



Financial Econometrics Series

SWP 2014/11

Importance of Skewness in Decision Making: Evidence from the Indian Stock Exchange

P.K. Narayan and H.A. Ahmed



Importance of Skewness in Decision Making: Evidence from the Indian Stock Exchange

Paresh Kumar Narayan¹ and Huson Ali Ahmed

ABSTRACT

In this paper our goal is to examine the importance of skewness in decision making, in particular on investor utility. We use time-series daily data on sectoral stock returns on the Indian stock exchange. We test for sectoral stock return predictability using commonly used financial ratios, namely, the book-to-market, dividend yield and price-earnings ratio. We find strong evidence of predictability. Using this evidence of predictability, we forecast sectoral stock returns for each of the sectors in our sample, allowing us to devise trading strategies that account for skewness of returns. We discover evidence that accounting for skewness leads not only to higher utility compared to a model that ignores skewness, but utility is sector-dependent.

Keywords: *Returns; Skewness; Predictability; Utility; Investor.*

¹ Email: paresh.narayan@deakin.edu.au; phone: +61 3 9244 6180

I. Introduction

The subject of asset pricing is at the forefront of research in financial economics. A popular sub-subject has been stock return predictability. Our interest in this paper is on stock return predictability. In this literature, two aspects of research has been dominant. The first aspect has been on the development of econometric methods for testing stock return predictability (see Lewellen 2004; Campbell and Yogo, 2006; Westerlund and Narayan, 2012, 2014a, b). The second aspect is related to the first in that upon finding evidence of stock return predictability, the focus has been on understanding the economic significance of such predictability. Typically, trading strategies are evaluated as part of this economic significance analysis. The most popular trading strategy has been motivated by a mean-variance utility function. Generally, the findings are rousing in that studies have confirmed that based on return forecasts successful trading strategies for an investor who faces a mean-variance utility function can be devised.

We extend this literature by focusing on the second aspect—that is, on the economic significance of stock return predictability. Our position is this. The utility function used to estimate investor utility takes account of only the first (mean) and second (variance) moments of stock returns. We, therefore, ask: will accounting for the third moment of returns (skewness) improve investor utility. By answering this question, we extend the utility function to a mean-variance-skewness (MVS) investor. Several studies have shown the importance of skewness in financial economics (see, *inter alia*, Arditti, 1967; Golec and Tamarkin, 1998; Garrett and Sobel, 1999; Bhattacharya and Garrett, 2008; Kraus and Litzenberger, 1976; Patton 2004; Prakash *et al.*, 2003; Jondeau and Rockinger, 2006; Mitton and Vorkink, 2007).

This contribution is discussed below. In light of the overall importance of skewness in understanding financial market and pricing behaviours in general, it is surprising that financial economists have not considered the role of skewness in the economic significance analysis.

More specially, three reasons motivate the need for accounting for skewness in tests of investor utility. First, skewness in financial time-series data, particularly high frequency data is prevalent and as Harvey and Siddique (1999) argue it varies through time and has a systematic relationship with expected returns and variance. Second, there is a relationship between trading volume and skewness. The negative skewness in returns, as found in the Hong and Stein (1999) model, is more pronounced during periods when trading volume is heavy. Third, Harvey and Siddique (2000) show that conditional skewness helps explain the cross-sectional variation of expected returns across assets.

Our main approaches and findings are as follows. First, we have monthly stock return and financial ratios (book-to-price ratio, price-earnings ratio, and dividend yield) for sectors listed on the Bombay Stock Exchange. We have a total of eight sectors. Analysing this sectoral data suggests three features; (a) the financial ratios are all, across all eight sectors, persistent, (b) most predictors in the eight sectors are endogenous, and (c) the predictive regression model is heteroskedastic. Second, we attempt to predict sectoral stock returns using these financial ratios as predictors. Using the Westerlund and Narayan (2014a) GLS estimator, we find strong evidence of predictability across all sectors. That sectoral returns are predictable allows us to forecast returns using each of the three financial ratios as predictors. We do forecast sectoral returns and use forecast returns to estimate an investor's utility function that accounts for skewness and variance and compare utility from this utility function with one that only accounts for the variance. The difference in utility allows us to gauge the relevance of skewness

for investors. We find that across all sectors the difference in utility is positive, suggesting that a utility function that accounts for skewness offers investors higher utility than one that makes use of only the variance of returns.

