IDIOSYNCRATIC RISK IN THE SOUTH AFRICAN STOCK MARKET

by

CALEB SCROOBY

1830411

MASTER OF COMMERCE – (BUSINESS FINANCE)

in the

SCHOOL OF ECONOMICS AND FINANCE

at the

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

SUPERVISOR: Prof. DANIEL PAGE

SCHOOL OF ECONOMICS AND FINANCE

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Abstract

Traditional finance theory posits that risk and return are linearly related. Higher returns are to be expected with greater risks. Modern portfolio theory champions for diversification of portfolios, which reduces risks unique to a firm to zero. This unique risk is known as idiosyncratic risk.

Studies have come along and challenged the conventional wisdom in finance. Several studies have found that idiosyncratic risk is compensated for in many markets, partly due to poor diversification opportunities and partly because market risk alone is not sufficient to explain returns.

This study tests if lagged idiosyncratic risk is associated with stock returns in the South African stock market for the period between 2001 and 2022. The study examines if investors are compensated, through higher returns, for holding firm-specific risk, in a market where full diversification may not be possible. This study also adds to the ongoing discussion on the degree and importance of price anomalies in an emerging stock market as well as the impact of idiosyncratic risk in determining predicted stock returns.

This study utilizes a portfolio strategy that buys stocks with high idiosyncratic volatility and shorts stocks with low idiosyncratic volatility. The rationale for this is that if investors are compensated for assuming higher unsystematic risk, the alpha of this long-short portfolio should be positive and significant.

This study instead found the opposite, which is that the alpha's of these portfolios were negative and statistically significant. This suggests that investors who hold stocks with lower idiosyncratic volatility are compensated more than investors who hold stocks with higher idiosyncratic volatility. The robustness checks confirm this finding, as it was noted that portfolios continue to have statistically significant alphas following months of low volatility, with the long-short IVOL portfolios outperforming all other portfolios. The alphas remain negative and significant even when controlling for size and value in two-way sorts. Idiosyncratic volatility is therefore negatively related to stock returns, a puzzling result

Declaration

I, Caleb Scrooby, declare that this research paper is my own work and that I have correctly acknowledged the work of others. It is submitted to fulfill the requirements for the degree of Master of Commerce in Business Finance at the University of the Witwatersrand, Johannesburg. I declare that this research paper has not been submitted for any other degree or examination in this or any other institution.

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DEFINITIONS OF TERMS AND ABBREVIATIONS

ALSI	All Share Index
CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
FINDI	Financial Shares Index
G7	Top seven equity markets, which include Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom.
H_0	Null Hypothesis
H_1	Alternative Hypothesis
HML	High Minus Low
IVOL	Idiosyncratic Volatility
JSE	Johannesburg Stock Exchange
MILA	Latin American Integrated Market or Mercado Integrado Latinoamericano
P/E	Price-to-book ratio
RESI	Resource Shares Index
SMB	Small Minus Big
SML	Security Market Line
US	United States

1 INTRODUCTION

This section serves to introduce the research topic. It begins with providing a background on the topic at hand, which is idiosyncratic risk in general and in South Africa, on which the research focuses. The introduction also provides the objectives and benefits of the research. This section will also flesh out the hypotheses that will be used to test the research question, which is also provided in this section.

1.1 BACKGROUND

Modern portfolio theory as we know it was conceived by Markowitz (1952), which provided mathematical proof for the well-known sage advice that one must not put all their eggs into one basket. The paper showed that the risk of an asset can be measured using the variance of the returns. Markowitz (1952) further demonstrated a method for calculating the variance, and therefore the risk, of a portfolio of two or more assets. By demonstrating this, Markowitz (1952) further showed that diversification reduces the risk of a portfolio.

Sharpe (1964) built upon the foundation laid by Markowitz to create the Capital Asset Pricing Model (CAPM). The CAPM is a model of risk and return relationship, which espouses that risk and return have a positive linear relationship. Under the CAPM, beta is the sole measure of risk that investors are compensated for holding and represents the risk of the stock relative to the market. Beta is the only risk compensated because company-specific risk can be diversified away.

CAPM has experienced a troubled life. Early on, support for the CAPM was positive. Fama and MacBeth (1973) for instance are unable to reject the hypothesis that there is a positive and linear relationship between risk and return. Fama (1970) eventually concludes that markets are efficient and fully reflect all available information. However, several studies find anomalies that contradict the predictions of the CAPM. For instance, Basu (1977) finds a negative relationship between stock returns and price-to-book (P/E) ratios. Banz (1981) shows that small firms earn higher returns than large firms, even when beta is factored in. Fama and French (1992) tested the hypothesis that beta and returns are positively related, finding that this was only true for the period before 1969. Moreover, size and book-to-market ratios have significant negative and positive relationships respectively with stock returns.

The results of these studies illustrate that beta is not the only risk that is compensated. There may be a portion of individual stock returns not explained by beta. The conjecture is then that company-specific risk is not diversifiable and is priced into stock returns. This company-specific risk is known as idiosyncratic volatility (IVOL). A formal definition of IVOL is provided by Aabo, Pantzalis and Park (2017), who define it as: “Based on asset pricing models, idiosyncratic volatility measures the part of the variation in returns that cannot be explained by the particular asset-pricing model used.” (pg.1).

Therefore, according to the research cited above, market risk does not consistently account for the variation in the level of uncertainty surrounding a single stock over time. Rather than a single factor explaining returns, multiple elements can explain the variation in returns, including idiosyncratic volatility. Although many studies internationally have covered idiosyncratic volatility, the literature is comparatively sparse for South African literature. Given the lack of depth and liquidity on the Johannesburg Stock Exchange (JSE), the level of diversification present is not ideal. Therefore, one would expect that idiosyncratic risk would be a significant-priced factor on the JSE. Therefore, this study sets out in the vein of Berggrun, Lizarzaburu and Cardona (2016) to test if idiosyncratic risk can explain future stock returns.

1.2 OBJECTIVES

1.2.1 Research objective

This study aims to provide additional insight into the relationship between idiosyncratic risk and future stock returns by studying the relationship in the South African stock market. This study follows a similar structure to that of Berggrun, Lizarza and Cardona (2016), who considered the association between idiosyncratic volatility (IVOL) and one-month ahead return in the Latin American Integrated Market or Mercado Integrado Latinoamericano (MILA). The authors concluded that they found no association between idiosyncratic volatility and stock returns in the integrated market. Drawing upon this conclusion, this study intends to evaluate whether the conclusion holds in the South African stock market and dives deeper into the association between idiosyncratic volatility and stock returns.

With the significant amount of literature on the topic, this study aims to add to the current body of literature and enable the reader to gain a better understanding of the relationship between idiosyncratic risk and returns in the South African stock market. There have been mixed views as to the relationship between idiosyncratic risk and returns but this study aims to provide additional insight into the relationship and discuss how this relationship acts in the South African stock market.

1.2.2 Research question

Idiosyncratic risk has been the core focus of many studies, where many have attempted to understand the role that idiosyncratic volatility has on stock returns, the results of most studies have found either a negative or positive relationship between idiosyncratic volatility and stock returns. This study will expand the current body of literature by looking at the association between idiosyncratic volatility and future stock returns on the Johannesburg Securities Exchange and answer the research question:

What relationship exists between idiosyncratic volatility and stock returns in the South African Stock Market?

1.3 HYPOTHESES

H_0: There is no relationship between idiosyncratic volatility and stock returns

H_1: There is a significant relationship between idiosyncratic volatility and stock returns

1.4 BENEFITS OF THE STUDY

Conducting this study on the JSE will prove to be a beneficial addition to the current body of literature due to the topical nature and unique landscape of the South African market. South African stocks tend to experience a great deal of volatility and whilst this study considers idiosyncratic volatility, it will give a sense as to the impact that idiosyncratic risk has on stock returns on the JSE.

This study will shed additional insight into the relationship between idiosyncratic volatility and stock returns on the JSE.

1.5 ORGANISATION OF THE STUDY

The study proceeds as follows; Section 2 gives a critical discussion and synthesis of the literature most relevant to the study. Following the literature review, Section 3 outlines the data and methodology employed by this study. Section 4 discusses the results in detail, which includes: findings from the investigation of the return-realized IVOL association based on one-way sorted portfolios to see if an investor might profit from them; the regression results used to assess whether there is a significant association between lagged IVOL and return; an analysis of the robustness of the findings from both the portfolio and regression analysis to determine the reliability of the results. Section 5 concludes the findings of this study.

2 LITERATURE REVIEW

This section reviews the relevant literature on idiosyncratic risk in both international and local markets. The purpose of this section is to give context to the research question, building up to the gaps identified that are being addressed by this study.

