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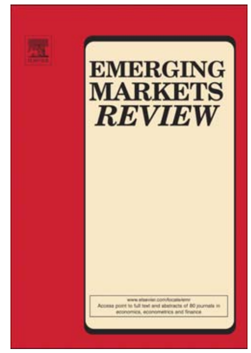


Stock Return Predictability and Determinants of Predictability and Profits

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**Stock Return Predictability and Determinants of Predictability and Profits**

ABSTRACT

We examine stock return predictability for India and find strong evidence of sectoral return predictability over market return predictability. We show that mean-variance investors make statistically significant and economically meaningful profits by tracking financial ratios. For the first time in this literature, we examine the determinants of time-varying predictability and mean-variance profits. We show that both expected and unexpected shocks emanating from most financial ratios explain sectoral return predictability and profits. These are fresh contributions to the understanding of asset pricing.

Keywords: *Stock Returns; Predictability; Profits; Sectors; Mean-Variance; India.*

## I. Introduction

Stock return predictability has been one of the most researched topics in empirical asset pricing. There is voluminous literature on the use of financial ratios as predictors of stock returns (see, *inter alia*, Fama and French, 1988; Lamont, 1998; Welch and Goyal, 2008; Rapach *et al*., 2010; Gupta *et al*., 2014). The empirical findings on predictability have not met with any consensus, thereby triggering a methodological response. Studies began by addressing fundamental econometric issues which were prevalent in the earlier literature. These issues mainly relate to the predictor variable, that is, whether or not the predictor variable is persistent and endogenous (see, *inter alia*, Campbell and Yogo, 2006; Lanne, 2002; Lewellen, 2004; and Stambaugh, 1999) and whether the predictive regression model is heteroskedastic (see, Westerlund and Narayan, 2012, 2015).

In this paper we contribute to the stock return predictability literature by investigating whether financial ratios predict sectoral stock returns on the Indian stock exchange. Our empirical investigation is based on four specific approaches. First, we use a time-series predictive regression model proposed by Westerlund and Narayan (2012, 2015) to examine the null hypothesis of no predictability based on a generalised least squares estimator (GLS). The main advantage of this test is that it accounts for all three salient features of the data and model, namely, predictor persistency and endogeneity, and model heteroskedasticity. Second, we extend the GLS-based predictive regression model to a time-varying model thereby extracting and observing predictability (or lack of it) over time. Third, using the time-series predictive regression estimates we treat them as a dependent variable and regress them on expected and unexpected financial ratio shocks. Our goal here is to examine what determines predictability over time. Fourth, we expand on the economic significance aspect of our paper by estimating, using forecasted returns, profits for a mean-variance investor who is faced with a mean-variance utility function. This analysis results in a time-series of profits per sector. We then examine the determinants of this sectoral profitability by regressing profits on expected and unexpected financial ratio shocks. To the best of our knowledge, ours is the first paper to undertake this type of analysis.

These approaches allow us to conclude with the following key findings. First, while evidence of market return predictability is weak, sectoral return predictability is strong. Second, dividend-payout ratio and dividend yield turn out to be the most popular predictors, predicting returns for all the 12 sectors, while earnings-price ratio turns out to be the second most popular predictor—it predicts returns for five sectors. The book-to-market ratio, by comparison, appears to be the least popular predictor, predicting returns for only two sectors. Third, the predictability of sectoral stock returns is supported by evidence that all financial ratio-based forecasting models offer investors statistically significant profits. However, profits vary by sector and some of the sectoral profits are in excess of the market profits. Fourth, we find that while expected financial ratio risks explain predictability and profitability in almost all sectors, unexpected financial ratio risks only explain predictability and profitability in some of the 12 sectors. From this, we conclude that one source of sectoral heterogeneity with respect to predictability and profitability is the unexpected financial ratio risk.

Our paper connects with and contributes to multiple strands of the literature. First, our study relates to the relatively small group of studies that examines stock return predictability for developing countries (see, Dicle *et al*., 2010; Harvey, 1995; Hjalmarsson, 2010; Gupta and Modise, 2012; Narayan and Bannigidadmath, 2015; Narayan *et al*., 2015; Westerlund *et al*., 2015). The differences between the present study and the Narayan and Bannigidadmath (2015) are multiple. First, we study time-varying predictability. Hence, with our model and results we have a dynamic predictive regression model while Narayan and Bannigidadmath (2015) have a static model. In other words, from our study one can observe predictability over time, allowing one to infer phases over which predictability exists and vice versa. By comparison, from the Narayan and Bannigidadmath (2015) study one only learns whether predictability exists or not on average. The second main difference is that Narayan and Bannigidadmath (2015) do not explain the determinants of predictability. We propose time-series models of the determinants of predictability. We further extend the analysis to study also the determinants of mean-variance investor profits. We are able to propose a time-series predictability and profitability determinants model because we use daily data which gives us sufficient sample sizes to conduct empirical tests.

We believe that a daily data model is a better predictor of returns than a monthly data model for two reasons. First, recent studies question hypotheses test based on the use of a single data frequency; see, for instance, Narayan and Sharma (2015a) and Narayan, Ahmed, and Narayan (2015). From this literature it is clear that hypotheses test can be data frequency dependent. Hence, the use of at least the commonly used data frequencies should be considered in order to ascertain the robustness of the outcomes regarding a particular hypothesis test. The Narayan and Bannigidadmath (2015) study is based on monthly data only. Therefore, the question that arises, motivated by the data-frequency debate alluded to earlier, is whether their results on predictability will hold when subjected to a daily data set, which contains richer information than monthly data.

Second, our goal in this paper is to propose a time-varying predictive regression model. Given that time-series data for India is available only from 1990, a time-varying predictive regression model based on monthly data will not be parsimonious, neither from a statistical point of view nor from an economic significance point of view. Since the theme of the paper revolves around a new statistical approach (time-varying predictive regression model) and economic implications of such time-varying predictability (time-varying profits and investor utility), we need a sample size that is not only rich (like daily data are) but one which gives us a sufficient number of observations (as daily data do) to conduct the statistical hypothesis test that we propose. Using daily data offer us a solution without costs.

Our choice of India is motivated by the fact that it is an emerging market which has been profitable for investors over the last decade and has, therefore, performed impressively (see, Narayan *et al*., 2014a, 2014b), yet, what determines time-series predictability and profits is unknown. Our study, by taking a rigorous investigation on the role of financial ratios in predicting returns, adds not only to an understanding of the asset pricing behaviour on the Indian stock exchange but also to the broader role and importance of financial ratios in an emerging market, particularly with respect to determinants of predictability and profits over time.

Our study also connects to the literature that shows that hypotheses tests are sector-specific. In terms of evidence on sectoral return predictability, Westerlund and Narayan (2014) examine sectoral return predictability using NYSE data. It is important to entertain sectoral return predictability because there are several hypotheses that point to the fact that investors in a market have different speeds of reaction to news. Some investors over-react to news while others under-react to news. The over-reaction to news is explained by the positive-feedback-trader model of DeLong *et al.* (1990) and the overconfidence model of Daniel *et al.* (1998). DeLong *et al.* (1990), in particular, argue that the prices initially over-react to news about fundamentals, and then continue to over-react further for a period of time due to the prevalence of positive feedback from investors, who buy stocks when prices rise and sell when prices decline. Investors' under-reaction to news occurs through different channels, as described in the limited information hypothesis (see, Merton, 1987), the conservatism hypothesis (Barberis *et al.*, 1998), and the gradual information diffusion hypothesis (Hong and Stein, 1999). A detailed discussion on these hypotheses is undertaken in the next section. The main message emerging from these theories is that investors are likely to be heterogeneous because: (a) some are more conservative than others; (b) some have more information than others; and (c) some receive information faster than others. In other words, how much investors are affected by information and, as a result, are different from each other, depends on "who they are". It is the "who they are" aspect that we take particular interest in. We define "who they are" by "investors in different sectors". Closely related to this idea is the work of Hong *et al.* (2007b), who contend that investors specialize in particular market segments and consider segmentation across US industries in forecasting stock returns. In this regard, our idea of considering sectoral stocks on the National Stock Exchange (India) seems reasonable and consistent with work done on the US market by Westerlund and Narayan (2015).

Using a time-series model, we confirm that predictability is sector-specific and that there are some financial ratios which are relatively more popular predictors of returns than others. By showing evidence of sector-specific predictability we contribute to a related strand of the literature that shows that hypotheses tests are sector-dependent. More specifically, this heterogeneity is captured when testing the predictability of macroeconomic variables (Hong *et al.*, 2007b), testing the effects of oil price shocks (see, Narayan and Sharma, 2011), examining the performance of mutual funds (see, Busse and Tong, 2012), testing cross-predictability of returns (Menzly and Ozbas, 2010), testing turn-of-the-month effects (Sharma and Narayan, 2014), and testing price discovery in stocks and CDS markets (see, Narayan *et al.*, 2014c), among others. In light of this relatively new body of evidence on sectoral heterogeneity, our study attempts to add to our understanding of sectoral heterogeneity beyond the US market. We contribute by showing that not only return predictability and mean-variance investor profits are sector-specific, but also the determinants of predictability and profits are different for different sectors.

Our third contribution relates directly to the stock return predictability literature. The focus of this literature has been on developing new approaches to testing for stock return predictability. For a review of this literature, see Westerlund and Narayan (2015). Therefore, it is easy to appreciate that this literature has not considered predictability in a time-varying manner. For this reason, no attempt has been made to test for the determinants of predictability. While we understand that stock returns are predictable, we have limited understanding of what the determinants of predictability are. By using a recursive window approach in testing for stock return predictability, we extract evidence of time-varying predictability, allowing us to test its determinants. We show that at the market level and for most sectors, both expected and unexpected financial ratio shocks determine predictability.

Our final contribution relates to the economic significance of stock return predictability. The bulk of the studies on stock return predictability tests the economic significance of predictability using a mean-variance investor utility function (see, *inter alia,* Rapach *et al*., 2010). The main finding from these studies is that by tracking financial ratios and using them to forecast returns, investors are able to make statistically significant profits. However, what actually determines these profits is unknown and has not been examined. We show that expected financial ratio shocks determine profitability in most of the sectors.

The balance of the paper proceeds as follows. In Section II, we discuss our motivation for sectoral analysis of stock return predictability. The data set and estimation approach is discussed in Section III. The preliminary statistical behaviour of data and the empirical findings are presented in Section IV. The penultimate section is devoted to understanding the determinants of sectoral predictability. The final section provides concluding remarks.