We organise the balance of the paper as follows. A discussion of data and preliminary features of the data are discussed in the next section. Section II discusses the literature and highlights our contribution. Section III contains a discussion of the main results. This section is actually divided into two parts; in the first part, we focus on sectoral return predictability, while, in the second part, we focus on estimating investor utility from a mean-variance and a mean-variance-skewness utility functions. The objective here is to examine if utility from MVS beats utility from MV utility function. The final section concludes with the key findings.

II. Literature on Indian Stock Market

The goal of this section is to provide a brief overview of the literature on the Indian stock market and draw out our paper's main contribution to the literature. The literature on the Indian stock market is growing, and has taken several directions. Principally, there are studies that investigate the efficiency of the Indian stock market through testing its integration properties (see Mishra, Mishra and Smyth., 2014); there are studies that examine whether exchange rates impact the Indian stock returns (see Narayan, 2009); recent studies analyse the relationship between stock returns and mutual fund flows for India (see Narayan, Narayan, and Prabheesh, 2014); momentum strategies have been used to test whether the Indian stock market is profitable (see Narayan, Ahmed, Sharma, and Prabheesh, 2014). The empirical evidence from these studies points to: (a) the importance of exchange rates for stock returns; (b) evidence in support of spillover effects in the mutual fund and equity markets; (c) predictability of stock returns; (d) evidence that the Indian stock market is profitable and that there are some sectors

of the market which are more predictable than other sectors; and (e) the stationarity of Indian stock indices, suggesting they are predictable.

Given this literature, nothing is known about the potential role that the skewness of returns can play in determining profitability of the Indian stock market. We show that the Indian stock market is profitable when an investor is faced with a mean-variance-skewness utility function. It is this which constitutes our main contribution to the literature on the Indian stock market.

III. Data and Preliminary Results

A. Data

The empirical analysis in this paper makes use of daily time-series data on sectoral stocks listed on the Bombay Stock Exchange (BSE). The sample period starts at 2 January 2001 and concludes at 31 December 2011. A total of eight sectors, dictated by availability of consistent time-series data, are chosen. These sectors are banking, energy, fast moving consumer goods (FMCG), information technology (IT), multinational corporations (MNC), pharmacy, metal, and automobile. For each of these eight sectors, four variables are extracted: stock prices, from which log returns are computed, price-to-book ratio (PB), dividend yield (DY), and price-earnings (PE) ratio. All data are downloaded by the Prowess Database. A plot of the sectoral returns is provided in Figure 1. As expected, sectoral returns are sector-specific.

INSERT FIGURE 1

B. Preliminary Results

Our approach is threefold and as a result follows three distinct steps. In the first step, we test for sectoral stock return predictability. For each of the eight sectors, three bivariate predictive regression models of the following form are estimated:

$$SSR_t = \alpha_0 + \beta_1 FR_{t-1} + \varepsilon_{SSR,t} \quad (1)$$

Where SSR is the sectoral stock return, FR represents the financial ratio variable, and the error term is represented by ε_{SSR} . The null hypothesis of no predictability—that is, $\beta_1 = 0$ is examined using the Westerlund and Narayan (2012, 2014a) flexible generalised least squares (FGLS) estimator. While the details on this methodology can easily be found in the several applications on predictability (see, *inter alia*, Narayan, 2013; Sharma and Thuraisamy, 2013; Narayan, Narayan, and Thuraisamy 2014; Makin, Narayan, and Narayan 2014; Narayan, Narayan, Prabheesh, 2014), here it is suffice to list the reasons for our choice of the WN-FGLS estimator. The first reason is that the WN-FGLS estimator is valid even when the predictor variable, which in our case is PB, DY, and PE, is persistent. This is an important consideration because the literature on financial ratio-based predictors of stock returns almost always show that financial ratio variables are persistent. We find the same. We run a first-order autoregressive model and find the AR(1) coefficient to be at least 0.70, suggesting persistent predictors. The second reason relates to the endogeneity of the predictor variable. Again the literature has shown that financial ratios are actually endogenous. The WN-FGLS estimator controls also for endogeneity. We also test for endogeneity by regressing the residuals from the predictive regression model, ε_{SSR} , on the residuals obtained from an AR(1) model of the financial ratio, say ε_{FR} . We find that in most cases the slope coefficient is statistically significant from zero and carries a negative sign, implying that the predictor variable is endogenous. A final attractive feature of the WN-FGLS estimator is its ability to control for heteroskedasticity. Financial data, particularly high frequency data, is well-known to be heteroskedastic. We test this by filtering all the return and financial ratio data through fitting an AR(12) model and subjecting the resulting residuals to a test of the null hypothesis of no ARCH effects. We strongly (at the 1% level) reject the null, suggesting that our data set is characterised by heteroskedastic behaviour (see Table I).

