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Is idiosyncratic risk ignored in asset pricing: Sri Lankan evidence?

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Abstract

The present study focused on one of the important South Asian nations—Sri Lanka—to examine the role of idiosyncratic volatility in asset prices. A four-factor model with idiosyncratic volatility was designed for capturing the market, size, value and idiosyncratic risk yields better than Fama and French's (J Financ Econ 33:3–56, 1993) three-factor model and performance of the model. Fama–MacBeth's cross-sectional regression, residual graphs and GRS test all confirm the superiority of four-factor model over 2 three-factor models. For all MC- and IVOL-based portfolios, idiosyncratic volatility is negatively related to the expected returns and positively related for all PB-based portfolios. Finally, study findings confirm that there is a high importance for idiosyncratic volatility risk factor while considering investment decision in Colombo stock exchange. Hence, investor should compensate for holding such risk factors in the portfolio.

Keywords: Asset pricing, Idiosyncratic risk, Factor models, Fama–MacBeth' cross-sectional regression, Risk

JEL Classification: G12

Introduction

Risk is broadly classified into two groups: one systematic and another unsystematic. Systematic risk is a risk which cannot be diversified like market risk, whereas unsystematic risk can be diversified, and hence, systematic risk should be priced by the investors. Earlier studies by Sharpe [1], Lintner [2] and Mossin [3] consider only the systematic risk to derive risk return relationship and argued that investor holds well-diversified market portfolio which, in turn, diversified the idiosyncratic volatility. In reality, capital markets are more complex, and simply holding well-diversified portfolios will not automatically reduce the idiosyncratic volatility completely. In such case, if investors are not able to distinguish between systematic and unsystematic risk clearly, investors will observe underperformance in its investment decision. Merton [4] argued that investor who holds undiversified portfolio should not be compensated. Previous studies show mixed results about the importance of the idiosyncratic volatility in stock returns. As a result, it is always a topic of discussion among the researchers whether idiosyncratic volatility should be priced or not by the investors?

Malkiel and Xu [5, 6], Goyal and Santa-Clara [7] and Fu [8] studies find a positive relationship between the idiosyncratic volatility and stock returns, whereas considerable number of studies by Ang et al. [9, 10], Guo and Savickas [11], Frieder and Jiang [12], Chua et al. [13] and Wagner and Winter [14] find a negative relationship between the idiosyncratic volatility and stock returns. One finding which is common in most of the above-mentioned studies is that CAPM neglects idiosyncratic volatility in asset pricing. Presently emerging capital markets are equally important like the other developed markets, and Blackrock [15] reports say that the shares of emerging markets, especially Asian markets, are increasing. Sri Lanka's Colombo stock exchange is one such important exchange that has seen significant development and foreign investment in the last decade. Colombo stock exchange is one of the important exchanges in South Asia that provides electronic trading. Considering the fact that the effect of idiosyncratic volatility of stock returns is mixed, the present study will be the maiden attempt

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to study comprehensively on Sri Lanka's Colombo stock exchange.

The present study will explicitly report how important idiosyncratic volatility is in Sri Lankan context, which is not addressed by any other previous studies. Study by Bali et al. [16] found that stock with small size tends to have more idiosyncratic volatility than big-size stocks. Second, the present study will address the same by following portfolio-based study results. Third study will deploy different designs and methodologies that are different from previous studies. Different researchers follow different frequencies and proxies for idiosyncratic volatility calculation. Daily data were used by Ang et al. [9] study, whereas Frieder and Jiang [12] study used monthly data for calculating idiosyncratic volatility. Many of the studies by Ang et al. [9] and Frieder and Jiang [12] used time series data for fixed time period, whereas Fu [8] study found that idiosyncratic volatility is time-varying. Hence, study findings based on fixed model are questionable and need dynamic check. Ang et al. [9, 10] used lagged realised idiosyncratic volatility as proxy, whereas Fu [8] used expected idiosyncratic volatility as proxy for idiosyncratic volatility. The present study uses Fama and French [17]-based approach in calculating the idiosyncratic volatility proxy. Finally, the study uses both time series and cross-sectional analysis to explore the significance of idiosyncratic volatility in asset pricing. The rest of the paper is divided into the following sections: literature review, data and methodology, empirical results, asset-pricing results, model performance test and conclusions.

Literature review

Traditional asset-pricing studies by Sharpe [1], Lintner [2] and Mossin [3] argue that unsystematic risk should not be price the investors as investors hold well-diversified market portfolio. Considerable number of studies in last few decades challenged the basic fundamental idea of not to compensate the unsystematic risk. Black and Scholes [18] and Merton [4] studies argued that increase in the stochastic volatility of the stocks or portfolios leads to increase in the value of the equity, and hence, idiosyncratic risk should be compensated by the investors. Idiosyncratic risk is a firm-specific risk, and considerable number of studies by Banz [19], Reinganum [20], Gibbons [21], Basu [22], Bhandari [23]. Ross [24], Fama and French [17], Balakrishnan and Maiti [25], Balakrishnan et al. [26], Maiti and Balakrishnan [27], Maiti [28, 29, 30], etc., proved that there are several firm-specific risks other than market risk. Campbell et al. [31] found that average total volatility increases over a period of time, whereas market volatility shows no pattern. Further study found that idiosyncratic volatility component of the total volatility factor is very important and time-varying. The study also argued that a well-diversified portfolio must contain over 50 stocks and practically idiosyncratic volatility cannot be diversified completely. A sizeable number of studies related to idiosyncratic risk have been carried out globally, and the results are mixed.

