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The five-factor model, stock returns and idiosyncratic volatility: evidence from Sri Lanka

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Abstract

Traditionally, the success of asset pricing models is assessed in the absence of idiosyncratic volatility, as it is believed that the role of idiosyncratic volatility is irrelevant. Nevertheless, the existing literature shows that idiosyncratic volatility matters in asset pricing decisions. Hence, this study aims to test the performance of the five-factor asset pricing model of Fama and French (2015) in the presence of idiosyncratic volatility. This study utilizes a sample of 214 companies listed on the Colombo Stock Exchange (CSE) except for those listed under the banks, finance, and insurance sectors over 163 months from September 2004 to March 2018. Nelson's (1991) Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) models are used to estimate the idiosyncratic volatility of individual stocks. The empirical findings of the study confirm that the five-factor asset pricing model of Fama and French (2015) is less successful and failed to explain the stock returns in the presence of unsystematic risk in the Sri Lankan context. This finding yields striking evidence of the success of the five-factor asset pricing model in the presence of idiosyncratic volatility while it casts doubts on the applicability of such factor models in estimating the cost of equity of firms in the real world. Although the impact of idiosyncratic volatility on stock returns is well-researched in the finance literature, there is little structured research on how idiosyncratic volatility affects the performance of asset pricing models in the Sri Lankan context. This study fills this gap by investigating the performance of the five-factor asset pricing model of Fama and French (2015) using the firms listed on the CSE. The research findings should help academia develop more pronounced asset pricing models while tackling the idiosyncratic volatility of stocks.

Keywords:- *Asset pricing, EGARCH, Five-factor model, Idiosyncratic volatility, Sri Lanka*

1 Introduction

For more than a decade, investigating the impact of idiosyncratic volatility on stock returns has been an important issue in corporate finance literature. Since the seminal work of Ang, Hodrick, Xing, and Zhang (2006) on idiosyncratic volatility, a substantial puzzle on the idiosyncratic volatility-return relationship has been created in asset pricing literature. Subsequently, voluminous studies have been conducted across the world, resulting in inconclusive inferences on the impact of idiosyncratic volatility on stock returns (Bali & Cakici, 2008; Fu, 2009, Pukthuanthong-Le & Visaltanachoti, 2009; Nartea, Wu, & Liu, 2013; Hou & Loh, 2016; Kumari, Mahakud, & Hiremath, 2017; Zohng, 2018).

Asset pricing theory marked its birth with the capital asset pricing model (CAPM) of Sharpe (1964) and significantly developed after that with the inclusion of different factors in the CAPM (Fama & French, 1993; Carhart, 1997; Fama & French, 2015). However, all these models assume the presence of frictionless markets where different scholars have empirically proven the existence of various trading frictions in the market (Miller & Scholes, 1982; Merton, 1987; Amihud, 2002; Hou & Moskowitz, 2005). Moreover, Hou and Moskowitz (2005) highlight that market frictions prevent investors from holding well-diversified investment portfolios. Firms that confront market frictions cannot be easily identifiable by the investors due to delays in responding share prices to information.

Idiosyncratic volatility is another friction in the market where conventional asset pricing models assume it can be eliminated by diversification. Nevertheless, Merton (1987) notes that asset pricing models fail to detect the rationality of diversification decisions of the investors due to information asymmetries. Given that the complete diversification of idiosyncratic volatility is questionable, failure to diversify the investment portfolios creates costly results for investors in terms of risk-return tradeoff (Goetzmann & Kumar, 2008). Hence, Wang and Zhang (2005) argue that a successful financial model should have fewer pricing issues.

Accordingly, on the empirical grounds, the relative success of the asset pricing models such as the CAPM and its extensions are tested in different markets (Fama & French, 2012; Fama & French, 2015; Abeysekera & Nimal, 2016; Fama & French, 2017; Abeysekera & Nimal, 2017). Moreover, Maiti (2019) tests the presence of idiosyncratic volatility in the Sri Lankan context while adding an idiosyncratic volatility factor to the three-factor model of Fama and French (1993) to show its explanation power on stock returns. So far, in the Sri Lankan context, there is a dearth of empirical evidence on the explanatory power of the five-factor model of Fama and French (2015) in the presence of idiosyncratic volatility. Thus, this study attempts to fill this gap in the existing literature.