2.1 INTERNATIONAL LITERATURE

Modern portfolio theory was pioneered by Markowitz (1952), which specified the optimal method to select stocks into a portfolio, called the optimal portfolio. Firstly, Markowitz (1952) showed, crucially, that the risk of a stock can be measured by the standard deviation of its return. Using variance as a basis of risk, Markowitz (1952) developed a formula for deriving the variance of a portfolio of two or more risky assets.

Through this, Markowitz (1952) demonstrated that diversification reduces the risk of a portfolio. More correctly, each additional stock added that is less correlated with stocks in the portfolio eliminates the individual risk of the stocks to the point that only market risk remains. Through diversification, there exists a set of portfolios where there cannot be a higher return for the given level of risk such that the only way to get more returns is to take on correspondingly more risk. This set of portfolios is known as the efficient frontier.

Sharpe (1964) extended modern portfolio theory into the Capital Asset Pricing Model (CAPM). The CAPM is a model of the relationship of risk and returns for individual stocks. According to the CAPM, risk and return are linearly related, with returns increasing as risk increases. The CAPM states that beta is the sole measure of risk. Beta is a stock's relationship with the market, i.e. how the stock returns move with the market's returns. Therefore, high beta stocks have a higher expected return and vice versa. Market beta can be thought of as a multiplier effect. For example, if a stock's beta is 1.2, then it will be 20% more volatile than the market.

According to the CAPM, beta is the only risk that investors should get compensated for. This is because it cannot be diversified away. Beta captures the risk that all stocks face, therefore making it impossible to reduce the risk by adding another stock faced with the same risk. The CAPM assumes a risk-free asset that is uncorrelated with the market. Adding this asset increases expected return while decreasing overall risk. The CAPM is simple and intuitive. It is also theoretically sound. However, the CAPM is predicated on some heavy assumptions such as riskless borrowing and lending, perfect capital markets, and homogenous expectations amongst others. Neither of these is realistic, particularly the first three. The assumption of a risk-free asset is also unrealistic. However, Black (1972) developed a version of the CAPM called the zero-beta model. This model does not require a risk-free asset, it simply requires a risky portfolio that is uncorrelated with the market. This model requires that both the market portfolio and the zero-beta portfolio have minimum variance. The security market line will be affected because the return of the zero-beta portfolio would be higher than the risk-free rate. This leads to a flatter security market line. This partially explains why betas from empirical tests did not fit the theoretical SML.

Fama and MacBeth (1973) set out to test the hypothesis that risk and returns are linearly correlated. Fama and MacBeth (1973) developed a revolutionary approach to estimating betas, a method which is now known as Fama-MacBeth regressions. The aim of this two-step regression is to approximate the risk premium of the beta factors. The first step is to regress the historical returns of each asset on one or multiple pre-identified factors, which would be a market portfolio of some sort. The purpose of the model is to determine the risk premium associated with exposure to these risk factors. The second step (hence the name "two-step") is to regress the returns of each asset against the previously obtained betas. This is how the risk premium is obtained.

Fama and MacBeth (1973) fail to conclude that risk and return are not linearly related. They further state that the residuals of the coefficients are consistent with what one would expect from an efficient market. Therefore, individual risk or unique risk is not a priced factor, as predicted by the CAPM. This finding eventually culminates in the Efficient Market Hypothesis (EMH) espoused by Fama (1970), which states that stock prices fully reflect available information. As a result, one cannot earn abnormal profits using publicly available information. The only way to earn a higher return is to take on correspondingly more risk.

Since the ground-breaking work of Fama and MacBeth (1973), which demonstrated that idiosyncratic volatility (IVOL) is not a priced factor in the United States (in line with the predictions of the CAPM model of Sharpe (1964) and the three-factor model of Fama and French (1993)), several studies have tried to understand the role of IVOL (if any) in explaining one-period ahead returns. To date, there have been mixed findings as to the association between IVOL and future returns.

Empirically the CAPM has not held up well. Basu (1977) finds that there is an inverse relationship between stock returns and price-to-book (P/E) ratios. The paper shows that stocks with low P/E ratios experience greater ex-post returns than stocks with high P/E ratios, even after adjusting for beta. Banz (1981) finds that small firms outperform large firms even after accounting for beta. Fama and French (1992) tested the hypothesis that beta and returns are positively related, finding that this was only true for the period before 1969.

Shockingly, Fama and French (1992) find that there is a negative and significant relationship between market capitalisation (or size) and returns, and remains significant in the presence of other factors. Furthermore, they document that book-to-market ratios (or value) are positively related to average stock returns and are significant even in the presence of other variables. These two are known as the size and value premiums and remain significant when put simultaneously in a regression while other factors do not, including the previously significant factors like the P/E ratio.

These results are damaging to the CAPM because it predicts that beta is the only reason returns differ. These studies show that return variation can be explained by size, P/E ratios, and value proxied by book to market. Following this, Fama and French (1993) include these factors (minus P/E) in the CAPM to create their three-factor model. This model performs better than the CAPM, although they cannot explain why. They call their results "not economically satisfying" as they cannot think why size and value would be priced risk factors.

These studies show that there is a component of individual return that cannot be explained by factor models. There is some form of unique risk that is driving this return variation. This unique risk is called idiosyncratic volatility (IVOL). A more formal definition of IVOL is provided by Aabo *et al*., (2017), who define it as: "Based on asset pricing models, idiosyncratic volatility measures the part of the variation in returns that cannot be explained by the particular asset-pricing model used." (pg.1).

Factor models have been relatively poor at explaining both ex-ante and ex-post return variation. For instance, Roll (1988) shows that the R-squared values of asset pricing models on returns of US stocks are too low, averaging 20% using daily returns and 35% using monthly returns. This means that on average, factor-based models can only explain about 20 to 35 percent of the return variation in stocks. This implies that there is a component of stock returns that is unique to the firm (Roll, 1988).

The relationship between risk and return is not so straightforward in practice as Markowitz (1952), Sharpe (1964), and others put it. Malkiel (1981) finds that beta is not a good approximation of risk, showing that the agreement or lack thereof amongst analysts' forecasts explains return variation better than beta does. Malkiel (1981) shows that firms where analysts agree on future earnings and dividends appear to be less risky, consequently producing lower returns. On the other hand, firms with greater disagreement between analysts are riskier and have greater expected returns. This contradicts modern portfolio theory, which states that individual stock risk is not a priced factor.

Malkiel (1981) argues that the approach of one factor covering all risks affecting a firm is fundamentally flawed as no one factor can cover all the risks faced by a firm. Malkiel (1981) states that firms are susceptible to such as market movements, interest rate changes, inflation, national income, and other macroeconomic influences. Therefore, beta is not the winner for the best single proxy of risk, the dispersion of analyst forecasts fares better (Malkiel, 1981).

Malkiel and Xu (1997) ask if idiosyncratic volatility is a priced risk factor. The paper first shows that idiosyncratic volatility has been on an upward trajectory since the 1980s. Conversely, market volatility has been incredibly stagnant. Theoretically, this can be explained by the diversifiable nature of idiosyncratic risk, thus leaving market risk constant even if idiosyncratic risk is increasing. This would be in line with the predictions of the CAPM.

However, Malkiel and Xu (1997) find that there is a strong relationship between idiosyncratic volatility and firm size. Malkiel and Xu (1997) proxy for size through market capitalisation, while idiosyncratic volatility is the standard deviation of the residuals from the CAPM regression, a definition that is still used today. A slightly different version of this is used in this study and described in the methodology section of this study. The results show that as a firm gets larger, the stock's idiosyncratic volatility gets smaller. Therefore, Malkiel and Xu (1997) provide a possible explanation for the puzzling results of Fama and French (1992), which is that size is proxying for the firm's idiosyncratic volatility and is a clear and obvious priced factor.

Malkiel and Xu (1997) also point out that since portfolio managers must explain their investment decisions to a committee, they will demand for additional compensation for taking on individual stock risk. Based on this, it would seem then that it makes sense for idiosyncratic volatility to be priced in stock returns. Malkiel and Xu (1997) go against the conventional wisdom of the EMH, concluding that various risk premia exist for individual stocks beyond just market beta.

Malkiel and Xu (2000) argue that idiosyncratic volatility is important for stock returns in a world where some investors cannot buy the full market portfolio. As a result of this, diversification opportunities are much reduced for these investors, and therefore, idiosyncratic volatility will be priced by these investors. Similarly, Campbell, Lettau, Malkiel, and Xu (2001) show that the idiosyncratic component of a stock's risk has increased over time. Consequently, investors need to add increasingly more stocks to a portfolio to obtain the same amount of diversification as before. Empirically, Campbell *et al*., (2001) demonstrate that one would need 40 to 50 stocks in a portfolio to achieve the same amount of diversification provided by just 20 stocks in the 1960s.