Chua et al. [13] studies found that the expected stock returns are positively related to the idiosyncratic volatility. A sizable number of studies by Jiang and Lee [32], Malkiel and Xu [6], Drew et al. [33], Huang et al. [34] and Zaremba [35] also found positive relationship between expected returns and idiosyncratic volatility. Similarly, other set of studies by Ang et al. [9, 10], Guo and Savickas [11], Frieder and Jiang [12], Chua et al. [13] and Peterson and Smedeman [36] found that idiosyncratic volatility is negatively related to the expect stock returns. Recent study by Liu and Di Iorio [37] in Australian context finds a positive relationship between the expected returns and idiosyncratic volatility. The study also finds that idiosyncratic factor is very much significant in explaining returns in both time series and cross-sectional set-up. Finally, study also finds that big stocks are systematically much riskier than the small stocks. From the above literature review, it is clear that idiosyncratic volatility is important factor in explaining the risk and return relationship. A sizeable number of studies related to idiosyncratic volatility and expected returns have been carried out on the developed markets, and as Sri Lanka is concerned, no study has been done so far related to the idiosyncratic volatility and expected returns.

Data and methodology

Data

Present study uses both daily and monthly data of 251 stocks listed in Colombo stock exchange for the period July 2008 to December 2016 of the following variables. Market capitalisation (MC) was used as proxy for size, P/B ratio was used as proxy for value, Standard and Poor's Sri Lanka 20 index return were used as the proxy for market (Rm), and 91-day T-Bill was used as the proxy for risk-free rate (Rf). Similar to Ang et al. [9, 10] study, standard deviation of Fama and French's [17] three-factor regression residuals was used as the proxy for idiosyncratic volatility. For the same period, daily excess returns are regressed with the daily excess market (Rm–Rf), size (SMB) and value (LMH) factor for the whole sample period to obtain the regression residuals.

$$R_{Pt} - R_{Ft} = aa + bb(R_{Mt} - R_{Ft}) + ss\ \mathrm{SMB}_t + ll\ \mathrm{LMH}_t + e_t \quad (1)$$

where $R_{Pt} - R_{Ft}$ is the daily excess return of the stocks, $R_{Mt} - R_{Ft}$ is the daily excess return of the market, SMB is the daily excess return of the size risk factor, LMH is the daily excess return of the value risk factor, ss and ll are the portfolio's responsiveness to (sensitivity coefficients) SMB and LMH factors, respectively.

Idiosyncratic volatility of the stock is calculated as the standard deviation of the residual obtained from the regression of equation number 1. Then the daily idiosyncratic volatility was converted to monthly idiosyncratic volatility (IVOL) by multiplying the daily value with the square root of number of trading days for that month.

Portfolio construction

Statman [38] argued that a well-diversified portfolio must contain at least 30 stocks, and further Campbell et al. [31] study added that in recent decades to achieve a certain level of diversification in portfolio returns, it must have more than 40 stocks. Our study sample has 251 stocks, and hence, six portfolios are formed to achieve the greater level of diversification. Using single-sorting technique, every year in the month of June (t), six equal-weighted portfolios are constructed based on each MC, P/B, and IVOL variables. The portfolios are names as P11 to P16. Revision of portfolios ranking again done in the month of June[1] next year ($t+1$) following the same procedure and repeated up to year 2016.

Mimicking risk factor construction

Using single-sorting technique every year in the month of June (t), two equal-weighted portfolios are constructed based on MC. Top 50% stocks with high value of MC stocks are named Big (B) and rest 50% names as Small (S). Revision of portfolios ranking again was done in the month of June next year ($t+1$) following the same procedure and repeated up to year 2016. Then using single-sorting technique every year in the month of June (t), three value-weighted portfolios ([17] break-points of 30:40:30) are constructed based on each P/B and IVOL variables. Top 30% stocks with high value of P/B named as high (H), bottom 30% stocks with less value of P/B named as low (L) and rest 40% named as neutral (N). Similarly, top 30% stocks with high value of IVOL (Hv) named as high IVOL, bottom 30% stocks with less value of IVOL named as low IVOL (Lv) and rest 40% named as neutral (Nv). Revision of portfolios ranking again was done in the month of June next year ($t+1$) following the same procedure and repeated up to year 2016.

Using double-sorting technique, every year in the month of June (t), six value-weighted portfolios are constructed from the cross of two MC and three P/B portfolios obtained from single sort. Six portfolios are named as *S/L*, *S/N*, *S/G*, *B/L*, *B/N* and *B/G*, where *S/L* portfolio contains 'small size and low value stocks' and *B/G* portfolio contains 'big size and high value stocks'. Revision of portfolios ranking again was done in the month of June next year ($t+1$) following the same procedure and repeated up to year 2016. Then using double-sorting technique, every year in the month of June (t), six value-weighted portfolios are constructed from the cross of two MC and three IVOL portfolios obtained from single sort. Six portfolios are named as S/Lv, S/Nv, S/Gv, B/Lv, B/Nv and B/Gv, where S/Lv portfolio contains 'small size and low idiosyncratic volatility stocks' and *B/G* portfolio contains 'big size and high idiosyncratic volatility stocks'. Revision of portfolios ranking again was done in the month of June next year ($t+1$) following the same procedure and repeated up to year 2016.

Present study uses three risk-mimicking portfolios SMB (size), LMH (value) and LvMHv (idiosyncratic volatility), and they are estimated as described below:[2]

$$\mathrm{SMB} = (S/L + S/M + S/H)/3 - (B/L + B/M + B/H)/3 \tag{2}$$

$$\mathrm{LMH} = (S/L + B/L)/2 - (S/H + B/H)/2 \tag{3}$$

$$\mathrm{LvMHv} = (S/\mathrm{Lv} + B/\mathrm{Lv})/2 - (S/\mathrm{Hv} + B/\mathrm{Hv})/2 \tag{4}$$

The present study uses four regressions as explained below:

Fama–French three-factor model

$$R_{Pt} - R_{Ft} = a + b(R_{Mt} - R_{Ft}) + s\ \mathrm{SMB}_t + l\ \mathrm{LMH}_t + e_t \tag{5}$$

where SMB mimics size risk factor, LMH mimics value risk factor, s and l are the sensitivity coefficients of SMB and LMH factors.