## II. Why Should We Care about Sectoral Return Predictability?

### *A. Background*

One feature of the stock return predictability literature is that it is based predominantly on the market. As a result, all we understand thus far is the relevance of financial ratio (or macroeconomic) predictors for predicting market returns. On this, our understanding extends to the fact that some financial ratios, such as book-to-market ratio and dividend yield, predict stock market returns better compared to other predictors, such as earnings-price ratio and cash-flow-to-price ratio. There are two aspects of return predictability we still do not understand. First, we are unsure of whether time-series evidence of stock market return predictability extends to all the different sectors that comprise the market, although in panel data models, Westerlund and Narayan (2014) show this to be the case. In other words, are sectors homogeneous or heterogeneous in terms of return predictability? The second issue that we have limited knowledge about is whether certain financial ratios predict time-series of sectoral returns for all sectors or only for some sectors.

In considering sectoral return predictability, an additional issue that comes to the fore is: if return predictability varies by sector then what are the determinants of this return predictability? In other words, why do financial ratios in some sectors predict returns much better than in other sectors? These are fresh questions and we make an attempt to answer them in this paper. However, before we do this, the lack of focus on sectoral return predictability demands that at the outset we set the motivation for why a sector-level analysis is warranted. That is the aim of this section. We accomplish this aim in three steps. In the first step, we review theoretical/conceptual work which argues that the sectors of a market are different from each other, and, therefore, analysing them individually will most likely expose any heterogeneity that may exist at the sector level. In the second step, we review the empirical literature that documents sectoral heterogeneity. In the third step, we draw motivation from our sectoral data set. Essentially, we test the null hypothesis that the financial ratios and book-to-market ratio, say, of one sector are different from the same financial ratios of the other eleven sectors. More importantly, our aim here is to show that the financial ratios of sectors are different. From these three steps, we are able to draw the conclusion that the sectors are heterogeneous, and to ignore this in any empirical analysis of stock return predictability will come at a cost, that is, the loss of information that one can simply extract from a group of heterogeneous sectors.

### *B. Theoretical Motivation*

Our theoretical motivation begins with the strand of literature that has examined the role of informed traders, who trade differently. Kadan *et al*. (2012: 95) argue that: "… analysts typically follow a top-down approach, trying to exploit sector-rotation strategies mostly driven by the cyclicality of different industries and their sensitivities to macroeconomic shocks". They find that sell-side analysts are more optimistic towards industries with higher levels of investment, past profitability, and past returns. In an earlier work along this line, Kacperczyk *et al*. (2005) show that some mutual fund managers hold portfolios concentrated in a few industries, motivated by the belief that these portfolios will outperform the overall market. Indeed, their empirical findings reveal that portfolios concentrated in few industries do perform better. There are two implications arising from these studies. First, there are some industries that enjoy higher levels of analyst coverage and institutional ownership relative to others. Second, macroeconomic cycles do not affect all sectors uniformly, and the returns on industry portfolios might convey additional information not available in aggregate market returns.

Hoberg and Phillips (2010) identify three hypotheses relating to the effect of industry level competition on stock returns. First, high valuation, high financing, and high investment in competitive industries, they argue, will be associated with lower ex-post industry and firm profitability and lower ex-post stock returns. Second, firms in competitive industries more aggressively pursue investment and financing activities during boom periods. These industries, therefore, are likely to be more pro-cyclical. Third, industry-level competition affects the firm risk and returns via industry demand.

Another strand of the literature examines the behaviour of investors and their effect on equity markets. Some investors have limited information-processing capabilities (Simon, 1955). Merton (1987) develops a static model, with multiple shocks, in which investors trade only a limited number of stocks about which they have information. In a similar vein, Barberis *et al*. (1998) find that investors suffer from a conservatism bias, in that they update their beliefs slowly when faced with new public information. Moreover, because it is costly for investors to choose complex forecasting models over simple models using a small subset of available information (Hong *et al*., 2007a), they tend to allocate more attention to sector-specific rather than firm-specific factors (Peng and Xiong, 2006). Menzly and Ozbas (2010) also provide evidence consistent with this conjecture. They find that investors specialize in fewer industries rendering the markets informationally segmented.

Another stream of the literature is built on the gradual information diffusion hypothesis proposed by Hong and Stein (1999). They suggest that investors cannot perform the rational expectations trick of extracting information from prices, and that information diffuses gradually through the investing public. Hou (2007) explore the gradual diffusion hypothesis across industries. He finds that information diffuses slowly in some industries leading to a strong intra-industry lead-lag effect. More recently, Narayan and Sharma (2011) examine the impact of oil shocks on sectoral returns and find strong empirical evidence of sectoral heterogeneity attributable to the gradual diffusion of oil price news.

### *C. Empirical Motivation*

In this section, we examine the empirical literature that has considered the role of sectors and/or industries in supporting the theoretical conjectures stated in the previous section. Busse and Tong (2012) examine all US mutual funds between January 1980 and September 2009. They find that the industry-selection skill of mutual funds drives the persistence in the overall performance of mutual funds, and that the industry-selection skill rather than stock-selection skill provides additional information enabling investors to achieve greater future performance.

Hou and Robinson (2006) find evidence of industry-specific behavior being reflected in stock returns. They show that firms in competitive industries earn higher stock returns, and firms in concentrated industries earn lower returns, even after controlling for factors such as size, book-to-market ratios, and momentum. Hong *et al*. (2007b) examine 34 industry returns and find evidence that some of the industry returns lead the macroeconomic variable, namely, industrial production growth. In addition, they find that 14 of the 34 industry returns lead the overall stock market. Menzly and Ozbas (2010) classify the industries into supplier and customer industries based on the amount of goods and services traded among industries. They find that customer industry returns predict supplier industry returns. This supports the theoretical conjecture that information in some industries diffuses gradually relative to other industries. The overall implication here is that industries in the US market are heterogeneous and that some of the industry returns contain more valuable information (about overall stock market and/or macroeconomic variables) relative to other industry returns.

### *D. Empirical Evidence from our Data*

Our objective here is to empirically ascertain whether or not the five financial ratios (book-to-market, dividend-payout, dividend yield, dividend-price, and earnings-price) in any two sectors are statistically different from zero. Before we test the null hypothesis that financial ratios between any two pairs of sectors are zero, in Table I, we report some selected descriptive statistics on the five financial ratio variables for all the twelve sectors. We observe that all five financial ratio variables show strong sectoral disparities. The book-to-market ratio is in the range of 0.132 (retail sector) to 0.714 (MNC sector). The earnings-price ratio has the widest range; it falls in the range of -3.577 (media sector) to -1.796 (MNC sector). Similar sectoral disparities are observed with respect to the other financial ratios. These features suggest that the predictability of returns may well be sector-specific.

**INSERT TABLE I**

We now test the null hypothesis that the financial ratio of any two pairs of sectors is equal. For each financial ratio, because we have 12 sectors, 66 pairs of null hypotheses are tested[1]. When considering book-to-market ratio and dividend-payout ratio, we reject the null hypothesis for 65 of the 66 pairs. This means that the book-to-market ratio for 65 pairs of sectors is statistically different. For the null hypothesis tests based on dividend yield, earnings-price ratio, and dividend-price ratio, we reject the null for all the 66 pairs of sectors, indicating that these three financial ratios are statistically different for all possible pairs of sectors. It is clear from this mean difference test of financial ratios that sectors are heterogeneous, and to ignore this in any empirical analysis of stock return predictability could be costly.

## III. Data and Estimation Approach

### *A. Data*

We use a daily dataset on the S&P CNX Nifty Index and each of the 12 sectoral indices representing firms listed on the National Stock Exchange (NSE). The S&P CNX Nifty Index is the leading stock index of India, consisting of 50 large, highly liquid, and well-diversified

[1] The tabulated results are available from authors upon request.

stocks listed on the NSE. This market constitutes around 66% of the market capitalization of stocks listed on the NSE as of 31/12/2012 (National Stock Exchange of India, 2013). For the purpose of the study, the dataset of the S&P CNX Nifty Index covers a sample period from 01/03/2000 to 31/10/2013. We consider eleven sectoral indices (automobile, banking, energy, pharmacy, finance, retail, metal, media, real estate, information technology, and public sector union banks) and one thematic index (multinational corporations) – a total of twelve, which we refer to as the twelve sectors in the paper. The time periods of the data on the twelve sectoral indices, however, vary conditional on data availability. Some sectoral indices, such as banking, retail, information technology, and multinational corporations (MNC),contain data only for the period 01/03/2001 to 31/10/2013; the energy and pharmacy sectors have data for the period01/03/2002 to 31/10/2013; the automobile, metal, and public sector union banks (PSU banks) sectors have data covering the period01/03/2005 to 31/10/2013; the media sector has data for the period 01/03/2006 to 31/10/2013; and data for the finance and real estate sectors cover the period01/03/2007 to 31/10/2013. We downloaded data on index prices, price-to-earnings ratio, price-to-book ratio, and dividend yield on the S&P CNX Nifty Index and on each of the 12 sectoral indices from NSE's statistical webpage (see http://www.nseindia.com/index_nse.htm). Given the dataset, the specific predictor variables are as follows:

- Dividend-payout ratio (DE) is defined as the difference between the log of dividends and log of earnings.
- Earnings-price ratio (EP) is the difference between the log of earnings and the log of share prices.
- Dividend-price ratio (DP) is the difference between the log of dividends and the log of share prices.

- Dividend yield (DY) is the difference between the log of dividends and the log of lagged share prices.
- Book-to-market ratio (BM) is defined as the ratio of book value to the market value of the index.

*B. Estimation Approach*

We employ the Westerlund and Narayan (2012, 2015) generalised least squares (GLS) based estimator to test for in-sample predictability. This method takes into account the persistency, endogeneity and heteroskedasticity features of data, features that, as we will soon show, characterise our data set. We then evaluate the out-of-sample forecasting performance using a range of evaluation metrics, which we will discuss in this section.

*B.1 Westerlund and Narayan Estimator*

A typical stock return predictive regression model has the following form:

$$r_t = \theta + \beta^{adj} FR_{t-1} + \gamma(FR_t - \rho_0 FR_{t-1}) + \eta_t \tag{1}$$

Here, $r_t$ is the stock return computed as the log difference in percentage form, and $FR_t$ is the predictor variable. In our case, $FR_t$ is either one of the five financial ratios mentioned and discussed earlier. The error term is characterised by a zero mean and variance $\sigma^2$, and $\beta^{adj} = \beta - \gamma(\rho - \rho_0)$ can be interpreted as the limit of the bias-adjusted OLS estimator of Lewellen (2004). Westerlund and Narayan (2012, 2015) assume that $\rho = 1 + \frac{c}{T}$, where $c \leq 0$ is a drift parameter that measures the degree of persistency in $FR_t$. The Westerlund and Narayan (2012, 2015) GLS-based t-statistic for testing the null hypothesis of no predictability $H_0{:}\, \beta = 0$, where the GLS estimator captures the ARCH structure in the errors by weighting all the data by $1/\sigma_{\eta t}$.