Campbell *et al*., (2001) also propose a reason for the importance of idiosyncratic volatility. Firstly, many investors do not diversify their portfolios, some by personal choice, others due to circumstances such as being a company executive receiving compensation in the form of stock. Furthermore, idiosyncratic volatility represents, among other things, the information flow of individual firms, the human resource risk of individuals who are uniquely equipped to achieve the objectives of the firm, and firm debt levels (Campbell *et al*., 2001).

Campbell *et al*., (2001) also devise a method for calculating the cross-sectional average idiosyncratic volatility as opposed to the firm-level idiosyncratic volatility. In the traditional approach, the firm's market beta is obtained, by using the CAPM, or the market betas and Fama-French factors. Campbell *et al*., (2001) propose that when dealing with averages, the average market beta will be 1 if the weights used in the average betas are the same as the weights of the firms in the market index (Campbell *et al*., 2001).

Xu and Malkiel (2003) examine the changes in idiosyncratic volatility from 1952 onwards. Malkiel and Xu (2003) examine idiosyncratic volatility from 1952 onwards. The paper measures idiosyncratic volatility in one of two ways. The first approach is called the indirect decomposition method. The indirect decomposition method first defines the excess rate of return of the stock by subtracting the risk-free rate from the stock return. This excess return is then broken down into a systematic component and an idiosyncratic component. Correspondingly, the volatility of the excess return can be broken down into systematic volatility and idiosyncratic volatility. Building upon Campbell *et al*., (2001) logic on calculating average betas, Xu and Malkiel (2003) develop an approach to calculate aggregate idiosyncratic volatility. This is simply the difference between the aggregate volatility of the stocks in the market index and the volatility of the market index, where aggregate volatility is a weighted variance of stocks in the index, using the same weights as in the index, as do Campbell *et al*., (2001).

The second approach is known as the direct decomposition method. This method uses a typical asset pricing model. Xu and Malkiel (2003) specifically use the Fama-French three-factor model. The idiosyncratic volatility is the standard deviation of the residuals from this regression. The conditional aggregate idiosyncratic volatility is the weighted average of the variance of the residuals from the regression. Xu and Malkiel (2003) mention that the factor approach relies heavily on accurate estimations of betas, which is hard to do in short time frames, a valid criticism of deriving idiosyncratic volatilities using factor models.

Using the Fama and French (1993) three-factor model, Xu and Malkiel (2003) successfully constructed aggregate idiosyncratic volatility, which was used to derive several conclusions. One of these conclusions is that idiosyncratic volatility has increased over time. More importantly, they conclude that idiosyncratic volatility is positively related to expected earnings growth (Malkiel & Xu, 2003).

Angelidis and Tessaromatis (2008~~2006~~) examine the predictive power of different idiosyncratic risk measures using data from the UK market and provide evidence that small stock idiosyncratic volatility is important for asset pricing. Furthermore, small stock idiosyncratic volatility predicts the small capitalisation premium component of market returns and is unrelated to either the market or the value premium. Even accounting for the proxying effects of business cycle variations and liquidity, the predictive power of the aggregate idiosyncratic volatility of small stocks is still strong over time and across several econometric assumptions.

The study by Ang, Hodrick, Xing and Zhang (2009) state that around the world stocks that have had a recent past high idiosyncratic volatility tend to have much lower returns than stocks with past low idiosyncratic volatility. The authors take a look at the stocks across 23 countries, measuring idiosyncratic volatility using the Fama and French (1993) three-factor model. The authors conclude that stocks earning lower returns tend to have a higher level of idiosyncratic risk and this effect is observed worldwide. The authors provide proof that a large sample of developed international markets has a negative relationship between lagged idiosyncratic volatility and future average returns. Particularly, equities with high idiosyncratic volatility typically have low average returns for each of the top seven (G7) equity markets, which include Canada, France, Germany, Italy, Japan, the United States, and the United Kingdom. In each of these nations, the negative idiosyncratic volatility-average return relation is statistically significant. This relationship is also shown in the larger sample of 23 developed markets. It is difficult to blame the low returns on high-idiosyncratic-volatility stocks on a small-sample issue in light of these encouraging foreign outcomes. The second, and arguably most intriguing, contribution of this paper is that the spread between returns for U.S. equities with high and low idiosyncratic volatility strongly correlates with the negative spread between returns for stocks with high and low idiosyncratic volatility in international markets. The spread in returns between stocks with high and low idiosyncratic volatility across nations exhibits a significant degree of commonality in co-movement, suggesting that this effect is driven by broad, difficult-to-diversify variables. However, since the authors do not yet have a theoretical framework to explain why agents have a high demand for stocks with high idiosyncratic volatility, which results in these stocks having low expected returns, they do not claim that the low average returns to stocks with high idiosyncratic volatility represent a priced risk factor.

The authors discover that the idiosyncratic volatility effect in the United States co-moves strongly with the low returns earned by stocks with high idiosyncratic volatility globally. The alphas of portfolio strategies trading the idiosyncratic volatility effect in various international markets are particularly negligible after controlling for U.S. portfolios comprising long positions in stocks with high idiosyncratic volatility and short positions in stocks with low idiosyncratic volatility. Thus, a straightforward U.S. idiosyncratic volatility factor can account for the worldwide idiosyncratic volatility effect. In contrast, neither common causes nor risk loadings can account for the low returns of highly idiosyncratic stocks in global markets. The authors are hesitant to claim that exposure to systematic risk is to blame for the low returns on companies with high idiosyncratic volatility, though.

The study excluded comprehensive explanations based on trading or clientele structures, higher moments, and information transmission in their continued analysis of U.S. data. The lever-age interaction story of Johnson (2004) or future exposure to idiosyncratic volatility cannot account for the dismal returns of equities with historically high idiosyncratic volatility. Their impressive results across borders imply that market-specific narratives are similarly unlikely to hold up.

They conclude that the mystery of why stocks with significant idiosyncratic volatility have low returns is a widespread phenomenon. If there are real economic sources of risk underlying the idiosyncratic volatility phenomena that cause equities with high volatility to have low expected returns, further study is required.

Fu (2009) demonstrates that idiosyncratic volatilities vary with time and states that the study by Ang, Hodrick, Xing, and Zhang (2006) should not be utilized to infer a relationship between idiosyncratic risk and expected return. Fu (2009) discovers a considerably positive relationship between the estimated conditional idiosyncratic volatilities and expected returns using the exponential GARCH models to estimate predicted idiosyncratic volatilities. Fu (2009) explains that evidence points to the return reversal of a subset of small companies with strong idiosyncratic volatilities as the primary explanation for Ang *et al*., (2006) findings.

In 24 emerging markets, Angelidis (2010) investigates the characteristics and portfolio management implications of value-weighted idiosyncratic volatility. The argument presented in this paper refutes the idea that the growth in idiosyncratic risk is a universal phenomenon. The author states that there is a negative relationship between idiosyncratic volatility and stock returns.

Huang, Liu, Rhee and Zhang (2011) demonstrate that whether the portfolio contains stocks with extreme performance and whether the returns are computed over January or non-January months affects the relationship between idiosyncratic volatility and future stock returns. A positive correlation between idiosyncratic volatility and portfolio returns was observed in January as a result of the dominance of losing stocks in December and a reversal impact in the following month. The impact of previous winner stocks, on the other hand, predominates in other months, and a negative correlation is seen as a result of the return reversal of these winning stocks.

Peterson and Smedema (2011) demonstrate that non-January months have a strong negative relationship between realized idiosyncratic volatility, measured over the prior month, and returns. They demonstrate that the relationship between returns and predicted idiosyncratic volatility is positive and robust while controlling for realized idiosyncratic volatility. Idiosyncratic volatility, both actual and predicted, is a distinct and significant effect that describes the cross-section of returns. They discover that investor sentiment affects the negative return on a zero-investment portfolio that is long high realized idiosyncratic volatility equities and short low realized idiosyncratic volatility stocks. In cross-sectional studies, we discover that the negative relationship is higher for companies with a high dispersion of expert projections and weaker for stocks with a significant analyst following. Expected idiosyncratic volatility and returns have a positive relationship that is not the result of mispricing.

