Dividend Yield as a Predictor of Stock Returns During Market Volatility: A Comparative Study of Volatile and Non-Volatile Periods in the Indian Equity Market

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Abstract

This study investigates the role of dividend yield as a predictor of equity premia in the Indian equity market across periods of market volatility and stability. It contributes to the broader understanding of the challenges associated with using dividend yield as a forecasting tool in an emerging market context and highlights the limitations of relying solely on fundamental indicators. Using a simplified Fama-French framework, the research analyzes a subset of NIFTY 50 stocks that were part of the index before 2013, selected based on their longevity and consistent dividend payment history, encompassing three volatile and three non-volatile phases from 2008 to 2022. The findings reveal that dividend yield exhibits limited and statistically insignificant predictive power across all periods. Out-of-sample analyses further confirm the model's poor forecasting performance, with large divergences between actual and predicted equity premia and negative Prediction R-squared values. Additional robustness checks were performed by incorporating sectoral indices and firm size. While sectoral effects only marginally improved explanatory power, the inclusion of firm size significantly increased R^2 in certain phases, particularly during COVID and Post-COVID, though dividend yield itself remained insignificant. The study acknowledges its limitations and offers directions for future research, including the incorporation of macroeconomic variables, the examination of sector-specific dynamics, and the use of advanced predictive modeling techniques to improve return forecasts in emerging markets.

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1 Introduction

The role of dividend yield in stock pricing and returns has been a cornerstone of financial research, with numerous studies focusing on its effectiveness as a predictor of stock performance. The primary purpose of this study is to investigate whether dividend yield can serve as a reliable predictor of stock returns during periods of market volatility in the Indian equity market. Although dividend yield has long been considered a key indicator of stock performance, its predictive power during turbulent market conditions, such as financial crises or pandemics, remains underexplored, especially in emerging markets like India. The study seeks to fill this gap by examining how dividend yield behaves as a predictor of stock returns in three specific volatile periods. The Global Financial Crisis (2008), the Taper Tantrum (2013), and the COVID-19 pandemic (2020). These periods are compared to more stable, non-volatile phases to assess how market volatility affects the relationship between dividend yield and stock returns.

Understanding the behavior of dividend yield during periods of market stress is crucial for investors, as it may offer insights into whether dividend-paying stocks remain a stable investment choice during uncertain times. This research aims to provide a clearer understanding of the role of dividend yield in asset pricing during volatile periods. The findings of this study have potential implications for investors, portfolio managers, and policymakers seeking to optimize investment strategies in emerging markets, particularly in India.

There is substantial literature on the relationship between dividend yield and stock returns, particularly in developed markets (Litzenberger and Ramaswamy 1979; Blume 1980; Hodrick 1992; Naranjo, Nimalendran, and Ryngaert 1998). However, emerging markets, such as India, have received comparatively less attention in this regard, particularly when examining the role of dividend yield during market volatility. Indian markets are characterized by different dynamics, such as a large retail investor base and unique regulatory environments, which can lead to divergent market behaviors during periods of volatility. Additionally, while market volatility has been shown to influence stock performance, the specific impact on dividend-paying stocks is under-researched. This study aims to fill this gap by focusing on the Indian equity market and analyzing how dividend yield influences stock returns during significant volatile periods. The research contributes to the broader literature by offering insights into whether dividend yield retains its predictive power in emerging markets under extreme market conditions. Furthermore, it provides a more nuanced understanding of dividend yield's role in asset pricing during times of crisis, which could be valuable for investors and financial analysts who seek to navigate market instability.

The research employs the Fama-French model, excluding the Small minus Big(SMB) and

High minus Low(HML) factors, to examine the impact of dividend yield on stock returns for NIFTY 50 stocks. The study focuses on stocks that were part of the index prior to 2013 and consistently paid dividends from 2007 to 2022. The analysis compares the behavior of dividend yield during volatile periods (Global Financial Crisis, COVID-19 pandemic, Taper Tantrum) with non-volatile periods of recovery (post-crisis stabilization periods). Stock returns are calculated by factoring in price changes and dividends, with dividend yield derived as the ratio of dividend paid to stock price at the beginning of each 6-month period. An out-of-sample analysis is also conducted, training the model on previous periods and testing it on subsequent periods to assess the model's predictive accuracy.