INSERT TABLE I

In Table II, we also report skewness for each of the four variables, namely, stock returns, and the three financial ratio variables—DY, PB, and PE—for each of the six sectors. In the second half of the table, we report unconditional correlations between returns-DY, returns-PB, and returns-PE for each of the six sectors. The null hypothesis that correlations are zero is also tested and the t-test statistic is reported in parenthesis. A 10% critical value of 1.64 is used to test the null hypothesis. The two main messages emerging from the skewness and the unconditional correlations is that (a) skewness is not only sector specific but also variable specific, and (b) the unconditional correlations do not suggest a strong relationship between sectoral returns and financial ratios with the exception of PE ratio.

INSERT TABLE II

III. Main Results

A. *Are sectoral stock returns predictable?*

Have established that our data set is characterised by well-known features associated with stock return predictive regression models, we next examine whether sectoral stock returns can be predicted. To test for predictability, we have a total of eight sectors. For each sectoral return, we test for return predictability by using three financial ratio predictors, as explained earlier. The WN-GLS estimator is used for this purpose. The null hypothesis of no predictability is tested for each sector using each of the three predictors one at a time. While the details on the WN-GLS test can be found in Westerland and Narayan (2012, 2014), here we provide a brief non-technical summary of the test. The attractiveness of the WN-GLS test lies in its statistical flexibilities. First, the test is able to accommodate an endogenous predictor. This is important. In empirical regression models, endogeneity is almost always an issue that practitioners need to deal with. In this regard, predictive regression models are no exception. Second, WN-GLS test caters for persistent predictors. This is important because time-series predictors are most

likely than not non-stationary; that is, they are persistent. Indeed one can remove this persistency by first differencing the predictor but doing so will be costly; changing the form of the predictor weakens the information it has, thereby, losing its ability to predict. Third, the WN-GLS test is friendly with heteroskedastic predictive regression model. This is important because high frequency data, including monthly and daily data, is almost always hetroskedastic.

The results, in the form of the WN-GLS t-test statistic, are generated (unreported). This is what we find. First, across all eight sectors there is some evidence that financial ratios predict returns. This is not surprising as a large volume of studies have documented the usefulness of financial ratios to predict returns. The bulk of the evidence in the literature is actually documented on empirical analysis of whether or not market returns could be predicted by financial ratios. This literature is clear in its findings; the consensus is that there are some financial ratios, such as book-to-market ratio and dividend yield, which predict market returns more successfully than do other ratios such as price-to-earnings; for evidence of return predictability based on the book-to-market ratio, see Kothari and Shanken (1997); Lewellen (2004); and Campbell and Thompson (2008), amongst others.

There is limited analysis on sectoral return predictability. To the best of our knowledge, there is only one study that examines whether financial ratios predict sectoral stock returns as opposed to market returns. Westerlund and Narayan (2014b), for example, study sectoral return predictability for as many as 15 sectors listed on the New York Stock Exchange. They propose and utilise a panel data predictive regression model, where stocks in each sector are treated as cross-sectional units. They use a range of financial ratios; namely, book-to-market ratio, cash-flow-to-price ratio, dividend-price ratio, dividend yield, earnings-price ratio, and dividend-

payout ratio. They find strong evidence of sectoral return predictability only when using book-to-market and cash-flow-to-price as predictors; when using other predictors, they discover relatively weak evidence of predictability.

B. Does a mean-variance-skewness utility function perform better than a mean-variance utility function?

Having ascertained that sectoral stock returns are predictable implies that we can forecast stock returns. With return forecasts, one can estimate an investor's utility function. For a mean-variance investor (MV), for example, the utility function is of the form:

$$U(MV) = E_t\{r_{t+1}\} - 0.5 \times \gamma \times var_t\{r_{t+1}\} \quad (2)$$

Similarly, for a mean-variance-skewness investor, for example, Scott and Horvath (1980) and Mitton and Vorkink (2007), among others, considered a utility function that accounts for skewness. The maximum value of the utility function takes the following form:

$$U(MVS) = E_t\{r_{t+1}\} - 0.5 \times \gamma \times var_t\{r_{t+1}\} + 1/6 \times \gamma_1 \times E(r - E\{r_{t+1}\})^3 \quad (3)$$

Investor utility from MVS and MV are computed and the difference between the two, which, if positive, suggests that investor utility based on the skewness factor leads to more investor utility than a utility function that simply ignores skewness.