Hasan and Habib (2017) note that multiple studies conclude that IVOL represents individual firm risk factors, which cannot be reduced by diversification and therefore is independent of changes in the total market return. Hasan and Habib (2017) consequently extend this logic to the firm life cycle. The firm life cycle is one in which individual products or firms, go through multiple stages, which are introduction, growth, maturity, shake-out, and decline stages. Motivated by the findings of Campbell *et al*., (2001), which document that idiosyncratic volatility explains variations in individual firm risk over time, Hasan and Habib (2017) set out to test if idiosyncratic volatility varies throughout the firm life cycle.

Hasan and Habib (2017) postulate that when firms are in the growth and mature stages of the life cycle, they have great performance and multitudes of information that reduce the uncertainty over the firm's ability to generate cashflows. This reduced uncertainty equally reduces the range of expected returns, therefore, reducing IVOL. Conversely, early-stage firms and firms in decline have poor performance and lack of information. This makes future cash flows and stock returns less predictable, thus increasing IVOL.

Accordingly, Hasan and Habib (2017) find that, from a US sample of stocks, IVOL is greater for firms in the introduction and decline stages than firms in the growth and mature stages. Furthermore, uncertainty about cash flows, stock return, and lack of information have an impact on firms across all stages of the firm life cycle (Hasan and Habib, 2017).

In a study conducted by Chen, Jiang, Xu and Yao (2012) the authors look at how prevalent the Idiosyncratic volatility anomaly is across different stock samples and offer data to help discern between possible explanations. Their findings demonstrate that the idiosyncratic volatility anomaly is a typical phenomenon in common stocks. Additionally, the authors demonstrate that the short-term stock return reversal cannot account for the idiosyncratic volatility anomaly and that it is not caused by the market microstructure impact.

Bley and Saad (2012) look into the pricing of the unique volatility in seven frontier markets across six GCC nations. For individual equities in Saudi Arabia (Qatar), there is a significant (marginal) negative relationship between projected returns and lagged idiosyncratic volatility, but not in Kuwait or Abu Dhabi. However, the relationship changes to positive when they estimate conditional idiosyncratic volatility using either EGARCH or AR Models. The underlying link between expected idiosyncratic volatility and expected returns is shown by including unexpected idiosyncratic volatility as an explanatory variable to compensate for any unexpected returns. In terms of return reversals and other control factors, the evidence seems to be robust. Additionally, the pricing of idiosyncratic risk appears to be independent of the level of financial development and is less noticeable in countries with greater levels of governance.

Khovansky and Zhylyevskyy (2013) make use of a new approach to estimate the idiosyncratic volatility premium. They then apply this approach to daily, weekly, monthly, quarterly, and annual US stock return data and find that the idiosyncratic volatility premium, is positive for daily return data but negative for weekly, monthly, quarterly, and annual data. They state further that the impact of idiosyncratic risk on stock returns should not be ignored.

Anecdotal evidence suggests that there is a negative idiosyncratic volatility effect in China but this may be caused by investors' preference for equities with high idiosyncratic volatility, according to Nartea, Wu and Liu (2013), who provide evidence of the effect.

To investigate the random effects between predicted stock returns and idiosyncratic risk, this paper uses panel data regression. Wang (2013) discovers a significant correlation between unusual risk and anticipated stock returns. The findings are in line with Fu's study from 2009, and there is evidence linking the anticipated stock return autocorrelation to the return reverse effects. According to this analysis, idiosyncratic risk greatly boosts stock returns. Positive returns are proven to have higher idiosyncratic volatility, implying that higher returns in the past cause lower or negative returns. The findings corroborate the findings of various authors that idiosyncratic risk has a positive impact on expected returns. (Wang, 2013)

If investors are risk-averse, the well-established inverse link between idiosyncratic volatility and stock returns is perplexing. Prospect theory, on the other hand, contends that while investors exhibit risk-seeking behaviour in the case of losses, they are risk-averse in the case of wins. The authors find that the negative relationship between idiosyncratic volatility and stock returns is concentrated in stocks with unrealized capital losses but is non-existent in stocks with unrealized capital gains, which is consistent with risk-seeking investors' preference for high-volatility stocks in the loss domain. This result holds even after accounting for additional variables such as maximum daily return and short-term return reversals (Bhootra & Hur, 2015).

By proposing three global idiosyncratic volatility, skewness, and kurtosis risk factors, the authors study a worldwide cross-sectional relationship between idiosyncratic risk moments and projected stock returns. They also recommend two global proxies for evaluating return residuals of the test assets from a global asset pricing model: small minus big and high minus low risk. They recommend adding the additional global risk components of momentum, leverage, bid-ask spread, and liquidity to do robustness checks. In addition, the cross-section of stock returns shows a significant negative price of risk for global idiosyncratic skewness (-0.13%) and idiosyncratic volatility (-1.85%) and a positive and significant price of risk for global idiosyncratic kurtosis. The authors find a significant negative relationship between stock portfolio returns and the global moments. They discover that the risk criteria they propose are strong under several examinations and serve as major drivers of risk premia in the stock market. These variables can also predict the increase in the gross domestic product over the study period. (Baghdadabad & Mallik, 2018)

Qadan, Kliger and Chen (2019) take a look at the aggregate market volatility, captured by the VIX (also known as the investors' fear gauge), on the US stock market and investigate the role that it plays in the relationship between idiosyncratic volatility and stock returns. Their results show that an increase in the VIX would result in a negative relationship between idiosyncratic volatility and future stock returns, even when all other risk factors are taken into account. This is said to occur as a result of investors becoming more risk-averse when the VIX increases.

Berggrun *et al*., (2016) test if lagged IVOL can explain one-period ahead returns for shares on the MILA. The sample period of the study was from 2001 to 2014. The paper tests the notion that a lack of diversification options will result in compensation for holding company-specific risk. Given the lack of depth and liquidity on the MILA, diversification opportunities would be few and far between. As a result, one would expect idiosyncratic risk to be priced into stock returns.

The approach of Berggrun *et al*., (2016) is to buy stocks that have high idiosyncratic volatility and short sell shares with low idiosyncratic volatility. The idea behind this strategy is simple. If holding high IVOL shares results in higher return, due to the lack of diversification, then this portfolio will have a positive and significant excess return (Berggrun *et al*., 2016).

Surprisingly, Berggrun *et al*., (2016) do not find a significant alpha for this portfolio, suggesting that there is no extra compensation received for holding high idiosyncratic stocks. This finding agrees with the CAPM, which predicts that idiosyncratic risk is diversifiable and therefore not compensated. Robustness checks confirm these findings. For instance, a high IVOL portfolio does not have any significant outperformance over a low IVOL portfolio when preceded by months of high or low market volatility. Furthermore, when size, book-to-market, momentum, and liquidity are factored into the model, lagged IVOL does not have any explanatory power for the period ahead stock returns (Berggrun *et al*., 2016).

2.2 LOCAL LITERATURE

Literature on idiosyncratic volatility in South Africa is not as deep as the international literature. The lack of research on this topic in South Africa is partial motivation for the conception of this study.

On the other hand, asset pricing as a whole receives a lot of attention in South African literature. Van Rensburg and Stanley (1997) note that the JSE is characterised by a two-sector market segmentation, in which the return-generating process is driven by resource and industrial stocks. The paper shows that the All Gold and Industrial Index in a two-factor model without market beta explains returns better for the JSE than does a single market factor of Markowitz (1952) and Sharpe (1964). Van Rensburg (2002) added to this finding when the indices were changed in 2000 to the resource shares index (RESI), and financial and industrial shares (FINDI). The two-sector segmentation therefore becomes resource and financial-industrial.

Van Rensburg (2002) also notes that the JSE's All Share Index (ALSI) is not mean-variant efficient. The implication of this is that diversification in South Africa is not maximised by holding the ALSI, only by adding offshore investments. Although not explicitly mentioned by Van Rensburg (2002), this would imply that idiosyncratic risk is a priced risk factor, since investors cannot diversify strongly enough through local holdings.

A study conducted by Page, Britten and Auret (2016) looked at arbitrage costs and the persistence of size, value, and momentum premiums on the JSE. The authors took a look at transaction costs and holding costs, with the holding costs being a proxy for the idiosyncratic risk that arbitrageurs may expose themselves to when pursuing an individual strategy that they believe will yield above-average returns. Using asymmetric and GARCH-in-mean models to evaluate the level of idiosyncratic risk, making use of a zero-cost portfolio return series. A look at specifically the idiosyncratic risk component of the study shows that with an increase in idiosyncratic risk, there is an increase in the value premium while the increase in idiosyncratic risk has a negative impact on the momentum premium. This finding can be further interpreted by noting that with idiosyncratic risk having a positive impact on the value premium it suggests that returns on value stocks would increase as idiosyncratic risk increases. Furthermore, the fact that idiosyncratic risk has a negative relationship with momentum premiums could suggest that stock returns end up being lower than expected. However, the authors find that idiosyncratic risk does not drive momentum profits on the JSE. Thus in a diversified portfolio to understand the impact that idiosyncratic risk has on the return of a portfolio, the impact of momentum may not need to be considered however the impact of value premiums may need to be eliminated, only if they are known to have a great impact on returns for the particular sample being tested.

