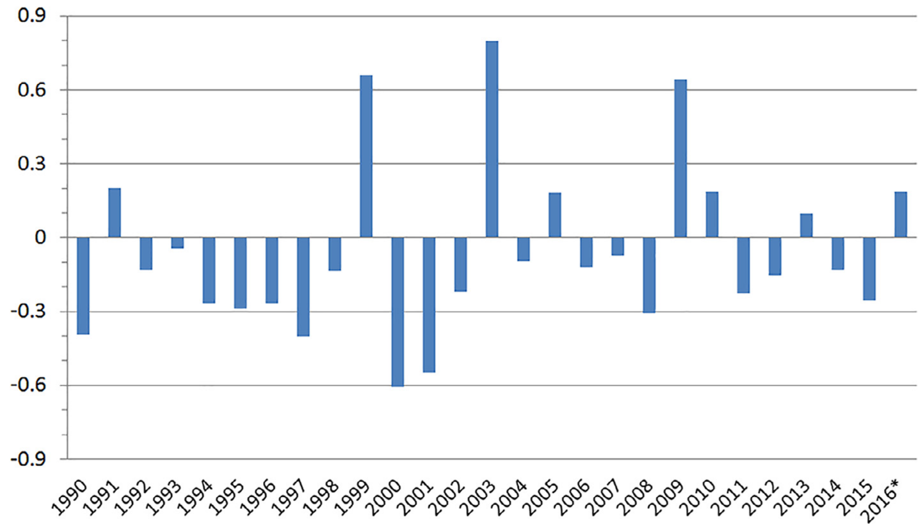

Fig. 2. Annual Excess Returns of Value-Weighted Portfolio 5 minus 1 for the period 1990–2016. *Notes:* The figure depicts the annual excess returns of value-weighted Portfolio 5 over value-weighted Portfolio 1 in the period 1990–2016. On average, value-weighted Portfolio 5 underperformed value-weighted Portfolio 1 by approximately 6.36% per year. Note that because our data end in December 2016, the results do not include December 2016, so we do not have data about the excess returns in January 2017.

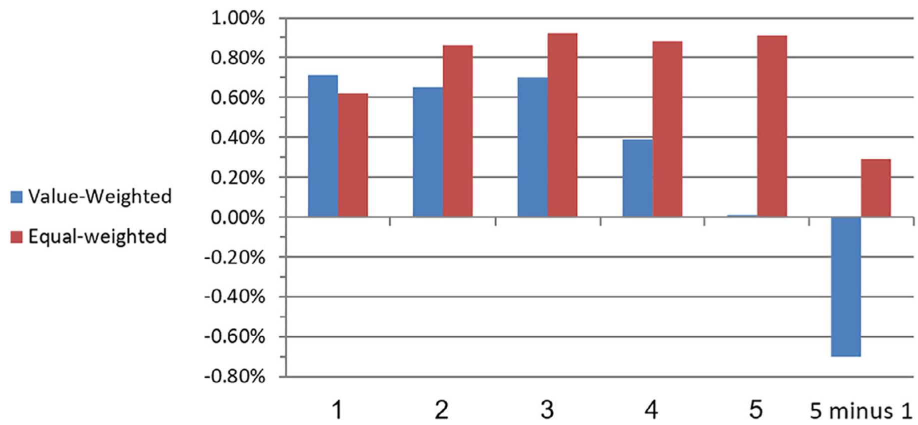

Fig. 3. Cross-Section and Excess Returns Arranged by Idiosyncratic Volatility Quintiles (1990–2016). *Notes:* The figure depicts the monthly excess returns of value-weighted and equal-weighted portfolios in the period 1990–2016. On average, the value-weighted Portfolio 5 underperformed the value-weighted Portfolio 1 by approximately 0.7% per month, and the equal-weighted Portfolio 5 outperformed the equal-weighted Portfolio 1 by approximately 0.29% per month.

in month t, and u_t is a random disturbance. For example, if Y_{t+1} is the excess return of Portfolio 5 over Portfolio 1 in February, then $\ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$ is the rate-of-change in the VIX in January.[5] Note that the portfolios' returns in February stem from the portfolios constructed in January according to the IVOL of the underlying assets.