Three factor model with idiosyncratic volatility

$$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\ \mathrm{SMB}_t + v\ \mathrm{LvMHv}_t + e_t \tag{6}$$

where SMB mimics size risk factor, LMH mimics idiosyncratic volatility risk factor, s and v are the sensitivity coefficients of SMB and LvMHv factors.

[1] Three months lag period given, generally in Sri Lanka the financial year ends in the month of March of every year.

[2] Fama and French [17] estimate HML, which stands for high minus low, and mimics the risk factor associated with company value. They form HML using BE/ME while this study estimates LMH (See [25]) using P/B ratio which is inversely related to BE/ME as BE/ME ratios for the sample companies are not directly available in the data source. Hence, our interpretations of the results of value factor are mirror image to those of FFTF model [17].

Table 1 Descriptive statistics for the independent variables

	Rm	SMB	LMH	LvMHv
Mean returns	0.006	0.003	0.001	0.001
SD	0.053	0.011	0.011	0.009

Four-factor model with market, size, value, and idiosyncratic volatility

$$R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\ \mathrm{SMB}_t + l\ \mathrm{LMH}_t + v\ \mathrm{LvMHv}_t + e_t \tag{7}$$

Fama–MacBeth's cross-sectional regression

It is a step regression as explained below

Step 1

$$\begin{aligned}
(R_{Pt} - R_{Ft})_{1,t} &= a + b_{1,\mathrm{beta}}(R_{Mt} - R_{Ft})_{1,t} + s_{1,\mathrm{smb}}\mathrm{SMB}_{1,t} + l_{1,t}\mathrm{LMH}_{1,t} + v_{1,t}\mathrm{LvMHv}_{1,t} + e_{1,t}\\
(R_{Pt} - R_{Ft})_{2,t} &= a + b_{2,\mathrm{beta}}(R_{Mt} - R_{Ft})_{2,t} + s_{2,\mathrm{smb}}\mathrm{SMB}_{2,t} + l_{2,t}\mathrm{LMH}_{2,t} + v_{2,t}\mathrm{LvMHv}_{2,t} + e_{2,t}\\
&\vdots\\
&\vdots\\
(R_{Pt} - R_{Ft})_{n,t} &= a + b_{n,\mathrm{beta}}(R_{Mt} - R_{Ft})_{n,t} + s_{\mathrm{smb},t}\mathrm{SMB}_{n,t} + l_{\mathrm{lmh},t}\mathrm{LMH}_{n,t} + v_{n,t}\mathrm{LvMHv}_{n,t} + e_{n,t}
\end{aligned} \tag{8}$$

Step 2

$$R_{Pt} - R_{Ft} = \lambda_0 + \lambda_{\mathrm{rm}}\,(R_{Mt} - R_{Ft}) + \lambda_{\mathrm{smb}}\ \mathrm{SMB}_t + \lambda_{\mathrm{lmh}}\ \mathrm{LMH}_t + \lambda_{\mathrm{ivol}}\ \mathrm{LvMHv}_t + e_t \tag{9}$$

Explanatory variables

Table 1 shows descriptive statistics for the explanatory variables. Average mean excess returns for all the variables are comparatively low and among all average excess market return outperformed others. Average mean excess market return is 0.7% ($t = 2.281$); size premium is 0.3% ($t = 2.754$); both value and idiosyncratic premium are 0.2%. Average return pattern reveals that investor will gain moderate return by aligning their investment strategies to market and size. Table 2 shows year-wise average monthly idiosyncratic volatility that prevails in Colombo stock exchange stocks.

Correlation between the explanatory variables is shown in Table 3. Except idiosyncratic volatility market is related weakly negatively to the other variables. Size is negatively related to value to idiosyncratic volatility factor. Value and idiosyncratic volatility factor are positively related.

Table 3 Correlation matrix for explanatory variables

	Rm	SMB	LMH	LvMHv
Rm	1			
SMB	−0.056	1		
LMH	−0.147	−0.092	1	
LvMHv	0.013	−0.196	0.269	1

Empirical results

Radar graph in Fig. 1 shows the average mean excess return pattern of portfolios based on MC, PB and IVOL. Portfolio P11 shows higher average mean excess return in case of MC- and *P*/*B*-based portfolios, whereas P16 of

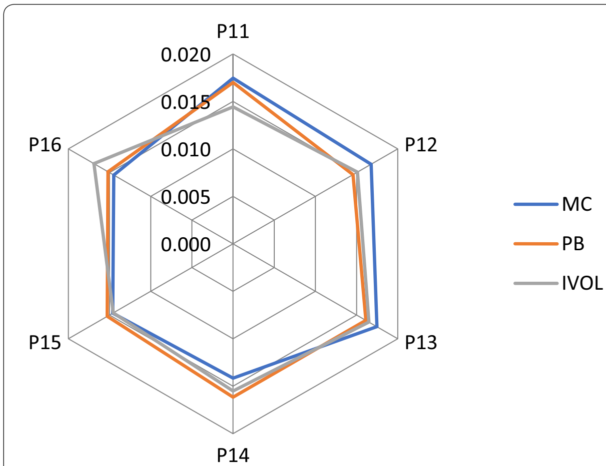

Fig. 1 Radar graph shows mean excess returns of six portfolios formed on MC, PB and IVOL

