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REVISITING THE RELATIONSHIP BETWEEN AVERAGE STOCK RETURNS AND IDIOSYNCRATIC VOLATILITY IN THE SRI LANKAN STOCK MARKET: AN EXAMINATION USING THE FAMA AND FRENCH FIVE-FACTOR ASSET PRICING MODEL

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Article Info
Keywords: idiosyncratic volatility, stock returns, Sri Lanka, Colombo Stock Exchange, non-financial firms.

Abstract
The idiosyncratic volatility puzzle in the asset pricing literature has been a topic of debate for several decades. This study aims to shed light on this puzzle from a South Asian market perspective, specifically in Sri Lanka. Using a sample of 214 non-financial firms listed on the Colombo Stock Exchange over a period of 163 months from September 2004 to March 2018, this study examines the impact of idiosyncratic volatility on average stock returns in Sri Lanka. The empirical results suggest that idiosyncratic volatility has a positive and statistically significant impact on average stock returns in the Sri Lankan market. Additionally, the findings reveal that idiosyncratic volatility is high among small stocks that are exposed to lower levels of profits and investments. These results raise questions about why there is a high demand for small stocks in the market. Furthermore, this study provides new evidence on the relationship between idiosyncratic volatility and profitability and investment, which departs from previous studies in this area. The findings of this study have significant implications for investors and policymakers in Sri Lanka and other emerging markets.

1. Introduction

The capital asset pricing model (CAPM), one of the major developments in the asset pricing literature, assumes investors hold the market portfolio in equilibrium (Fu, 2009). Hence, it denotes that only market risk should be priced in stock returns as the idiosyncratic volatilitycan be fully eliminated through diversification (PukthuanthongLe &Visaltanachoti, 2009). Therefore, all the empirical asset pricing models assume that the investors holdthe market portfolio in equilibrium so that they are not expecting a return for holding the idiosyncratic volatility as it can be fully eliminated through diversification. Hence, it is assumed only systematic risk should be priced in average stock returns and idiosyncratic volatility is irrelevant.

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However, Merton (1987) argues that due to existence of information asymmetries in the market, investors cannot fully diversify the idiosyncratic volatility as they unable to hold a well-diversified portfolio. Supporting Merton's argument, Goetzmann and Kumar (2008) depict that out of a sample of more than 62,000 households in the United States during the period of 1991-1996, over 25 percent of the investor portfolios have only one stock whereas more than 50 percent of the investor portfolios have not more than three stocks. They further show that very smaller amount of investor portfolios (five percent to ten percent) have more than ten stocks. Hence, this shows that the idiosyncratic volatility is an important factor in asset pricing as the investors are holding undiversified investment portfolios.

Accordingly, Merton (1987) anticipates a positive relationship between average stock returns and idiosyncratic risk. He argues that investors are expecting a premium for bearing the idiosyncratic volatility. However, some empirical findings have created a substantive puzzle in the asset pricing literature in relation to the aforementioned relationship.

For instance, Ang, Hodrick, Xingand Zhang(2006) demonstrate that the portfolios with the highest idiosyncratic volatility yield significantly lower returns where they conclude that it has created a puzzling surprise in the asset pricing literature. However, Bali and Cakici (2008) note that this relation mainly depends on several factors such as choices of data frequency, portfolio weighting schemes, break point calculations and choice of screens in sample selection. This is clearly in line with Fama (1998) who reports that changes in the long term returns of the stocks are highly sensitive to the methodology and statistical approaches that are used to measure them in different studies.

In addition to that, it is surprising to observe the existence of idiosyncratic volatility in the United States, as it is considered to be one of the highly transparent markets in the world (Pukthuanthong-Le &Visaltanachoti, 2009). Nevertheless, the existence of idiosyncratic volatility becomes further complicated in the context of other markets. For instance, Kumari, MahakudandHiremath(2017) note the existence of idiosyncratic volatility becomes complicated in the context of emerging markets as these markets characterize with features such as higher transaction costs, multiple tax regimes, lack of transparency, illiquidity which are unique to such markets.Therefore, this clearly challenges the standpoint of empirical asset pricing models such as CAPM on the relation between risk and returns of an asset.Hence, it is questionable whether the systematic risk is the only risk that should be priced in stock returns (Pukthuanthong-Le &Visaltanachoti, 2009).