If we assume that the VIX has a significant role in affecting the excess returns of high vs. low IVOL stocks, then we should expect to have a negative β. In other words, an increase in the VIX in month t will result in investors' selling high IVOL stocks and buying lower IVOL stocks. As a result, we expect lower values of Y_{t+1} (the excess returns of high IVOL stocks in the following month). We test this hypothesis on both value-weighted and equal-weighted portfolios. Table 3 reports the estimation results of Eq. (3).

The results indicate a statistically significant effect of the rate of change in the VIX on Y_{t+1}. In particular, an increase of 1% in the VIX in a specific month is followed by an average decrease of approximately 0.053% in the monthly excess return of the highest IVOL value-weighted portfolio over the lowest IVOL value-weighted portfolio. Given that the standard deviation of $\ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$ for the period considered is 18.5%, an increase of one standard score in $\ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$ is followed by an average decrease of approximately 1% in the monthly excess returns of the highest IVOL stocks in the following month. We ensure that the variables of interest are stationary using

[5] The closing value of the VIX in January divided by the closing value of the VIX in December.

Table 3
Estimation Results of Eqs. (3)–(6).

	Eq. (3) Results		Eq. (4) Results		Eq. (5) Results		Eq. (6) Results	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
Panel A: Value-Weighted Portfolios								
Constant	−0.007	0.105	−0.007	0.074	−0.002	0.73	−0.001	0.76
	[−1.63]		[−1.79]		[−0.34]		[−0.3]	
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$	−0.053	0.026	−0.083	0.000	−0.071	0.003	−0.066	0.038
	[−2.24]		[−3.64]		[−3.02]		[−2.08]	
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right)$			−0.149	0.000	−0.143	0.000	−0.117	0.28
			[−6.53]		[−6.15]		[−1.06]	
BW_t					−0.026	0.000	−0.026	0.000
					[−3.73]		[−3.59]	
Adjusted R^2	0.012		0.126		0.166		0.162	
F-Statistic	5.01	0.026	24.15	0.000	20.12	0.000	7.84	0.000
DW Stat	1.90		1.91		1.99		1.99	
Panel B: Equal-Weighted Portfolios								
Constant	0.002	0.534	0.002	0.55	0.007	0.128	0.007	0.145
	[0.62]		[0.59]		[1.52]		[1.46]	
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$	−0.064	0.007	−0.09	0.000	−0.083	0.001	−0.089	0.006
	[−2.74]		[−3.94]		[−3.49]		[−2.77]	
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right)$			−0.129	0.000	−0.121	0.000	−0.15	0.178
			[−5.63]		[−5.13]		[−1.34]	
BW_t					−0.018	0.001	−0.018	0.019
					[−2.61]		[−2.36]	
Adjusted R^2	0.02		0.106		0.124		0.12	
F-Statistic	7.51	0.007	19.98	0.000	14.36	0.000	6.16	0.000
DW Stat	1.8		1.78		1.81		1.81	

Notes: For every month, we sort U.S. firms into quintile portfolios; using the same method as Ang et al. (2006) (see Eq. (1)). In Eq. (3), we regress the excess returns of the portfolio with the highest idiosyncratic volatility stocks (R5) over the portfolio with the lowest idiosyncratic volatility stocks (R1) on a constant and the percentage changes in the VIX in the previous month. In Eq. (4), we add the percentage changes in the VIX in the current month, and in Eq. (5), we add the investor sentiment built by Baker and Wurgler (2006). In Eq. (6) we use the closing value of the VIX in the last month, VIX_t, as an instrumental variable for the change in the VIX in the next month. We report robust t-statistics in square brackets below each coefficient. The sample period is from February 1990 to December 2016 for Eqs. (3) and (4) and February 1990 to September 2015 for Eqs. (5) and (6).

the Augmented Dickey and Fuller (1979) and Phillips and Perron (1988) tests.[6] The results obtained with the equal-weighted portfolios are even stronger.

