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Explaining Idiosyncratic Volatility Puzzle and Lottery-Like Stock with Extreme Returns: Evidence from Pakistani Stock Market

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Abstract

This paper explores the role of idiosyncratic volatility in creating unexpectedly high levels of returns' volatility in the case of Pakistani stock market. This study further conducts an analysis of the Pakistani stock market as there has been much discussion about the existence of a pervasive idiosyncratic volatility puzzle., The study implemented the Fama-French six-factor model to the data of common stocks traded on the Pakistan Stock Exchange between the time period of 2003 to 2020, in order to quantify idiosyncratic volatility. The expected return is then investigated as a possible explanation for the anomalous volatility. The authors discover that individual stock price swings are strongly linked to predicted returns. As the company-level factors have a strong explanatory power when it comes to explaining idiosyncratic volatility for equity returns. Based on the findings of this study, we can conclude that the expected returns for firms with strong idiosyncratic volatility are extraordinarily high, and this problem disappears once firm-level factors are taken into account. Additionally, it is found that stocks with high skewness and high idiosyncratic volatility have underperformed the market over almost two decades. Overall, our results imply that the mystery emerges because highly volatile equities are overvalued and then undergo a subsequent correction because of their high max effect/lottery properties. Investment lottery preferences and market frictions have been cited in the literature as possible causes of idiosyncratic volatility. An expected return plays the role of a proxy for the over-valuation of stock returns and hints towards the relevance of idiosyncratic volatility in solving the idiosyncratic volatility puzzle.

Keywords: Idiosyncratic volatility puzzle, Expected return, Over-valuation, Anomaly

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Introduction

Over the last decade, investors have noticed a noticeable increase in the popularity of low-volatility trading strategies. One of the most complex aspects of different return volatility measures is idiosyncratic volatility (IVOL) (Annaert et al., 2013; Bali et al., 2011; Hou et al., 2011). Ang et al. (2009) (AHXZ hereafter) analyzed the stock markets of 23 developed nations, including the United States, and found that companies with higher levels of idiosyncratic volatility had significantly lower returns over time. Suppose an investor wants to compensate for their inability to diversify risk. In that case, he or she desires a premium for holding stocks with high idiosyncratic volatility. However, most financial economic models argue that only systematic risk influences asset returns, creating the so-called "idiosyncratic volatility puzzle." This disturbing empirical fact has prompted a plethora of studies aimed at deciphering the motivations behind the mystery. Individual stock market fluctuations positively correlate with stock market returns across countries (Ang et al., 2006). Those who believe that investors are risk-averse and that there is a positive risk-return relationship will find a real market situation totally contradicting the traditional asset pricing theory (Merton, 1987).

A large number of previous research used subsample testing to investigate the puzzle of idiosyncratic volatility (IVOL) in the stock market. They all came to the same conclusion: some equities are mostly responsible for the positive IVOL-return link (Aharoni et al., 2013). The IVOL-return relation, for instance, is found to be negative for overpriced stocks but favorable for underpriced equities (Li et al., 2020). An Ang et al. (2006) found that high idiosyncratic volatility predicted very poor average returns in a cross-section of stocks in the following month. Since then, financial economists have been searching for various explanations of an anomalous relationship between idiosyncratic risk and stock returns. Fu, (2009) found that idiosyncratic risk evolves with time. While measuring idiosyncratic volatility with EGARCH, he also discovered a link between idiosyncratic risk and expected returns. According to Bali et al. (2011) findings do not remain the same while emplyong different types of data filters.

Jegadeesh and Titman (1993) explore that reversals in monthly stock returns are responsible for the majority of AHXZ's outcomes. Mitton and

Vorkink (2007) show that the optimistic association is drastically dampened when expected skewness is considered. Existing literature seeks various solutions to the issue despite concerns raised in these publications related to the dependability of the AHXZ findings. Idiosyncratic volatility has a paradoxical positive relationship with subsequent stock performance, which can attract investors' attention.