Since, a considerable body of extant literature on idiosyncratic volatility is focused on developed stock markets such as the United States, it is important to investigate the existence of idiosyncratic volatility from another market context's point of view. Accordingly, the present study focuses on the idiosyncratic puzzle from the Sri Lankan context as there is a dearth of research on idiosyncratic volatility in Sri Lanka and particularly in the frontier market context. Though, Pukthuanthong-Le and Visaltanachoti (2009) examine the pricing of idiosyncratic volatility by using the CAPM, Sri Lankan stock market has been given only a cursory attention in that study. Hence, there is a need of an in-depth study focusing only on the Sri Lankan stock market. Thus, this study revisits the relationship between average stock returns and idiosyncratic volatility with an updated data while using thefive-factor asset pricing model ofFama and French (2015). Moreover, the current study employs the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model to estimate the idiosyncratic volatility of stocks.

Therefore, the contribution of the present study to the existing literature is two-fold. Firstly, it sheds light on idiosyncratic volatility puzzle from a frontier market point of view and thereby it explains the influence of idiosyncratic volatility on average stock returns. Secondly and more importantly, this study provides novel striking evidence on the characteristics of idiosyncratic volatility particularly in terms of profitability and investment factors with the use of a five-factor asset pricing model of Fama and French (2015). The remainder of the paper consists as follows; section 2 discusses the existing literature in the light of idiosyncratic volatility while section 3 elaborates the data and methodology employed in the current study. Section 4 provides a comprehensive analysis of data whereas section 5 provides the conclusion of the study.

2. Review of Related Literature

Based on the foundation laid by the portfolio selection problem of Markowitz (1952), Modern Portfolio Theory (MPT) notes that the investment portfolios are constructed based on the performance of different assets and risk appetite of the investors. However, being a normative theory, portfolio selection explains how investors should behave while as a positive theory, asset pricing attempts to predict investment decisions based on mean-variance analysis (Fabozzi, Gupta&Markowitz, 2002). Hence, the asset pricing theory builds a nexus between risk and return of an asset.

Even though the asset pricing theory emerges with the CAPM of Sharpe (1964), Famaand French (2004) note that simplified assumptions of CAPM made it empirically less successful; many extensions have been made to the CAPM in order to examine the relation between risk and return of an asset. For instance, arbitrage pricing model (Ross, 1976), three-factor asset pricing model (Fama& French, 1993), four-factor asset pricing model (Carhart, 1997) and five-factor asset pricing model (Fama& French, 2015) are some of the popular factor models that develop to determine the price of an asset.

Nevertheless, all factor models expect investors to act upon the changes in the market as quickly as they observe them.This is so because the financial models presume that markets are frictionless and investors are equipped with all information (Merton, 1987). On contrary, the empirical evidence shows various trading frictions in the market that prevent investors from making accurate investment decisions (Hou&Moskowitz, 2005; Miller & Scholes, 1982; Amihud&Mendelson, 1986; Amihud, 2002; Pastor &Stambaugh, 2003).

Moreover, the information asymmetries in the market prevent the investors from holding diversified portfolios. In the context of a stock market, there are low priced securities with high idiosyncratic volatility where Kumar (2009) identifies them as 'lottery-like' securities. Confirming the findings of Kumar (2009), Bali, Cakiciand Whitelaw (2011) highlight that investors tend to choose 'lottery-like' securities to overcome the imperfect diversification problem. Hence, it is questionable to what extent the role of idiosyncratic volatility can be ignored in asset pricing decisions.

Moreover, in the presence of information asymmetries in the market, factor models poorly perform in capturing the diversification decisions of investors (Merton, 1987). Therefore, Ang et al. (2009) argue that there is a possibility of generating a nexus between average stock returns and idiosyncratic volatility since the factor models fail to specify the role of idiosyncratic volatility in asset pricing decisions. This clearly highlights that idiosyncratic volatility plays a critical rolein investment decisions.

Despite its relative significance in investment decisions, scholars have used different methods to estimate the idiosyncraticvolatility of stocks. For instance, in the path breaking seminal work of Ang et al. (2006) on idiosyncratic volatility, the authors use one month lagged idiosyncratic volatility as a proxy for idiosyncratic volatility of stocks while Bali andCakici, (2008) also adopt the same technique in their study. In contrast, while highlighting the estimation errors of the previous techniques, Fu (2009) suggeststhe EGARCH technique of Nelson (1991) to estimate the idiosyncratic volatility of stocks. Similarly, Pukthuanthong-Le and Visaltanachoti(2009)and Kumariet al.(2017) also follow Fu's approach in order to estimate the idiosyncratic volatility of stocks.