For robustness, using Eq. (4), we also investigate whether the results remain similar when we add the rate of change in the VIX in month t + 1 to the regression:

$$Y_{t+1} = c + \beta_1 \ln\left(\frac{VIX_t}{VIX_{t-1}}\right) + \beta_2 \ln\left(\frac{VIX_{t+1}}{VIX_t}\right) + u_t \tag{4}$$

The term $\ln\left(\frac{VIX_{t+1}}{VIX_t}\right)$ denotes the rate of change in the VIX in month t + 1. This step is motivated by the observation that the changes in the VIX are positively and serially correlated, and may be correlated with contemporaneous excess returns.

As reported in Table 3 (Panel A of Table 3, under Eq. (4) results), changes in the VIX in the previous month (captured by β_1) have a strong and statistically significant effect on the excess returns of high IVOL stocks over low IVOL stocks in the next month. Stated differently, an increase of 1% in the VIX in a specific month is associated with a decrease of about 0.083% in the excess returns of Portfolio 5 over Portfolio 1 in the following month (using value-weighted portfolios). This result is evident regardless of the effect caused by the contemporaneous changes in the VIX. Converting the beta coefficient into annual terms underscores that if the VIX increases by 1%, a decline is followed by a difference in the annual excess returns of Portfolio 5 over Portfolio 1 of approximately 1%. Moreover, an increase of 1% in the VIX in a specific month is accompanied by a decrease of roughly 0.15% in the difference in the monthly excess returns, suggesting that the VIX also has a simultaneous effect on the excess returns of high IVOL stocks. Similar results are obtained with the equal-weighted portfolios (see Panel B of Table 3).

The negative relationship revealed here may remind us of the leverage effect, which refers to the negative correlation between asset returns and changes in volatility (Figlewski & Wang, 2000; Ait-Sahalia, Fan, & Li, 2013; Choi & Richardson, 2016). However, we are not tracking the returns of market indexes or the firms' asset value. Instead, our focus is on the difference in the returns of the two portfolios: Portfolio 5 (with the highest IVOL) and Portfolio 1 (with the lowest IVOL). Thus, our findings reveal that in addition to the known effect of the VIX on future stock returns, the VIX also affects the difference in the returns of the two portfolios. Furthermore,

[6] Results are available upon request.

Table 4
Estimation Results of Eqs. (3)–(6) with the VIX3M and VIXMT.

	Eq. (3) Results		Eq. (4) Results		Eq. (5) Results		Eq. (6) Results	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
Panel A: Using the VIX3M in Explaining Y_{t+1}								
Constant	−0.003	0.564	−0.004	0.46	−0.01	0.083	−0.012	0.084
	[−0.58]		[−0.74]		[−1.75]		[−1.75]	
$\ln\left(\frac{VIX3M_t}{VIX3M_{t-1}}\right)$	−0.076	0.034	−0.087	0.009	−0.061	0.085	−0.052	0.194
	[−2.15]		[−2.67]		[−1.74]		[−1.31]	
$\ln\left(\frac{VIX3M_{t+1}}{VIX3M_t}\right)$			−0.142	0.000	−0.128	0.000	−0.034	0.868
			[−4.35]		[−3.75]		[−0.17]	
BW_t					−0.043	0.023	−0.05	0.046
					[−2.32]		[−2.02]	
Adjusted R^2	0.033		0.174		0.20		0.131	
F-Statistic	4.64	0.033	12.19	0.000	8.66	0.000	3.66	0.015
DW Stat	1.58		1.67		1.67		1.63	
Panel B: Using the VIXMT in Explaining Y_{t+1}								
Constant	−0.003	0.663	−0.003	0.518	−0.01	0.026	−0.011	0.057
	[−0.44]		[−0.65]		[−2.26]		[−1.93]	
$\ln\left(\frac{VIXMT_t}{VIXMT_{t-1}}\right)$	−0.102	0.006	−0.116	0.001	−0.083	0.01	−0.078	0.03
	[−2.78]		[−3.62]		[−2.65]		[−2.21]	
$\ln\left(\frac{VIXMT_{t+1}}{VIXMT_t}\right)$			−0.142	0.002	−0.128	0.005	−0.078	0.727
			[−3.24]		[−2.88]		[−0.35]	
BW_t					−0.042	0.04	−0.046	0.001
					[−2.09]		[−3.34]	
Adjusted R^2	0.038		0.179		0.202		0.183	
F-Statistic	5.16	0.025	12.42	0.000	8.68	0.000	4.00	0.000
DW Stat	1.59		1.69		1.69		1.66	