The remainder of this paper is structured as follows. Section 2 presents a comprehensive review of the literature on the relationship between dividend yield and stock returns. Section 3 outlines the methodology used to conduct the analysis. Section 4 reports the results and provides relevant interpretations. Section 5 discusses the study's limitations and suggests directions for future research. Finally, Section 6 concludes the paper with a summary of key findings.

2 Literature Review

The relationship between dividend policy and stock returns has long been debated in financial literature, with mixed conclusions, Bachmeier and Sinha (2023) note that dividend policy can act as a signal to investors, conveying information about a firm's future prospects. Similarly, Hussainey, Oscar Mgbame, and Chijoke-Mgbame (2011) highlight that investors, especially those who are risk-averse, often perceive dividend-paying stocks as safer during turbulent periods. This perception underscores the broader importance of examining how dividends may influence stock performance.

The theoretical rationale for a positive dividend–return relationship is primarily rooted in the Bird-in-Hand Theory, developed by Gordon (1962), Lintner (1962), and Walter (1963). This theory posits that investors prefer certain, immediate returns from dividends over uncertain capital gains, which in turn should increase the value of dividend-paying stocks. This perspective directly challenges the Modigliani-Miller (MM) Theorem, which asserts that dividend policy is irrelevant in a perfect market. The Bird-in-Hand viewpoint suggests that dividend yields may serve as a useful signal for future returns.

A substantial body of empirical research supports the notion that higher dividend yields predict higher stock returns. Several key studies including Litzenberger and Ramaswamy (1979), Blume (1980), Hodrick (1992), Naranjo, Nimalendran, and Ryngaert (1998), and Lewellen (2004) provide consistent evidence using extensive NYSE datasets spanning multiple decades. Fama and French (1988) adds that the predictive power of dividends strengthens over longer horizons, reinforcing the long-term relevance of dividend yields in return forecasting.

More recent studies reaffirm these findings in broader contexts. Profilet (2013) find that firms with higher dividend yields tend to exhibit lower stock price volatility, implying greater investor confidence. Kang, Kim, and Oh (2019), examining NYSE, AMEX, and NASDAQ stocks from 1971 to 2015, also report a significantly positive relationship. Similarly, Ahn et al. (2024) demonstrate that dividend yield remains a statistically significant predictor of returns, supporting the view that investors value dividends as both immediate income and a signal of financial stability.

Despite this strong empirical support, some studies challenge the universality of the dividend–return relationship. For example, Allen and Rachim (1996), in a study of the Australian stock market, identify a significant negative correlation between dividend yield and stock price volatility, suggesting that high dividend payouts may not always reduce risk. Miller and Scholes (1982) report no significant relationship between expected returns and dividend yields, calling into question the predictive role of dividends. Likewise, Baskin (1989) acknowledges a correlation with volatility, but argues it does not necessarily indicate a causal link between dividends and stock price movements. These findings suggest that dividend yield alone may not reliably predict returns across all markets and conditions.

The literature also points to the importance of context in interpreting the dividend–return relationship. Farooq, Saoud, and Agnaou (2012), analyzing firms on the Casablanca Stock Exchange, note that the impact of dividend policy is less pronounced during periods of economic growth. This indicates that broader macroeconomic conditions can moderate the influence of dividends on stock performance. Monteiro, Sebastião, and Silva (2020), in a comprehensive cross-country study covering the US, UK, Japan, France, Germany, Italy, and Spain, find no consistent predictive pattern across developed markets. Their findings emphasize the time-varying and country-specific nature of the dividend–return link, challenging the assumption of a universal relationship.

While developed markets have been extensively studied, there is a notable gap in the literature when it comes to emerging markets. Prior research has primarily concentrated on the U.S. and European equity markets, where investor behavior and market structures differ significantly from those in emerging economies. Moreover, while sectoral indices and macroeconomic factors are often analyzed in developed contexts, they remain underexplored in markets like India. Another gap lies in the time frame of analysis — most studies emphasize multi-year return horizons, with limited attention to short-term windows (e.g., 6-month periods) or market phase distinctions such as volatility versus stability.