*B.2 Out-of-Sample Forecast Evaluation Measures*

We examine the out-of-sample forecasting performance using a recursive window approach, following Narayan *et al*. (2013). We estimate the predictive regression model for the in-sample period $t_0$ to $T_0$ and forecast the returns for the period $T_0 + 1$. Here, $T_0$ is the number of in-sample observations. We then re-estimate the model over the period $t_0$ to $T_0 + 1$ and forecast the returns for the period $T_0 + 2$. This process continues until all the data are exhausted. Since we are undertaking recursive forecasting, we are taking into account the information available up to the previous day, thereby mimicking real-time forecasting. The out-of-sample period is set to 50% of the full-sample of data. Due to the different sample sizes of the Nifty Index, and the sectors, the out-of-sample sizes vary but the 50% rule is maintained. The out-of-sample forecasting period for the Nifty Index and six of the sectors (banking, retail, information technology, MNC, energy, and pharmacy) covers the sample 01/01/2007 to 31/10/2013. For sectors such as the automobile, metal, and PSU bank, the out-of-sample forecasting is conducted over the period 01/01/2009 to 31/10/2013. For the media and finance sectors, the out-of-sample forecasting spans the period 01/01/2010 to 31/10/2013; while, for the real estate sector, it covers the period 01/07/2010 to 31/10/2013.

We use the following three well-known measures to evaluate the accuracy of the forecasts. The Clark and McCracken (2001) forecast encompassing statistic called "Enc-new" is given by:

$$Enc - new = \frac{(T - T_0)^{-1} \sum_{t=T_0}^{T} \hat{u}_{0,t+1}\left(\hat{u}_{0,t+1} - \hat{u}_{1,t+1}\right)}{\widehat{\sigma}_1^2} \tag{2}$$

where,
$$\widehat{\sigma}_1^2 \equiv (T - T_0)^{-1} \sum_{t=T_0}^{T} \hat{u}_{1,t+1}^2 \tag{3}$$

It has been shown through extensive Monte Carlo simulations in Clark and McCracken (2001, 2004) that the $Enc - new$ statistic has a power advantage over the Diebold and

Mariano (1995) statistic. So we exclude reporting the results of Diebold and Mariano (1995) test statistic.[2]

The $MSE - F$ statistic of McCracken (2007) tests the null hypothesis that the predictive regression model and the historical average model have equal forecasting ability. The null is tested against the one-sided alternative hypothesis that the $MSE$ for the predictive regression model forecasts is less than the $MSE$ for the historical average model forecasts.

Lastly, we employ the Fama and French (1989) out-of-sample $R^2$ $(OR^2)$[3] statistic given by:

$$OR^2 = 1 - (MSE_M / MSE_H) \tag{4}$$

where, $MSE_M$ and $MSE_H$ are the mean squared errors of the predictive regression model and the historical average model, respectively.

## IV. Main Results

### *A. Preliminary Statistical Features of the Data*

Our main objective in this section is to gauge the extent to which our predictive regression model is characterised by persistent and endogenous predictors and, to what extent, if at all, our predictive regression model suffers from heteroskedasticity.

We begin with the test of the null hypothesis of a unit root in variables relating to the Nifty Index and each of 12 sectoral indices in our sample. These are reported in Table II. The unit root test is based on the familiar augmented Dickey-Fuller (1981) time-series regression model and is implemented by including only the intercept term. We use the Schwarz Information Criterion and a maximum of eight lags to obtain the optimal lag length. The test statistics, together with the p-value, are reported for each of the variables. The optimal lag length is reported in square brackets. The unit root null is rejected for returns of Nifty and for

[2] We thank one referee of this journal for making this point.
[3] This test statistic is popular and recent studies have also used it; see Burns and Moosa (2015), and Narayan and Sharma (2014, 2015b).

each of the 12 sectors, rendering returns, as expected, to be strongly stationary. When we consider the predictor variables of Nifty, the unit root null is rejected at the 5% level for DE and EP, and at the 10% level for DP and DY; while, for BM, the unit root null is not rejected. At the sector-level, we find mixed evidence of integration amongst the predictor variables. For the automobile, metal and MNC sectors, we find that the unit root null is not rejected for any of the predictor variables. For the banking and media sectors, the unit root null is rejected only for DE. For the PSU bank sector, the unit root null is rejected for four out of the five predictors; while, for the energy and information technology sectors, the null hypothesis is rejected for three predictors only. For the pharmacy and retail sectors, variables DP, DY and DE are strongly stationary; the null hypothesis is rejected at the 1% level. For the finance sector, the null hypothesis is rejected only for two predictors; while, for the real estate sector, the null hypothesis is rejected only for the EP variable.

**INSERT TABLE II**

However, since the rejection of the null does not imply that the variables are not persistent, we test the first-order autoregressive coefficient for each of the variables[4]. What we notice immediately is that for all the proposed predictors of the Nifty Index, the coefficient is close to one. For all the sectors, the autoregressive coefficient is again close to one for the five predictors, implying that they are highly persistent.

In unreported results, we test for autocorrelations associated with the square of each variable. When we consider the Nifty Index, we notice that the autocorrelations are significant for returns and for all the predictors. In the case of each of the twelve sectors, we find the autocorrelations to be significant for all the predictors. When we consider the sector returns, except for the information technology sector, we find the autocorrelations to be significant for the other eleven sectoral returns. The autocorrelation in squared variables can

[4] The tabulated results are available from authors upon request.

be thought of as estimated ARCH coefficients, thus signalling strong ARCH effects in both the predictors and the returns.

We undertake further tests of ARCH effects by filtering each series and running an autoregressive regression model with twelve lags. We then apply the Lagrange Multiplier test to examine the null hypothesis of 'no ARCH' in the filtered series; results are not reported here but available from authors upon request. When we consider the return series, except for the information technology sector, the null hypothesis of 'no ARCH' is strongly rejected at the 1% level for both the market and for all 12 sectors. In the case of the proposed predictor variables for the Nifty Index, we again find that the null of 'no ARCH' is rejected at the 1% level for all the predictors except BM. In the case of the predictor variables for sectors, for 10 out of the 12 sectors, the null hypothesis is rejected for at least two predictors at the 1% level. A strong presence of the ARCH effect is seen in predictor variables for the banking, information technology, and retail sectors. Overall, the ARCH test implies that both the returns and the predictors are characterised by ARCH, and this needs to be accounted for in testing for stock return predictability.

Finally, we test for the extent of endogeneity in the predictive regression models; results are not reported here but are available from authors upon request. The predictor variable is deemed endogenous if the coefficient $\gamma$ from Equation (5) is statistically different from zero.

$$\varepsilon_{r,t} = \gamma \varepsilon_{fr,t} + \eta_t \tag{5}$$

Here, $\varepsilon_{r,t}$ and $\varepsilon_{fr,t}$ are error terms from a predictive regression model and an AR(1) model of financial ratios, respectively. For the Nifty Index, we find that predictors BM, DP, DY, and EP are all endogenous. The evidence of endogeneity is stronger in the sectors; for most of the predictors, the null hypothesis is rejected at the 1% level. In six out of the 12 sectors, the null hypothesis is rejected at conventional levels of significance for all the predictors. For the remaining six sectors, we notice that all the predictors, except DE, show evidence of endogeneity.

*B. Predictability Test Results*

In this section, we examine both in-sample and out-of-sample evidence of stock return predictability. We begin with the WN test, for which we report the t-statistic for $\beta$ based on both the asymptotic GLS t-test as well as the sub-sample GLS t-test. We give greater weight to results based on the sub-sample test for the reason that it works best when the predictor variable is persistent, as shown in the Monte Carlo simulations conducted and reported in Westerlund and Narayan (2015).

Our main findings, as reported in Table III, can be summarised as follows. First, when we consider market (Nifty) return predictability, we find that only two financial ratios (DE and DY) predict market returns. There is no evidence that BM, DP, and EP predict market returns. This is in sharp contrast to evidence found in the existing literature. The existing empirical evidence is strongly in favour of BM as the most popular predictor of market returns. This is not the case with India, however. Our result here is consistent with the evidence obtained from the Chinese stock market, suggesting that the BM ratio is a weak predictor of returns compared to DP, DY, and EP (Jiang *et al.*, 2011; Wang and Xu, 2004).

**INSERT TABLE III**

Several time-series studies and cross-sectional studies on the US and other major developed markets document evidence of return predictability using BM as the predictor (see, Lettau and Nieuwerburgh, 2008; Kothari and Shanken, 1997; Pontiff and Schall, 1998; Pincus *et al.*, 2007; Polk *et al.*, 2006). The BM ratio captures information about expected future returns because the book value proxies for expected cash flow (see, Berk, 1995; Sharathchandra and Thompson, 1994; Ball, 1978). Thus, the price level changes with the change in discount rate and is reflected in the BM ratio. The evidence for the null of no predictability for the U.S. and major developed markets appears to be weaker or rather inconsistent when it comes to the predictors EP, DP, and DY. For example, Hjalmarsson (2010) examines 40 international markets and finds no strong or consistent evidence of predictability when considering the EP and DP ratios. Avramov and Chordia (2006) and Kothari and Shanken (1997) find that DY predicts returns, while the evidence from Campbell and Yogo (2006) indicates that DP predicts returns.

Second, very little is known about sectoral return predictability. Our findings provide several new insights on the predictive ability of financial ratios, which can be best summarised as follows:

- DE and DY predict returns for all 12 sectors.
- EP predicts returns for five sectors, namely, automobile, finance, retail, information technology, and energy.
- The financial ratios that have the least predictive ability are DP and BM. DP predicts returns for four sectors (real estate, MNC, information technology, and energy), while BM predicts returns for the pharmacy and real estate sectors.
- There are three sectors (real estate, information technology, and energy) where return predictability is most evident, that is, for those sectors four out of the five financial ratios predict returns. They are followed by the automobile, pharmacy, finance, retail and MNC sectors, for which three financial ratios predict returns.
- For the banking, metal, media, and public sector union banks, only two financial ratios (DE and DY) predict returns.