Because idiosyncratic volatility does matter in the Sri Lankan context (Maiti, 2019; Perera & Ediriwickrama, 2020; Perera & Ediriwickrama, 2021), it is essential to examine the success of the five-factor model of Fama and French (2015). Further, among other factors, Malagon, Moreno, and Rodriguez (2015) note that firms' profitability and investment decisions significantly affect the idiosyncratic volatility of stocks. Therefore, based on the companies listed on the Colombo Stock Exchange (CSE), the purpose of this study is to evaluate the validity of the five-factor model of Fama and French (2015) in the presence of idiosyncratic volatility. More specifically, this study investigates to what extent the five-factor model of Fama and French (2015) explains the stock returns of the listed firms in the CSE in the presence of idiosyncratic volatility.

The remainder of the paper is organized as follows; section 2 discusses the existing literature in light of idiosyncratic volatility, while section 3 presents the data and variables employed in the current study; section 4 provides a detailed analysis of data, and section 5 provides the conclusion of the study.

2 Literature review

Most asset pricing theories are built on a specified way to draw a relationship between expected returns and risk premiums of assets depending on their variance and covariance with others (Engle, Ng, & Rothschild, 1990). Moreover, Fabozzi, Gupta, and Markowitz

(2002) note that grounded on a hypothesized behavior of investors, the asset pricing models estimate the anticipated return of a portfolio of assets constructed based on mean-variance analysis. Hence, at the market equilibrium, the role of idiosyncratic volatility is completely ignored as it is assumed to be firm-specific and deviates from the common market movements (Fu, 2009).

Thus, the success of asset pricing models has been tested while ignoring the presence of idiosyncratic volatility of stocks. For instance, Fama and French (2012) report that the CAPM, three-factor, and four-factor models can explain global stock returns. However, they further note that these models fail to explain the stock returns at the regional level, where the four-factor model successfully captures the average returns on local *size-B/M* portfolios. Although Fama and French (2015) reject the five-factor asset pricing model in capturing the average return patterns, they document that the five-factor model uncovers 71 per cent to 94 per cent of the changes in average returns related to size, value, operating profits, and investment portfolios.

In the Sri Lankan context, previous empirical studies have used different asset pricing models to explain the stock returns. For instance, Samarakoon (1997) and Nimal (1997) use the CAPM, whereas Nanayakkara (2008) and Seneviratne and Nimal (2008) employ the three-factor model to explain the stock returns in the CSE. Moreover, Pathirawasam and Weerakoon Banda (2008) and Anuradha and Nimal (2013) test the presence of the momentum factor in the Sri Lankan context, while Abeysekera and Nimal (2016) test the ability of the four-factor model to explain the stock returns in the CSE. Abeysekera and Nimal (2017), among others, note that the four-factor model can capture the average returns in the CSE, where they further note that the four-factor model performs better than the CAPM. However, the four-factor model is marginally successful in explaining the stock returns compared to the three-factor model in the Sri Lankan context (Abeysekera & Nimal, 2017).

Despite the relative success of different asset pricing models due to market imperfections and misspecifications in the factor models, there is a possibility of creating a nexus between idiosyncratic volatility and stock returns (Ang, Hodrick, Xing & Zhang, 2009). Moreover, information availability differs from individual to individual, making investors limit their portfolio diversification with different securities in the market (Klein & Bawa, 1977). This clearly shows that idiosyncratic volatility does matter in asset pricing decisions.

Interestingly, Maiti (2019) and Perera & Ediriwickrama (2020) highlight the presence of idiosyncratic volatility in the CSE. After incorporating an idiosyncratic volatility factor, Maiti (2019) notes that the three-factor model better explains the average stock returns in the CSE.[1] However, Merton (1987) highlights that the asset pricing models are incapable of explaining the stock returns in the presence of idiosyncratic volatility. More importantly, profitability and investment are considered management-driven decisions, and such decisions significantly affect the

[1] Based on the GRS test results, Maiti (2019) notes that the three-factor model (Fama & French, 1993) is capable of explaining 97 percent of the changes in the stock returns when the stock portfolios are formed based on the idiosyncratic volatility.

idiosyncratic volatility of stocks (Malagon et al., 2015). Hence, it is clear that the five-factor asset pricing model is less successful in explaining the stock returns in the presence of idiosyncratic volatility of stocks. Accordingly, the following research hypothesis is developed:

H1: the five-factor asset pricing model of Fama and French (2015) fails to explain the stock returns in the presence of idiosyncratic volatility of stocks.