Although, Ang et al. (2006) assume that idiosyncratic volatility follows a random walk, Fu (2009) denies the assumption of time varying property of idiosyncratic volatility can be approximated by a random walk process.

Supporting Fu's argument, based on a cross country analysis with a sample of 36 countries, Pukthuanthong-Le and Visaltanachoti (2009) state that adoption of one month lagged idiosyncratic volatility estimation method leads to severe estimation errors. Therefore, based on the empirical evidence, Fu (2009) and Pukthuanthong-Le and Visaltanachoti (2009) negate the use lagged idiosyncratic volatility of stocks to derive at the inferences between average stock returns and idiosyncratic volatility.

In spite of the strengths and weaknesses of each estimation method, the empirical findings on idiosyncratic volatility have created a substantive puzzle in the asset pricing literature. However, as per Bali and Cakici (2008), the existence of methodological differences among previous studies leads to conflicting arguments. Therefore, Fu (2009) emphasises that idiosyncratic volatility warrants not only a special attention but also a quality estimation process in deriving at the inferences between average returns and idiosyncratic volatility.

3. Data and Methodology 3.1Data

The data includes monthly stock returns and other accounting details pertinent to 214 non-financial firms listed on the Colombo Stock Exchange (CSE) over a period of 163 months from September 2004 to March 2018. All required data is obtained from CSE data library, annual reports of listed companies and annual reports of Central Bank of Sri Lanka. Further, following Sriyalatha (2008), monthly stock returns are adjusted for bonus issues and rights issues. As in Fama and French (1992), Samarakoon (1997), and Abeysekera and Nimal (2016), this study excludes the firms with negative book-to-market ratio and firms listed under the banks, finance and insurance sector since such firms are heavily geared and higher level of gearing indicates distress risk for non-financial firms (Fama& French, 1992). The data includes with respect to the following variables; all share total return index (ASTRI) is used as the proxy for market return (R_m) while three-month government Treasury-Bill rate is used as a proxy for risk free rate of return (R_f).

The market capitalization is used as a proxy for size (*Size*) while the book-to-marketequity *(B/M)* ratio is used as the proxy for value. Moreover, net profit as a fraction of book equity is used as a proxy for profitability (*Prof*) while the annual growth rate of the assets is used as the proxy for investment (*Inv*).

3.2Factor Construction

At the end of September each year *t*, the factor return portfolios are constructed and reformed at the end of September year *t*+1 (Samarakoon, 1997;Abeysekera&Nimal, 2017). According to Abeysekera and Nimal (2016), this enables to overcome the look-ahead biasness problem. In the current study, the factor return portfolios are constructed based on independent 2 x 3 sorts on *Size-B/M*, *Size-Prof*, and *Size-Inv*. The stocks are sorted as big and small stocks based on the market caiptalisationwhere the stocks in the top 50 percent of the market capitalization is categorized as Big (*B*) stocks while bottom 50 percent is categorized as the Small (*S*) stocks (Fama& French, 1993).

Moreover, based on *B/M*, the stocks are categorised as growth (*G*), neutral (*N*) and value (*V*) stocks (bottom 30 percent, middle 40 percent, top 30 percent) and the intersection of independent 2 x 3 sorts produce six portfolios: *SG*, *SN*, *SV*, *BG*, *BN*, *BV*(Fama& French, 1993). Similarly, the stocks are categorised as weak (*W*), neutral (*N*), robust (*R*) based on *Prof* and as aggressive (*A*), neutral (*N*), conservative (*C*) based on *Inv* which leads to generate 2 x 3 sorts of *Size-Prof* (*SW, SN, SR, BW, BN, BR*) and *Size-Inv* (*SA*, *SN*. *SC*, *BA*, *BN*,*BC*) (Fama& French 2015). In addition to conventional size factor based on 2 x 3 sort of *Size-B/M*($SMB_{B/M}$), the use of 2x3 sorts on *SizeProf* and *Size-Inv*produce two additional size factors namely, SMB_{Porf}andSMB_{Inv}. Therefore, size factor *(SMB)* from the three 2x3 sorts is defined as the average of $SMB_{B/M}$, SMB_{Porf}andSMB_{Inv}. Table 1 shows a summary of factor construction process in the current study.