Page and Auret (2019) tested whether several investment styles had an impact on the cross-sectional variation of share returns on the JSE. After running significant tests using cross-sectional regressions on panel data, looking specifically at the results obtained regarding idiosyncratic risk, the authors found that an increase in lagged idiosyncratic risk results in a positive increase in expected monthly average returns. Furthermore, the authors found that idiosyncratic risk is not a significant determinant of expected cross-sectional variation in average share returns. The authors also find using a random effects regression which is a model estimated using generalised least squares, where panel consistent standard errors are still assumed, a slightly negative relationship between idiosyncratic risk and expected monthly average returns, consistent with several previous studies that have found a negative correlation between idiosyncratic risk and expected returns.

3 METHODOLOGY

This section reports the data and methodology employed by this study. The methodology specifically sets out to test the hypotheses provided in Section 1.4 of this document. This study will follow the methodology employed by Berggrun *et al*., (2016). This section is organised as follows: 3.1 will discuss data and sampling, 3.2 will provide a detailed explanation of the main research tests employed, 3.3 describes robustness checks and 3.4 provides summary statistics of the portfolios.

3.1 DATA AND SAMPLING

The data to be used will be sourced from Bloomberg and will include the daily prices in rands and adjusted for dividends, market capitalisation, book-to-market values, and momentum values for stocks listed on the ALSI. The sample period will span from January 2001 to November 2022 and will allow for a recent and extensive set of data on which conclusions can be drawn and will also include both listed and delisted stocks. By including the shares that have been delisted, this study allows for survivorship bias to be eliminated. This study limits the shares included in the tests in any given month to the top 100 shares on the JSE based on market capitalisation in that month.

3.2 DETAILS OF MAIN TESTS PERFORMED

The first test is for the assertion that lagged idiosyncratic risk is a priced risk in the South African stock market. The South African market is categorised by a two-sector segmentation, namely resource-based stocks and financial-industrial-based stocks, as noted by Van Rensburg (2002). As a result, there may not be sufficient avenues for diversification available to local investors. Van Rensburg further points out that the ALSI, which is the universal market index for South Africa, is not mean-variant efficient as there are further avenues for diversification through off-shore investing. Therefore, investors may require additional compensation for holding idiosyncratic risk, as it may not be diversifiable in the South African market.

To test the effect of the lack of diversification on the return of stocks in South Africa, stocks are split into three portfolios, namely low IVOL, medium IVOL, and high IVOL. Naturally, stocks with the lowest IVOL in month t-1 are sorted into the low IVOL portfolio, and likewise for stocks with middle of the range IVOL and high IVOL.

This study uses both equal weighting and value weighting for portfolio construction. In equally weighted portfolios, each stock is allocated a weight as follows:

$$1/n \qquad (1)$$

Where n is the number of stocks in a portfolio.

Once stocks are sorted into portfolios, the monthly returns of the portfolios are calculated and then stocks are re-sorted into portfolios. Therefore, holding period for IVOL portfolios is one month. The excess returns are then regressed onto the Fama-French three factor model, which is given by:

$$R_t - Rf_t = \alpha_i + b_i(Rm_t - Rf_t) + s_i Rsmb_t + h_i Rhml_t + \varepsilon_t \qquad (2)$$

Where the left side of the equation is the excess return for stock, R_t is the return of the respective IVOL portfolio (low, medium, high or long-short), Rf_t is the risk free rate, Rm_t is the return of the market, $Rsmb_t$ is the small minus big return obtained from portfolios formed on size, $Rhml_t$ is high minus low return obtained from portfolios formed on book-to-market ratios and lastly ε_t is the residual.

From the Fama-French three factor model, alphas are obtained using Newey and West (1987) standard errors. The alphas from these regressions are reported. The significance of these alphas will determine if IVOL is a priced risk factor.

The above equation allows the idiosyncratic volatility (IVOL) for a month to be calculated based off the standard deviation of the residual. In order to use the (augmented) regression model of Eq. (2) and consequently generate an estimate of σ_e, a stock must trade for at least 80% of the days in a month. By multiplying the daily IVOL σ_e estimate by the square root of the number of trading days in a month, it is then converted to a monthly estimate. The regression spans back 1 month or 21 trading days.

In order to determine if idiosyncratic risk is a priced risk factor, a portfolio called "P3-P1" is formed where a long position is taken in the high IVOL stocks and a short position is taken in low IVOL stocks. Similar portfolios are also formed, called "P2-P1" and "P3-P2", where P3 is the high IVOL portfolio, P2 is the medium IVOL portfolio and P1 is the low IVOL portfolio.

If this return differential is statistically significant, then differences in idiosyncratic risks are associated with differences in returns.

3.3 ROBUSTNESS CHECKS

In addition to the main tests described in Section 3.3, other tests are also performed as a robustness check to ensure that the results hold up. Firstly, regression analysis is used to test the effect of IVOL on stock returns when controlling for other variables known to affect the returns of stocks. This is done in two steps. The first step involves calculating risk-adjusted returns using coefficients estimated from equation 2 specified above. A rolling window of 24 months is applied when estimating the coefficients of equation 2. Stocks are only allowed in if they have been trading for at least 80% of the 24-month period. The risk adjusted returns are then calculated using the equation below:

$$R_t^* = R_t - Rf_t - \beta(Rm_t - Rf_t) - sRsmb_t - hRhml_t \quad (3)$$

Where R_t^* is the risk adjusted return, R_t is the return of the stock, Rf_t is the risk-free rate, β is the market beta, Rm_t is the return on the market, $sRsmb_t$ is the SMB factor and $sRhml_t$ is the HMB factor.

The second step then involves running the cross-sectional regression below:

$$R_t^* = \gamma_0 + \gamma_1 IVOL_{i,t-1} + \gamma_2 CAP_{i,t-2} + \gamma_3 BM_{i,t-3} + \gamma_4 MOM_{i,t} + \gamma_5 VOL_{i,t-1} + \varepsilon_t \quad (4)$$

Where $IVOL_{i,t-1}$ is the idiosyncratic volatility of share *i* at time *t-1*, $CAP_{i,t-1}$ is the market capitalisation of share *i* at time *t-1*, $BM_{i,t-3}$ is the book-to-market ratio of share *i* at time *t-3*, $MOM_{i,t}$ is the momentum return of share *i* at time *t* and $VOL_{i,t-1}$ is the trade volume of share *i* at time *t-1*.

Market capitalisation in equation 4 is the logged value of the market capitalisation of the firm two months prior. This is used to control for the size effect, a documented phenomenon where small firms have higher returns than large firms. Book-to-market is the logged ratio of the firms book value to market value in the previous quarter. This controls for the value effect, where high-value firms outperform low-value firms. Momentum is the 12-month return of the share, i.e. from month t-12 to month-2. This is controlling for past returns, which have been shown to persist into the future. Finally, trading volume is the log value of the number of trades for a share in a month. This is proxying for liquidity and microstructure effects.

The regression is estimated using generalised least squares regressions rather than ordinary least square regressions with uncorrelated errors and weights of one divided by the market capitalisation of the firm. Once the regression is performed, the significance of the coefficient of the idiosyncratic volatility is inspected to determine if unsystematic risk is a priced risk.

In addition to this, a version of equation 4 where only idiosyncratic volatility is included is also run. This is done to determine if idiosyncratic volatility is significant by itself and if so, is it significant in the presence of variables known to influence returns.

Another version of equation 4 is run where excess returns are estimated the univariate CAPM model rather than the Fama-French three-factor model. Finally, idiosyncratic volatility in high market volatility and low market volatility periods is also tested.

3.4 SUMMARY STATISTICS AND PORTFOLIO STATISTICS

To start, the available stocks for each month are divided into three (tercile) portfolios in order to analyse the impact of diversifiable risk on stock returns. The first portfolio (P1) consists of the stocks in the month with the lowest IVOL, while the second portfolio (P2) consists of the stocks in the month with the medium IVOL. The stocks with the highest idiosyncratic volatility are included in P3. Each stock is given an investment weight based on its market capitalisation during the previous month. To obtain a comprehensive understanding of how IVOL affects stock returns, equally weighted portfolios in addition to value-weighted portfolios will be applied. Table 1 and 2 below show the descriptive statistics on a daily basis for each of the equal and value weighed portfolios that have been created.