Table 2 Year-wise monthly IVOL

Average monthly IVOL								
2008	2009	2010	2011	2012	2013	2014	2015	2016
0.295	0.245	0.443	0.365	0.250	0.189	0.166	0.166	0.180

Table 4 Summary statistics of six portfolios formed on MC, PB and IVOL

Portfolio	MC			PB			IVOL		
	Mean excess returns	SD	*T*-statistics	Mean excess returns	SD	*T*-statistics	Mean excess returns	SD	*T*-statistics
P11	0.017	0.109	1.566	0.017	0.106	1.559	0.014	0.107	1.310
P12	0.017	0.108	1.518	0.015	0.106	1.333	0.015	0.108	1.369
P13	0.017	0.106	1.611	0.016	0.107	1.476	0.016	0.108	1.490
P14	0.014	0.108	1.281	0.016	0.105	1.502	0.016	0.105	1.436
P15	0.015	0.105	1.351	0.015	0.108	1.373	0.015	0.105	1.349
P16	0.014	0.107	1.316	0.015	0.109	1.363	0.017	0.109	1.515

Table 5 Regression results of Fama–French's three-factor model for six portfolios $R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\ \mathrm{SMB}_t + l\ \mathrm{LMH}_t + e_t$

	MC						PB					
	P11	P12	P13	P14	P15	P16	P11	P12	P13	P14	P15	P16
c	0.003	0.003	0.004	0.003	0.003	0.003	0.004	0.002	0.004	0.004	0.003	0.002
Rm	2.001	2.005	1.958	1.991	1.944	1.991	1.991	1.981	1.971	1.936	1.995	1.993
SMB	0.619	0.578	0.490	− 0.268	− 0.218	− 0.214	0.544	0.263	0.049	0.018	− 0.120	0.099
LMH	− 0.380	0.063	− 0.079	− 0.153	− 0.265	− 0.068	0.650	0.061	− 0.168	− 0.253	− 0.327	− 0.754
tc	1.535	1.463	1.963	1.304	1.600	1.527	1.786	0.850	1.878	2.055*	1.470	1.298
tr	5.664*	5.412*	5.756*	5.047*	5.837*	6.194*	5.836*	5.142*	5.378*	5.283*	5.552*	6.872*
ts	3.228*	3.291*	2.665*	− 1.554	− 1.263	− 1.335	3.085*	1.505	0.274	0.104	− 0.626	0.620
tl	− 2.072*	0.376	− 0.449	− 0.925	− 1.610	− 0.441	3.849*	0.363	− 0.979	− 1.500	− 1.781	− 4.957
R^2	0.967	0.972	0.968	0.973	0.972	0.976	0.971	0.972	0.970	0.970	0.967	0.977

	IVOL					
	P11	P12	P13	P14	P15	P16
c	0.002	0.003	0.004	0.003	0.001	0.004
Rm	1.997	1.996	1.997	1.951	1.950	2.008
SMB	− 0.159	0.097	− 0.013	0.371	0.393	0.223
LMH	− 0.063	0.123	− 0.122	0.124	− 0.171	− 0.281
tc	1.453	1.207	2.018*	1.141	0.729	1.835
tr	6.885*	5.827*	5.658*	4.996*	5.585*	5.768*
ts	− 1.030	0.508	− 0.069	1.878	2.307*	1.210
tl	− 0.424	0.676	− 0.693	0.654	− 1.049	− 1.586
R^2	0.978	0.967	0.969	0.963	0.972	0.969

s and *l* are the sensitivity coefficients of SMB and LMH factors

*Significant at 5% level

IVOL-based portfolios shows higher average mean excess return than other portfolios.

Further from Table 4, it is observed that average return pattern falls from P11 (small-size) portfolio to P16 (big-size) portfolio in case of MC-based portfolio. These decreasing pattern of average mean excess return from P11 (1.7%, $t = 1.566$) to P16 (1.4%, $t = 1.316$) is known as size effect. Similarly, average return pattern falls from P11 (low P/B) portfolio to P16 (high P/B) portfolio in case of P/B-based portfolio. These decreasing pattern of average mean excess return from P11 (1.7%, $t = 1.559$) to P16 (1.5%, $t = 1.363$) is known as value effect, and it is similar to Maiti [28, 29] study in Indian context. The size and value effect pattern are quite similar to Balakrishnan and Maiti [25] study in Indian context. Average return pattern increases from P11 (low IVOL) portfolio to P16 (high IVOL) portfolio in case of IVOL-based portfolio confirms weak idiosyncratic volatility effect.

Results and discussion

Asset-pricing results

Fama–French's Three-factor regressions (market, size and value)

Any good asset-pricing model must able to capture all alpha values equal to zero. Results of Fama–French's three-factor regressions are shown in Table 5. Portfolio P11 (first portfolio) is well captured by the model for MC-, *P*/*B*- and IVOL-based portfolios. Further result shows one portfolio of PB (P14) and one portfolio of IVOL (P13) are significant at 5% level. Market (Rm) coefficients of all portfolios based on MC, *P*/*B* and IVOL are highly positive and significant. Size (SMB) coefficients are positive for small-size portfolios and become negative towards big-size portfolios in case of MC-based portfolios, whereas SMB coefficients are mostly positive in case of *P*/*B*- and IVOL-based portfolios. SMB coefficients of 3 MC- (P11, P12 and P13), 1 PB- (P11) and 1 IVOL (P15)-based portfolios are found to be significant. Value (LMH) coefficients are mostly negative for MC-, *P*/*B*- and IVOL-based portfolios. First two portfolios of PB-based portfolios have positive LMH coefficient and are significant, whereas LMH coefficient changes its sign towards high *P*/*B* portfolios. LMH coefficients of 1 MC- (P11) and 1 PB (P11)-based portfolios are significant. Average alpha value and R-square values are 0.003 and 97% for Fama–French's three-factor regressions. The study results do not support the Fama and French [17] findings in US context.