Notes: This table basically replicates the previous table. The VIX in Eq. (3) to Eq. (6) is replaced by the 3-month and 6-month VIX indices (VIX3M in Panel A, and VIXMT in Panel B, respectively) in order to capture the long-term effects of the implied volatility on the IVOL-future returns relationship. The results are qualitatively unchanged. Data for the VIX3M and VIXMT variables were obtained from the CBOE website. http://www.cboe.com/products/vix-index-volatility/volatility-indexes.

while the VIX affects both portfolios, its impact is stronger on the highest IVOL portfolio, resulting in a more negative relationship between IVOL and future returns.

Finally, we show that the effect of the VIX on the relationship between IVOL and returns exists even when accounting for the effect of Baker and Wurgler's (2006) investor sentiment (BW hereafter). Using their measure, Stambaugh et al. (2015) establish that the negative effect of IVOL on returns is stronger following months when investor sentiment is high, and that the variation over time in the IVOL effect is stronger among overpriced stocks. In order to demonstrate the robustness of the VIX in explaining next period IVOL returns, we control for BW's investor sentiment and incorporate it into the regression in Eq. (5):

$$Y_{t+1} = c + \beta_1 \ln\left(\frac{VIX_t}{VIX_{t-1}}\right) + \beta_2 \ln\left(\frac{VIX_{t+1}}{VIX_t}\right) + \beta_3 BW_t + u_t \tag{5}$$

As Table 3 illustrates, an increase in BW's investor sentiment is followed by an increased negative relationship between IVOL and returns. Moreover, the presence of the BW sentiment in the regression has a minor effect on the coefficients that represent the changes in the VIX. These results indicate that the effect of the change in the VIX on the IVOL-return relationship is still evident despite the inclusion of BW's investor sentiment as a control variable.

However, we emphasize that the rate of change in the VIX is computed as the change between the VIX at the beginning of the month and the VIX at the end of the month, which ignores the possible effect of variations in the VIX during the month. Thus, the effect of changes in the VIX in a specific month on the returns in the same month must be interpreted carefully, as it provides only a rough indication of the correlation between changes in the VIX and future returns. Moreover, we should take into account that there might be simultaneous effects between the excess returns of Portfolio 5 over Portfolio 1 and changes in the VIX in the same months. In other words, $\ln\left(\frac{VIX_{t+1}}{VIX_t}\right)$ affects Y_{t+1}, but also vice versa.

For robustness purposes, we also estimate the effects of changes in the VIX on Y_{t+1} using the two-stage least squares (2SLS) method. We choose the closing value of the VIX in the last month, VIX_t, as an instrumental variable for the rate of change in the VIX in the next month, $\ln\left(\frac{VIX_{t+1}}{VIX_t}\right)$. The logic behind this instrumental variable is that the VIX has a mean-reverting property (Psychoyios, Dotsis, & Markellos, 2010). Thus, generally speaking, we expect that a high value for the VIX in a specific month will be followed by a decrease in the VIX, and vice versa. After we estimate $\ln\left(\frac{VIX_{t+1}}{VIX_t}\right)$, using the reduced-form equation, we estimate the following regression:

Table 5
Estimation Results of Eq. (7).

	Coefficient	Prob.
Constant	0.001	0.000
	[6.4]	
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$	−0.004	0.000
	[−3.8]	
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right)$	0.0002	0.79
	[0.26]	
Z_t	0.43	0.000
	[8.67]	
Adjusted R^2	0.21	
F-Statistic	29.54	0.000

Notes: For every month, we sort U.S. firms into quintile value-weighted portfolios, using the same procedure used in Ang et al. (2006) (see Eq. (1)). We then regress the estimated alpha of the portfolio with the highest idiosyncratic volatility stocks over the estimated alpha portfolio with the lowest idiosyncratic volatility stocks on a constant, the change in the closing value of the VIX in the previous month, the changes in the VIX in the current month and the difference in alphas in the previous month. We report the t-statistics in square brackets below each coefficient. The sample period is from February 1990 to December 2016. Eq. (7) is given by: $Z_{t+1} = c + \delta_1 \ln\left(\frac{VIX_t}{VIX_{t-1}}\right) + \delta_2 \ln\left(\frac{VIX_{t+1}}{VIX_t}\right) + \delta_3 Z_t + \varepsilon_t$.