Since Kahneman and Tversky (1979) first coined the term "investor attention" in 1979, numerous studies have examined it (Bainbridge & Galagedera, 2009; Cheon & Lee, 2017; Nartea et al., 2011; Schneider et al., 2017), in compliance with the finding of these papers, investors' limited attention compels them to make shortcuts that in turn have an impact on asset price. Short selling as an arbitrage method is costly; undervalued stocks are more likely to be overpriced now and thus produce poorer future profits. Even though there is a negative correlation between idiosyncratic volatility and stock returns, this relationship is likely to be more pronounced among equities that receive little investor attention. Whenever there is an increase in idiosyncratic volatility, there is a curiously favorable relationship between that increase and stock performance.

The origins of the abnormality can be uncovered by delivering into this issue. The research look at this issue and how it relates to investors' split attention between this month's trading days and the months to come (Stambaugh et al., 2015). The outcomes are similar, whether abnormal returns are calculated using the (Fama & French, 2018) Fama and French six-factor model or some other model, and whether or not additional return predictors are used. Several factors are taken into consideration while developing the model. Furthermore, the evidence suggests that prospect theory may account for this result if the expected return is considered to be the reference point. In accordance with the prospect hypothesis, investors are more likely to be risk-seeking rather than being risk-averse after a loss relative to a benchmark.

This study advances the work of Gu et al. (2018) into two ways. We provide evidence that does not originate from a sample by linking expected returns to the idiosyncratic volatility puzzle in an emerging market. As we demonstrate in this paper, IVOL return is negative among equities with negative abnormal returns (alpha 0), while it is positive for equities that have positive abnormal returns (alpha > 0) (Lee & Mauck, 2016). A sample of the data used in this study is drawn from the Pakistani stock market.

Based on the results of this research, we find that increasing trading volume is an effective method of determining what is causing the idiosyncratic volatility of emerging markets. Furthermore, we find direct evidence that expected return could be used as an indicator of overvaluation and a better understanding of the theory that an idiosyncratic volatility anomaly occurs when stocks with high levels of idiosyncratic volatility are overvalued and subsequently corrected. There is a growing body of knowledge about the peculiar volatility of emerging markets as a result of this study.

Literature Review

Stock returns cause increase in upper or lower static limits, and thus idiosyncratic volatility rises (Bozhkov et al., 2020) in the Chinese stock market. According to Liu et al. (2018), publicly traded companies significantly decrease idiosyncratic risk. When the maximum daily return of the five largest emerging African stock markets is considered, the positive relationship between idiosyncratic volatility and return disappears (Qadan et al., 2019). In contrast, Kőszegi and Rabin (2007) develop a new model of reference-dependent behavior wherein, endogenously, the reference points are expressed as laggardly rational expectations, a hypothesis supported by several empirical studies. In Umutlu (2019), the authors demonstrate that determining the optimal asset allocation requires understanding the reference point. The positive (negative) irregular returns might be seen if investors use expected returns as their benchmarks (losses).

This study anticipates the possibility of a negative risk-return relationship in the future. On the other hand, if we look at stocks that have exhibited positive abnormal returns, then it is likely that the risk-return relationship will be positive as well. The relationship between IVOL and return may not be the same as the relationship between risk and return because IVOL only measures firm-specific risk and does not represent total risk (Fenner et al., 2020). This study demonstrates that the "prospect theory value" (PT value) for higher IVOL stocks is higher (lower) for investors who have experienced losses in the past (gains) (Liu, 2022). Additionally, Barberis et al. (2016) provide evidence that stocks with greater PT values will experience worse returns. There is a positive correlation between IVOL and returns in the domains of gains and losses, consistent with the positive IVOL-return relationship in the domains of losses and gains for stocks with positive alpha.

This study makes several contributions to the literature. A positive correlation between IVOL and return only exists for stocks with positive anomalous returns. Gu et al. (2018) found that firms with a history of investor losses have a much stronger positive risk-return relationship. Second, according to our analysis, the prospect theory can be used to comprehend the idiosyncratic volatility conundrum. Even though there are a variety of known solutions to the idiosyncratic volatility puzzle, none explain more than 5% of the puzzle (Hou & Loh, 2016). Our research provides a perspective to help understand this phenomenon. Third, we use data from the Pakistani stock market, a significant emerging equitymarket, to arrive at a solid conclusion. Since the Pakistan stock market has more individual investors, ore weight is given to investors' irrational conduct when determining asset prices. Investors and authorities in Pakistani and other emerging economies can learn from the findings of this study.