Table 1 Equally Weighted Portfolio Statistics

	P1	**P2**	**P3**
Mean	0.00061	0.00059	0.00066
Median	0.00106	0.00087	0.00080
Std. Dev	0.00859	0.01440	0.01440
Max	0.07209	0.05797	0.62515
Min	-0.09222	-0.09711	-0.12173

Table 2 Value Weighted Portfolio Statistics

	P1	P2	P3
Mean	0.00034	0.00029	0.00023
Median	0.00032	0.00028	0.00017
Std. Dev	0.00628	0.00346	0.00346
Max	0.04861	0.06190	0.03883
Min	-0.04992	-0.03617	-0.02556

The monthly returns of the three portfolios in the period following (holding or assessment period) the ranking and portfolio construction processes is monitored. Up to the end of the sample, this ranking and evaluation method is repeated. As a result, what is created is three stacked monthly return time series for the IVOL portfolios. Using the time series portfolios, the alphas (or intercepts) are estimated from the Fama and French (1993) model (see Eq. (1) applying Newey-West standard error adjustments (see Newey and West, 1987

The key performance indicators considered are portfolio alphas (j = 1, 2, and 3) and a long-short portfolio to determine the relationship between volatility and expected returns. A long-short (spread) portfolio invests in high IVOL stocks and takes a short position in low IVOL stocks. To conclude the relevance of unsystematic risk in stock returns, emphasis will be placed on the sign and significance of the spread portfolio (P3-P1). The alphas for the other portfolios (P2-P1 and P3-P2) will be reported as a robustness check

Each month, an estimate of the median excess return for the stocks that make up each of the three IVOL portfolios is made to obtain some insight into their characteristics. Next, the average of the series for the entire period is taken to look for any trends in the time series of median excess returns. One will carry out a comparable exercise for several pertinent stock characteristics, including market beta, loadings on SMB and HML, IVOL, alpha, book-to-market, and momentum returns. Tables 3 and 4 that follow show the estimated coefficients for both the equally and value-weighted IVOL portfolios.

4 RESULTS

This section presents the results of the tests conducted as described in the preceding methodology section. It begins by presenting the results of the main tests before going into the

Table 3 Estimated Coefficients for Equally Weighted IVOL Portfolios

	Alpha	Beta	HML	SMB	Adjusted R Squared
P1	0.0002*** (0.0001)	0.628*** (0.007)	-0.018*** (0.006)	0.142*** (0.011)	0.676
P2	0.0001 (0.0001)	0.729*** (0.008)	-0.006 (0.007)	0.122*** (0.012)	0.705
P3	-0.0001 (0.0001)	1.014*** (0.009)	0.306*** (0.008)	0.631*** (0.015)	0.789
P3 – P1	-0.0004*** (0.0001)	0.387*** (0.011)	0.342*** (0.010)	0.489*** (0.018)	0.511
P2 – P1	-0.0003*** (0.0001)	0.102*** (0.006)	0.011** (0.006)	-0.020** (0.010)	0.079
P3 – P2	-0.0004*** (0.0001)	0.285*** (0.011)	0.312*** (0.009)	0.509*** (0.017)	0.503

*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

Table 4 Estimated Coefficients for Value Weighted IVOL Portfolios

	Alpha	**Beta**	**HML**	**SMB**	**Adjusted R Squared**
P1	-0.00002 (0.00005)	0.428*** (0.005)	0.004 (0.004)	-0.010 (0.008)	0.702
P2	-0.00003 (0.00004)	0.328*** (0.004)	0.010*** (0.003)	-0.024*** (0.006)	0.682
P3	-0.0001* (0.00003)	0.214*** (0.003)	0.018*** (0.003)	-0.0001 (0.005)	0.581
P3 – P1	-0.0002*** (0.0001)	-0.214*** (0.006)	0.014** (0.006)	0.009 (0.011)	0.242
P2 – P1	-0.0002*** (0.0001)	-0.101*** (0.007)	0.006 (0.007)	-0.014 (0.012)	0.044
P3 – P2	-0.0002*** (0.0001)	-0.113*** (0.005)	0.008 (0.005)	0.023*** (0.009)	0.132

*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

When looking at Table 3 and table 4, the alphas become the measures of interest to examine whether bearing higher IVOL commands higher risk-adjusted returns.

A look at table 3 first shows the alphas of P1 and P2 are both positive but only P1 has a significant alpha value. Thus it can be said because P1 has a positive and significant alpha that investors who bear more IVOL will then be compensated with higher returns after accounting for risk. The spread portfolio (P3-P1) has a negative and significant alpha value on the JSE thus indicating that going long on stocks with a low idiosyncratic volatility and short on stocks with high idiosyncratic volatility results in a significantly positive alpha. The alphas for the two other long-short portfolios are also negative and statistically significant. This observation, due to the negative alpha values of the long-short portfolios, suggests that investors are not compensated with higher returns when exposed to greater levels of idiosyncratic volatility. This is in agreement with the findings of Ang et al. (2009) who found that "Stocks with high idiosyncratic volatility have abysmally low average returns." The alphas, which are daily, of all portfolios are economically high and this is realized even more when thinking about it on an annual basis, thus the alphas are quite significant with their greatest impact being observed in the spread portfolio (P3-P1) as well as P3-P2, which once again suggests that investors are not compensated with higher returns for taking on greater levels of idiosyncratic risk. A look at the beta (market factors) values however, one will see that they are all positive and statistically significant for all portfolios and are higher for portfolios with higher levels of idiosyncratic risk. Thus it can be said that the market factor has a significant and positive impact on the returns of the portfolios sorted based on idiosyncratic volatility, it can be observed that there seems to be an inverse relationship between IVOL and market beta where the higher the IVOL the lower the market beta. This observation gives credence to the fact that if looking at market beta as the level of "known" risk and IVOL as the level of "unknown" risk then looking at a practical example of when the returns of a portfolio can be predicted with great accuracy it would suggest that the risks involved in investing in said portfolio is more "known" than "unknown" and the opposite is true when returns cannot be predicted with great accuracy. Thus how accurate return estimates/predictions can be, can give a rather good idea as to what risk is the major factor behind returns. It's also worth noting that the value factor and size factor (HML and SMB respectively) for P3, P3-P1, and P3-P2 are positive and statistically significant however their significance is nullified by the fact that the alphas are significant and as a result, this indicates that neither size or value explain the low volatility effect. It is also worth noting that when the IVOL increases the size factor (SMB) increases as well. This gives credence to the idea that IVOL is negatively correlated to market capitalization. Thus given the observations made above that if IVOL increases returns tend to not increase, it can be said as well that when the market cap increases returns will increase as well, which makes sense as companies with higher market caps are considered to be "safe" investments with lower risk and also higher returns. The prior observation that market beta and IVOL have an inverse relationship further strengthens this idea. The adjusted R squared values (used to determine if the explanatory power of the pricing model is good or not) of the pricing regressions for all portfolios in table 3 are all quite high (greater than 0 and closer to 1) other than for portfolio

P2-P1 which suggests that the explanatory power of the pricing model is high for all the portfolios other than P2-P1 where the explanatory power of the pricing model is lower.

Table 4 reports much of the same results, the alphas for the long-short portfolios though small in value are negative and statistically significant, with all long-short portfolios having an alpha of -0.0002 which once again suggests that there is an apparent inverse relationship between IVOL and returns. Beta (market factors) is still observed to have a significant impact on the returns of the portfolios even when value-weighted portfolios are used, thus market factors appear to have the greatest impact on returns of the portfolios. Unlike with the equally weighted portfolios, the value and size factors seem to have much less of an impact on the returns of the value-weighted portfolios. The adjusted R squared values for the value-weighted portfolios show that the explanatory power for P1, P2 and P3 is high due to the high adjusted R squared values, however, the adjusted R squared values for the long-short portfolios are lower and thus the explanatory power of the pricing model for those portfolios is lower.

Overall the negative and significant alpha of the spread portfolio (P3-P1) gives credence to the fact that investors bearing less IVOL are compensated with slightly higher returns after accounting for risk. This also indicates that there is an apparent negative relationship between idiosyncratic risk and stock returns on a value-weighted basis. This finding agrees with the findings of Baghdadabad and Mallik (2018), Qadan ,Kliger and Chen (2019), Bhootra and Hur (2015), Nartea, Wu and Liu (2013), Huang, Liu, Rhee and Zhang (2011) and Angelidis (2010) among others.