3 Data and methodology

3.1 Data

This study is quantitative research with a deductive approach, and data is sourced from secondary sources. The monthly stock returns and accounting data are derived from the CSE data library and annual reports of the listed companies. Monthly risk-free rates are derived from the Central Bank of Sri Lanka. Unlike the non-finance companies, finance companies are relatively high geared, indicating the distress risk for non-financial firms (Fama & French, 1992). Hence, the companies listed under the banks, finance, and insurance sector and the stocks with negative book-to-market ratios are excluded from the sample (Fama & French, 1992; Samarakoon, 1996; Abeysekera & Nimal, 2016).

Accordingly, the sample includes 214 companies listed on the CSE over 163 months from September 2004 to March 2018 of the following variables. The all share total return index (ASTRI) is utilized as the proxy for market return (R_m), while the three-month government Treasury-Bill rate is used as a proxy for the risk-free rate of return (R_f). The market capitalization is used as a proxy for size (Size), while the book-to-market equity ratio (B/M) is used as a 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).

3.2 Idiosyncratic volatility estimation

To reach the objective of this study, firstly, the idiosyncratic volatility of stocks needs to be estimated. Following Fu (2009), the author has employed the EGARCH (p,q) model of Nelson (1991) to estimate the idiosyncratic volatility of stocks. The study has used $1\leq p\leq 3$, $1\leq q\leq 3$ order where the permutation of these orders generates nine different EGARCH models. The Akaike Information Criterion (AIC) has been used to determine the best model for each stock. The square root of the conditional variance from the five-factor asset pricing model residuals estimated using an EGARCH model is the idiosyncratic volatility of stocks (Ivol). Further, the study excluded the firms that do not have at least 30 monthly return observations overcoming the look-ahead bias problem (Fu, 2009; Pukthuanthong-Le & Visaltanachoti, 2009). The mean and variance equations of the EGARCH (p,q) model are specified in Equation (1) and Equation (2).

$$R_{it} - R_{ft} = \alpha_i + b_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it}$$
$$\text{where } \varepsilon_{it} \sim N(0, \sigma_{it}^2) \qquad (1)$$

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

where $R_{it} - R_{ft}$ is the monthly excess return of stock i at month t. (R_m–R_f) is the market factor which denotes the excess market return over risk-free rate of return. SMB, HML,RMW, and CMA are monthly size, value, profitability, and investment risk factors, respectively. ln σ_{it}^2 is the log of the conditional variance of the stock returns of stock i at time t while α_i b_i, c_i, and γ 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. The conditional variance (σ_{it}^2) in the variance equation is a function of the 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.

3.3 RHS portfolio returns

Testing empirical asset pricing models requires forming portfolios to create explanatory and dependent variables. The portfolios on the explanatory variables are known as right-hand side (RHS) portfolios, and the portfolios generating the dependent variables are known as left-hand side (LHS) portfolios. The regression specification of the five-factor asset pricing model is as follows:

$$R_{it} - R_{ft} = \alpha_i + b_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + u_{it} \qquad (3)$$

The RHS portfolio returns include the 2 x 3 sorts of the factor return portfolios constructed on Size-B/M, Size-Prof, and Size-Inv. As in Samarakoon (1996) and Abeysekera and Nimal (2016), the factor return portfolios are constructed at the end of September each year t and renewed at the end of September, year t+ 1, which also enables to avoid the look-ahead bias problem (Abeysekera & Nimal, 2016). Following Fama and French (1993), stocks are sorted as big and small stocks based on the market caiptalisation (Size). Accordingly, the top 50 per cent of the market capitalization depicts the Big (B) stocks while the bottom 50 per cent is categorized as the Small (S) stocks.