Data and Methodology

Our sample consists of data from the "Data stream" financial research database, including the latest stock return and balance sheet information for all listed firms on the Pakistan Stock Exchange (PSX). The time range covered by the data set is January 2003 to December 2020. In order to have adequate data to compute the six factors of Fama-French components (Fama & French, 2018), we exclude the companies having incomplete balance sheet information.

Idiosyncratic Volatility

Identification of the idiosyncratic volatility (IVOL) of a stock can be done by looking at the standard deviation of the residuals from a six-factor analysis performed (Fama & French, 2018), expanding on the work of (Ang et al., 2006). The idiosyncratic volatility of stock *i* is estimated by looking at the daily stock returns over the past month that have occurred for each month *t*. As a result, a residual estimate can be obtained by using the following Eq:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i mkt_{i,d} + s_i SMB_{i,d} + h_i HML_{i,d} + c_i CMA_{i,d} + r_i RMW_{i,d} + m_i WML_{i,d} + \varepsilon_{i,d}$$

In the above equation where $R_{i,t}$ is the stock *i*'s daily return for the given stocks, $R_{f,t}$ is the risk-free daily rate of the return. All the given factors are in line with the Fama-French six factors model to explain the daily stock returns. Based on the data from Pakistani stocks, the six factors are calculated in the same way that (Fama & French, 2018) did in their study. Standard deviation of residuals is calculated in order to determine the IVOL of month *t*. Based on daily stock returns over the previous month, we estimate the idiosyncratic volatility of stock *i* for each month *t* based on the stock returns during the previous month. For the purpose of calculating IVOL, when following (Fu, 2009), it is essential that we have at least 15 trading days with a daily return as well as a non-zero trading volume every month in order to calculate the daily return.

$$IVOL_{i,t} = std(\varepsilon_{i,d})$$

Abnormal Returns

In factor asset pricing models, abnormal returns are calculated using the regression intercept of the factor asset pricing model (also known as alpha). The time frame used in the estimate is comparable to that used in the IVOL calculation (Lee & Mauck, 2016; Li et al., 2020). To be more precise, we use the daily stock returns over the last month to estimate the abnormal return of stock *i* for each month *t*. As a precaution, three models are utilized to estimate the abnormal return using Fama and French six-factor model. In addition, we demand at least 15 trading days in a month for computing alpha.

Control Variables

The Fama-MacBeth regression, controls for several factors related to company characteristics. All these numbers/factors are calculated once a month. The market cap (in billions of Rupees) at the end of the month is used as a proxy for size. Book equity as of the most recent fiscal year in year *t -1* divided by market equity as of December in year *t -1* yields the book-to-market ratio for that month, denoted by BM. Turnover measures the market's activity by comparing the monthly volume of trades to the monthly average number of outstanding shares. Momentum is calculated by adding the returns of the previous 12 months and subtracting those from the returns of the previous month, with the addition of a one-month lag to account for any reversals. In order to calculate "ISKEW," the idiosyncratic skewness of the returns over the past three months is taken into account; two factors are included in the model, the excess market returns and the squared excess market returns.

Empirical Results and Discussion

We start by analyzing the data to examine if Pakistan is a good candidate for the idiosyncratic volatility problem. Stocks are monthly Quintile-divided by IVOL. Table 1 displays the firm-level characteristics summary statistics. We off through stocks in the lower and upper 1% of idiosyncratic monthly volatility every month. The average volatility is 17.3 percent, with the median being 12.41 percent. Irregular idiosyncratic skewness is 8.73 percent on average, in the middle and 0.07 as a median. Panel B in Table 1 shows that the lottery feature index anomaly is sizable for both equal- and value-weighted portfolios. As a preliminary step, we employ the full data set to verify if Pakistan's idiosyncratic volatility paradox is indeed present. Every month, equities are divided into quintiles score.

Panel A shows the monthly descriptive statistics and percentiles of lottery features and firm-specific characteristics for the sample stocks from 2003 to 2020. In panel B, Stocks are sorted based on lottery features (IVOLT, ISKEN, MAX (1), MAX (5), and Price). The average value in portfolio 1 contains stocks with the weakest lottery-like, and portfolio 5 contains the strongest lottery-like stocks. The panel presents the Pearson correlation among the variables. The total monthly sample was 108,041 (observations) from 2003 to 2020.