Table 1: Construction of size, value, profitability and investment factors

Sort	Breakpoints	Factors and their components
2x3 sorts on *Size* and *B/M*, or *Size* and *Prof*, or *Size* and *Inv*	*Size*: CSE median	$SMB_{B/M} = (SG + SN + SV)/3 - (BG + BN + BV)/3$ $SMB_{Porf} = (SR + SN + SW)/3 - (BR + BN + BL)/3$ $SMB_{Inv} = (SA + SN + SC)/3 - (BA + BN + BC)/3$ $SMB = (SMB_{B/M} + SMB_{Prof} + SMB_{Inv})/3$
	B/M: 30th and 70th percentiles	$HML = (SV + BV)/2 - (SG + BG)/2$
	Prof: 30th and 70th percentiles	$RMW = (SR + BR)/2 - (SW + BW)/2$
	Inv: 30th and 70th percentiles	$CMA = (SC + BC)/2 - (SA + BA)/2$

Note: Researchers' construction based on Fama and French (2015). *Size, B/M, Prof* and *Inv* are market capitalisation, book-to-market ratio, profitability and investment respectively. In the 2x3 sorts, the *Size* group, small (*S*), neutral (*N*) and big (*B*), the *B/M* group, growth (*G*), neutral (*N*) andvalue (*V*), the *Prof*group, robust (*R*), neutral (*N*) and weak (*W*), the *Inv* group, conservative (*C*), neutral (*N*) and aggressive (*A*). The factors are *SMB* (small minus big), *HML* (value minus growth), *RMW* (robust minus weak), *CMA* (conservative minus aggressive).

3.3 Estimation of Idiosyncratic Volatility

As in Fu (2009), in the current study the authors have employed the EGARCH (p,q) model of Nelson (1991) to estimate the idiosyncratic volatility of stocks and generated nine different EGARCH models for each stock using the permutation of $1 \leq p \leq 3$, $1 \leq q \leq 3$ order. Akaike Information Criterion (AIC) has been used in order to determine the best model for each stock.The mean and variance equations of the EGARCH (p,q) model are specified in the Equation (1) and Equation (2).

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \underline{\varepsilon_{it}}$$

where $\varepsilon_{it} \sim N(0, \sigma_{it}^2)$ (1)

$$ln\sigma_{it}^2 = \alpha_i + \sum_{l=1}^{p} b_{i,l} \ln\sigma_{it-1}^2 + \sum_{k=1}^{q} c_{i,k} \left\{ \theta \left(\frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right) + \gamma \left[\left| \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right| - \sqrt{\frac{2}{\pi}} \right] \right\} \quad (2)$$

whereR_{it} - $R_{ft}$is excess return of stock *i* at month *t* where (R_m-R_f) is the market factor and *SMB* is the monthly size factor.*HML* is the monthly value factor while*RMW* and *CMA* are monthly profitability and investment risk factors respectively. $ln\ \sigma_{it}^2$is log of the conditional variance of the stock returns of stock *i* at time *t* while α_i b_i , c_i and θ are constant in the EGARCH model, vector of coefficients and asymmetric coefficient respectively. Further, the conditional distribution of residuals (ε_{it}) in the mean equation is based on the set of information at *t-1* which is assumed to be normal with the mean of zero and variance of σ_{it}^2 whereas the conditional variance (σ_{it}^2) in the variance equation is a function of past p-period of residual variance and past q-period of return shocks where $\alpha_i > 0$, $b_i + c_i < 1$, and $\lambda < 0$ if volatility is asymmetric.

The idiosyncratic volatility (*IVOL*) of stocks is measured as the square root of the conditional variance of residuals of five-factor asset pricing model estimated using the EGARCH model. Furthermore, the selected firms in the sample of the current study have at least 30 monthly return observations in order to overcome the look-ahead biasness problem (Fu, 2009; Pukthuanthong-Le &Visaltanachoti, 2009).