This study aims to address these gaps by focusing on the Indian equity market, specifically NIFTY 50 stocks during both volatile and stable market phases. By concentrating on stocks with consistent dividend payouts, the study offers a nuanced perspective on how dividend yields interact with varying market conditions. Additionally, the research incorporates out-of-sample analysis to test the robustness of the predictive relationship and explores alternative model specifications. Through these contributions, the study seeks to enrich the literature on dividend-based return prediction in emerging markets and enhance understanding of its context-specific nature.

3 Methodology

This study aims to investigate whether dividend yield can predict stock returns during periods of market volatility. To achieve this, the study applies a modified Fama-French model to the selected stocks from the NIFTY 50 index. The model is adapted to include dividend yield as the primary explanatory variable. This study draws inspiration from existing research to design its methodology and calculations. The use of dividend yield as a primary explanatory variable is guided by Fama and French (1988), which highlights its significance in explaining stock returns over longer horizons, and Hodrick (1992), which emphasizes its predictive relevance in volatile market conditions. The approach to calculating dividend yield is influenced by Keim (1985), who demonstrated its application during periods of market stress. This study tailored the calculation of stock returns and equity premia to the specific needs of NIFTY 50 stocks across volatile and non-volatile phases. For the out-of-sample analysis, the methodology follows Goyal and Welch (2003), using coefficients derived from training periods to test their predictive power in subsequent periods. This framework allows for robust testing of the relationship between dividend yield and equity premia. While this research tailored these methodologies to suit its unique focus on the Indian equity market, the foundational insights from these influential studies provided the theoretical basis and methodological structure for the analysis.

3.1 Data Collection

The data for this study were collected from three primary sources: Money Control, Yahoo Finance, and Bloomberg. These platforms provide reliable financial data, including stock prices, dividend yields, and other necessary financial indicators for the period of analysis. The time span for stock prices covers 2007 to 2022, ensuring that both volatile and non-volatile periods are included for comparison.

Stock Selection Criteria : The stocks selected for analysis were drawn from the NIFTY 50 index. The selection criteria focused on stocks that were part of the index before 2013, ensuring that the companies had consistent size, longevity, and that they experienced at least two of the volatile periods while being part of the NIFTY 50 index. In addition, only stocks that paid dividends annually from 2007 to 2022 and paid dividends during both the volatile and non-volatile periods under consideration were included. After applying these criteria, 18 stocks were selected for further analysis. The complete list of these stocks is provided in Table 1 of the Appendix.

Data Frequency and Return Calculation : For each of the selected periods, daily stock price data was gathered for the 18 selected NIFTY 50 stocks. To calculate each stock's return for a given six-month period, the price on the first trading day and the last trading day of that period was used, along with any dividends paid during the same period. This method was applied consistently to all stocks and periods, ensuring comparability across both volatile and non-volatile phases. The sample size, defined as the total number of observations used in the regression, is 108, covering 18 stocks over 6 periods.

3.2 Time Periods

The analysis focuses on three volatile and three non-volatile periods. To ensure consistency and comparability across all periods, this study adopts uniform six-month windows for both volatile and non-volatile phases. A six-month duration strikes a balance between being long enough to capture meaningful market reactions and short enough to isolate the effects of specific economic events. This window length also aligns with common practice in event-based financial research, where intermediate-term horizons are used to avoid noise from unrelated macroeconomic developments (MacKinlay 1997). Each six-month period, both volatile and non-volatile, has been carefully selected based on: (i) Recognized economic or policy shock events affecting the Indian market, (ii) India Volatility Index (VIX) levels and market behavior, as shown in Figure 1 in the Appendix, and (iii) A consistent six-month window structure to allow for balanced comparison.

The volatile periods include the Global Financial Crisis, Taper Tantrum, and COVID-19 pandemic:

Global Financial Crisis (May to October 2008) This six-month window captures the most intense phase of the 2008 financial crisis as it unfolded in India. The India VIX rose sharply beginning in May and remained at historically elevated levels throughout the entire period. This time frame includes key market events such as the collapse of Lehman Brothers in September, which triggered systemic fear in global markets. Although the Bear Stearns collapse occurred earlier in March, selecting May as the starting point avoids including the early rumblings and instead focuses on the core distress phase. During this period, the Nifty 50 declined by over 40%, and October itself witnessed one of the worst-performing weeks in Indian market history. By ending in October, the analysis avoids overlap with early signs of stabilization that began emerging in November, making this window a highly representative snapshot of sustained market volatility.