$$Y_{t+1} = c + \beta_1 \ln\left(\frac{VIX_t}{VIX_{t-1}}\right) + \beta_2 \ln\left(\frac{\widehat{VIX}_{t+1}}{VIX_t}\right) + \beta_3 BW_t + u_t \tag{6}$$

where $\ln(\frac{\widehat{VIX}_{t+1}}{VIX_t})$ is the estimated rate of change in the VIX in the current month, derived from the reduced-form equation. If β_1 is still negative, we can conclude with confidence that the excess returns of the highest IVOL stocks are negatively affected by changes in the VIX in the previous month.

Table 3 also reports the coefficients of the regression in Eq. (6). As the table illustrates, considering simultaneous effects does not substantially change the result of the estimators. Given that the VIX represents one measure of the market's expectations about stock market volatility over the next 30-day period, this result supports the notion that an increase in the VIX in a specific month means that investors see a greater risk that the market will be volatile. As a result, they pull their money out of stocks they find risky, namely, high IVOL stocks.

Moreover, note that, unlike the alphas in Eq. (1), the excess returns are not risk-adjusted, meaning that, as Ang et al. (2009) note, these numbers do not take into account exposure to risk factors. In order to address this issue, we must investigate the relationship between changes in the VIX and the difference in the time-series alpha of Portfolio 5 over the alpha of Portfolio 1 with respect to the model built by Ang et al. (2006), as described in Eq. (1). These alphas are the estimates of α^i in Eq. (1). Thus, we built the following regression:

$$Z_{t+1} = c + \delta_1 \ln\left(\frac{VIX_t}{VIX_{t-1}}\right) + \delta_2 \ln\left(\frac{VIX_{t+1}}{VIX_t}\right) + \delta_3 Z_t + \varepsilon_t \tag{7}$$

in which Z_{t+1} is the difference in the time-series alpha of the value-weighted Portfolio 5 over that of the value-weighted Portfolio 1 in month t + 1 (the alphas are α^i, estimated from Eq. (1), Z_t is the difference in alpha in month t, and VIX_t is the closing value of the VIX in month t. The expression $\left(\frac{VIX_t}{VIX_{t-1}}\right)$ is the rate of change in the VIX computed using the closing value of the VIX in month t and the closing value in month t − 1, and ε_t is the residual from the regression. If δ_1 is negative, we can conclude with confidence that changes in the VIX negatively affect the difference in average returns between the extreme quintile portfolios sorted on IVOL in the next month.

For robustness purposes, we re-estimated Eqs. (4) and (5) with different, but related volatility indices. In Panel A of Table 4, we replaced the VIX (i.e., the 30-day forward looking Volatility Index) with the VIX3M, which captures the 3-month implied volatility of the S&P 500. In Panel B, we regressed Y against the CBOE mid-term implied volatility Index (VIXMT), which is a 6-month volatility index. The overall picture remained the same and even improved, as indicated by the increased adjusted-R^2 values and the strong statistical significance of the coefficients. The findings indicate that the effect found here is long term, and that part of the effect detected here can be attributed to the changing risk aversion of market participants.[7]

In Table 5, we report the estimation results of the regression in Eq. (7).

As the table illustrates, changes in the VIX in the previous month have a strong and statistically significant effect on the difference in the average returns of high IVOL stocks in the next month. An increase of 1% in the VIX in a specific month results in a decrease of

[7] We would like to thank an anonymous referee for raising this point.

Table 6
Estimation Results of Eq. (8) and Eq. (9).