3.4 Portfolio Formation

In order to draw inferences between idiosyncratic volatility and average stock returns, the authors have formed idiosyncratic volatility sorted portfolios in the current study. Accordingly, five equal-weight and value-weight idiosyncratic volatility sorted portfolios formed to analyze the association between average stock returns and idiosyncratic volatility.

3.5 Gibbons, Ross and Shanken (1989) Test

The null hypothesis of Gibbons, Ross, and Shanken (GRS) (1989) test notes that regression intercepts of different asset portfolios developed through the asset pricing models are not significantly different from zero. Thus, in order to achieve the objective of the current study the authors have used the GRS test for idiosyncratic volatility sorted portfolios.

4. Summary Statistics

4.1 Descriptive Statistics

Table 2 shows the descriptive statistics of the variables used in the study. The average stock return is found to be 0.93 percent in Sri Lanka while Fu (2009) reports a mean return value of 1.18 percent with respect to the United States. Further, market factor is found to be highly volatile compared to other risk factors whereAbeysekera and Nimal (2017) note similar findings in relation to the CSE. Also, Ang et al. (2009) highlight that market factor seems to be highly volatile in the Asian context.

Even though, the mean value of size factor (0.37 percent) slightly deviates from the previous findings, a mean size factor closer to zero is in line with the findings ofFama and French (2012) and Abeysekera and Nimal (2017). However, the average value factor of 0.6 percent (see Table 2) is found to be parallel with both local and international findings. For instance, Abeysekera and Nimal (2016) reports a mean value factor of 0.54 percent in the Sri Lankan context whileFama and French (2012) and Ang et al. (2009) report average value factors of 0.62 percent and 0.72 percent forAsia Pacific and Asia respectively.

Table 2: Descriptive statistics

	R	R_m-R_f	*SMB*	*HML*	*RMW*	*CMA*	*IVOL*
Mean	0.93%	-8.89%	0.37%	0.60%	0.45%	0.06%	10.61%
Std. Dev.	7.15%	7.42%	3.04%	4.22%	3.82%	3.27%	1.81%
t-Mean	1.655	-15.233	1.542	1.798	1.506	0.241	74.758

Note: *R*is the average stock returns. R_m-$R_f$is the market factor where the market risk premium is the excess of ASTRI return over risk free rate of return (i.e. three-month government treasury bill rate). *SMB* is the monthly size factor where *HML* is the monthly value factor. *RMW* and *CMA* are monthly profitability and investment risk factors respectively. *IVOL* is the monthly idiosyncratic volatility of stocks estimated through the EGARCH model by using Fama and French (2015) five-factor asset pricing model.

Despite the relative consistence with previous empirical findings on mean values of popular risk factors, the average values on profitability (0.45 percent) and investment (0.06 percent) factors are contrasted considerably to that of the previous findings. For instance, in the United States,the mean values of profitability and investment factors are found to be 0.25 percent and 0.33 percent respectively (Fama& French, 2015) while in the Asian Pacific region, the mean values of these factors are found to be 0.21 percent and 0.39 percent respectively (Fama& French, 2017). Interestingly, the mean value of idiosyncratic volatility (10.61 percent) is slightly closer to the average value of 12.67 percent in the United States (Fu, 2009). Nevertheless, in a cross country analysis, Pukthuanthong-Le and Visaltanachoti (2009) record a mean value for idiosyncratic volatility as high as 15.98 percent for Sri Lanka.

4.2 Equal-weight and Value-weightPortfolio Return Analysis

Table 3 shows the results of portfolio return analysis where the Panel A shows the equal-weight average portfolio returns while Panel B shows the value-weight average portfolio returns.Accordingly, some interesting empirical findings can be observed with respect to idiosyncratic volatility of stocks. The empirical results in Panel A depict that portfolio 5 (stocks with highest idiosyncratic volatility) has generated substantially higher average return (1.90 percent) compared to the average return of portfolio 1 (lowest idiosyncratic volatility)(0.14 percent). Further, the average return differential of 1.76 percent between portfolio 5 and portfolio 1 is found to be highly statistically significant. Hence, this confirms the existence of idiosyncratic volatility in the Sri Lankan context and it is statistically significant and positively related with the average stock returns.