There are three key messages from our in-sample predictability results. First, DE and DY are the most popular predictors of returns. They not only predict market returns but also predict returns for each of the 12 sectors. Second, the least popular return predictors are BM and DP — BM predicts returns for only two sectors while DP predicts returns for four sectors, and there is no evidence that they predict market returns. Our final message is that return predictability is sector-specific, giving credence to our idea of considering return predictability at the sector-level. What we mean is that there are some sectors where high evidence of predictability is found while for others there is limited evidence of predictability. There are, for example, eight sectors in which at least three financial ratios predict returns, whereas there are four sectors in which only two financial ratios predict returns. Our evidence of variation in results by sector is consistent with the recent literature on sectoral heterogeneity (see Narayan *et al*., 2011; Narayan and Sharma, 2011; Hong *et al*., 2007b).

We now turn to the out-of-sample predictability results, which are reported in Table IV. We begin with predictability of market returns. We find that the BM and EP are the most successful out-of-sample predictors, for which at least two of the three metrics support our predictive regression model. For the remaining three predictors (DE, DP and DY), only one metric supports predictability. At the sector-level, similar to in-sample predictability, evidence for out-of-sample predictability varies, and the results are summarised as follows:

- BM turns out to be the most popular out-of-sample predictor of sectoral returns. At least two of the three metrics reveal that the BM ratio-based predictive regression model beats the historical average model in four out of 12 sectors.
- DP and EP are the second most popular out-of-sample predictors of sectoral returns. At least two of the three metrics reveal that the DP and EP ratio-based predictive regression model beats the historical average model in three sectors.
- DY and DE provide the weakest evidence of sectoral return predictability. DY predicts returns in only one sector. There is no evidence that at least two metrics support out-of-sample predictability for DE ratio-based predictive regression model.

- In terms of the most predictable sectors, we find two financial ratios for which at least two of the three metrics support out-of-sample predictability. The most predictable sectors are energy and finance.
- In terms of sectors with limited evidence of out-of-sample predictability, we find six sectors for which there are at least two metrics that supports out-of-sample predictability in one of the five predictive regression models. They are automobile, banking, retail, media, metal and pharmacy.
- The sectors with the weakest evidence of predictability are information technology, MNC, public sector union banks and real estate.

**INSERT TABLE IV**

There are two main messages from our out-of-sample evaluation of stock return predictability. First, evidence of out-of-sample predictability of market returns is weak, with only BM and EP variables predicting returns. At the sector-level, the evidence of return predictability is stronger. We find strong evidence of return predictability for three of the 12 sectors. This compares to strong evidence of in-sample predictability for eight sectors. There is only one sector—energy—for which strong evidence of both in-sample and out-of-sample predictability is found. The second message is that while in in-sample tests the DE ratio turned out to be one of the strongest predictors of returns, in out-of-sample evaluation it turns out to be one of the weakest predictors of returns. Similarly, ratios BM and DP that turned out to be the weakest predictors of returns in in-sample tests show strong out-of-sample predictability. On the whole, then, our analysis has three implications: (a) it adds to the lack of consensus on in-sample versus out-of-sample tests, consistent with the literature (see, *inter alia*, Ashley *et al*., 1980; Lo and MacKinlay, 1990); (b) regardless of whether we judge predictability based on in-sample or out-of-sample tests, our main finding that predictability is sector-specific holds; and (c) in-sample evaluations provide stronger evidence of predictability than out-of-sample tests, consistent with earlier studies; see, for example, Bossaerts and Hillion (1999), Campbell and Thompson (2008).

*C. Economic Significance*

In the return predictability literature, it is common to test for economic significance of return predictability using a mean-variance utility function. We follow this literature (see, *inter alia*, Marquering and Verbeek, 2004; Campbell and Thompson, 2008; Rapach *et al*., 2010; Kumar, 2015) and compute profits and utility gains (that is, the difference between utility from our proposed model and utility from the historical average model). Specifically, we compute the average portfolio return and utility for a mean-variance investor who allocates his portfolio between a risky asset and a risk-free asset, and who aims to maximise his utility function given by:

$$Max\left[E_t\left(r_{t+1}^p\right)-\frac{\gamma}{2}Var_t\left(r_{t+1}^p\right)\right] \tag{6}$$

where $r_{t+1}^p$ denotes the portfolio return and $\gamma$ is the relative risk aversion parameter. The portfolio return is given by:

$$r_{t+1}^p = r_{t+1}^f + \omega_t r_{t+1} \tag{7}$$

The optimal portfolio weight for risky asset $\omega_t$ is given by:

$$\omega_t = \frac{E_t(r_{t+1})}{\gamma Var_t(r_{t+1})} \tag{8}$$

The estimated portfolio weights are restricted to between 0.5 and 1.5 allowing for limited borrowing and limited short-selling. The risk aversion parameter is set to 6, which typically represents a medium level of risk position for an investor. The results are reported in Table V. We begin with profits from investing in the market. All five predictors offer a mean-variance investor statistically significant and positive profits. Profits range from 8.11% per annum when the return forecast is based on the BM ratio, to 16.57% per annum when the return forecast is based on the EP ratio. The utility gains are also positive, suggesting that a mean-variance investor is willing to pay a portfolio management fee in order to track forecast returns using our proposed financial ratio-based predictive regression models, as opposed to using the historical average. We notice that, as with profits, utility is maximised when the predictive regression model uses the EP ratio as the predictor, and is least when the BM ratio is the predictor.

**INSERT TABLE V**

We now read the profits and utility gains results for each of the 12 sectors. There are two interesting features of the results. First, we notice that while all five predictors offer investors statistically significant profits, profits are different and vary from sector-to-sector. For example, profits are generally higher for some sectors (such as PSU banks, real estate, finance, MNC, and information technology) while they are relatively small for other sectors (such as banking, media, retail, and pharmacy). Second, we notice that utility gains are positive for all sectors when the predictive regression model uses DY as the predictor, and positive for six sectors (energy, retail, media, metal, pharmacy, and real estate) when using EP as the predictor. When using the other three financial ratios as predictors, utility gains are positive in only three sectors. When using BM as the predictor, the three sectors are retail, information technology, and media; when using DE as the predictor, the three sectors are media, metal, and pharmacy; and, when using DP as the predictor, the three sectors are automobile, energy, and retail. In terms of the most popular sectors for which investors are willing to pay a portfolio management fee, they turn out to be the retail and media sectors, for which utility gains are positive with four of the five predictors, followed by the metal, pharmacy, and energy sectors, where utility gains are positive with three of the five predictors.

## V. Why are Predictability and Profits Sector-dependent?

Our contribution in this paper has been to show that stock return predictability is sector-specific and that there are certain financial ratios that predict sectoral returns better than others. Not surprisingly, we also discover that profits and investor utilities are also sector-specific. The resulting question is: why are predictability and profits sector-dependent? Since both profits and utilities are computed for an investor faced with a mean-variance utility function, we only consider determinants of profits (together with the determinants of time-varying predictability). Our proposal to test sectoral predictability and profits is simple and proceeds as follows. Since predictability and, indeed, estimated profits are based on each of the five financial ratios, based on bivariate predictive regression models, we test whether, when predictability and profits are based on BM, say, expected and unexpected BM ratio risks determine profits and predictability. We compute expected and unexpected financial ratio risks by using a first-order autoregressive model of the financial ratio (FR), as in French *et al*. (1987), Amihud (2002) and Berkman *et al*. (2011):

$$FR_t = \alpha_0 + \alpha_1 FR_{t-1} + \epsilon_t \tag{9}$$

We estimate five of these regression models (one for each financial ratio variable) per sector using the ordinary least squares estimator, where the standard errors have been corrected for heteroskedasticity and autocorrelation using eight lags. In other words, FR stands for the financial ratios - BM, DE, DY, DP, and EP. We find the estimated slope coefficients to be statistically different from zero. This is true for all five financial ratio variables and holds across all 12 sectors. We also test whether the coefficients from the model are stable over time. We use Hansen's (1992) parameter instability test and find that in each of the five regression models across all 12 sectors the parameters are stable. These are preliminary results and, to conserve space, we do not report them here. They are, however, available upon request. With these results confirmed, we interpret the fitted value from the above model as the level of expected financial ratio risk $(FR^{E})$, and the residual from the model as our measure of unexpected financial ratio risk $(FR^{UE})$. To test the hypothesis that financial ratio expected and unexpected risks determine time-varying predictability and profits by sector, we run the following time-series regression models (estimated using OLS) for each sector, where the standard errors have been corrected for heteroskedasticity and autocorrelation using eight lags:

$$Pred_t = \theta_1 + \theta_2 FR_t^E + \theta_3 FR_t^{UE} + \vartheta_t \tag{10}$$

$$Profits_t = \theta_1 + \theta_2 FR_t^E + \theta_3 FR_t^{UE} + \vartheta_t \tag{11}$$

The time-varying predictability variable, $Pred_t$, is computed based on the predictive regression model (1). The way we extract the time-varying *t*-test statistics is through using a rolling window approach. The initial sample is set to be equal to 50% of the full-sample data forecasts are undertaken recursively. In this way, while we forego the first 50% of data, we gain a time-varying *t*-test statistic examining the null hypothesis of no predictability, allowing us to then estimate a time-series regression model of the determinants of this time-varying predictability. The determinants of the predictability regression model are, therefore, estimated over the sample period, the same as for the out-of-sample period for the market and for each of the 12 sectors. A plot of the time-varying predictability (*t*-test statistics) for the Nifty Index is plotted in Figure I just to provide an understanding of our data. In a similar way, we extract time-varying predictability *t*-test statistics for each of the 12 sectors.

In the second determinants equation (see Equation 11), we have a time-series of profits $(Profits_t)$. In Table V, we had already computed time-series of profits using the mean-variance utility function and had only reported the average of those profits per financial ratio predictor for each of the 12 sectors. Now, we use the same time-series of profits in the regression model to examine whether or not expected and unexpected financial ratio risks actually determine sectoral profits and, if they do, whether some of these risk factors are relatively more important to some sectors than others. To reduce the bias associated with Equations (10) and (11), we follow the West and McCracken (1998) correction procedure and divide the t-statistics by an adjustment factor that properly accounts for such a bias.