Three factor regressions (market, size and idiosyncratic volatility)

Portfolio P11 (first portfolio) is well captured by the model for MC-, *P*/*B*- and IVOL-based portfolios. Further result shows that one portfolio of PB (P14) and one portfolio of IVOL (P16) are significant at 5% level. It implies that high idiosyncratic volatility stocks portfolio is not captured by the model. Market (Rm) coefficients of all portfolios based on MC, *P*/*B* and IVOL are highly positive and significant. Size (SMB) coefficients are positive for small-size portfolios and become negative towards big-size portfolios in case of MC-based portfolios, whereas SMB coefficients are mostly positive in case of *P*/*B*- and IVOL-based portfolios. Value (LMH) coefficients are mostly negative for MC-, *P*/*B*- and IVOL-based portfolios. SMB coefficients of 3 MC-based (P11, P12 and P13) and 1 PB-based (P11) portfolios found to be significant. In most of the cases, IVOL coefficient is found to be positive and is significant for 4 IVOL (P11, P12, P13 and P16), 1 MC (P12) and 1 PB (P11) portfolios, respectively. First four portfolios of IVOL-based portfolios have positive IVOL coefficient, and IVOL coefficient changes its sign towards high IVOL portfolios. Average alpha value and R-square values are 0.003 and 97% for three-factor regressions with idiosyncratic volatility.

Four-factor regression results (market, size, value and idiosyncratic volatility)

Portfolio P11 (first portfolio) is well captured by the model for MC-, *P*/*B*- and IVOL-based portfolios. Further result shows that one portfolio of PB (P14) and one portfolio of IVOL (P16) are significant at 5% level. It implies that high idiosyncratic volatility stock portfolio is not captured by the model. Market (Rm) coefficients of all portfolios based on MC, *P*/*B* and IVOL are highly positive and significant. Size (SMB) coefficients are positive for small-size portfolios and become negative towards big-size portfolios in case of MC-based portfolios, whereas SMB coefficients are mostly positive in case of *P*/*B*- and IVOL-based portfolios. Value (LMH) coefficients are mostly negative for MC-, *P*/*B*- and IVOL-based portfolios. First portfolio of IVOL portfolios SMB coefficient is negative that implies that among low idiosyncratic volatility stocks big stocks have less idiosyncratic risk. SMB coefficients of 3 MC-based (P11, P12 and P13), 1 PB-based (P11) and 1 IVOL-based (P15) portfolios found to be significant. In most of the cases, IVOL coefficient found to be positive and is significant for 4 IVOL (P11, P12, P13 and P16) and 1 MC (P12) portfolios, respectively. First four portfolios of IVOL-based portfolios have positive IVOL coefficient and IVOL coefficient changes its sign towards high IVOL portfolios. Average alpha value and R^2 values are 0.003 and 97% for four-factor regressions.

From the above results, it is concluded that both three-factor models yield similar results. Four-factor models do not improve the results much from both of the three-factor models, but investors who are interested in idiosyncratic volatility premium may consider four-factor models with *P*/*B*-based portfolios for better results. Study results shows that idiosyncratic volatility is related to the expected returns of all MC-, *P*/*B*- and IVOL-based portfolios. Investor who ranks their portfolios based on IVOL must be careful with the high idiosyncratic volatility portfolios (Tables 6, 7).

Fama–MacBeth's cross-sectional regression results

Then study runs Fama and MacBeth's [39] cross-sectional regression to verify the importance of idiosyncratic volatility in explaining portfolios expected returns, and results are shown in Table 8. All the models used in the study are well accepted by the Fama–MacBeth's cross-sectional regression test. Fama–MacBeth's cross-sectional regression test also confirms that idiosyncratic volatility is significantly related to the portfolio expected returns. Fama–MacBeth's cross-sectional regression of two-factor, three-factor, and four-factor model with idiosyncratic

Table 6 Regression results of three-factor model with idiosyncratic volatility for six portfolios $R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\ \mathrm{SMB}_t + v\ \mathrm{LvMHv}_t + e_t$

	MC						PB					
	P11	P12	P13	P14	P15	P16	P11	P12	P13	P14	P15	P16
c	0.003	0.003	0.004	0.002	0.003	0.003	0.003	0.002	0.004	0.004	0.003	0.002
Rm	2.014	2.003	1.961	1.996	1.953	1.993	1.970	1.979	1.977	1.944	2.006	2.017
SMB	0.642	0.648	0.527	− 0.240	− 0.177	− 0.166	0.548	0.280	0.068	0.044	− 0.063	0.180
LvMHv	− 0.112	0.476	0.180	0.075	0.076	0.258	0.458	0.147	0.004	− 0.006	0.142	0.008
tc	1.512	1.376	1.917	1.272	1.547	1.461	1.600	0.814	1.859	2.019*	1.402	1.121
tr	5.469*	5.490*	5.560*	5.626*	5.994*	6.476*	5.988*	5.840*	5.879*	5.488*	5.647*	5.334*
ts	3.227*	3.730*	2.834*	− 1.365	− 1.001	− 1.026	2.902*	1.583	0.370	0.245	− 0.317	0.991
tv	− 0.459	2.244*	0.794	0.349	0.350	1.307	1.983*	0.681	0.019	− 0.027	0.590	0.035
R^2	0.966	0.973	0.968	0.973	0.971	0.977	0.967	0.972	0.970	0.969	0.966	0.971