Table 3: Idiosyncratic volatility (*IVOL*) sorted portfolios

Panel A: Equal-weight average returns

	Portfolios formed on*IVOL*					
	1 (Low)	2	3	4	5 (High)	(5-1)
R	0.14%	0.16%	0.42%	0.94%	1.90%**	1.76%*
	(0.0014)	(0.0016)	(0.0042)	(1.3530)	(2.0308)	(2.9720)
Market share	29.04%	20.90%	17.29%	16.82%	15.94%	
Profitability	11.32%	9.30%	7.24%	3.05%	-0.09%	
Investment	133.71%	46.73%	61.34%	86.79%	31.56%	

Panel B: Value-weight average returns

	Portfolios formed on*IVOL*					
	1 (Low)	2	3	4	5 (High)	(5-1)
R	0.07%	-0.05%	0.15%	0.25%	-0.24%-	-0.30%
	(0.4790)	(-0.0005)	(0.0015)	(0.0025)	(-0.0024)	(-1.2576)
Market share	29.04%	20.90%	17.29%	16.82%	15.94%	
Profitability	11.32%	9.30%	7.24%	3.05%	-0.09%	
Investment	133.71%	46.73%	61.34%	86.79%	31.56%	

Note: *R*is the average stock returns. The market share of each *IVOL* sorted portfolio is calculated by using the market capitalisation of each *IVOL* portfolio as a percentage of the total market capitalisation of all *IVOL* sorted portfolios. Profitability is the average of the net profit-to-book equity ratio of each *IVOL* sorted portfolio. Investment is the average of the growth of total assets of each *IVOL* sorted portfolio. Newey-West (1987) adjusted *t*-statistics are reported in parentheses. * and ** indicate 1 percent and 5 percent significance levels respectively.

Interestingly, the empirical results of the value-weight average returns in Panel B of Table 3 present a contradictory argument for the positive relation between average stock returns and idiosyncratic volatility.

The empirical results depict that portfolio 5 (stocks with highest idiosyncratic volatility) has generated substantially lower average return (-0.24 percent) compared to the average return of portfolio 1 (lowest idiosyncratic volatility) (0.07 percent). Moreover, the difference of value-weight average returns of portfolio 5 and portfolio 1 is 0.30 percent with a *t* statistic of -1.2576. However, this average return differential is found to be economically and statistically insignificant.

Additional to the above empirical findings, Table 3 demonstrates more striking evidence on idiosyncratic volatility of stocks. The results depict that stocks with highest idiosyncratic volatility have the lowest market share of 15.94 percent compared to the stocks with lowest idiosyncratic volatility (29.04 percent). This indicates that the stocks with high idiosyncratic volatility tend to be small in the CSE. In fact, this empirical finding is consistent with the previous studies where Hou and Moskowitz (2005), Ang et al. (2006), Bali and Cakici (2008) and Fu (2009) also note that idiosyncratic volatility is high with small stocks

Moreover, the empirical findings on profitability and investment yield novel evidence in relation to the idiosyncratic volatility. The empirical evidence in Table 3 shows that profitability of the idiosyncratic volatility sorted portfolios has drastically declined as the idiosyncratic volatility of stocks increases. For instance, the profitability of the lowest idiosyncratic volatility sorted portfolio (portfolio 1) is found to be 11.32 percent while the profitability of the highest idiosyncratic volatility sorted portfolio (portfolio5) is found to be -0.09 percent. In other words, this implies that when the idiosyncratic volatility of stocks increases the profitability of stocks starts to fall. This confirms the argument of Fu (2009) on the idiosyncratic volatility where he notes that idiosyncratic volatility is firm specific and it does not move in line with the market. Hence, the impact of idiosyncratic volatility varies from one firm to another where the results show that when the idiosyncratic volatility becomes high, it negatively affects the profitability of the firms.

Furthermore, Fama and French (2015) highlight that small stocks tend to be less profitable compared to big stocks; the profitability premium is higher for small stocks compared to big stocks. The empirical findings of Table 3 pertinent to characteristics of the idiosyncratic volatility sorted stock portfolios lend direct support for this argument. For instance, as discussed earlier, small stocks tend to have higher idiosyncratic volatility compared to big stocks, indicating less profitability of small stocks due to their high idiosyncratic volatility. Hence, this clearly supports the argument of Fama and French (2015) on higher profitability premium on small stocks.