The expected return is denoted by $E\{r_{t+1}\}$, and the risk aversion parameter, γ , is set to six while the skewness preference level, γ_1 , is set to two. Finally, the scaling parameters relating to variance and skewness are $1/2$ and $1/6$, respectively.

There are several insights offered by the results (see Table III). Let us read first the results based on a trading strategy that does not allow for any short-selling. In this case, the portfolio

weight is simply the expected future excess returns (forecasts) divided by the variance of the future portfolio return (sector return) interacted with the risk aversion parameter, which we set to six. Three results are worth noting here. First, in five out of the eight sectors, the utility gain is positive, suggesting that skewness is important in maximising investor utility. These sectors are banking, energy, FMCG, IT, and metal. For the remaining three sectors, namely, MNC, pharmacy, and auto, the gain in investor utility is negative, suggesting that utility is maximised without accounting for skewness in the utility function.

INSERT TABLE III

Second, of the five sectors where utility gain is positive, the range of gain, when compared across the three predictors, varies; for IT sector, it is in the [0.019, 0.027] range; for FMCG, it is in the [0.06-0.020] range; for metal, it is in the range [0.01, 0.02]; while for banking and energy sectors, the range is wider at [0.008, 0.015] and [0.0002, 0.002], respectively.

Third, we can also infer something about the most popular predictor—that is, the predictor that offers investors the highest utility gain. In four of the five models, where utility gain is positive, we find that the DY predictor-based forecasting model maximised investor utility gain from a skewness-based utility function, while in a comparison of PE and PB predictors there is not much of a difference.

We now turn to a trading strategy that allows for 10% short-selling. In this case, the portfolio weight obtained, as explained under trading strategy one, is allowed to be outside the [0,1] range by 10%. The results suggest that: (a) short-selling improves utility gain as expected; and (b) for the pharmacy sector, which previously (without short-selling) suggested that skewness was not an important factor, utility gain becomes positive. Therefore, by accounting for

skewness, and when the trading strategy allows for short-selling, a total of six out of eight sectors reveal positive utility gains, suggesting that skewness is an important factor.

IV. Concluding Remarks

Stock return predictability, both statistical approaches as well as ascertaining the economic significance of stock return predictability, has become a subject of lively research in financial economics over the last decade. The bulk of the innovations in this literature has been on the statistical side, where researchers have attempted to correct for persistent and endogenous predictors and any heteroskedasticity in the predictive regression model. This line of research has attracted a rich body of research. Therefore, in this paper, we emphasise on the second aspect of return predictability literature—that is, on the economic significance of return predictability, where typically trading strategies are devised based on a mean-variance (MV) utility function.

We argue that like the second moment of returns (variance), the third moment (skewness) carries significant implications for investors. We, therefore, extend the MV utility function to a mean-variance-skewness (MVS) utility function. Using time-series daily data for sectors listed on the BSE of India, we find strong evidence that financial ratios predict sectoral stock returns. We then test for economic significance by way of devising trading strategies assuming an investor has a preference for a mean-variance-skewness utility function. We find that investor utility—that is, the amount of portfolio management fee that an investor is willing to pay to have access to information contained in the financial ratio-based forecasting model—when the utility function accounts for skewness is on average 2% per annum more than when the utility function does not include the skewness factor. Overall, our results imply that future studies on the economic significance of stock return predictability will benefit from utilising a

utility function that accounts for the skewness factor in addition to expected returns (forecasts) and variance of returns.

There is generally a paucity of research on the profitability of the Indian stock market. We see at least two avenues for future research on the profitability of the Indian stock exchange, building on Narayan, Narayan, and Prabheesh (2014) and Narayan, Ahmed, Sharma, and Prabheesh (2014). The first direction of research has roots in the idea that nothing is known about the profitability of penny versus non-penny stocks. There is a large number of penny stocks; therefore, it will be interesting to know how profitable these are compared to non-penny stocks. The second direction of research should focus on non-conventional predictors of returns. For example, in a recent paper, Narayan, Narayan and Thuraiamy (2014) examine whether institutional quality predicts stock returns for emerging market stock returns. Futures studies could consider the role of institutions, including democracy, rule of law, and political connections, on stock returns.