The results on the determinants of time-varying predictability by sector are reported in Table VI, while the results on the determinants of time-varying profits by sector are reported in Table VII. Reading first the results on the determinants of predictability, this is what we find. For the Nifty Index, we find that only when return forecasts are based on DE, DP, and DY both the expected and unexpected risks determine predictability. With respect to forecasts generated using the BM ratio, only expected financial ratio risk determines predictability and with respect to forecasts generated using EP, only unexpected financial ratio risk determines predictability. Next, we consider evidence obtained for each of the 12 sectors. The main findings can be summarised as follows:

- Expected risks from DP and DY explain predictability in nine out of the 12 sectors, but unexpected risks explain predictability in five sectors.
- Expected risks from BM and DE explain predictability in six and five of the 12 sectors, respectively, while unexpected risks determine predictability in one sector (BM) and five sectors (DE).
- Expected EP ratio risk and unexpected EP ratio risk explain predictability for five out of the 12 sectors.
- There is no evidence that expected and unexpected ratio risks explain predictability in the finance sector.

In summary, we observe that while expected risk helps determine return predictability for most sectors, the unexpected financial risk does not. With unexpected financial risk, the number of sectors in which it determines predictability varies. Therefore, it is apparent that one source of sectoral heterogeneity is the unexpected financial ratio risk.

**INSERT TABLE VI**

Next, we read the results reported in Table VII on the determinants of time-varying profits for the Nifty Index and for each of the 12 sectors. For the Nifty, we find that the expected risks from BM, DE, DY and unexpected risks from DE explain profitability. The results on sectors are clear in that expected DY ratio risk determines profits for eleven out of the 12 sectors; expected ratio risks from BM and DE determine profits for ten of the 12 sectors, while DP and EP expected ratio risks explain profitability in nine sectors. By comparison, unexpected DE ratio risk determines profitability in seven sectors (automobile, banking, energy, finance, retail, metal, MNC and public sector union banks), unexpected DP ratio risk determines profitability in six sectors (banking, retail, information technology, media, metal, and PSU banks), unexpected BM ratio risk explains profitability in four sectors (automobile, banking, retail and PSU banks ), unexpected DY ratio risk explains profitability in four sectors (banking, retail, finance and MNC), and unexpected EP ratio risk also explains profitability in four sectors (automobile, energy, metal and MNC). Again, as we found with the determinants of predictability, the determinants of profitability are relatively more heterogeneous with respect to unexpected financial ratio risks.

**INSERT TABLE VII**

## VI. Concluding Remarks

This paper examines stock return predictability for both the market and for the sectors of the market. The study makes use of daily data from the Indian stock exchanges and uses a time-series predictive regression model estimated using the feasible generalized least squares estimator. A range of financial ratio variables are used as predictors to gauge the robustness of the predictive ability of financial ratios. Four findings are unravelled. First, of the five financial ratio variables, not all predict returns. There are some predictors which are more popular than others. Moreover, evidence of predictability is stronger at the sector-level and weaker at the market level. Second, return predictability is sector-specific; some sectoral returns are predictable, others are not. Third, a mean-variance investor is able to make statistically significant profits from all financial ratio-based predictive regression models, and some sectors enjoy higher profits compared to market profits. Fourth, both expected and unexpected shocks from most financial ratios are found to be determinants of sectoral return predictability and mean-variance investor profits; however, the determinants of predictability and profitability are more heterogeneous with respect to unexpected financial ratio risks.

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## Table I: Descriptive statistics of returns and predictors over full sample period

This table reports descriptive statistics of data, namely, mean, standard deviation, skewness, and kurtosis of returns and five financial ratios - book-to-market (BM), dividend-payout (DE), dividend-price (DP), dividend yield (DY), and earnings-price (EP). The data is daily and covers the period of 01/03/2000 to 31/10/2013 for market (Nifty). The time periods of the data on twelve sectors, however, vary conditional on data availability. The banking, retail, information technology and multinational corporations (MNC) sectors have data covering the period1/3/2001 to 31/10/2013; energy and pharmacy have data for the period 01/03/2002 to 31/10/2013; automobile, metal, and public sector union banks (PSU banks) have data covering the period 01/03/2005 to 31/10/2013; media has data for the period 01/03/2006 to 31/10/2013; data for finance and real estate cover the period 01/03/2007 to 31/10/2013.

| | Mean | SD | Skew | Kurt. | Mean | SD | Skew | Kurt. | Mean | SD | Skew | Kurt. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Returns | | | | BM | | | | DE | | | |
| Nifty | 0.051 | 1.566 | -0.203 | 10.809 | 0.277 | 0.071 | 0.505 | 3.308 | -1.370 | 0.179 | -1.101 | 9.032 |
| Automobile | 0.064 | 1.546 | -0.241 | 8.581 | 0.224 | 0.063 | 1.969 | 7.280 | -1.333 | 0.274 | -0.347 | 2.861 |
| Banking | 0.071 | 1.974 | -0.155 | 8.997 | 0.514 | 0.211 | 1.323 | 3.648 | -1.640 | 0.099 | 0.056 | 3.213 |
| Energy | 0.062 | 1.695 | -0.495 | 12.022 | 0.463 | 0.129 | 0.656 | 3.129 | -1.301 | 0.289 | -1.687 | 7.598 |
| Finance | 0.050 | 2.073 | 0.092 | 8.265 | 0.326 | 0.079 | 1.694 | 10.095 | -1.557 | 0.069 | -1.140 | 4.980 |
| Retail | 0.052 | 1.336 | -0.333 | 8.216 | 0.132 | 0.031 | 0.396 | 3.037 | -0.723 | 0.218 | -1.002 | 4.438 |
| Info. Tech | -0.039 | 4.602 | -38.995 | 1996.2 | 0.214 | 0.298 | 3.671 | 15.37 | -1.497 | 0.512 | -0.605 | 2.382 |
| Media | 0.028 | 1.814 | -0.234 | 7.954 | 0.220 | 0.068 | 0.745 | 4.785 | -1.199 | 0.350 | 0.131 | 2.078 |
| Metal | 0.032 | 2.385 | 0.221 | 13.801 | 0.485 | 0.253 | 1.248 | 4.337 | -1.857 | 0.277 | -0.123 | 2.831 |
| MNC | 0.039 | 1.295 | -0.493 | 9.870 | 0.714 | 0.381 | 1.111 | 3.502 | -1.464 | 0.588 | -0.397 | 2.908 |
| Pharmacy | 0.060 | 1.230 | -0.383 | 9.482 | 0.187 | 0.044 | 0.602 | 2.489 | -1.248 | 0.398 | -0.091 | 3.416 |
| PSU banks | 0.035 | 2.206 | -0.244 | 8.278 | 0.640 | 0.175 | 1.340 | 5.668 | -1.738 | 0.119 | -0.619 | 4.210 |
| Real Estate | -0.099 | 3.071 | -0.417 | 9.687 | 0.522 | 0.424 | 0.622 | 2.606 | -2.211 | 0.725 | -0.183 | 2.866 |
| | DP | | | | DY | | | | EP | | | |
| Nifty | -4.259 | 0.291 | 0.312 | 2.871 | -4.250 | 0.295 | 0.301 | 2.850 | -2.889 | 0.194 | 0.195 | 2.408 |
| Automobile | -4.237 | 0.319 | -0.126 | 2.672 | -4.223 | 0.315 | -0.135 | 2.610 | -2.905 | 0.210 | 1.256 | 5.411 |
| Banking | -4.070 | 0.426 | 0.275 | 2.036 | -4.059 | 0.431 | 0.284 | 2.111 | -2.430 | 0.397 | 0.229 | 1.989 |
| Energy | -3.817 | 0.400 | 0.497 | 2.647 | -3.805 | 0.411 | 0.516 | 2.611 | -2.515 | 0.395 | 0.505 | 2.244 |
| Finance | -4.448 | 0.248 | -0.246 | 3.906 | -4.438 | 0.253 | -0.381 | 4.115 | -2.891 | 0.234 | 0.184 | 3.790 |
| Retail | -3.983 | 0.275 | 0.283 | 2.880 | -3.969 | 0.278 | 0.226 | 2.913 | -3.260 | 0.227 | 0.515 | 2.519 |
| Info. Tech | -4.760 | 0.723 | -0.824 | 3.344 | -4.758 | 0.734 | -0.912 | 3.579 | -3.263 | 0.458 | -1.312 | 6.343 |
| Media | -4.776 | 0.414 | -0.102 | 2.507 | -4.764 | 0.406 | -0.149 | 2.583 | -3.577 | 0.285 | 0.885 | 4.287 |
| Metal | -4.211 | 0.444 | 0.197 | 1.981 | -4.202 | 0.448 | 0.163 | 1.994 | -2.354 | 0.387 | 0.256 | 2.784 |
| MNC | -3.259 | 0.516 | -1.087 | 3.395 | -3.254 | 0.522 | -1.012 | 3.288 | -1.796 | 0.734 | -1.553 | 4.348 |
| Pharmacy | -4.653 | 0.270 | -1.056 | 7.106 | -4.639 | 0.269 | -1.172 | 7.755 | -3.406 | 0.365 | -0.266 | 2.261 |
| PSU banks | -3.879 | 0.272 | 0.241 | 2.895 | -3.878 | 0.269 | 0.059 | 2.887 | -2.140 | 0.261 | 0.303 | 2.778 |
| Real Estate | -5.428 | 1.125 | -0.077 | 3.049 | -5.427 | 1.106 | -0.010 | 3.054 | -3.217 | 0.631 | 0.589 | 3.441 |

## Table II: ADF unit root test results

This table reports the augmented Dickey–Fuller (ADF) unit root test results for the returns and five financial ratios - book-to-market (BM), dividend-payout (DE), dividend-price (DP), dividend yield (DY), and earnings-price (EP). The results are reported for market (Nifty) and each of the twelve sectors. The unit root test results are based on the augmented Dickey-Fuller (1981) model and are implemented by including only the intercept. We use the Schwarz Information Criterion and apply a maximum of eight lags to obtain the optimal lag length. The test statistics and the resulting p-values are reported for each of the variables. The optimal lag length is reported in square brackets.