	IVOL					
	P11	P12	P13	P14	P15	P16
c	0.002	0.002	0.004	0.002	0.001	0.004
Rm	1.998	1.992	2.001	1.947	1.955	2.017
SMB	− 0.078	0.200	0.073	0.384	0.394	0.161
LvMHv	0.462	0.727	0.456	0.167	− 0.110	− 0.576
tc	1.355	1.093	1.936	1.105	0.747	2.006*
tr	6.767*	5.061*	5.446*	4.472*	5.152*	5.802*
ts	− 0.517	1.089	0.400	1.919	2.267*	0.879
tv	2.494*	3.240*	2.038*	0.681	− 0.520	− 2.569*
R^2	0.980	0.970	0.970	0.963	0.972	0.971

s and *v* are the sensitivity coefficients of SMB and iVOL factors

*Significant at 5% level

volatility factor found that idiosyncratic volatility is negatively related to the expected portfolio returns for MC- and IVOL-based portfolios, whereas idiosyncratic volatility is positively related to the expected portfolio returns for PB-based portfolio. Market return is also important factor that explains risk return relationship, and it is related negatively to the excepted portfolio returns for all MC- and PB-based portfolios, whereas it is positive for IVOL-based portfolios, and findings are similar to Liu and Di Iorio [37] findings in Australian context. Fama–MacBeth's cross-sectional regression confirms that three-factor model with idiosyncratic volatility is equally significant as Fama–French's three-factor model in explaining risk return relationship. Finally, higher R-square value and F-Statistics value of four-factors Fama–MacBeth's cross-sectional regression results confirm its superiority over two of the three-factor models used in the study.

Residual graphs

Residual graphs of first portfolio (P11) of MC, PB and IVOL portfolios for different factor models are shown in Fig. 2. A model is said to be a good model fit if its residual is closer to zero or if it is zero. Not much significant difference was observed in the residual graphs of 2 three-factor models used in the study. Residual graphs for four-factor regressions state that the higher peaks reduced to much greater extent than both the three-factor models. Results of residual graphs again confirm the superiority of four-factor model over the 2 three-factor models.

Model performance test

Regression intercepts and residual graphs are not always good in measuring the performance of the model, and hence the present study uses GRS test [40] to test the model performance. GRS model performance test results for all factor models are shown in Table 9. Except for PB-based portfolios, all factor models are passed by GRS test. The study results do support the Fama and French's [17] findings in US context for MC- and IVOL-based portfolios. Four-factor models show comparatively higher proportion of the potential efficiency than other two-factor models.

Conclusion

Due to high transaction cost and incomplete information, investors generally does not hold well-diversified portfolio, and as a result, idiosyncratic volatility associated with

Table 7 Regression results of four-factor model for six portfolios $R_{Pt} - R_{Ft} = a + b\,(R_{Mt} - R_{Ft}) + s\ \mathrm{SMB}_t + l\ \mathrm{LMH}_t + v\ \mathrm{LvMHv}_t + e_t$

	MC						PB					
	P11	P12	P13	P14	P15	P16	P11	P12	P13	P14	P15	P16
c	0.003	0.003	0.004	0.002	0.003	0.003	0.003	0.002	0.004	0.004	0.003	0.002
Rm	2.001	2.002	1.957	1.990	1.943	1.989	1.989	1.980	1.971	1.935	1.993	1.991
SMB	0.622	0.646	0.520	− 0.249	− 0.193	− 0.173	0.579	0.281	0.058	0.030	− 0.083	0.137
LMH	− 0.384	− 0.035	− 0.124	− 0.180	− 0.301	− 0.128	0.598	0.033	− 0.181	− 0.271	− 0.381	− 0.811
LvMHv	0.018	0.488	0.222	0.136	0.177	0.301	0.256	0.136	0.065	0.085	0.271	0.281
tc	1.520	1.366	1.906	1.263	1.549	1.451	1.722	0.811	1.850	2.021*	1.407	1.224
tr	5.336*	5.432*	5.635*	5.775*	5.643*	6.457*	5.821*	5.872*	5.046*	5.964*	5.516*	6.061*
ts	3.173*	3.695*	2.787*	− 1.418	− 1.101	− 1.065	3.240*	1.583	0.318	0.167	− 0.424	0.856
tl	− 2.008*	− 0.203	− 0.678	− 1.049	− 1.760	− 0.811	3.427*	0.192	− 1.014	− 1.539	− 2.009*	− 5.171
tv	0.072	2.208*	0.941	0.610	0.799	1.471	1.133	0.604	0.282	0.374	1.102	1.384
R^2	0.967	0.973	0.968	0.973	0.972	0.977	0.971	0.972	0.970	0.970	0.967	0.978

	IVOL					
	P11	P12	P13	P14	P15	P16
c	0.002	0.002	0.004	0.002	0.001	0.004
Rm	1.993	1.991	1.993	1.950	1.950	2.011
SMB	− 0.087	0.199	0.061	0.389	0.385	0.152
LMH	− 0.167	− 0.024	− 0.229	0.097	− 0.160	− 0.177
LvMHv	0.518	0.736	0.534	0.134	− 0.057	− 0.517
tc	1.347	1.085	1.932	1.104	0.739	1.997*
tr	6.854*	5.068*	5.747*	4.738*	5.258*	5.945*
ts	− 0.575	1.075	0.335	1.934	2.214*	0.827
tl	− 1.127	− 0.135	− 1.286	0.491	− 0.940	− 0.986
tv	2.705*	3.146*	2.310*	0.527	− 0.257	− 2.224*
R^2	0.980	0.970	0.971	0.963	0.972	0.971