Further, the stocks are sorted as low, neutral, and high book-to-market ratio (B/M) stocks based on the bottom 30 per cent of B/M as Low (L), the middle 40 per cent of B/M as Neutral (N), and the top 30 per cent of B/M as High (H) stocks (Fama & French, 1993). Thus, the intersection of the independent 2 x 3 sorts on Size and B/M constructs six portfolios: SL, SN, SH, BL, BN, and BH. A similar process is followed to construct the profitability and investment factors. The stocks are sorted as weak, neutral, and robust profitability (Prof) stocks based on the bottom 30 per cent of Prof as Weak (W), the middle 40 per cent of Prof as Neutral (N), and the top 30 per cent of Prof as Robust (R) stocks. The stocks are sorted as conservative, neutral, and aggressive investment (Inv) stocks based on the bottom 30 per cent of Inv as Aggressive (A), the middle 40 per cent of Inv as Neutral (N), and the top 30 per cent of Inv as Conservative (C) stocks (Fama & French, 2015). This leads to producing six 2 x 3 sorts on Size-Prof portfolios: SW, SN, SR, BW, BN, and BR and six 2 x 3 sorts on Size-Inv portfolios: SC, SN, SA, BC, BN, and BA.

The size factor, $SMB_{B/M}$ (small minus big), is the difference between the equal-weight average return of the 2 x 3 Size-B/M sorts on three small and big stock portfolios. The author constructs HML_S = SH – SL and HML_B = BH – BL, and the value factor, HML (high minus low), is the average of HML_S and HML_B. A similar approach is used to construct the profitability factor, RMW (robust minus weak), and investment factor, CMA (conservative minus aggressive). In addition to conventional $SMB_{B/M}$, the use of RMW and CMA factors generates two supplementary size factors: SMB_{Porf} and SMB_{Inv}. Therefore, SMB from the three 2 x 3 sorts is defined as the average of $SMB_{B/M}$, SMB_{Porf}, and SMB_{Inv}. Table 1 shows a summary of the factor construction of the 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	$SMB_{B/M} = (SL + SN + SH)/3 – (BL + BN + BH)/3$
		$SMB_{Porf} = (SW + SN + SR)/3 – (BW + BN + BR)/3$
		$SMB_{Inv} = (SC + SN + SA)/3 – (BC + BN + BA)/3$
		$SMB = (SMB_{B/M} + SMB_{Prof} + SMB_{Inv})/3$
	B/M: 30th and 70th percentiles	$HML_S = (SH – SL)$
		$HML_B = (BH – BL)$
		$HML = (HML_S + HML_B)/2$
	Prof: 30th and 70th percentiles	$RMW_S = (SR – SW)$
		$RMW_B = (BR – BW)$
		$RMW = (RMW_S + RMW_B)/2$
	Inv: 30th and 70th percentiles	$CMA_S = (SC – SA)$
		$CMA_B = (BC – BA)$
		$CMA = (CMA_S + CMA_B)/2$

Note: *Size, B/M, Prof* and *Inv* are market capitalization, book-to-market ratio, profitability, and investment, respectively.

3.4 LHS portfolio returns

Using the independent double-sorting portfolio method, 25 equal-weight Size-Ivol, Prof-Ivol, and Inv-Ivol portfolios are constructed as LHS assets in the asset pricing regressions. The 25 Size-Ivol, 25 Prof-Ivol, and 25 Inv-Ivol portfolios are the intersections of 5 x 5 Size and Ivol, Prof and Ivol, and Inv and Ivol sorts.

3.5 Gibbons, Ross, and Shanken (1989) test

The author uses the Gibbons, Ross, and Shanken (GRS) (1989) test to evaluate the success of the five-factor model in explaining the cross-sectional returns. The null hypothesis of the GRS test is common to all risk-based asset pricing theories, where it tests the hypothesis of regression intercepts of different asset portfolios that are not significantly different from zero. Accordingly, the five-factor asset pricing model performs better if each 25 equal-weighted average return portfolio's regression intercepts are not significantly different from zero.