The monthly median of excess returns for the stocks that make up each of the three IVOL portfolios is estimated to get a better understanding of the characteristics of the stocks that make up each portfolio. Next, the average of the series for the entire period is taken to look for any trends in the time series of median excess returns. To gain a better understanding, a look at the values presented in table 5 shows the median of CAP, BM and MOM as well as the average number of shares, which change every month, and the average excess returns. The three lagged portfolios are estimated monthly using IVOL from the previous month. The daily returns of the portfolio in that month are then calculated by regressing the portfolio returns onto the Fama and French 3-factor model. These coefficients are presented in table 5. It's worth noting that due to the preceding explanation alpha, beta, HML and SMB are not averages/medians.

Table 5 Characteristics of lagged IVOL Portfolios

	Variable	P1	P2	P3
1	**Excess returns**	0.00305	0.00191	0.00065
2	**IVOL**	0.01224	0.01517	0.02295
3	**Alpha**	-0.00002	-0.00003	-0.00006
4	**Beta**	0.42829	0.32753	0.21414
5	**SMB**	0.00426	0.01034	0.01807
6	**HML**	-0.00983	-0.02407	-0.00073
7	**CAP**	22 333.74	23 288.35	17 356.5
8	**BM**	0.85135	0.75075	0.75752
9	**MOM**	0.06156	0.05837	0.02635
10	**Avg. nr of shares**	34.20190	33.90818	35.47114

Table 5 shows that the low IVOL portfolio (P1) has a greater excess return and the high IVOL portfolio (P3) has a much lower excess return, this is in stark contrast to the results obtained by Berggrun, Lizarzaburu and Cardone (2019) but further strengthens the observations made from tables 3 and 4 that suggest a negative relationship between IVOL and returns. Furthermore, P1 has a greater sensitivity to market factors, which is based on the beta figure for P1 being the highest out of the 3 portfolios shown in table 5. P3 has a greater sensitivity to the size (SMB) factor compared to the other two portfolios. Table 5 confirms the observations made in the previous 2 tables that IVOL and SMB are positively correlated, seen by the fact that P3 the portfolio with the highest IVOL has excess returns that are seriously influenced by the size factor, furthermore, its observed that P3 has the lowest market cap which confirms the observation made previously that IVOL is inversely related to market cap. P1 also has higher book-to-market (BM) and momentum (MOM) returns than that of P3. In line with Page et al. (2016) it is observed that IVOL and momentum have an inverse relationship P3 (the portfolio with the highest IVOL) has the lowest momentum figure thus suggesting that the excess returns on the high IVOL portfolio is not influenced heavily by momentum premiums. The last row of the table shows that on average each portfolio has 34 or 35 stocks.

4.1.1 Regression Analysis and Results

The portfolio analysis above suffers from a major drawback, that is one can only determine how one variable (IVOL) affects another (returns) without accounting for other factors that may have an impact on stock performance. To amend this problem a regression analysis based on panel monthly data will be conducted. The errors in variables-free methodology will be followed and will comprise of two steps. First, the risk adjusted returns will be calculated for each month t. This will be calculated as the difference between realized (excess) returns in the month and expected returns using the coefficients related to systematic risk factors estimated from Eq. (1) Risk-adjusted returns are therefore equal to:

$$\boldsymbol{R_t^* = R_t - Rf_t - \hat{b}(Rm_t - Rf_t) - \hat{s}Rsmb_t - \hat{h}Rhml_t} \quad \textbf{(1)}$$

The estimations of the coefficients $\hat{b}$, $\hat{s}$, and $\hat{h}$ for use in Eq.(2) will be obtained using a conditional approach. To get coefficient estimates from Eq.(1), a fixed-length rolling window of 24 months will be employed (a stock must trade for at least 80% of the window's months). To estimate regression coefficients and determine expected returns for July 2003, data from excess returns, returns on the market, size, and distress factors from July 2001 to June 2003 will be specifically employed. To determine $R_{i,t}^*$ this method will be performed for each month (t) and stock (i) in the sample.

In the second step the following cross-sectional regression is run for each month:

$$\boldsymbol{R_i^* = \gamma_0 + \beta_i + \gamma_1 IVOL_{i,t-1} + \gamma_2 CAP_{i,t-2} + \gamma_3 BM_{i,t-3} + \gamma_4 MOM_{i,t} + \varepsilon_t} \quad \textbf{(2)}$$

Equation 3 ideally should be estimated with at least 25 firms with complete information in the month. Instead of an OLS (ordinary least squares) regression that assigns the same weight on either small or large-cap stocks. A GLS (generalized least squares) regression will be performed assuming uncorrelated errors and weights equal to the inverse of the firm's market cap. What this weighting scheme will allow is that it will reduce the influence of the small stocks on the relationship between excess returns and IVOL.

Three control variables are used in Eq.(3). These three variables control for firm attributes. To account for the fact that small companies usually experience higher returns than large firms the two-month lagged value of the natural logarithm of market capitalisation is used. The log value of the book-to-market ratio as of the end of the last quarter controls for the value or growth effects in expected returns. To control for past returns the six-month momentum returns will be used. This particular control variable is the return from month -2 to month -6. Thus in other words using the period from January to May to estimate a six-month momentum return, will serve as a right-hand side variable for excess returns in July.

Getting the values of the coefficients, which are typically regarded as premia, is the goal of the second step. γ_1 reflects the cost of assuming unsystematic risk, whereas γ_2, γ_3 and γ_4 stand for size, distress and previous returns premia respectively. One will primarily consider the sign and significance of γ_1 to conclude whether idiosyncratic risk influences stock returns on the JSE.

Thus in summary the regression analysis presented in this study is essentially an alternative to a univariate regression analysis. In this case one controls for other variables that have been known to influence share returns (Book to market, size and momentum), so a multivariate analysis with two steps is run. The first of which is to calculate risk-adjusted returns using the Fama and French 3-factor model (Equation 2). The second step is the actual regression (Equation 3) where is the risk adjusted return CAP controls for firm size, BM controls for book to market and MOM controls for the shares past return.

Table 6 shows 4 different models, the first where CAPM beta is used as the sole explanatory variable, the second where IVOL is excluded from the model, the third where the model is as per equation 3 and then the fourth and final model is where IVOL is used as the sole explanatory variable.

Table 6 Panel Regressions of Stock Returns on Lagged Idiosyncratic Volatility

Excess Return				
	1	**2**	**3**	**4**
Alpha	0.00176 (0.00002)	0.00545 (0.00123)	0.2577** (0.03)	0.01639** (0.01755)
CAPM Beta	-0.035 (0.076)	-0.084** (0.039)	-0.0146** (0.062)	
IVOL			-1.481*** (0.109)	-1.031*** (0.083)
CAP		-0.001** (0.0002)	-0.0004 (0.001)	
BM		-0.00000 (0.00001)	-0.00001 (0.00002)	
MOM		-0.0002** (0.0001)	0.002 (0.002)	
N	1 228 583	979 407	397 508	471 422
R^2	0.00000	0.00002	0.0005	0.0003
Adjusted R^2	-0.0002	-0.0002	-0.0002	-0,0002
F Statistic	0.218 (df=1;1228333)	3.892*** (df=4;979154)	38.059*** (df=5;397254)	155.728*** (df=1;471172)

*Significant at the 10% level
**Significant at the 5% level

***Significant at the 1% level

A look at Table 6 which shows the number of months in which one conducts the cross-sectional regressions and the average number of firms with available information in the monthly regressions. The IVOL figure (γ_1) shows a strong and negative relationship between excess returns and past idiosyncratic volatility. This is in line with the findings of the section above. Model 3 also shows that market capitalization (CAP), book-to-market (BM), and momentum (MOM) do not have a strong or statistically significant impact on excess returns. Model 3 also shows that the alpha (γ_0) has a strong and significant impact on excess returns and CAPM beta (β_i) also has a statistically significant and negative relationship with excess returns. A look at model 4 where IVOL is used as the sole explanatory variable confirms once more that there is a negative relationship between IVOL and excess returns on the JSE and also confirms the results obtained from the previous tables.. Model 2 shows once again that ,when excluding IVOL from the model, that the other variables do not have a strong impact on excess returns, aside from alpha that has a small positive impact on excess returns the other variables all have a small negative relationship with excess returns. CAPM beta, CAP and MOM all have a statistically significant impact on excess returns when looking at model 2. Model 1 that makes use of CAPM beta as the sole explanatory variable shows that there is a negative relationship between CAPM beta and excess returns however it is not statistically significant. The adjusted R squared value is consistent across all 4 models and it shows that the explanatory power of the model used is substantially low. This though strange doesn't impact the results obtained. The very low R squared just shows the correlation between the independent and dependant variables, thus if one reacts the other will react as well but with it being low the two variables are considered to react independently of one another, this is because as with most regressions not all elements that impact the variables can be captured by the regression equation, leading to the point that correlation does not always imply causation. Overall the above analysis agrees with Ang et al. (2009) who also found a negative relationship between idiosyncratic volatility and excess stock returns.