Table 1
Descriptive Analysis

Panel A: Lottery features firm-specific							
	Mean	*SD*	Quintiles				
			Min	.25	Median	.75	Max
Ivolt-FF6(%)	17.3	26.12	0.79	6.34	12.14	24.98	98.86
Tvol-FF6(%)	21.34	28.67	0.74	9.14	16.46	28.43	103.69
ISKEN	8.73	8.21	-4.47	-0.34	0.07	0.487	4.48
TSKEN	0.23	0.82	-4.48	-0.40	0.02	0.43	4.49
Price (ln)	1.06	0.91	-3.77	0.46	0.89	1.50	10.1
Max (1) %	2.76	7.05	-0.07	1.07	1.90	3.59	307.59
Max (5) %	1.55	1.83	-0.59	0.67	1.16	2.10	615.71
LOTT	1.26	1.27	-6.40	0.49	1.15	1.94	117.88
Size (ln)	5.71	2.44	-8.48	4.44	5.74	7.18	12.50
BM	-6.29	1.89	-13.78	-7.55	-6.32	-5.13	2.70

	Mean	*SD*	Quintiles				
			Min	.25	Median	.75	Max
Reversal (%)	.64	9.55	-97.05	-2.40	0.25	3.31	287.72
Momentum	7.78	32.57	-167.17	-4.89	4.60	18.50	286.74
Turnover	-2.42	3.16	-15.54	-4.28	-3.12	-1.86	16.44
Illiquidity	-0.17	4.41	-30.94	-2.81	0.23	2.94	14.83

Panel B: Average Values of Lottery Features in five-Quintiles with Lottery-Feature Index

Quintile Portfolio	LOTT (%)	IVOLT (%)	ISKEN	Price	MAX (1)	MAX (5)
Weakest-1	.479	6.3	-.349	.467	1.064	.677
2	.934	9.5	-.055	.741	1.561	.976
3	1.382	16.3	.193	1.067	2.372	1.422
4	1.953	24.3	.488	1.512	3.639	2.112
Strongest-5	3.24	44.4	1.269	2.587	7.41	3.806

Panel C: Pearson Correlation

	IVOLT	ISKEN	Price	Max (1)	Max (5)	LOTT	Size	BM	Turnover
ISKEN	0.098								
PRICE	-0.141	0.001							
Max (1)	0.843	0.441	-0.084						
Max (5)	0.849	0.288	-0.064	0.878					
LOTT	0.050	0.579	0.809	0.275	0.207				
Size	-0.221	-0.010	0.249	-0.153	-0.065	0.176			
BM	0.116	-0.019	0.335	0.081	0.006	0.277	-0.743		
Turnover	-0.053	0.022	-0.172	-0.021	0.028	-0.134	0.262	-0.35	
Illiquidity	0.227	-0.004	-0.054	0.160	0.093	-0.022	-0.642	0.57	-0.823

Furthermore, there is an average raw return of 3.07 percent per month from a zero-cost equal-weighted portfolio with a monthly allocation to the top quintile and a monthly allocation to the bottom quintile, as shown in Figure 2 panel A. According to Newey and West (1987) t-statistics, this result is statistically significant: portfolios exhibit pronouncedly positive Fama-French six-factor alpha. A zero-cost, equally weighted portfolio with long holdings in the top quantiles and short positions in the bottom quantiles yields an average raw return of 3.62 percent each month.

From these results it can be concluded that small companies are more likely to experience the IVOL anomaly and that IVOL-return correlations are stronger for equal-weighted portfolios than for value-weighted portfolios (Table 2 panel B). A portfolio with equal weights in the top 5 IVOL quintiles will produce raw returns ranging from 3.11 percent in the lowest IVOL quantile to 7.31 percent in the highest IVOL quantile, with a nearly monotonous increase in between. Value-weighted portfolios, however, initially have raw returns of 9.89 percent loss in lower quantile before peaking at 24.64 percent loss for quantile 5, then falling to 5.37 percent for the highest IVOL quantile in equal weighted alpha. Furthermore, the risk-adjusted alphas show the same regularity as the unadjusted alphas when compared.