REFERENCES

- Arditti, F. D.,(1967) Risk and the Required Return on Equity, *Journal of Finance*, 22 19-36.
- Bhattacharya, N., Garrett, T. A., (2008) Why people choose negative expected return assets – an empirical examination of a utility theoretic explanation, *Applied Economics*, 40, 27–34.
- Campbell, J.Y., and Thompson, S.B., (2008) Predicting excess stock returns out of sample: can anything beat the historical average, *Review of Financial Studies*, 21, 1509-1531.
- Campbell, J.Y. and Yogo, M., (2006) Efficient Tests of Stock Return Predictability, *Journal of Financial Economics*, 8, 27-60.
- Garrett, Th. A., and Sobel, R.S., (1999) Gamblers favor skewness, not risk: Further evidence from United States' lottery games, *Economics Letters*, 63, 85–90.
- Golec, J., and Tamarkin, M., (1998) Bettors love skewness, not risk, at the horse track, *Journal of Political Economy*, 106, 205–225.
- Harvey, C.R., and Siddique, A., (1999) Autoregressive conditional skewness, *Journal of Financial and Quantitative Analysis*, 34, 465-487.
- Harvey, C.R., and Siddique, A., (2000) Conditional skewness in asset pricing tests, *Journal of Finance*, LV, 1263-1295.
- Hong, H., Stein, J.C., (1999) Difference of opinion, rational arbitrage and market crashes, NBER Working Paper.

Jondeau, E., and Rockinger, M., (2006) Optimal Portfolio Allocation Under Higher Moments, *European Financial Management*, 12, 29-55.

Kothari, S.P., and Shanken, J., (1997) Book-to-market, dividend yield, and expected market returns: A time series analysis, *Journal of Financial Economics*, 44, 169-203.

Kraus, A., Litzenberger, R.H., 1976. Skewness preference and the valuation of risky assets. *Journal of Finance* 31, 1085-1100.

Lewellen, J., (2004) Predicting returns with financial ratios, *Journal of Financial Economics*, 74, 209-235.

Makin, T., Narayan, P.K., and Narayan, S., (2014) What expenditure does Anglosphere foreign borrowing fund? *Journal of International Money and Finance*, 40, 63-78.

Mishra, A., Mishra, V., and Smyth, R., (2014) The Random Walk on the Indian Stock Market, Department of Economics Monash University Discussion Paper No. 07/14, ISSN 1441-5429

Mitton, T., and Vorkink, K.,(2007) Equilibrium Underdiversification and the Preference for Skewness, *Review of Financial Studies*, 20, 1255-1288.

Narayan, S., (2012) Foreign exchange markets and oil prices in Asia, *Journal of Asian Economics*, 28, 41-50.

Narayan, P.K., (2009) On the relationship between stock prices and exchange rates for India, *Review Of Pacific Basin Financial Markets And Policies*, 12, 289-308.

Narayan, P.K., Ahmed, H.A., Sharma, S., and K.P., Prabheesh (2014) How profitable is the Indian stock market? *Pacific-Basin Finance Journal* (In Press).

Narayan, P.K., and Narayan, S., (2014) Psychological Oil Price Barrier and Firm Returns, *Journal of Behavioral Finance* (In Press).

Narayan, P.K., Narayan, S., and K.P. Prabheesh (2014) Stock returns, mutual fund flows and spillover shocks, *Pacific-Basin Finance Journal*, 29, 146-162.

Narayan, P.K., Narayan, S., and Thuraisamy, K. S., (2014) Can institutions and macroeconomic factors predict stock returns in emerging markets? *Emerging Markets Review*, 19, 77-95.

Patton, A.J., (2004) On the out-of-sample importance of skewness and asymmetric dependence for asset allocation, *Journal of Financial Econometrics*, 2, 130–168.

Prakash, A.J., Chang, C., Pactwa, T.E., (2003) Selecting a portfolio with skewness: Recent evidence from US, European, and Latin American equity markets, *Journal of Banking and Finance*, 27, 1375-1390.

Scott R.C., and Vorvath, P.A., (1980) On the Direction of Preference for Moments of Higher Order than the Variance, *The Journal of Finance*, 35, 915-919

Sharma, S.S., and Thuraisamy, K., (2013) Oil price uncertainty and Sovereign risk: Evidence from Asian Economies, *Journal of Asian Economics*, 28, 51-57.

Westerlund, J., and Narayan, P., (2014a) Testing for predictability in conditionally heteroskedastic stock returns, *Journal of Financial Econometrics*, doi:10.1093/jfinec/nbu001.