| | Test stat[LL] | P-value | Test stat[LL] | P-value | Test stat[LL] | P-value |
|---|---|---|---|---|---|---|
| | Returns | | BM | | DE | |
| Nifty | -57.523[0] | 0.000 | -2.501[1] | 0.115 | -3.357[8] | 0.013 |
| Automobile | -44.142[0] | 0.000 | -2.006[1] | 0.284 | -2.118[0] | 0.238 |
| Banking | -51.100[0] | 0.000 | -2.059[1] | 0.262 | -4.383[1] | 0.000 |
| Energy | -52.027[0] | 0.000 | -2.628[2] | 0.087 | -3.422[6] | 0.010 |
| Finance | -38.929[0] | 0.000 | -2.753[1] | 0.066 | -3.343[0] | 0.013 |
| Retail | -56.087[0] | 0.000 | -1.638[0] | 0.463 | -4.807[3] | 0.000 |
| Info. Tech | -58.288[0] | 0.000 | -3.186[0] | 0.021 | -1.767[2] | 0.397 |
| Media | -39.628[0] | 0.000 | -1.995[1] | 0.289 | -2.597[0] | 0.094 |
| Metal | -45.690[0] | 0.000 | -0.920[1] | 0.782 | -2.054[0] | 0.264 |
| MNC | -53.070[0] | 0.000 | -2.313[0] | 0.168 | -2.044[0] | 0.268 |
| Pharmacy | -52.436[0] | 0.000 | -1.991[0] | 0.291 | -3.577[0] | 0.006 |
| PSU banks | -43.522[0] | 0.000 | -1.881[1] | 0.342 | -4.588[0] | 0.000 |
| Real Estate | -37.243[0] | 0.000 | -0.734[1] | 0.836 | -1.702[1] | 0.430 |
| | DP | | DY | | EP | |
| Nifty | -2.688[5] | 0.076 | -2.700[5] | 0.074 | -3.448[1] | 0.010 |
| Automobile | -2.084[0] | 0.252 | -2.087[0] | 0.250 | -2.127[1] | 0.234 |
| Banking | -2.181[1] | 0.213 | -2.118[1] | 0.238 | -2.141[1] | 0.229 |
| Energy | -2.677[6] | 0.078 | -2.497[6] | 0.116 | -2.055[1] | 0.263 |
| Finance | -2.170[1] | 0.218 | -2.016[1] | 0.280 | -2.258[1] | 0.186 |
| Retail | -4.076[3] | 0.001 | -4.070[3] | 0.001 | -1.707[0] | 0.428 |
| Info. Tech | -2.507[6] | 0.114 | -2.915[4] | 0.044 | -3.243[0] | 0.018 |
| Media | -2.436[0] | 0.132 | -2.454[0] | 0.127 | -2.373[0] | 0.150 |
| Metal | -1.879[0] | 0.343 | -1.844[0] | 0.359 | -1.904[1] | 0.331 |
| MNC | -1.290[2] | 0.636 | -2.043[1] | 0.268 | -0.630[0] | 0.862 |
| Pharmacy | -4.516[0] | 0.000 | -4.474[0] | 0.000 | -2.434[1] | 0.132 |
| PSU banks | -2.856[1] | 0.051 | -2.838[1] | 0.053 | -2.578[1] | 0.098 |
| Real Estate | -1.849[1] | 0.357 | -1.868[1] | 0.348 | -2.617[1] | 0.090 |

## Table III: In- sample predictability test results

This table reports the in-sample predictability test results for the market (Nifty) and the twelve sectors, based on the following predictive regression model: $r_t = \theta + \beta^{adj} FR_{t-1} + \gamma(FR_t - \rho_0 FR_{t-1}) + \eta_t$. Here, $r_t$ is stock return computed as the log difference in percentage form, $\beta^{adj} = \beta - \gamma(\rho - \rho_0)$, and $FR_t$ is the predictor variable, which takes the form of one of the five financial ratios, namely, book-to-market (BM), dividend-payout (DE), dividend-price (DP), dividend yield (DY), and earnings-price (EP). Westerlund and Narayan (2012, 2015) assume that $\rho = 1 + \frac{c}{T}$, where $c \leq 0$ is a drift parameter that measures the degree of persistency in $FR_t$.We employ the following Westerlund and Narayan (2012, 2015) GLS-based t-statistic for testing $\beta = 0$:

$$t_{GLS} = \frac{\sum_{t=q_m+2}^{T} \pi_t^2 FR_{t-1}^d r_t^d}{\sqrt{\sum_{t=q_m+2}^{T} \pi_t^2 (FR_{t-1}^d)^2}}$$

where , $\pi_t = 1/\sigma_{\eta_t}$ is the FQGLS weight, and $r_t^d = r_t - \sum_{s=2}^{T} r_s / T$ with a similar definition of $FR_t^d$, where $T$ is the sample size, and the optimal lag length $q = \max\{q_x, q_{r,x}\}$ is using Schwarz Bayesian criteria. We report the t-statistics for $\beta$ based on both the sub-sample GLS test ($t_{GLS}^{sub}$) and the asymptotic GLS t-test ($t_{GLS}$).

| | $t_{GLS}^{sub}$ | $t_{GLS}$ | $t_{GLS}^{sub}$ | $t_{GLS}$ | $t_{GLS}^{sub}$ | $t_{GLS}$ |
|---|---|---|---|---|---|---|
| | BM | | DE | | DP | |
| Nifty | 0.258 | 1.009 | 1.731 | 1.583 | 0.943 | 2.619 |
| Automobile | 0.150 | 1.932 | 1.743 | 1.760 | -0.980 | 0.362 |
| Banking | 0.331 | 1.702 | 1.742 | 1.958 | 1.439 | 2.435 |
| Energy | -1.220 | 1.593 | 1.738 | 1.123 | 2.143 | 3.086 |
| Finance | 1.065 | 1.243 | 1.943 | 2.178 | 1.570 | 2.262 |
| Retail | -0.155 | 1.245 | 2.414 | 2.530 | 0.056 | 1.333 |
| Info. Tech | -1.465 | 0.862 | 1.830 | 1.109 | 1.862 | 1.790 |
| Media | 1.102 | 1.850 | 1.877 | 1.994 | -0.695 | 0.634 |
| Metal | 0.259 | 0.695 | 1.993 | 1.973 | 0.670 | 1.563 |
| MNC | -1.393 | -1.660 | 2.319 | 1.870 | -1.743 | -1.736 |
| Pharmacy | 1.811 | 1.436 | 1.934 | 1.775 | -0.074 | 1.028 |
| PSU banks | 0.765 | 1.710 | 2.253 | 2.499 | 1.446 | 2.714 |
| Real Estate | 1.871 | 1.402 | 1.852 | 1.038 | -1.731 | -1.197 |
| | DY | | EP | | | |
| Nifty | 3.336 | 3.286 | -0.547 | 2.755 | | |
| Automobile | 1.716 | 1.299 | -4.268 | -0.681 | | |
| Banking | 2.694 | 2.744 | 0.843 | 3.396 | | |
| Energy | 3.336 | 3.349 | 2.166 | 2.950 | | |
| Finance | 2.534 | 2.578 | 1.762 | 1.720 | | |
| Retail | 1.942 | 2.006 | -1.993 | -0.089 | | |
| Info. Tech | 4.318 | 1.778 | 1.711 | 1.577 | | |
| Media | 1.749 | 1.654 | -1.231 | -0.398 | | |
| Metal | 2.390 | 2.372 | -1.015 | 1.112 | | |
| MNC | 1.816 | 1.397 | 0.055 | 0.254 | | |
| Pharmacy | 1.704 | 1.697 | -1.188 | -0.141 | | |
| PSU banks | 3.311 | 3.441 | 0.039 | 1.868 | | |
| Real Estate | 1.995 | 1.272 | -0.692 | -0.303 | | |

## Table IV: Out-of-sample forecast evaluation results

This table reports the out-of-sample forecast performance of the traditional predictive regression model given by Equation (1) and noted in Table III. The out-of-sample period is 50% of the full sample. The forecasted returns are generated using a recursive window. We take the first 50% of the sample and generate the first forecast; then we take the first 50% plus the observation containing the forecasted return and generate return for the next day. The process continues until all the data are exhausted. We use three forecast evaluation metrics, Clark and McCracken (2001) forecast encompassing test ($ENC-NEW$); McCracken (2007) $MSE-F$ statistic; and Campbell and Thompson (2008) out-of-sample $R^2$ statistic ($OR^2$). The bootstrapped p-values for $ENC-NEW$ statistics are reported in parenthesis.

| | $ENC-NEW$ | $MSE-F$ p-value | $OR^2$ | $ENC-NEW$ | $MSE-F$ p-value | $OR^2$ | $ENC-NEW$ | $MSE-F$ p-value | $OR^2$ |
|---|---|---|---|---|---|---|---|---|---|
| | BM | | | DE | | | DP | | |
| Nifty | -0.076 (0.000) | 0.000 | 0.173 | 48.403 (0.200) | 0.200 | 0.007 | 37.959 (0.200) | 0.200 | 0.121 |
| Automobile | -0.238 (0.000) | 0.000 | -0.037 | 3.545 (0.500) | 0.400 | -0.139 | 15.770 (0.000) | 0.000 | -0.054 |
| Banking | -0.017 (0.000) | 0.000 | 0.111 | 148.858 (0.300) | 0.300 | 0.082 | 34.878 (0.600) | 0.400 | 0.155 |
| Energy | 2.968 (0.000) | 0.100 | 0.066 | 12.671 (0.700) | 0.600 | -0.070 | 140.413 (0.300) | 0.400 | 0.150 |
| Finance | 8.759 (0.100) | 0.500 | 0.340 | 331.22 (0.700) | 0.700 | -0.203 | 24.774 (0.000) | 0.000 | 0.268 |
| Retail | 0.257 (0.100) | 0.000 | 0.010 | 16.684 (0.400) | 0.300 | -0.043 | 1.902 (0.300) | 0.300 | 0.006 |
| Info. Tech | 4.049 (0.400) | 0.400 | -0.042 | 14.959 (0.700) | 0.700 | 0.097 | 72.922 (0.600) | 0.700 | 0.053 |
| Media | 0.131 (0.000) | 0.000 | 0.076 | 1.579 (0.100) | 0.100 | -0.283 | 20.039 (0.100) | 0.200 | -0.081 |
| Metal | 0.994 (0.900) | 0.800 | -0.219 | 8.848 (0.800) | 0.700 | -0.138 | 9.878 (0.300) | 0.100 | 0.136 |
| MNC | 4.028 (0.600) | 0.200 | -0.228 | 0.528 (0.100) | 0.100 | -0.368 | 1.552 (0.800) | 0.700 | -0.419 |
| Pharmacy | -0.969 (0.000) | 0.000 | -0.012 | 19.805 (0.700) | 0.700 | -0.071 | 2.537 (0.000) | 0.000 | -0.114 |
| PSU banks | 3.843 (0.900) | 0.700 | -0.479 | 177.918 (0.900) | 0.800 | -0.162 | 49.437 (0.900) | 0.700 | -0.038 |
| Real Estate | 3.749 (0.800) | 0.900 | -2.268 | 0.34 (0.200) | 0.200 | 0.004 | 1.082 (0.200) | 0.300 | 0.009 |