4 Results and discussion

4.1 Summary statistics - RHS portfolio returns

The market risk premium (R_m-R_f,) is found to be the highest volatile explanatory variable with a standard deviation of 7.42 percent (see Table 2), while Ang et al. (2009) also note a higher standard deviation in the market risk premium for the countries in Asia. Further, the mean values of size (SMB) and value (HML) factors are also found to be more or less in line with the previous findings on the CSE (Abeysekera & Nimal, 2017) and Asian (Ang et al., 2009) and the Asia Pacific (Fama & French, 2012) contexts. However, the average values of profitability (RMW) and investment (CMA) factors are drastically different from the previous results of the Asian Pacific region (Fama & French, 2017).

Table 2. Summary statistics for explanatory variables

	R_m-R_f	*SMB*	*HML*	*RMW*	*CMA*	*Ivol*
Mean (%)	-8.89	0.37	0.60	0.46	0.06	10.60
Std. Dev.(%)	7.42	3.04	4.22	3.82	3.27	1.81
t-mean	-15.233	1.542	1.798	1.506	0.241	74.758

Note: R_m-R_f*, SMB, HML, RMW, and CMA are the monthly risk factors of the* Fama and French (2015) five-factor asset pricing model. *Ivol* is the monthly idiosyncratic volatility of stocks estimated through the EGARCH model.

Interestingly, the mean value of the CSE's idiosyncratic volatility is different from the previous empirical findings. For instance, even though the current study reports an average idiosyncratic value of 10.60 per cent, Pukthuanthong-Le and Visaltanachoti (2009) note it as high as 15.98 per cent. Perhaps this might be due to methodological differences between the two studies, as the present study used a more updated data set for analysis. Moreover, Maiti (2019) also records higher idiosyncratic volatility mean value (25.55 per cent per year) for the CSE. Nevertheless, Bali and Cakici (2008) highlight that methodological differences in the studies can generate different empirical results.

4.2 Summary statistics - Average excess returns for LHS portfolios

The average excess returns of the Size-Ivol, Prof-Ivol, and Inv-Ivol sorted portfolios are depicted in Table 3. In general, a weak size effect can be observed in the CSE during the period under consideration which is in line with previous empirical evidence by Abeysekera and Nimal (2016), who reports there is no persistent size effect can be observed in the Sri Lankan context. However, a precise size effect can be observed between the extreme quintiles (Small-Low Ivol, Big-Low Ivol, and Small-High Ivol, Big-High Ivol). Similarly, as per the results in Table 3, persistent profitability and investment effects cannot be observed in the CSE over the period under consideration. Fama and French (2017) also report that these effects are not observable in the Asia Pacific region.

Some interesting results can be observed in terms of idiosyncratic volatility. According to Table 3, the Small-High Ivol quintile records the highest excess return value while the Big-High Ivol quintile records the lowest excess return value out of the 25 Size-Ivol portfolios. This is consistent with the previous findings on idiosyncratic volatility, which note that stocks with high idiosyncratic volatility produce higher returns while they tend to be small in size (Bali & Cakici, 2008; Perera & Ediriwickrama, 2020; Perera & Ediriwickrama, 2021). In addition, this evidence supports the broadly documented

Table 3. Average excess returns for LHS portfolios

Panel A: Size-Ivol portfolios

	Low *Ivol*	2	3	4	High *Ivol*
Small	-0.0327	-0.0323	-0.0321	-0.0308	-0.0104
2	-0.0336	-0.0339	-0.0301	-0.0290	-0.0195
3	-0.0318	-0.0333	-0.0297	-0.0263	-0.0303
4	-0.0367	-0.0286	-0.0320	-0.0325	-0.0261
Big	-0.0346	-0.0312	-0.0243	-0.0324	-0.0411

Panel B: Prof-Ivol portfolios

	Low *Ivol*	2	3	4	High *Ivol*
Low *Prof*	-0.0424	-0.0366	-0.0313	-0.0296	-0.0192
2	-0.0355	-0.0298	-0.0279	-0.0300	-0.0164
3	-0.0332	-0.0284	-0.0291	-0.0298	-0.0233
4	-0.0276	-0.0300	-0.0306	-0.0270	-0.0310
High *Prof*	-0.0298	-0.0319	-0.0318	-0.0323	-0.0197