Westerlund, J., and Narayan, P., (2014b) A random coefficient approach to the predictability of stock returns in panels, *Journal of Financial Econometrics*, doi:10.1093/jfinec/nbu003.

Westerlund, J., and Narayan, P., (2012) Does the choice of estimator matter when forecasting returns? *Journal of Banking and Finance*, 36, 2632-2640.

Figure I: A plot of the stock returns by sector

This figure plots stock returns for each of the eight sectors, namely, banking, energy, FMCG, IT, MNC, pharmacy, auto, and metal.

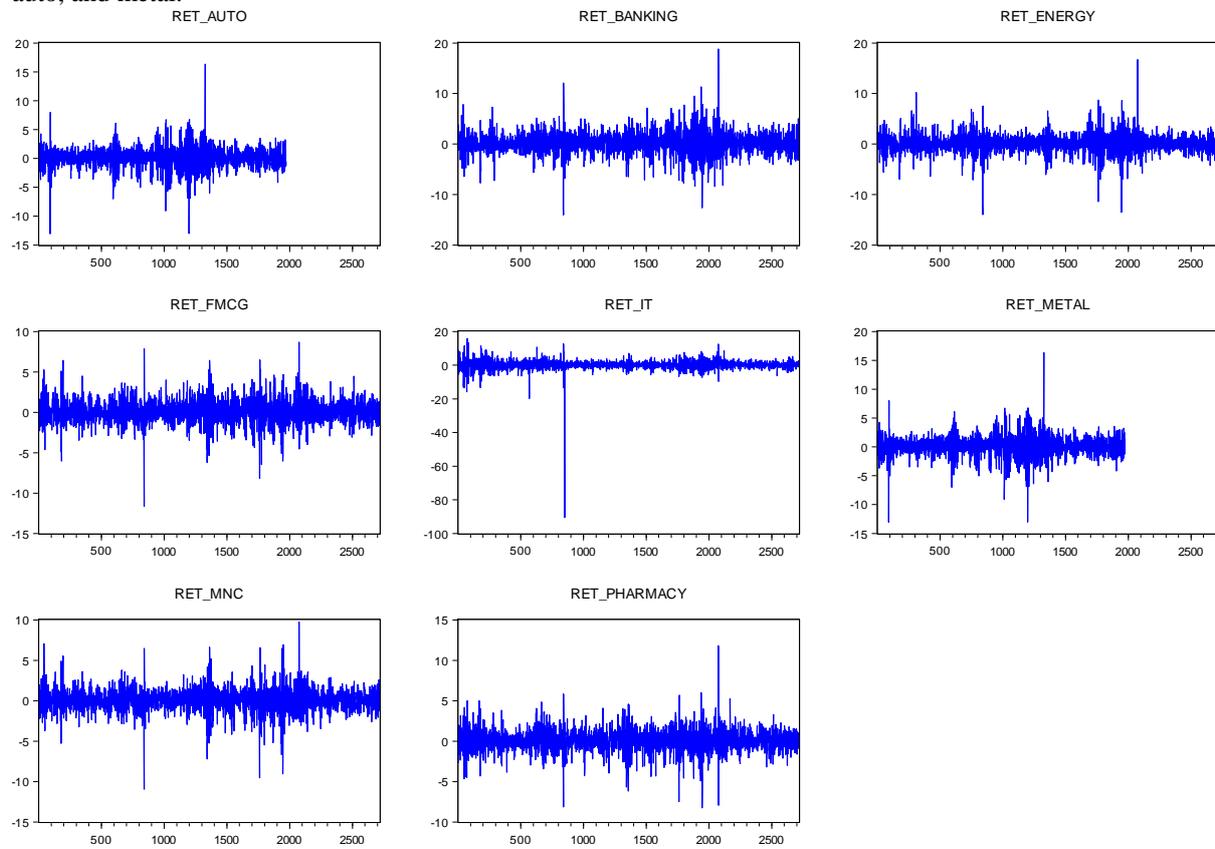


Table I: Descriptive statistics

This table reports a range of basic statistics of the data. These statistics, namely the ADF test, the first-order autoregressive (AR(1)) coefficient, a test of predictor endogeneity, and the ARCH LM test, are undertaken to check the data properties and whether these properties are consistent with the predictability tests. The ADF test statistic is reported in column 2 and in square brackets appears the optimal lag length used to control for potential serial correlation in the regression model. The optimal lag length is chosen by using the Schwarz Information Criterion (SIC). Our approach is that we begin with a maximum of eight lags and obtain the optimal lag using SIC. The AR(1) coefficient of all three predictors and stock returns are reported in column 3; in parenthesis appears the p-value testing the null hypothesis that the coefficient is zero. The residuals from the predictive regression model are regressed on residuals from an AR(1) model of the predictor variable and the slope coefficient is reported in column 4; the null hypothesis that the slope coefficient is zero is also tested and the resulting p-value is reported in parenthesis. The last column reports the F-test through filtering the variable with an AR(12) model and subjecting the resulting residuals from this model to a test of the null hypothesis of ‘no ARCH’. The p-value used to take a decision on the null hypothesis is reported in parenthesis. The results are divided into eight panels with each panel representing a sector. There are a total of eight sectors.

Panel A: Banking sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	-36.483 [1]	0.136 (0.00)	-	-
DY	-39.87(1)	.996(.00)	-27.201 (0.00)	31.511 (0.00)
PB	-51.63(1)	.997(.00)	20.056 (0.00))	31.345(0.00)
PE	-48.760	.995(.00)	4.710 (0.00)	31.345(0.00)
Panel B: IT sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	-50.964(0)	0.022 (0.25)		