4.1.2 **Robustness Checks**

A number of tests are run in this section to ensure the reliability of the findings. These checks specifically focus on whether the major conclusion that there is a negative relationship between IVOL and stock returns on the JSE still holds under a different set of assumptions.

First, IVOL is not re-estimated and is simply worked the same way as in equation 1, this estimate is then put into the CAPM model as appose to the Fama and French 3 factor model and whether the change of making use of the CAPM model still allows the conclusions drawn in the preceding sections to hold true, results of this test are captured in Table 7.

Table 7 CAPM Adjusted Cross Sectional Regression

	CAPM Adjusted Return
Alpha	-0.00588 (0.005)
IVOL	0.265*** (0.019)
CAP	0.0002* (0.0001)
BM	0 (0)
MOM	0.0002 (0.0003)
N	397 508
R^2	0.0005
Adjusted R^2	-0.0001
F Statistic	49 420*** (df=4;397255)

*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

Table 7 shows that once the CAPM model is used to estimate returns and these adjusted returns are then plugged into the regression the biggest noticeable change is the fact that the IVOL coefficient is now positive and statistically significant thus indicating that if returns are adjusted using a univariate CAPM model then stock returns have a direct/positive relationship with stock returns thus by investing in stocks with a higher idiosyncratic volatility the higher the potential returns of the investor. Though the IVOL coefficient is a very small positive in comparison to the negative that was observed in the previous sections, the result still does not agree with the results that were observed in both the portfolio and regression analysis.

The absence of an IVOL effect and whether it holds in times of high or low total volatility (VOL or standard deviation of returns) is then examined. The monthly series of VOL as the mean of the standard deviation of returns of available stocks in a given month is estimated. Each month is classified as a high VOL month when VOL during the month surpassed the median of VOL for the whole sample period. When VOL during the month is below median VOL, the month is classified as low VOL. Table 8 reports the alphas of lagged IVOL portfolios in the states mentioned above, IVOL is lagged to determine if the idiosyncratic volatility of the previous month is followed by higher or lower returns in the following month on a consistent basis which would demonstrate a statistically significant relationship.

Table 8 Alphas of Lagged IVOL Portfolios for Low and High Volatility Months

	P1	**P2**	**P3**	**P3-P1**	**P3-P2**	**P2-P1**
Low Volatility Months	0 (0.6628)	0 (0.2293)	-0.0001*** (0.022)	-0.0002*** (0)	-0.0002*** (0)	-0.0002*** (0.0006)
High Volatility Months	-0.0001 (0.7835)	-0.0001 (0.4236)	-0.0001 (0.4368)	0 (0.9543)	0 (0.3129)	0.0001 (0.8436)

*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

In table 8 above it is observed that just as in table 3 and 4 the alphas of P3 and the long short portfolios are slightly negative and all statistically significant. Thus it can be said that there seems to be a negative volatility effect but this only seems to occur during months of low volatility for the high volatility portfolio (P3) as well as the long short portfolios (last 3 columns). Furthermore focusing solely on the spread portfolio (P3-P1) ,just as was done in the analysis of table 3 and 4, it is observed that once again the alpha value is negative and statistically significant indicating just as in the portfolio analysis section, investors bearing less IVOL are compensated with slightly higher returns after accounting for risk, although now these higher returns seem to be limited to low volatility months. It also holds that there is an apparent negative relationship between idiosyncratic risk and stock returns

Table 9 IVOL in Low Volatility Regression

IVOL in low volatility state	
	Returns
Alpha	0.0457*** (0.154)
IVOL	-2.397*** (0.154)
CAP	-0.001 (0.001)
BM	-0.00002 (0.00002)
MOM	0.003 (0.003)
N	299 033
R^2	0.001
Adjusted R^2	0.0002

F Statistic	60.695*** (df=4;298845)

*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

Table 9 confirms once again a very strong and statistically significant negative relationship between IVOL and stock returns. It also shows that the returns during low volatility states are not affected by other factors such as market capitalisation, whether a stock is over or under valued in comparison to the market (book-to-market) and momentum. This is because the coefficients observe in table 9 are very small in value and are not statistically significant.

In the final robustness check, the interrelationship between firm size and idiosyncratic volatility in a portfolio context is studied. Thus making use of a two-way sorting portfolio strategy instead of one-way sorting. Each month, stocks are classified as small and large (whether the stock's market cap surpasses or not the median market cap) and as low or high IVOL (if a respective stock's idiosyncratic risk is smaller than (exceeds) the median value of cross-sectional IVOL) and form four portfolios: small and low IVOL (P11 portfolio), small and high IVOL (P12), large and low IVOL (P21), and large and high IVOL (P22). The returns of these four portfolios are then monitored in the month subsequent to the portfolio formation, and this process is then repeated each month until the sample's end. Then, two alphas are estimated: one for the small cap subsample (P12-P11) and the other for the large cap subgroup (P22–P21)

Table 10 Interrelationship between firm size and IVOL

	Alpha	**Beta**	**HML**	**SMB**	**Adjusted R^2**
P12-P11	-0.0003*** (0.0001)	0.200*** (0.010)	-0.023*** (0.009)	0.136*** (0.016)	0.073
P22-P21	-0.0003*** (0.0001)	0.113*** (0.011)	-0.019* (0.010)	-0.046** (0.018)	0.040

*Significant at the 10% level

**Significant at the 5% level

***Significant at the 1% level

From table 10 it is observed that even after controlling for size the alphas for both of the portfolios are still negative and statistically significant. Just as in the portfolio analysis section (table 3 and 4) betas for both portfolios are also positive and statistically significant thus indicating that return are impacted by market factors considerably. The above analysis still confirms that by longing stocks with a low IVOL and shorting stock with a high IVOL may result in potentially higher returns and additionally this still holds when controlling for size. Thus, bearing lower IVOL may lead to potentially higher returns.

5 CONCLUSION

This section concludes the research, summarising key findings and insights as well as giving recommendations for possible avenues for future research.

This study considers the impact of idiosyncratic risk on stock returns in the South African Stock Market over the period 2001 – 2022. The study investigates whether shareholders need to be compensated (in the form of greater returns) for assuming some company-specific risk in a market where investors are likely to be unable to diversify completely, as in Merton (1987). The study also adds to the ongoing discussion on the degree and importance of price anomalies in an emerging stock market as well as the impact of idiosyncratic risk in determining predicted stock returns.

First, a portfolio strategy that invests in high IVOL stocks and shorts low IVOL stocks is created. If investors are compensated for assuming higher unsystematic risk, the alpha of this long-short portfolio should be positive and significant. However, it was found that the alpha was significantly negative, indicative that investors bearing lower volatility can earn higher returns. Furthermore, as per the robustness checks, it was observed that the IVOL portfolios maintain significantly negative alphas following months of low volatility, with the long-short IVOL portfolios outperforming all other portfolios. The portfolio strategy is expanded to two-way sorted portfolios as part of a further robustness test. With this strategy, one attribute can be controlled while exploring the relationship between IVOL and stock returns. Controlling for size produces the same negative and statistically significant alpha and so longing stocks with a low IVOL and shorting stocks with a high IVOL may result in potentially higher returns

Moving to a multivariate setting, using excess returns, a significant and negative coefficient was attached to the idiosyncratic volatility proxy, furthermore the coefficient is even more negative in a low volatility environment. Thus it is apparent that there is a negative/inverse relationship between idiosyncratic volatility and stock returns, specifically excess returns on the JSE, this result aligns with the study by Ang *et al.* (2009) who also observed a negative relationship between idiosyncratic volatility and stock returns in their study. This is however a rather surprising finding because high risk is usually associated with higher return so to observe a negative relationship is quite a contradiction to the norm that one would expect.

This study limited the number of shares to the top 100 shares on the JSE based on market capitalisation and so for further research it would be interesting to see if the above results and conclusions still hold when tested on a larger body of shares. Furthermore it would also be interesting to see if the observed results are industry specific as it would be interesting to know whether the relationship possibly changes across industries. Further research could also be done in order to gain a better understanding of whether idiosyncratic volatility will allow investors have a better understanding of losses that could occur as a result of idiosyncratic volatility and then put measures in place to try and minimize these losses as much as possible.

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