Panel C: Inv-Ivol portfolios

	Low *Ivol*	2	3	4	High *Ivol*
Low *Inv*	-0.0357	-0.0275	-0.0328	-0.0329	-0.0152
2	-0.0323	-0.0331	-0.0261	-0.0278	-0.0215
3	-0.0321	-0.0318	-0.0249	-0.0292	-0.0163
4	-0.0323	-0.0338	-0.0314	-0.0301	-0.0221
High *Inv*	-0.0326	-0.0321	-0.0298	-0.0308	-0.0338

Note: At the end of September each year, 25 *Size-Ivol, Prof-Ivol* and *Inv-Ivol* portfolios are constructed. The intersections of the 5 × 5 independent *Size-Ivol, Prof-Ivol* and *Inv-Ivol* sorts produce 25 *Size-Ivol,* 25 *Prof-Ivol* and 25 *Inv-Ivol* portfolios.

size effect of small stocks generating higher returns than big stocks.

On the other hand, as per Table 3, stock portfolios with low profitability with high idiosyncratic volatility incline to generate higher returns than stock portfolios with high profitability with low idiosyncratic volatility. This can be observed for the Low Ptof-High Ivol quintile and High Prof-Low Ivol quintile. Moreover, the empirical results, particularly on Low Ptof-High Ivol and High Prof-Low Ivol quintiles, lend direct support to the profitability effect of robust stocks generating lower returns compared to weak stocks (Fama & French, 2015). Table 3 also shows that the Low Inv-High Ivol quintile generates higher excess returns than the High Inv-Low Ivol quintile. Perhaps, this might be the reason for the investment effect which shows that conservative stocks generate higher returns than aggressive stocks.

4.3 Model performance test (hypothesis testing)

The regression results of 5x5 Size-Ivol (Panel A), Prof-Ivol (Panel B), and Inv-Ivol (Panel C) portfolios are presented in Table 4. Except for the market factor, most other factor coefficients are insignificant, while most regression intercepts are found to be significant for the idiosyncratic volatility sorted portfolios. This indicates that the five-factor model is unlikely to explain the stock returns in the CSE in the presence of idiosyncratic volatility. This contradicts the findings of Maiti (2019), who notes a better performance of the three-factor model in the CSE in the presence of idiosyncratic volatility. However, the unsuccess of the five-factor model in the presence of idiosyncratic volatility strongly supports Merton's (1987) argument that the financial models are incapable of capturing the asset prices in the presence of idiosyncratic volatility. In sum, these findings support the research hypothesis of the study.

Table 4. Regression results for 5x5 double sorted portfolios

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

Panel A: *Size-Ivol portfolios*

	α_i	b_i	s_i	h_i	r_i	c_i	R^2
1,1	-0.010	0.287***	0.315	0.162	0.099	-0.164	0.114
1,2	0.010	0.456***	0.067	-0.076	-0.324	-0.255	0.199
1,3	0.009	0.481***	0.358	0.158	-0.14	-0.034	0.236
1,4	0.022*	0.591***	0.071	0.1	-0.223	-0.274	0.221
1,5	0.055***	0.715***	0.076	-0.218	-0.064	-0.070	0.153
2,1	-0.001	0.284***	0.205	0.135	-0.056	-0.046	0.126
2,2	0.007	0.466***	0.237	0.024	-0.150	0.0226	0.197
2,3	0.002	0.393***	0.124	0.301*	0.063	-0.114	0.172
2,4	0.031***	0.680***	0.006	0.144	-0.132	0.032	0.265
2,5	0.042**	0.687***	0.215	-0.049	-0.110	-0.187	0.166
3,1	0.005	0.419***	0.168	0.095	-0.059	-0.282	0.250
3,2	0.014	0.532***	-0.031	0.116	-0.118	-0.09	0.272
3,3	0.017	0.528***	-0.011	0.147	-0.154	0.006	0.236
3,4	0.021	0.558***	0.388*	0.171	-0.126	0.136	0.226
3,5	0.020	0.589***	0.327	0.267	-0.047	-0.303	0.165
4,1	-0.004	0.377***	-0.037	0.079	0.097	-0.080	0.192
4,2	0.013	0.477***	0.060	0.093	-0.057	0.083	0.251
4,3	0.016	0.530***	0.0116	0.061	-0.140	-0.108	0.281
4,4	0.037***	0.726***	-0.623**	0.0666	-0.615***	-0.630***	0.339
4,5	0.028*	0.599***	-0.153	0.0532	-0.0445	-0.356	0.166
5,1	-0.001	0.375***	-0.014	0.001	0.049	-0.324**	0.28
5,2	0.008	0.434***	-0.197	0.095	-0.051	-0.028	0.266
5,3	0.026***	0.571***	-0.246	0.197	-0.059	-0.090	0.307