Taper Tantrum (April to September 2013), the April to September 2013 period captures the build-up, announcement, and aftermath of the U.S. Federal Reserve's tapering signal. Following Ben Bernanke's remarks in May 2013 regarding the potential scaling back of quantitative easing, the Indian market experienced a sharp increase in volatility. The India VIX spiked to around 30 in June, reflecting heightened investor panic and uncertainty. The Indian rupee depreciated significantly, bond yields rose, and equity indices showed adverse reactions well into September. Starting this window in April allows for the inclusion of pre-announcement uncertainty, while ending in September ensures that the peak volatility is captured without overlapping into the post-taper recovery that began later in the year.

Covid-19 pandemic (March to August 2020), This six-month period effectively captures the economic and financial turmoil induced by the COVID-19 pandemic. Beginning in March 2020, the Nifty 50 experienced a dramatic crash of nearly 30%, coinciding with the initiation of nationwide lockdowns in India. Investor panic surged, and the India VIX reached an all-time high of 86.63 in late March. The volatility remained elevated through April, May, and June, as markets struggled to price in the scale of the pandemic's economic impact. July and August saw tentative signs of recovery, yet uncertainty persisted.

The non-volatile comparison periods are selected from post-crisis and recovery phases, specifically May to October 2010 (Post-Crisis Recovery), April to September 2015 (Post-Taper Tantrum Stabilization), and March to August 2022 (Post-COVID Recovery). Each non-volatile period is selected exactly two years after its corresponding volatile event to ensure sufficient time for market recovery, dissipation of systemic shock effects, and the return of investor confidence. India VIX values during these periods remained consistently below 20, reflecting calm market conditions. These windows are free from major domestic or global disruptions, making them suitable control periods for comparative analysis. To ensure that the classification of these periods as "volatile" or "non-volatile" is not arbitrary, each one is validated using India VIX data, which reflects investor sentiment and market uncertainty. The use of consistent six-month windows across all periods also adds structure to the comparison, helping avoid issues that can arise from unequal time frames. This approach follows the spirit of methodologies used in earlier academic work, including Ditzen, Karavias, and Westerlund (2021), who emphasize the importance of identifying regime shifts or structural breaks when analyzing financial time series data.

3.3 Variables and Measures

The study's primary dependent variable is the equity premium ($R_{s,t} - R_{f,t}$), for this study, 18 stocks meeting the selection criteria were analyzed for each of the selected periods. For each stock during each period:

Returns ($R_{s,t}$) were calculated as:

$$R_{s,t} = \frac{P_{\text{end}} - P_{\text{start}} + D}{P_{\text{start}}}$$

where:

P_{end} : Stock Price at the end of the period

P_{start} : Stock Price at the beginning of the period

D : Dividend paid during the period

Additionally, the risk-free rate (R_f) is taken from the 10-year government bond rate in India. The risk-free rate, as shown in Table 2 in the Appendix, is divided by two as the data is for annualized rates, but for this research, the periods considered are 6-month periods. The independent variable is the lagged dividend yield, calculated as the total dividends paid over the previous 12-month period divided by the stock price at the beginning of that period. This yield is then used to predict stock returns in the following 6-month period.

$$\text{Dividend Yield}_{t-1} = \frac{D_0}{P_{\text{start}}}$$

where:

D_0 : Dividend paid during the 12 months prior to a period

P_{start} : Stock Price at the beginning of the period

In this study, dividend yield is used as a predictive variable, calculated over the 12 months preceding the return measurement window. This lagged approach reflects the common practice in financial literature where historical dividend information is employed to forecast future returns. By separating the periods of dividend yield measurement and return realization, the study ensures a clear temporal structure, reducing potential look-ahead bias. This method is consistent with the predictive frameworks adopted in works such as Campbell and Shiller (1988), and Goyal and Welch (2003), where past dividend yields serve as indicators of expected returns. Moreover, this approach is particularly useful in the Indian equity market, where dividend announcements may be irregular and firm-specific, making lagged yields a more stable and observable input for prediction. Overall, using lagged dividend yield supports the study's objective of assessing its ability to forecast stock returns under varying market volatility conditions.