	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	% of observations that exceeded the threshold
Panel A- Estimations Results of Eq. (8)						
Constant	−0.000	−0.002	−0.005	−0.005	−0.006	
	[−0.1]	[−0.59]	[−1.1]	[−1.25]	[−1.42]	
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) > 10\%$	−0.026**					25.15%
	[−2.58]					
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) > 20\%$		−0.032**				13.04%
		[−2.51]				
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) > 30\%$			−0.032*			6.2%
			[−1.79]			
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) > 40\%$				−0.079**		1.86%
				[−2.43]		
$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) > 50\%$					−0.081*	0.9%
					[−1.77]	
R^2	0.02	0.02	0.01	0.018	0.01	
Panel B - Estimations Results of Eq. (9)						
Constant	0.005	0.001	−0.004	−0.005	−0.006	
	[1.11]	[0.24]	[−0.87]	[−1.24]	[−1.37]	
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right) > 10\%$	−0.05***					25.15%
	[−5.06]					
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right) > 20\%$		−0.062***				13.04%
		[−4.94]				
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right) > 30\%$			−0.05***			6.2%
			[−2.76]			
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right) > 40\%$				−0.08**		1.86%
				[−2.5]		
$\ln\left(\frac{VIX_{t+1}}{VIX_t}\right) > 50\%$					−0.106**	0.9%
					[−2.33]	
R^2	0.074	0.071	0.023	0.019	0.017	

Notes: The table reports the estimation results of Eqs. (8) and (9). Panel A reports the results of Eq. (8) and Panel B report the results of Eq. (9). The left column denotes the dummy variable capturing the rate of change in VIX. The numbers in parenthesis are the t-statistics. The asterisks (***, ** and *) indicate statistical significance at the 1%, 5% and 10% levels, respectively. Eq. (8) is given by: $Y_{t+1} = c + \beta \cdot DM_t + u_t$, while Eq. (9) is: $Y_{t+1} = c + \beta \cdot DM_{t+1} + u_t$.

~0.004% in the average returns of Portfolio 5 over Portfolio 1 in the following month. This result reinforces those in the previous regressions by suggesting that the VIX also negatively affects the average returns of high IVOL stocks, even when taking into account exposure to risk factors.

For robustness considerations, we also investigate whether the *increase* in the VIX above a certain percentage has an effect on the relationship between IVOL and future returns. Thus, we estimate the following equation:

$$Y_{t+1} = c + \beta \cdot DM_{t+1} + u_t \tag{8}$$

where DM_t is a dummy variable that receives the value of 1 if the expression $ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$ is higher than a certain threshold level, and 0 otherwise. In our analysis, we use the following thresholds: 10%, 20%, 30%, 40% and 50%. We report the results of Eq. (8) in Panel A of Table 6. As the results indicate, an increase in the VIX above the threshold increases the negativity of the relationship between IVOL and future returns.

Moreover, it seems that a higher threshold level results in a stronger effect on Y_{t+1}, suggesting that the effect of increase in the VIX is not limited to small changes only. In a similar way, we also estimate whether Y_{t+1} is affected by a contemporaneous increase in the VIX above certain level:

$$Y_{t+1} = c + \beta \cdot DM_{t+1} + u_t \tag{9}$$

where DM_{t+1} is the dummy variable as defined above. Panel B of Table 6 reports the results of Eq. (9). As is evident, the results are similar to those of Eq. (8), suggesting that our results are robust and that the VIX plays a significant role in the relationship between IVOL and future returns.

5. Conclusion

Previous research has provided contradictory conclusions as to whether idiosyncratic volatility has a positive or negative impact on stock returns. Furthermore, the reasons behind such possible effects are still unclear. Using U.S. data for 1990–2016, we establish that the effect is not constant over time and that it is negatively correlated with changes in the VIX. Our findings indicate that in periods associated with an increase in the VIX, idiosyncratic volatility has a negative effect on future stock returns, while in periods associated with a decrease in the VIX, idiosyncratic volatility has a positive effect on future stock returns. This result suggests that the effect of IVOL on stock returns may not be unidirectional. In other words, claiming that IVOL invariably affects stock returns over time (positively or negatively) may be an oversimplification of a complicated reality. Adopting the view of some of the research literature that the VIX reflects investors' risk preferences, we raise the possibility that the effect of the VIX on the excess returns of high idiosyncratic volatility stocks over low idiosyncratic volatility stocks may be rooted in investors' tendency to balance and reduce their portfolios' volatility. In other words, investors will trade high IVOL stocks for low IVOL stocks. By doing so, they increase the price of the latter, compared to the former, and strengthen the negative relationship between IVOL and returns.

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