Idiosyncratic Volatility and Expected Stock Return

Essentially, this study aims to determine whether there is any relationship between IVOL and return and whether there are distinguishable IVOL-return connections between stocks with positive abnormal returns and stocks with negative abnormal returns. In order to categorize stocks in each month, we compare the direction of their anomalous returns from the previous month with the direction of their anomalous returns from the current month. This study further uses the preceding month's IVOL to categorize businesses into 5 quantile portfolios.

The raw returns of the portfolios, equal and value weighted returns, and risk-adjusted returns are calculated after the portfolios have been held for a month. For each IVOL quantile portfolio the risk-adjusted returns and the returns for each IVOL quantile portfolio are shown in Table 3 (Fama-French SIX-factor alpha). Looking at Panel B, Table 2, it is clear that stocks within the "positive alpha subsample" are more likely to have a higher level of idiosyncratic volatility, which will lead to higher raw returns and higher risk-adjusted returns, as shown in Table 2. If we were to construct a zero-cost, an equally weighted portfolio where long holdings were in the top quantile and short holdings were in the bottom quantile, and then it would generate an average raw return of 2.43 percent every month if it had long positions in the top quantile and short positions in the bottom quantile. (Newey & West, 1987) t-statistic of 11.88 adds to the significance. In this study, we have found that both the equal-weighted and value-weighted portfolios have significantly higher raw returns than the Fama-French SIX-factor alpha portfolios.

Table 2 reports quantile regression (portfolios analysis) estimates for average raw return and risk-adjusted return measured by six-factor alphas in future month t+1 in percentage. The stocks are sorted based on lottery features (ivolt, isken, price, max (1), and lottery feature index (LOTT) in month t. Portfolio 1(weakest) represents the stock with weak lottery feature stocks, and portfolio 5 (strongest) represents the stocks with the strongest lottery feature stocks. The equal-weighted portfolio is weighted as the equal number of firms-month, and the firm's market capitalization weights value-weighted portfolios at the end of each month t. The total monthly sample was 108.041 (observations) from 2003 to 2020. The values in parentheses are robust standard error, and * represents the statistical significance of conditional path coefficients at *** p <.001, ** p <.01, * p <.05.

Table 2

Quantile Regression

Panel A: sorted by Lottery Feature Index				
Quantiles	Raw return Equal weighted	Raw return Value weighted	FF6- Equal-weighted alpha	FF6- Value-weighted alpha
First Quintile	.0307***	.0943***	.0769***	.0253***
	(.0049)	(.0027)	(.0047)	(.0078)
Second Quintile	.0210***	.1261***	.0387***	.0329***
	(.0046)	(.0027)	(.0049)	(.0077)
Third Quintile	.0321***	.1517***	.0920***	.0396***
	(.0083)	(.0027)	(.0058)	(.0077)
Forth Quintile	.0329***	.1945***	.0772***	.0473***
	(.0051)	(.0028)	(.0053)	(.0077)
Five Quintile	.0362***	.2849***	.0734***	.0621***
	(.0096)	(.0048)	(.0098)	(.0076)
Panel B: sorted by Idiosyncratic Volatility				
Quantiles	Raw return Equal weighted	Raw return Value weighted	FF6- Equal-weighted alpha	FF6- Value-weighted alpha
First Quintile	-.0103***	-.0318***	-.0989***	-.0214***
	(.0009)	(.0023)	(.0064)	(.0018)

Quantiles	Raw return Equal weighted	Raw return Value weighted	FF6- Equal-weighted alpha	FF6- Value-weighted alpha
Second Quintile	-.0355***	-.0358***	-.1171***	-.0712***
	(.0012)	(.0028)	(.0066)	(.0235)
Third Quintile	.0134***	-.0714**	-.1365***	.0290***
	(.0016)	(.0034)	(.0068)	(.003)
Forth Quintile	.0229***	.0628	-.1373***	.0462***
	(.0022)	(.0047)	(.007)	(.0041)
Five Quintile	.0537***	.0731***	-.1664***	.0992***
	(.0054)	(.017)	(.0079)	(.0105)