3.4 Model Specification

The study employs a modified version of the Fama-French model, with a focus on dividend yield as the key explanatory variable. The model used in this study is:

$$R_{s,t} - R_{f,t} = \alpha + \gamma \cdot \mathrm{DY}_{t-1}$$

where:

$$\begin{aligned} R_s &\quad : \text{Stock return} \\ R_f &\quad : \text{Risk-free rate} \\ \alpha &\quad : \text{Intercept term (alpha)} \\ \gamma &\quad : \text{Coefficient for dividend yield} \\ \mathrm{DY}_{t-1} &\quad : \text{Lagged Dividend yield} \end{aligned}$$

For each period, the α (intercept) and γ (coefficient of dividend yield) were calculated by regressing the equity premium($R_{s,t} - R_{f,t}$) on the dividend yield for all 18 stocks. This allowed the study to explore the relationship between dividend yield and equity premia during different market conditions. The model is adapted to include dividend yield as the primary explanatory variable, in this study, the size factor (SMB) and value factor (HML) from the Fama-French model were excluded due to the nature of the stock selection. Since all stocks are from the NIFTY 50 index, comprising large-cap, well-established blue-chip companies, the size and value effects are less relevant. Additionally, the focus of the study is on the relationship between dividend yield and equity premia during periods of market volatility, and including SMB and HML could dilute this focus.

A key modeling decision in this study was the exclusion of the overall market return (R_m) commonly included in traditional asset pricing models such as the CAPM or full Fama-

French framework. However, for the purposes of this research, which focuses exclusively on a sample of NIFTY 50 large-cap stocks over matched time periods, this exclusion is both theoretically sound and empirically justified. The fundamental reason for omitting (R_m) is that all 18 stocks in the sample belong to the same broad market index (NIFTY 50) and are analyzed over identical time windows. As a result, the market return is uniform across all observations within each period. Including it would introduce a non-varying regressor that offers no cross-sectional variation, thus providing little to no additional explanatory power.

Similarly, while the India VIX plays a central role in defining market regimes (i.e., identifying volatile vs. non-volatile periods), it is not included directly as an explanatory variable in the regression model. This is because VIX is also constant across all stocks in a given period and serves primarily as a regime-classification tool. Including it in the regression would blur its structural role in the study design and contribute no variation in the cross-sectional setup. The objective is to evaluate the predictive power of dividend yield within these volatility regimes—not to explain returns using volatility as a regressor. Hence, its role is intentionally limited to period selection, not model estimation.

These exclusions simplify the model, enabling a sharper focus on the role of dividend yield while aligning with the study's objectives, this choice is grounded in both theoretical rigor and empirical precedent. The model specification follows the approach of Fama and French (1988), Keim (1985), Lewellen (2004), and Ahn et al. (2024), who all demonstrate that dividend yield alone can serve as a powerful predictor of equity returns.

Nonetheless, in recognition of the need for robustness, this study did explore extended specifications. Specifically, sectoral returns were considered as an additional independent variable—by introducing a sector-specific equity premium ($R_{si,t}$–$R_{f,t}$) to account for common shocks within industry groupings. This variation allowed for testing whether dividend yield retained its predictive power after controlling for sector-wide performance. Other possible extensions, such as the inclusion of VIX (volatility index), were also considered for future work. These exploratory additions and alternative formulations are discussed further in Section 4.2 of this paper. However, the core findings confirm that even in its simple form, the model provides meaningful insights into the role of dividend yield in predicting equity premia across varying market conditions.

3.5 Out-of-Sample Analysis

An out-of-sample analysis is performed to assess the predictive power of the model. For each volatile and non-volatile period, a training period of 6 months prior to the test period is used to calculate the regression coefficients (α and γ). These coefficients are then applied to the test periods (the volatile and non-volatile periods) to predict the stock returns, and the predicted values are compared with the actual returns to evaluate the model's accuracy. The accuracy of the predictions is assessed by comparing the predicted equity premiums ($R_{s,t} - R_{f,t}$) with the actual ones. A comparison of these values will allow for the evaluation of how well dividend yield can serve as a predictor for stock returns, hence assesses the predictive ability of the model in forecasting equity premia.