*Continued Overleaf*

**Table IV: Continued**

| | $ENC-NEW$ | $MSE-F$ p-value | $OR^2$ | $ENC-NEW$ | $MSE-F$ p-value | $OR^2$ |
|---|---|---|---|---|---|---|
| | DY | | | EP | | |
| Nifty | 694.205 (0.700) | 0.600 | 0.181 | -0.046 (0.000) | 0.000 | 0.088 |
| Automobile | 90.524 (0.600) | 0.500 | 0.032 | 163.585 (0.400) | 0.400 | -0.106 |
| Banking | 141.553 (0.500) | 0.600 | 0.212 | 2.008 (0.200) | 0.100 | 0.126 |
| Energy | 312.008 (0.200) | 0.500 | 0.128 | 40.342 (0.000) | 0.000 | 0.208 |
| Finance | 398.632 (0.500) | 0.000 | 0.443 | 2.397 (0.100) | 0.000 | 0.118 |
| Retail | 184.212 (0.900) | 0.800 | -0.049 | 32.184 (0.200) | 0.100 | -0.011 |
| Info. Tech | 556.435 (0.200) | 0.400 | 0.146 | 4.552 (0.200) | 0.200 | 0.332 |
| Media | 88.003 (0.100) | 0.000 | -0.185 | 153.641 (0.600) | 0.600 | 0.011 |
| Metal | 126.564 (1.000) | 1.000 | 0.282 | 0.568 (0.000) | 0.100 | 0.048 |
| MNC | 20.616 (0.500) | 0.400 | -0.300 | 0.609 (0.600) | 0.600 | -0.480 |
| Pharmacy | 294.697 (0.800) | 0.800 | -0.083 | 23.34 (0.000) | 0.100 | -0.244 |
| PSU banks | 451.729 (1.000) | 1.000 | 0.307 | -0.529 (0.100) | 0.100 | 0.084 |
| Real Estate | 5.115 (0.100) | 0.100 | 0.050 | 32.561 (0.300) | 0.400 | -0.034 |

**Table V: Economic significance results from a mean variance investor framework**

This table reports the profits from a dynamic trading strategy based on a mean–variance investor utility function, using which we calculate the portfolio weights. The forecasted returns are generated using a recursive window for the out-of-sample period which is 50% of the full-sample data. We take the first 50% of the sample and generate the first forecast; then we take the first 50% plus the observation containing the forecasted return and generate return for the next day. This process is repeated until all the data are exhausted. The estimated portfolio weights are restricted to between 0.5 and 1.5, allowing for limited borrowing and limited short-selling. The risk-aversion factor is set to 6, which typically represents a medium level of risk position for an investor. We report the average daily profits in percentage, the corresponding t-statistic examining the null hypothesis that profits are zero, and utility gains for the five models representing each of the predictor variables – book-to-market ratio (BM), dividend-payout ratio (DE), dividend-price ratio (DP), dividend yield (DY), and earnings-price ratio (EP). Utility gain is the difference between utility from our proposed model and utility from the historical average model.

| | Mean | t-stat | Utility gain | Mean | t-stat | Utility gain | Mean | t-stat | Utility gain |
|---|---|---|---|---|---|---|---|---|---|
| | | BM | | | DE | | | DP | |
| Nifty | 0.030 | 138.115 | 0.000 | 0.054 | 87.108 | 0.023 | 0.056 | 90.009 | 0.025 |
| Automobile | 0.035 | 74.360 | -0.002 | 0.087 | 61.746 | -0.070 | 0.038 | 136.444 | 0.002 |
| Banking | 0.033 | 89.729 | -0.006 | 0.043 | 67.972 | -0.023 | 0.034 | 162.151 | -0.004 |
| Energy | 0.050 | 77.222 | -0.004 | 0.064 | 57.059 | -0.025 | 0.046 | 129.275 | 0.014 |
| Finance | 0.061 | 43.742 | -0.082 | 0.145 | 31.545 | -0.884 | 0.067 | 48.567 | -0.085 |
| Retail | 0.037 | 143.763 | 0.011 | 0.043 | 54.349 | -0.019 | 0.039 | 106.332 | 0.003 |
| Info. Tech | 0.084 | 196.905 | 0.008 | 0.047 | 138.704 | -0.027 | 0.051 | 67.170 | -0.064 |
| Media | 0.031 | 99.949 | 0.001 | 0.033 | 55.022 | 0.003 | 0.025 | 121.142 | 0.000 |
| Metal | 0.139 | 44.418 | -0.150 | 0.034 | 92.629 | 0.002 | 0.045 | 54.915 | -0.022 |
| MNC | 0.065 | 63.275 | -0.009 | 0.068 | 59.829 | -0.009 | 0.099 | 55.767 | -0.100 |
| Pharmacy | 0.068 | 53.151 | -0.029 | 0.036 | 122.792 | 0.004 | 0.035 | 61.317 | -0.015 |
| PSU banks | 0.133 | 41.663 | -0.708 | 0.046 | 56.027 | -0.007 | 0.079 | 46.848 | -0.058 |
| Real Estate | 0.191 | 41.737 | -0.497 | 0.087 | 61.746 | -0.070 | 0.079 | 140.939 | -0.003 |

*Continued Overleaf*

**Table V: Continued**

| | Mean | t-stat | Utility gain | Mean | t-stat | Utility gain |
|---|---|---|---|---|---|---|
| | | DY | | | EP | |
| Nifty | 0.042 | 82.885 | 0.030 | 0.059 | 81.802 | 0.028 |
| Automobile | 0.082 | 58.951 | 0.034 | 0.054 | 54.594 | -0.022 |
| Banking | 0.032 | 156.382 | 0.037 | 0.031 | 178.920 | -0.006 |
| Energy | 0.043 | 120.572 | 0.030 | 0.036 | 132.759 | 0.004 |
| Finance | 0.107 | 40.465 | 0.031 | 0.052 | 60.313 | -0.012 |
| Retail | 0.040 | 63.796 | 0.025 | 0.031 | 174.945 | 0.006 |
| Info. Tech | 0.068 | 51.055 | 0.073 | 0.042 | 99.344 | -0.033 |
| Media | 0.048 | 57.964 | 0.026 | 0.027 | 94.321 | 0.001 |
| Metal | 0.079 | 44.424 | 0.032 | 0.035 | 73.820 | 0.002 |
| MNC | 0.091 | 67.785 | 0.025 | 0.068 | 59.038 | -0.010 |
| Pharmacy | 0.058 | 48.060 | 0.030 | 0.034 | 112.254 | 0.002 |
| PSU banks | 0.112 | 40.549 | 0.032 | 0.051 | 53.840 | -0.004 |
| Real Estate | 0.058 | 108.105 | 0.080 | 0.086 | 120.482 | 0.004 |

## Table VI: Determinants of time-varying predictability

This table reports the coefficients $\theta_2$(E) and $\theta_3$(UE) from the model: $Pred_t = \theta_1 + \theta_2 FR_t^E + \theta_3 FR_t^{UE} + \vartheta_t$. Here, $Pred_t$ is the time-varying predictability variable (t-test statistics), computed based on the predictive regression model given by Equation (1). The time-varying t-test statistics are extracted through a rolling window approach. The rolling window is set to be equal to 50% of the full-sample data and we roll the window every day. In this way, we obtain the rolling test statistics for the out-of-sample period. $FR_t^E$ and $FR_t^{UE}$are the expected and the unexpected financial ratio (FR) shocks computed using an $AR(1)$model of the FR, that takes the form of either book-to-market ratio (BM), dividend-payout ratio (DE), dividend-price ratio (DP), dividend yield (DY), or earnings-price ratio (EP). The t-statistics that test the null hypothesis that $\theta_2 = 0$ and $\theta_3 = 0$ are reported in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | BM | | DE | | DP | | DY | | EP | |
|---|---|---|---|---|---|---|---|---|---|---|
| | E | UE | E | UE | E | UE | E | UE | E | UE |
| Nifty | 5.571*** | 2.778 | 2.205*** | 3.089** | 0.497*** | 0.608*** | 0.555*** | 0.884*** | -0.046 | 0.497** |
| | (2.988) | (1.293) | (3.693) | (3.801) | (3.422) | (3.212) | (3.238) | (4.498) | (-0.355) | (2.014) |
| Automobile | -6.084 | -3.309 | -1.268*** | -3.301 | -0.425*** | -1.783** | -0.427** | -2.188** | 0.553 | -1.595*** |
| | (-1.161) | (-0.569) | (-4.662) | (-1.544) | (-3.815) | (-2.613) | (-2.378) | (-2.545) | (1.005) | (-3.093) |
| Banking | 4.087 | 1.077 | -1.227 | 0.088 | 1.244*** | 0.819*** | 1.135** | 1.329 | 1.094*** | 0.225 |
| | (1.622) | (0.57) | (-1.015) | (0.137) | (3.301) | (3.000) | (2.535) | (1.462) | (3.731) | (1.247) |
| Energy | 0.136 | -0.239 | 1.282*** | 0.822*** | 1.096*** | -0.003 | 1.061 | 0.357 | 0.272 | 0.058 |
| | (0.111) | (-0.119) | (3.157) | (4.086) | (4.003) | (-0.015) | (1.587) | (1.139) | (0.593) | (0.178) |
| Finance | -3.437 | -2.634 | 0.495 | 2.330 | 0.326 | 0.166 | 0.749 | -1.158 | 0.127 | 0.152 |
| | (-0.820) | (-0.970) | (0.233) | (1.402) | (0.487) | (0.300) | (0.709) | (-1.640) | (0.159) | (0.253) |
| Retail | -8.467** | -12.213*** | 0.960 | 0.251 | 0.447** | 0.028 | 1.101*** | 0.440 | -3.164*** | -2.270*** |
| | (-2.002) | (-3.522) | (1.071) | (0.506) | (2.027) | (0.121) | (3.378) | (1.381) | (-4.461) | (-4.085) |
| Info. Tech | 2.404 | -1.484 | -3.168*** | -0.954* | -0.876 | -0.445 | -0.516** | -0.956*** | -0.426* | -0.208 |
| | (0.418) | (-0.287) | (-4.012) | (-1.669) | (-1.277) | (-0.936) | (-2.746) | (-3.012) | (-1.747) | (-0.369) |
| Media | 6.687* | 0.170 | -0.358 | 1.034 | -0.195 | 0.392 | -0.066 | 0.276 | 0.183 | -0.663 |
| | (1.964) | (0.064) | (-0.677) | (1.149) | (-0.449) | (1.112) | (-0.067) | (0.259) | (0.442) | (-1.755) |
| Metal | -1.285*** | 0.269 | 0.115 | 0.766 | -0.286** | 0.964*** | -0.271* | 0.837** | 0.112 | -0.285 |
| | (-3.083) | (0.412) | (0.291) | (0.999) | (-2.090) | (5.290) | (-1.888) | (2.254) | (1.196) | (-0.972) |
| MNC | -0.405 | 0.219 | -0.287 | 0.678*** | -0.173 | 0.303 | 0.093 | 0.518 | 0.300** | 0.573** |
| | (-1.419) | (0.710) | (-1.203) | (3.022) | (-0.765) | (0.722) | (0.472) | (1.834) | (2.207) | (2.826) |
| Pharmacy | 0.502 | -1.076 | 0.015 | -0.652* | 0.922** | -0.069 | 1.053*** | -0.004 | 1.722** | 0.232 |
| | (0.213) | (-0.339) | (0.033) | (-1.738) | (2.921) | (-0.197) | (4.177) | (-0.011) | (2.710) | (0.416) |
| PSU banks | -2.179** | -0.366 | -2.681 | -2.192 | -1.702*** | -0.726*** | -1.257*** | -1.008*** | -0.723 | -0.163 |
| | (-2.905) | (-0.968) | (-0.290) | (-0.360) | (-4.599) | (-3.473) | (-3.808) | (-3.478) | (-1.503) | (-0.644) |
| Real Estate | -2.445*** | 0.716 | -1.033* | -0.209 | 1.696** | -0.836 | 2.051* | 0.247 | 0.047 | -1.367** |
| | (-4.387) | (0.912) | (-1.882) | (-0.524) | (2.287) | (-0.887) | (1.817) | (0.364) | (0.081) | (-2.042) |