5,4	0.017	0.536***	-0.143	-0.210	0.138	-0.191	0.22
5,5	0.038*	0.770***	-1.633***	0.006	-0.821**	-1.518***	0.227
Panel B: *Prof-Ivol portfolios*							
1,1	-0.005	0.411***	-0.011	-0.081	-0.186	0.011	0.144
1,2	0.009	0.492***	0.057	0.005	-0.465**	-0.040	0.202
1,3	0.014	0.509***	0.212	0.200	-0.324	0.001	0.205
1,4	0.028**	0.650***	0.146	0.215	-0.277	0.251	0.239
1,5	0.048***	0.740***	0.295	-0.082	-0.352	-0.190	0.182
2,1	-0.002	0.369***	0.009	-0.012	-0.052	-0.078	0.206
2,2	0.007	0.399***	0.088	0.090	-0.354**	-0.161	0.23
2,3	0.019**	0.526***	-0.079	0.199	-0.235	-0.103	0.286
2,4	0.026**	0.593***	-0.170	-0.049	-0.535***	-0.215	0.214
2,5	0.047***	0.710***	0.308	-0.148	-0.150	-0.332	0.183
3,1	-0.003	0.344***	0.078	0.072	-0.075	-0.524***	0.201
3,2	0.019**	0.529***	-0.009	0.076	-0.114	-0.037	0.302
3,3	0.015	0.504***	-0.075	0.114	-0.024	0.083	0.226
3,4	0.023**	0.601***	0.091	0.043	0.107	-0.021	0.281
3,5	0.028*	0.609***	-0.081	0.246	0.363	0.106	0.156
4,1	-0.0005	0.326***	0.244	0.078	0.138	-0.198	0.231
4,2	0.015	0.509***	0.021	0.003	0.053	-0.138	0.24
4,3	0.0121	0.498***	0.124	0.128	0.081	-0.075	0.279
4,4	0.033***	0.670***	0.358	-0.212	-0.027	-0.484**	0.275
4,5	0.030**	0.664***	-0.27	0.074	-0.146	-0.585**	0.212
5,1	0.002	0.380***	0.134	0.100	0.124	-0.158	0.225
5,2	0.004\	0.422***	0.017	0.112	0.125	-0.046	0.221
5,3	0.015	0.542***	0.082	0.143	0.062	-0.126	0.271
5,4	0.023*	0.606***	-0.412	0.290	-0.375*	-0.510**	0.273
5,5	0.035*	0.589***	-0.386	-0.151	0.0647	-0.334	0.105
Panel C: *Inv-Ivol portfolios*							
1,1	-0.012	0.279***	0.183	0.097	-0.028	0.081	0.138
1,2	0.010	0.431***	0.157	0.139	-0.141	0.058	0.206
1,3	0.007	0.471***	0.296	0.237	-0.120	-0.078	0.21
1,4	0.016	0.557***	0.020	0.261	-0.331*	0.118	0.229
1,5	0.047***	0.664***	0.003	-0.259	-0.316	0.061	0.149
2,1	0.003	0.406***	0.165	0.001	0.084	-0.038	0.232
2,2	0.011	0.496***	0.164	0.086	-0.173	0.018	0.278
2,3	0.015	0.467***	-0.007	0.157	-0.095	0.107	0.236
2,4	0.029**	0.631***	-0.005	-0.111	0.005	0.063	0.236
2,5	0.043**	0.728***	-0.107	-0.006	0.066	-0.072	0.153