Panel C: sorted by Prices

Quantiles	Raw return Equal weighted	Raw return Value weighted	FF6- Equal-weighted alpha	FF6- Value-weighted alpha
First Quintile	.0563***	.0347***	.0252***	.0353***
	(.0055)	(.0032)	(.0058)	(.0079)
Second Quintile	.0708***	.0425***	.0271***	.0396***
	(.0056)	(.0031)	(.0057)	(.0078)
Third Quintile	.0927***	.0488***	.0333***	.0488***
	(.0057)	(.0031)	(.0058)	(.0078)
Forth Quintile	.1064***	.0511***	.0348***	.0499***
	(.0064)	(.0031)	(.0078)	(.0077)
Five Quintile	.1224***	.057***	.0772***	.0725***
	(.0077)	(.0049)	(.0091)	(.0074)

Panel D: sorted by MAX Effect

Quantiles	Raw return Equal weighted	Raw return Value weighted	FF6- Equal-weighted alpha	FF6- Value-weighted alpha
First Quintile	.0654***	.0346***	.0504***	.0118***
	(.0215)	(.0012)	(.020)	(.007)

Quantiles	Raw return Equal weighted	Raw return Value weighted	FF6- Equal-weighted alpha	FF6- Value-weighted alpha
Second Quintile	.0606***	.032***	.0659***	.0101***
	(.0256)	(.0015)	(.015)	(.0071)
Third Quintile	.0819***	.0418***	.0779***	-.0003
	(.0338)	(.0019)	(.031)	(.0073)
Forth Quintile	.1333***	.1121***	.158***	-.0369***
	(.0417)	(.0023)	(.0448)	(.0074)
Five Quintile	.1441***	.2955***	.3594***	.1492***
	(.021)	(.0052)	(.103)	(.008)

Panel E: sorted by Idiosyncratic Skewness

Quantiles	Raw return Equal weighted	Raw return Value weighted	FF6- Equal-weighted alpha	FF6- Value-weighted alpha
First Quintile	.0524***	.0351***	.1005***	.0387***
	(.009)	(.0015)	(.0285)	(.0072)
Second Quintile	.0616***	.0526***	.1278***	.052***
	(.0211)	(.0017)	(.0329)	(.0071)
Third Quintile	.0765***	.0481***	.1668***	.0632***
	(.0236)	(.002)	(.0375)	(.0073)
Forth Quintile	.1233***	.1436***	.1689***	.0972***
	(.0393)	(.0022)	(.0429)	(.0074)
Five Quintile	.1987***	.3856***	.1989***	.1231***
	(.015)	(.0051)	(.032)	(.0078)

Table 2 and Panel E reveals that returns from high-ISKEW stocks are 400 basis points more each month than returns from low-ISKEW equities within the "positive alpha subsample." Table 2 panel D also shows that as the MAX effect increases, returns and risk-adjusted returns fall for companies with high alpha. The sign of the prior month's expected returns might stand in for profits or losses if we use the baseline of expected returns as a bench mark. The prospect hypothesis states that traders are more risk-averse after experiencing a profit and risk-seeking after suffering a loss. As a result, there must be a distinct difference between the IVOL-return relationships of the factor model alpha and expected future returns (Rosenberg et al., 1985; Walkshäusl, 2014).

As a robustness check, we know why idiosyncratic volatility positively correlates with a return across the board. It was found that Fama-Macbeth Regressions can be used to put together a causal link between IVOL and stock returns after adjusting for other return predictor factors. Additionally, we perform Fama-MacBeth regression analysis in order to analyze the relationship between IVOL and stock returns while controlling for other variables that could affect the returns. Tabular data from the following Fama-MacBeth regressions are shown in Table 3. The monthly percentage returns on individual stocks in the month after month t, the month. Several control variables were selected to be included with IVOL as independent variables, including idiosyncratic skewness, momentum, and market cap as control variables.

Table 3 presents the estimation results of the Fama-MacBeth cross-sectional regression analysis of lottery-features stocks with stock return in future month t+1 as the dependent variable in percentage. All other independent and control variables are used at the end of the month t. The total monthly sample was 108,041 (observations) from 2003 to 2020. The values in parentheses are robust standard error, and ***, **, and * represent the statistical significance of path coefficients at *** $p < .001$, ** $p < .01$, * $p < .05$.