## Table VII: Determinants of time-varying profits

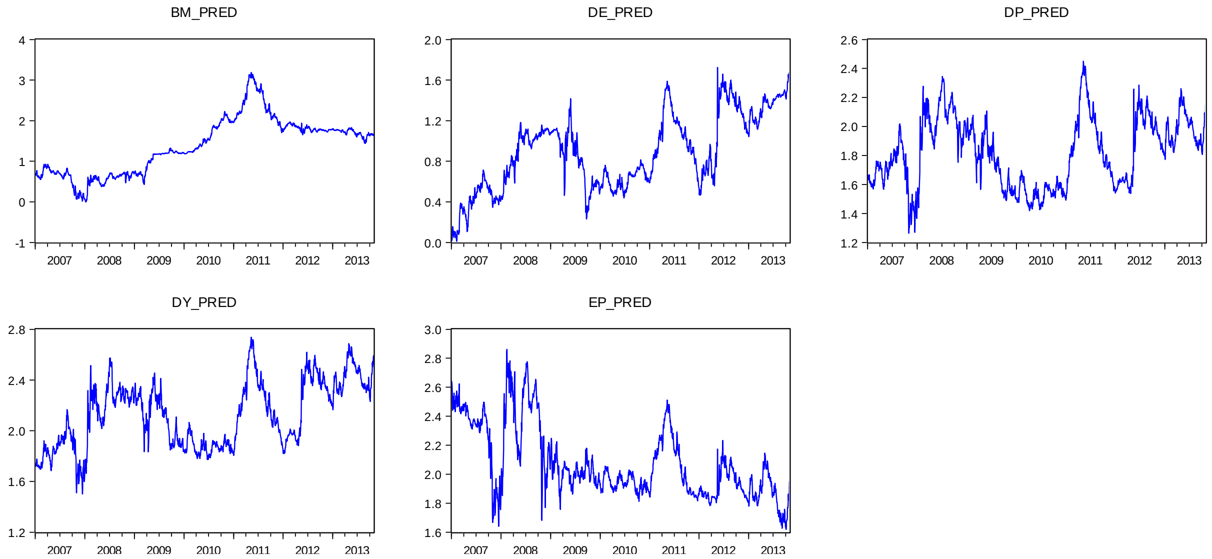
This table reports the coefficients $\theta_2$(E) and $\theta_3$(UE) from the model: $Profits_t = \theta_1 + \theta_2 FR_t^E + \theta_3 FR_t^{UE} + \vartheta_t$. Here, $Profits_t$ are thepreviously computed time-series of profits using the mean-variance utility function. The same time-series of profits that are available for the out-of-sample period are used to determine whether or not expected and unexpected financial ratio risks actually predict the time-varying profits. $FR_t^E$ and $FR_t^{UE}$are the expected and the unexpected financial ratio (FR) shocks computed using an $AR(1)$ model of the FR, that takes the form of either book-to-market ratio (BM), dividend-payout ratio (DE), dividend-price ratio (DP), dividend yield (DY), or earnings-price ratio (EP). The t-statistics that test the null hypothesis that $\theta_2 = 0$ and $\theta_3 = 0$ are reported in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | BM | | DE | | DP | | DY | | EP | |
|---|---|---|---|---|---|---|---|---|---|---|
| | E | UE | E | UE | E | UE | E | UE | E | UE |
| Nifty | 0.036** | -0.018 | -0.132** | -0.107** | -0.0260 | -0.014 | 0.059*** | -0.014 | -0.009 | 0.018 |
| | (2.111) | (-0.725) | (-2.193) | (-2.129) | (-1.035) | (-0.537) | (4.838) | (-0.787) | (-0.230) | (0.497) |
| Automobile | 0.216*** | 0.148** | 0.043 | -0.096** | 0.008*** | 0.000 | 0.081*** | -0.031 | -0.055** | 0.055* |
| | (3.721) | (2.064) | (1.346) | (-2.420) | (3.184) | (-0.041) | (6.523) | (-0.979) | (-2.246) | (1.714) |
| Banking | -0.057** | -0.037** | 0.147** | 0.127*** | -0.014*** | 0.012** | -0.009** | 0.022*** | -0.011** | 0.001 |
| | (-2.228) | (-2.543) | (2.306) | (4.197) | (-3.495) | (2.246) | (-2.183) | (3.535) | (-2.772) | (0.187) |
| Energy | 0.156*** | 0.028 | 0.117*** | -0.014 | -0.055*** | 0.007 | -0.043*** | 0.006 | 0.006 | 0.019*** |
| | (4.440) | (0.785) | (3.257) | (-1.011) | (-4.090) | (1.415) | (-6.762) | (0.872) | (0.368) | (3.125) |
| Finance | 0.653*** | -0.058 | 2.167*** | 0.601** | 0.183*** | 0.016 | 0.401*** | -0.221** | 0.066** | 0.003 |
| | (3.161) | (-0.360) | (3.600) | (2.115) | (4.476) | (0.375) | (5.349) | (-2.804) | (2.479) | (0.094) |
| Retail | -0.299*** | -0.139** | 0.162*** | 0.035* | -0.031*** | -0.025** | 0.052* | -0.036** | -0.032*** | 0.006 |
| | (-5.691) | (-2.338) | (4.072) | (1.860) | (-3.139) | (-2.111) | (1.824) | (-2.171) | (-4.213) | (0.866) |
| Info. Tech | -0.213*** | 0.073 | -0.065*** | 0.014 | 0.037** | 0.040** | 0.088*** | -0.027 | -0.056*** | 0.009 |
| | (-3.011) | (1.045) | (-6.688) | (1.568) | (2.477) | (2.446) | (3.308) | (-1.019) | (-5.326) | (1.049) |
| Media | 0.088* | 0.082 | -0.009 | 0.024 | 0.000 | 0.010** | 0.037*** | -0.019 | 0.039*** | -0.003 |
| | (1.996) | (1.306) | (-1.062) | (1.465) | (-0.048) | (2.019) | (4.961) | (-1.119) | (4.399) | (-0.467) |
| Metal | 0.099 | 0.108 | 0.014* | -0.055*** | 0.020* | 0.045** | 0.064** | 0.083 | -0.011 | -0.069* |
| | (0.840) | (0.947) | (1.825) | (-3.525) | (1.953) | (2.185) | (2.453) | (1.615) | (-0.775) | (-1.680) |
| MNC | 0.027 | 0.005 | -0.006 | -0.028** | -0.060 | -0.035 | -0.053* | -0.041* | 0.014** | 0.017** |
| | (1.486) | (0.402) | (-0.335) | (-2.416) | (-1.229) | (-1.008) | (-1.912) | (-1.700) | (2.556) | (2.490) |
| Pharmacy | 0.775* | -0.049 | 0.012* | 0.001 | 0.045** | 0.006 | 0.150*** | 0.008 | 0.004 | -0.005 |
| | (1.993) | (-0.271) | (1.806) | (0.491) | (2.414) | (0.668) | (6.218) | (0.470) | (0.824) | (-0.833) |
| PSU banks | 0.328** | 0.276*** | 0.092*** | 0.109*** | 0.151*** | 0.133*** | 0.270*** | 0.087 | 0.073** | 0.002 |
| | (2.674) | (3.280) | (3.217) | (5.944) | (5.894) | (4.661) | (5.202) | (1.292) | (2.460) | (0.053) |
| Real Estate | -0.069 | -0.092 | -0.074*** | 0.004 | -0.008 | -0.004 | -0.021 | 0.013 | 0.061*** | 0.007 |
| | (-0.473) | (-0.693) | (-6.835) | (0.601) | (-0.607) | (-0.219) | (-1.910) | (1.163) | (6.717) | (0.775) |

## Figure I: Plots of time-varying predictability and profits

In Panel A, the figure displays the plots of rolling predictability variable $Pred_t$ for the market (Nifty), used in Equation (10). Here, $Pred_t$ is the time-varying t-test statistic, computed based on the predictive regression model given by Equation (1). The time-varying t-test statistics are extracted through a rolling window approach. The rolling window is set to be equal to 50% of the full-sample data and we roll the window every day. In this way, we obtain the rolling test statistics for the out-of-sample period. The rolling t-test statistics based on five financial ratios - book-to-market (BM), dividend-payout (DE), dividend-price (DP), dividend yield (DY), and earnings-price (EP) - are shown in the plot. In Panel B, the figure displays the plots of time-varying profit variable $Profits_t$ for the market (Nifty), used in Equation (11). Here, $Profits_t$ are the time-series of profits computed over the out-of-sample period using the mean-variance utility function. The time-varying profits based on five financial ratios - book-to-market (BM), dividend-payout (DE), dividend-price (DP), dividend yield (DY), and earnings-price (EP) - are shown in the plot. The y-axis represents the t-test statistics (Panel A) and the profits (Panel B). The x-axis represents the time period.

Panel A: A plot of time-varying predictability




Panel B: A plot of time-varying profits