On the other hand, Table 3 demonstrates another piece of interesting evidence on idiosyncratic volatility of stocks. That is, as per the results, it can be observed that stocks with higher idiosyncratic volatility have the lowest investment value compared to stocks with lower idiosyncratic volatility. Hence, it seems that stocks with higher idiosyncratic volatility suffer from future growth prospects due to higher level of volatility in the firm specific risks which hinder the capital investments of such firms.

Furthermore, Fama and French (2015) argue that expected investment premium is quite larger for small firms. The findings of this study clearly in line with this argument where the stocks with higher idiosyncratic volatility tend to be small and their investment values are relatively lower compared to big stocks. Hence, the investors expect a higher investment premium (Fama& French, 2015). Moreover, Fama and French (2015) report that small firms tend to invest more despite their lower level of profitability. Perhaps as shown in the results of Table 3, presence of high idiosyncratic volatility with small stocks might be the reason which hinders the ability of such firms to reap benefits from their investments.

4.3 GRS Test

In the GRS test, the null hypothesis denotes that there is no significant difference between the intercepts of the asset returns under consideration. In other words, tailoring to the current study, this indicates that the intercepts of the idiosyncratic volatility sorted stock portfolios are not significantly different from each other. Thus, it rejects the presence of idiosyncratic volatility of stocks. Moreover, it should be noted that GRS test has been carried out only for equal-weight portfolios as value-weight portfolio returns generate statistically insignificant results (see Table 3).

According to empirical results depicted in Table 4,Fama and French five-factor (FF 5) alpha of lowest *IVOL* portfolio is -4.44 percent while it is as high as 1.03 percent for the highest *IVOL* portfolio. Similar to a hedging portfolio strategy highlighted by Fu (2009), longing highest *IVOL* portfolio and shorting lowest *IVOL* portfolio produces a statistically significant monthly return of 5.47 percent. The GRS test statistic of 26.28 strongly rejects the null hypothesis of GRS test which states that all intercepts are not significantly different from zero. In other words, GRS test reconfirms the findings of the portfolio analysis of this study and it validates the presence of idiosyncratic volatility of stocks in the CSE.

Table 4: Fama and French five-factor (FF 5) alpha values

	Portfolios formed on*IVOL*				
	1 (Low)	2	3	4	5 (High)
FF 5 Alpha	-4.44%*	-3.37%*	-2.70%*	-1.47%	1.03%
	(-5.2669)	(-3.2757)	(-2.4387)	(-1.3003)	(0.7089)

Note:Newey-West (1986) adjusted *t*-statistics are reported in parentheses. * indicates 1 percent level of significance.

5. Conclusion

All empirical asset pricing models assume that the role of idiosyncratic volatility is irrelevant as the investors can avoid the exposure to the idiosyncratic volatility by holding well-diversified portfolios with many securities (Bali, Engle& Murray, 2016). Further, in the absence of market imperfections Merton (1987) notes that theoretically investors have zero level of exposure to the firm specific risk. However, the empirical studies provide strong evidence against this theoretical stance and highlight that investors are commanding areasonable compensation for bearing the idiosyncratic volatility (Ang et al., 2006; Bali &Cakici, 2008; Ang et al., 2009; Fu, 2009).

This study attempted to shed a light on the idiosyncratic volatility puzzle from a South Asian market point view where both portfolio analysis and GRS test results confirmed the presence of idiosyncratic volatility in the Sri Lankan context. Furthermore, the empirical results revealed that idiosyncratic volatility has a statistically strong and positive influence on the average stock returns. Therefore, it indicates that investors expect an adequate return for bearing idiosyncratic risk.

Moreover, the current study yields some novel striking empirical evidences in terms of the characteristics of the idiosyncratic volatility of stocks. Accordingly, the results of the portfolio analysis demonstrated that the stocks with higheridiosyncratic volatility are less profitable while having lower growth prospects. Hence, it seems high idiosyncratic volatility is coupled with less profitable firms with lower level of investments. Moreover, it is also found that idiosyncratic volatility is high with small stocks. In other words, this indicates that small stocks carry high idiosyncratic volatility while being exposed to lower level of profits and investments. Hence, as Fama and French (2015) argue, the results of the current study also document that critical issues in asset pricing models are coupled with small stocks. Thus, one of the key messages of this study is that it is still questionable as to why there is a high demand for small stocks in the market despite their lower level of exposure to profits and investments while bearing a higher level of idiosyncratic volatility.

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