DY	46.180	.993(.00)	-11.243(.00)	.210(.998)
PB	-4.459	.993(.00)	6.841(.00)	.208(.998)
PE	4.317	.992(.00)	1.616(.00)	.209(.998)
Panel C: FMCG sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	-50.521	0.0306(0.11)		
DY	-3.715	.984(.00)	-4.871(.00)	36.078(0.00)
PB	-50.881	.995(.00)	9.193(.00)	36.940(0.00)
PE	-51.997	.996(.00)	3.039(.00)	37.347(0.00)
Panel D: Energy sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	47.371	0.0950(.00)		
DY	-38.315	.994(.00)	-5.715(.00)	28.336(0.00)
PB	47.992	.997(.00)	39.124(.00)	28.469(0.00)
PE	50.140	.997(.00)	3.718(.00)	28.272(0.00)
Panel E: MNC sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	-47.620	.0895(.00)		
DY	-30.600	.992(.00)	-6.541(.00)	42.969(0.00)
PB	-49.809	.996(.00)	8.453(.00)	43.064(0.00)
PE	-51.314	.994(.00)	2.151(.00)	42.979(0.00)

Panel F: Pharmacy sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	-47.755	0.087(.00)		
DY	-4.586	.985(.00)	-10.543(.00)	40.622(0.00)
PB	-48.805	.996(.00)	12.020(.00)	40.462(0.00)
PE	-51.517	.994(.00)	.3859(.00)	40.257(0.00)
Panel G: Auto sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	-20.046	0.064(0.00)		
DY	-42.083	.995(0.00)	-18.791(0.00)	17.841(0.00)
PB	-40.709	.996(0.00)	12.066(0.00)	17.880(0.00)
PE	-40.884	.994(0.00)	3.412(0.00)	17.834(0.00)
Panel H: Metal sector				
	ADF unit root	AR(1) (p-value)	Endogeneity (p-value)	ARCH LM test F-test (p-value)
Returns	-19.997	0.063(.00)		
DY	-34.453	.995(.00)	-14.012(00)	17.976(0.00)
PB	-41.102	.996(.00)	13.440(0.00)	17.896(0.00)
PE	-38.095	.997(0.00)	2.923(0.00)	17.924(0.00)

Table II: Skewness and unconditional correlations

This table reports statistics on skewness for each of the four variables, namely, stock returns, and the three financial ratio variables—DY, PB, and PE. The second half of the table reports unconditional correlations between returns-DY, returns-PB, and returns-PE. The null hypothesis that correlations are zero is also tested and the t-test statistic is reported in parenthesis. A 10% critical value of 1.64 is used to test the null hypothesis. The results are reported for each of the six sectors represented by each of the six panels. The two main messages emerging from the skewness and the unconditional correlations is that (a) skewness is not only sector specific but also variable specific, and (b) the unconditional correlations do not suggest a strong relationship between sectoral returns and financial ratios with the exception of PE ratio.