s, *l* and *v* are the sensitivity coefficients of SMB, LMH and iVOL factors

*Significant at 5% level

the investment does not diversify completely. This signifies the importance of idiosyncratic volatility in investment decision, and investors should compensate for holding idiosyncratic risk. The present study in Sri Lankan contest evaluates the role of idiosyncratic volatility in pricing Colombo stock exchange in both time series and cross-sectional set-up for a period of July 2008 to December 2016. The study result shows that IVOL-based investment strategy will yield comparatively less average returns than market-, size- and value-based investment strategies. Idiosyncratic volatility risk factor is positively weakly correlated with the market risk and size risk factors, whereas negatively weakly correlated with the value risk factor. Average portfolio means excess return pattern based on MC, PB and IVOL that shows weak size, value and idiosyncratic volatility effects in Colombo stock exchange portfolios.

Asset-pricing results show that both Fama–French's three-factor model and three-factor model with idiosyncratic volatility factor yield similar results. Hence, investors may align their investment decision based on market and size along with value or idiosyncratic volatility factor as both will yield similar results. However, four-factor model yields comparatively better results than 2 three-factor models as some of the information which is omitted by the three-factor models is captured by the four-factor model. Times series regressions with different factor model yield almost similar results, but cross-sectional set-up estimates give more vivid view of the risk variables. For all MC- and IVOL-based portfolios idiosyncratic volatility is negatively related to the expected returns, whereas it is positively related to all PB-based portfolios. This implies that high idiosyncratic risk prevails in the small size, big P/B value and low IVOL stocks of the Colombo stock exchanges stocks. Further Fama–MacBeth cross-sectional regression confirms that idiosyncratic volatility captures information omitted by the Fama–French three-factor model, and study findings are similar to Liu and

Table 8 Fama–Macbeth's cross-sectional regression result

	Parameters	λ_0	λ_{rm}	λ_{lvmhv}	Adjusted R^2	*F*-statistics(*P* value)	
Two factors with market and idiosyncratic volatility							
MC	Mean	0.025	− 0.005	− 0.004	23.8	0.468	0.665
	SD	0.314	0.166	0.024			
	T-statistics	0.787	− 0.269	− 1.475			
PB	Mean	0.049	− 0.017	0.002	44.2	1.187	0.417
	SD	0.316	0.168	0.042			
	T-statistics	1.498	− 0.966	0.530			
IVOL	Mean	− 0.019	0.018	− 0.001	42.1	1.091	0.441
	SD	0.345	0.181	0.010			
	T-statistics	− 0.540	0.941	− 0.839			

	Parameters	λ_0	λ_{rm}	λ_{smb}	λ_{lmh}	Adjusted R^2	*F*-statistics (*P* value)	
Fama–French three factor								
MC	Mean	0.028	− 0.006	0.005	0.005	41.1	0.466	0.736
	SD	0.323	0.170	0.043	0.032			
	T-statistics	0.838	− 0.365	1.214	1.516			
PB	Mean	0.062	− 0.023	0.001	0.001	66	1.292	0.464
	SD	0.396	0.207	0.009	0.012			
	T-statistics	1.526	− 1.108	0.966	0.519			
IVOL	Mean	0.008	0.004	− 0.004	− 0.001	44.2	0.527	0.706
	SD	0.504	0.259	0.035	0.042			
	T-statistics	0.155	0.164	− 1.001	− 0.124			

	Parameters	λ_0	λ_{rm}	λ_{smb}	λ_{lvmhv}	Adjusted R^2	*F*-statistics (*P* value)	
Three factors with idiosyncratic volatility								
MC	Mean	0.035	− 0.011	0.010	− 0.003	80.8	2.809	0.273
	SD	0.315	0.167	0.037	0.024			
	T-statistics	1.091	− 0.617	2.573*	− 1.357			
PB	Mean	0.047	− 0.016	0.001	0.002	62.5	1.110	0.506
	SD	0.316	0.168	0.008	0.062			
	T-statistics	1.461	− 0.926	0.966	0.242			
IVOL	Mean	0.003	0.007	− 0.002	− 0.001	43.9	0.521	0.709
	SD	0.693	0.346	0.069	0.012			
	T-statistics	0.038	0.192	− 0.345	− 0.585			

	Parameters	λ_0	λ_{rm}	λ_{smb}	λ_{lmh}	λ_{lvmhv}	Adjusted R^2	*F*-statistics (*P* value)	
Four factors									
MC	Mean	0.041	− 0.012	0.003	0.008	− 0.005	98.9	22.012	0.158
	SD	0.319	0.168	0.041	0.033	0.025			
	T-statistics	1.252	− 0.712	0.811	2.264*	− 2.017			
PB	Mean	0.065	− 0.025	0.001	0.001	0.001	66.2	0.490	0.774
	SD	0.458	0.239	0.008	0.012	0.083			
	T-statistics	1.393	− 1.033	0.965	0.511	0.106			
IVOL	Mean	− 0.005	0.011	− 0.002	0.000	− 0.001	44.8	0.203	0.910
	SD	0.842	0.423	0.070	0.048	0.012			
	T-statistics	− 0.053	0.243	− 0.330	− 0.042	− 0.585			