3,1	-0.005	0.292***	0.104	-0.084	-0.189	-0.313	0.123
3,2	0.008	0.424***	-0.065	-0.088	-0.185	-0.236	0.185
3,3	0.025**	0.586***	0.175	0.138	0.088	-0.075	0.263
3,4	0.035***	0.715***	0.082	0.039	-0.195	-0.292	0.29
3,5	0.037**	0.621***	0.055	0.182	0.079	-0.098	0.158
4,1	0.001	0.406***	0.197	0.129	0.324**	-0.430**	0.271
4,2	0.019**	0.590***	-0.23	0.074	-0.087	0.109	0.311
4,3	0.013	0.498***	-0.072	0.143	-0.066	-0.016	0.239
4,4	0.028**	0.637***	-0.100	0.056	-0.280	-0.571**	0.261
4,5	0.031*	0.637***	0.140	0.330	0.325	-0.076	0.172
5,1	0.002	0.378***	-0.026	0.028	-0.121	-0.266	0.202
5,2	0.006	0.425***	0.061	0.082	-0.204	-0.206	0.193
5,3	0.013	0.480***	0.024	0.171	-0.177	-0.313	0.265
5,4	0.023**	0.602***	0.054	0.140	-0.178	-0.265	0.275
5,5	0.0392**	0.753***	-0.371	-0.125	-0.677**	-1.494***	0.274

Note: α_i , b_i, s_i , h_i, r_i , and c_i are the intercept and factor loadings of the five-factor model, respectively. ***, **, and * are 1%, 5%, and 10% significance level, respectively.

Table 5. GRS test results – five-factor asset pricing model

	F-statistic	*P-value*	$\mid a \mid$	R^2
Size-Ivol portfolios	3.1285	0.0000	0.0166	0.2211
Prof-Ivol portfolios	2.0298	0.0056	0.0253	0.2236
Inv-Ivol portfolios	2.5820	0.0003	0.0203	0.2220

Note: $\mid a \mid$ is the average absolute intercept for a set of regressions; R^2 is the average adjusted R^2.

To further strengthen the findings of the failure of the five-factor model to explain the stock returns, the author conducts the GRS test (see Table 5). As per the empirical results of the GRS test in Table 5, it rejects the five-factor model in the Sri Lankan context. Even though this finding contradicts Maiti (2019), it directly supports the theoretical argument that systematic risk is not the only risk that should be considered when it comes to asset pricing decisions. In addition to that, according to Fama and French (2012), the performance of asset pricing models can be marginally successful in the formation of portfolios in different ways. Nonetheless, the rejection of the five-factor asset pricing model in the presence of idiosyncratic volatility is a novel finding in the extant literature on empirical asset pricing. Overall, the empirical results support the research hypothesis developed in the study.

5 Conclusion

As the central theorem in finance, diversification assumes that systematic risk is the only risk that should be priced in equilibrium as the impact of idiosyncratic volatility can be wholly eliminated through diversification. Hence, the success of the asset pricing models is questionable in the presence of idiosyncratic volatility. Accordingly, this study tested this phenomenon in the Sri

Lankan context by using the firms listed on the CSE.

Accordingly, the study's findings revealed that the five-factor model is less successful and failed to explain the stock returns of idiosyncratic volatility sorted portfolios in the Sri Lankan context. More importantly, this supports the doubts cast by Fama and Franch (2017) in estimating the cost of equity through asset pricing models. Thus, it offers tantalizing glimpses into the validity of asset pricing models in the real world. The contribution of this study to the existing literature is mainly three-fold. First, to the author's best knowledge, this is the first attempt to test the performance of the five-factor asset pricing model in the presence of idiosyncratic volatility. Second, the empirical findings highlight the importance of considering the firm-level risks when making portfolio level decisions. Third, the results show the vitality of idiosyncratic volatility in improving the effectiveness of asset pricing models to enhance equity financing decisions. Therefore, the empirical findings of this study show that academia and practitioners should consider firm-level risk in developing asset pricing models so that they will address the firm-level changes to make more effective investment decisions. Further, despite the significant role of the banks and other financial institutions in the CSE, this study has excluded the banks and other financial firms while limiting the study to the Sri Lankan context. Hence, the author calls for future research to expand this study by including financial firms while conducting a cross-country analysis to understand better the role of asset pricing models in the presence of idiosyncratic volatility.

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