Panel A: Banking sector		
	Skewness	Unconditional correlation
Returns	0.0691	
DY	0.8544	-0.0065 (-0.3412)
PB	0.5417	0.0277 (1.444)
PE	0.2041	0.0416 (2.1716)
Panel B: IT sector		
	Skewness	Unconditional correlation
Returns	-10.5186	
DY	1.1600	-0.0006 (-0.0326)
PB	2.4219	0.0154 (0.8011)
PE	2.3064	0.0129 (0.6773)
Panel C: FMCG sector		
	Skewness	Unconditional correlation
Returns	-0.1561	
DY	0.9339	-0.0154 (-0.8039)
PB	-0.0019	0.0339 (1.7669)
PE	-0.0631	0.0513 (2.6781)
Panel D: Energy sector		
	Skewness	Unconditional correlation
Returns	-0.1564	
DY	1.1931	0.0144 (0.7550)
PB	-0.1469	0.0224 (1.1687)
PE	0.0588	-0.0048 (-0.2538)
Panel E: MNC sector		
	Skewness	Unconditional correlation
Returns	-0.3378	
DY	0.4499	-0.0283 (-1.4763)
PB	0.7091	0.0298 (1.5529)
PE	0.1684	0.0521 (2.7222)
Panel F: Pharmacy sector		
	Skewness	Unconditional correlation
Returns	-0.2115	
DY	0.1289	-0.0303 (-1.5814)
PB	0.2714	0.0378 (1.9707)
PE	1.2931	0.0376 (1.9601)
Panel G: Auto sector		
	Skewness	Unconditional correlation
Returns	-0.2244	

DY	0.9765	-0.0448 (-1.9886)
PB	0.2616	0.0392 (1.7393)
PE	-0.2215	0.0657 (2.9198)
Panel H: Metal sector		
	Skewness	Unconditional correlation
Returns	-0.2252	
DY	0.7634	-0.0063 (-0.2806)
PB	0.9458	0.0175 (0.7764)
PE	1.0359	0.0074 (0.3290)

Table III: Utility results difference between MVS-MV

This table reports the difference between investor utility obtained from a utility function based on skewness (MSV) and those obtained from a utility function without skewness (MV) (or the mean-variance utility function). When MVS-MV is positive it implies that investors are willing to pay a relatively higher portfolio management fee to track information from a forecasting model when the utility function includes the skewness factor as opposed to a utility function which excludes the skewness factor. Column 2 contains results based on a forecasting model when DY is the predictor, column 3 has results when PB is the predictor, and the final column contains results from a model where PE is the predictor variable. Two trading strategies are considered; one which does not allow for any short-selling in which case the optimum portfolio weight is constrained to be between 0 and 1, while the second trading strategy allows for a 10% short-selling. The results are organised into eight panels with each panel representing a sector. There are a total of eight sectors; namely, banking, energy, FMCG, IT, MNC, pharmacy, auto, and metal.

Panel A: Banking sector			
Strategy	DY-model	PB-model	PE-model
Optimal μ	0.0146	0.0075	0.0080
Optimal μ (-.10-1.1)	0.0871	0.0706	0.0702
Panel B: Energy sector			
Strategy	DY-model	PB-model	PE-model
Optimal μ	0.0021	0.0002	0.0002
Optimal μ (-.10-1.1)	0.0211	0.0197	0.0197
Panel C: FMCG sector			
Strategy	DY-model	PB-model	PE-model
Optimal μ	0.0202	0.0155	0.0155
Optimal μ (-.10-1.1)	0.0440	0.0374	0.0378
Panel D: IT sector			
Strategy	DY-model	PB-model	PE-model
Optimal μ	0.0272	0.0193	0.0192
Optimal μ (-.10-1.1)	0.0443	0.0364	0.0363
Panel E: MNC sector			
Strategy	DY-model	PB-model	PE-model
Optimal μ	-0.0127	-0.0248	-0.0251
Optimal μ (-.10-1.1)	-0.0098	-0.0201	-0.0202
Panel F: PHARMACY			
Strategy	DY-model	PB-model	PE-model
Optimal μ	-0.0091	-0.0194	-0.0183
Optimal μ (-.10-1.1)	0.0112	0.0026	0.0006
Panel G: AUTO sector			
Strategy	DY-model	PB-model	PE-model
Optimal μ	-0.0183	-0.0159	-0.0168
Optimal μ (-.10-1.1)	-0.0188	-0.0162	-0.0171
Panel H: METAL sector			
Strategy	DY-model	PB-model	PE-model
Optimal μ	0.0150	0.0202	0.0150
Optimal μ (-.10-1.1)	0.0149	0.0202	0.0149