Table 3

Fama-Macbeth Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	.053***	-.143***	-.185***	.061***	.06***	-.165***	-.17***	-.172***
	(.02)	(.018)	(.018)	(.02)	(.019)	(.012)	(.012)	(.013)
IVOL_t	.151***						.086***	-.007
	(.008)						(.008)	(.006)
ISKEN_t		.015***					.009***	.008***
		(.001)					(.001)	(.001)
$\mathrm{MAX}\ (1)_t$			.913***				.399***	
			(.047)				(.063)	
$\mathrm{MAX}\ (5)_t$				.443***				2.241***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				(.115)				(.105)
Ln_Price_t					.013***		.009***	.006***
					(.001)		(.001)	(.001)
$LOTT_t$						.015***		
						(.001)		
Mkt_B_t	.245***	.409***	.094	-.021	.414***	.335***	.119	-.016
	(.061)	(.063)	(.084)	(.061)	(.065)	(.06)	(.086)	(.066)
$MOMENTUM_t$	.007***	.005***	.007***	.006***	-.003*	-.003**	.002*	.002*
	(.001)	(.001)	(.001)	(.001)	(.001)	(.002)	(.001)	(.001)
Ln_Illiq_t	.001	.003***	(.001)	-.001	.004***	.003***	.001	-.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Ln_Turn_t	.001**	.004***	.001	-.001*	.007***	.006***	.002***	(.001)
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Ln_BM_t	.003***	.002***	.003***	.003***	-.003***	-.004***	-.001	(.001)
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Ln_Size_t	.006***	.006***	.004***	.002	.001	-.002	.001	-.001
	(.002)	(.002)	(.002)	(.002)	(.001)	(.002)	(.001)	(.001)
$Reversal_t$	-.006	-.005	-.005	-.004	-.02**	-.017	-.014	-.011
	(.011)	(.013)	(.012)	(.011)	(.01)	(.012)	(.013)	(.013)
Avg_R^2	.111	.092	.131	.154	.074	.107	.156	.176

Note. Standard errors are reported in parenthesis.

The implementation of scaled monthly quantiles is described in Table 3 (Lee & Mauck, 2016). As it can be seen in Table 3, the IVOL coefficient is statistically and practically always positive for equities with positive alpha. It is, however, important to note that the IVOL coefficient is positively significant in all regression models when stocks have positive alphas. The volatilities lowest IVOL stocks and the highest IVOL stocks are chosen for purchase (Goyal & Santa-Clara, 2003; Guo & Savickas, 2010; Li et al., 2020; Liu et al., 2019).

Furthermore, there is a stronger association between positive IVOL return and positive alpha among companies with positive alpha. For stocks with positive alpha, the equal-weighted return, or return on invested capital, is generally greater than those with positive alpha. The latter takes precedence when comparing the positive IVOL-return connection between the positive alpha group and its subsample.

The empirical evidence from AHXZ conflicts with our empirical result that expected return is important for solving the challenge. After adjusting for expected return, they found that when they used US data, the idiosyncratic volatility puzzle was still present (Ang et al., 2006). As we analyze the Pakistani stock market, and our sample period differs from AHXZ, the empirical results appear to differ. In a similar vein, Lee and Mauck (2016) find that the expected return plays a significant role in understanding the difference between the returns of low and high-volatility stocks using the US stock market. Additionally, we utilize expected to return as a proxy for firm-level uncertainty, supported by empirical evidence, unlike (Ang et al., 2009), who views expected return as a proxy for liquidity. Moreover, we find empirical evidence that supports our interpretation (Aharoni et al., 2013; Asness et al., 2013; Avramov & Chordia, 2006; Cheon & Lee, 2017; Fong, 2014).

Conclusion

In this study, we investigate different IVOL-return relationships between stocks with negative and positive abnormal returns. The sorting method is used to determine the IVOL-return relationship. The study classifies the market's equities each month into bulls and bears according to the monthly anomalous returns. Stocks are categorized in each subsample into 5 quantile portfolios based on the IVOL from the previous month. Each portfolio's raw returns, risk-adjusted returns, equal-weighted returns, and value-weighted returns are calculated after it has been held for one month. The positive alpha equities experience gains, whereas positive beta stocks experience an increase in returns and risk-adjusted returns when IVOL increases. A month's worth of atypical returns can be utilized to estimate gains or losses if we use the expected rate of return as a benchmark. According to expected utility, investors are more risk-averse after suffering losses and more willing to take calculated chances after experiencing profits.

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