*Significant at 5% level

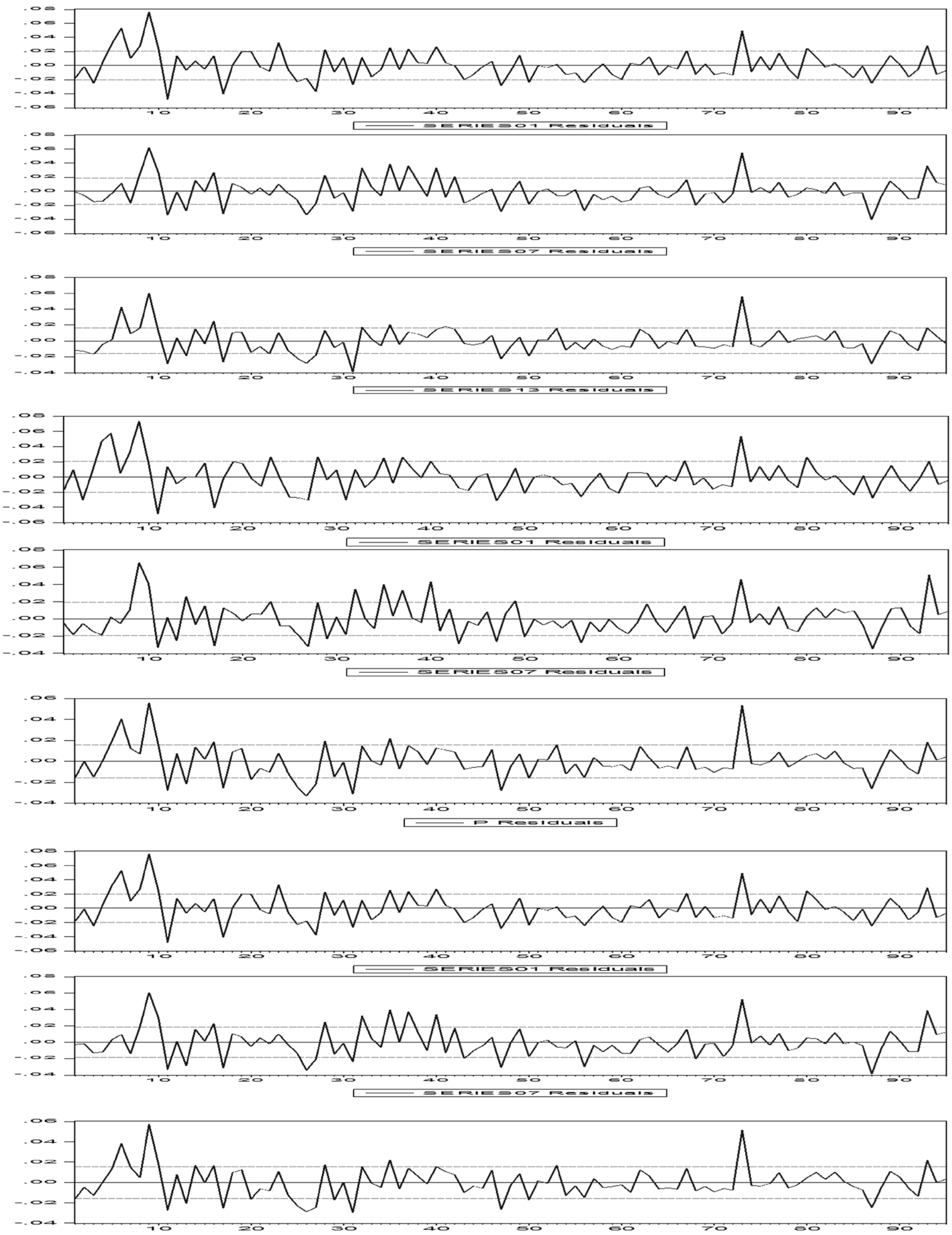

Fig. 2 Residual graphs for Fama–French's three-factor, three factor with idiosyncratic volatility and four-factor model of first portfolio (P11)

Di Iorio [37] findings in Australian context. Further Fama–MacBeth's cross-sectional regression, residual graphs and GRS test all confirm the superiority of four-factor model over 2 three-factor models. Except PB-based portfolios, all other portfolios based on MC and IVOL passes GRS model performance test for all the factor models used in the study.

The study findings imply that there is a high importance for considering idiosyncratic volatility risk factor while considering investment decision in the Colombo

Table 9 Summary of GRS test results for all the factor models

	GRS *F*-statistics	*P* value	Theta/thetas, proportion of the potential efficiency	Average absolute alpha value	Average R^2 (%)
Fama–French three factor					
MC	0.746	0.614	0.826	0.003	97.1
PB*	2.371	0.036	0.635	0.003	97.1
IVOL	1.153	0.339	0.762	0.003	97.0
Three factors with idiosyncratic volatility					
MC	0.710	0.642	0.839	0.003	97.1
PB*	2.617	0.022	0.626	0.003	96.9
IVOL	1.095	0.372	0.779	0.003	97.1
Four factors					
MC	0.732	0.625	0.835	0.003	97.2
PB*	2.627	0.022	0.625	0.003	97.1
IVOL	1.144	0.344	0.772	0.003	97.1

*Significant at 5% level

stock exchange. Idiosyncratic volatility relationship to the portfolio expected returns is highly dependent on the portfolio construction factor variables. It is advisable not to form portfolios completely based on the P/B ratio of the stocks as it may leads to higher risk. Further study results imply that investment decision on Colombo stock exchange should not be solemnly based on the time series analysis, but one must also consider cross-sectional analysis or both for high precisions. Finally, study concludes that idiosyncratic volatility is an equally important factor similar to market, size and value factors in pricing Colombo stock exchange for the study sample period. The study findings are in line with Liu and Di Iorio [37] findings in Australian context. Hence, investor should compensate for holding idiosyncratic risk stocks in the portfolio.

Abbreviations

MC: market capitalisation; Rf: risk-free rate; SMB: size; LMH: value; IVOL: idiosyncratic volatility.

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Authors' contributions

Complete work. The author read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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