3.6 Statistical Analysis

The analysis is carried out using Excel and MATLAB to compute stock returns, dividend yields, and the regression coefficients for each of the volatile and non-volatile periods. The stock price and dividend yield data are cleaned, ensuring that any missing or inconsistent data points are addressed.

4 Results And Analysis

This section presents the regression results for each period, focusing on the relationship between dividend yield (DY_{t-1}) and equity premia ($R_{s,t} - R_{f,t}$). The analysis examines both volatile and non-volatile periods to assess the predictive power of dividend yield under varying market conditions. Detailed regression results for all periods are provided in Table 3 in the Appendix.

During period one, the Global Financial Crisis (May–Oct 2008), a volatile market phase, the DY coefficient (γ) was 0.0849, indicating a very weak positive relationship between dividend yield and equity premia. The R-squared value of 0.0020 suggests almost no explanatory power. Statistical testing shows that the DY coefficient is not significant at the 5% level, implying that the dividend yield did not meaningfully predict the equity premia during this period of market distress.

In period two, the Post-Global Financial Crisis (May–Oct 2010), a non-volatile recovery phase, the DY coefficient rose to 0.6650, with an improved R-squared of 0.0459, suggesting a somewhat stronger relationship. However, the coefficient was still statistically insignificant at the 5% level, indicating that dividend yield remained a weak predictor of equity premia even in a relatively stable post-crisis environment.

For period three, the Taper Tantrum (Apr–Sep 2013), another volatile episode, the DY coefficient was slightly negative at –0.0203, indicating no meaningful relationship. The R-squared was nearly zero, and the statistical tests again showed no significance, confirming that dividend yield had virtually no predictive power during this market disruption.

In period four, the Post-Taper Tantrum (Apr–Sep 2015), a stable, non-volatile phase, the DY coefficient was 0.0572, with an R-squared of just 0.0012. The relationship was again statistically insignificant, suggesting minimal explanatory power even during market calm.

In period five, the COVID-19 Pandemic (Mar–Aug 2020), a highly volatile period, the DY coefficient increased to 0.5567, which might indicate moderate potential. However, the R-squared value remained low at 0.0288, and statistical significance was not achieved at the 5% level. This suggests that the heightened uncertainty of the pandemic overshadowed any predictive role of dividend yield.

Lastly, in period six, the Post-COVID Recovery (Mar–Aug 2022), a non-volatile phase, the DY coefficient turned negative at –0.2344, and the R-squared was 0.0141. The results again failed to show statistical significance, pointing to a weak and inconclusive relationship during the recovery phase.

The results of this study provide consistent evidence that dividend yield lacked predictive power across all six periods, regardless of market volatility. Although dividend yields are often believed to have stronger predictive power in stable market environments, empirical evidence, including the results of this thesis, does not consistently support this view. This analysis finds that even in non-volatile periods like 2010 and 2015, the relationship remains weak and statistically insignificant.

Volatile phases such as the global financial crisis and the COVID-19 pandemic showed no meaningful relationship, likely due to macroeconomic uncertainty and investor sentiment playing a greater role in pricing. These findings suggest that in the Indian market context, dividend yield alone is not a reliable predictor of equity premia, particularly during or after crisis events.

Overall, the results indicate that dividend yield does not exhibit strong predictive power for future stock returns in the Indian equity market across both volatile and non-volatile periods. Despite theoretical expectations that stable market conditions may enhance forecasting accuracy, the empirical findings show consistently low explanatory power and largely insignificant coefficients across all sub-periods. This suggests that the limited effectiveness of dividend yield as a predictor is not necessarily exacerbated by market volatility, but rather reflects broader limitations in its applicability within the Indian market context. These findings underscore the importance of considering additional market-specific factors when evaluating the predictive utility of valuation ratios such as dividend yield.

4.1 Out-of-Sample Forecasts

The out-of-sample (OS) analysis evaluates the predictive accuracy of the model across all six periods by assessing the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Out-of-Sample R-squared values (Prediction R-squared). The Prediction R-squared indicates how well the model explains the variation in the dependent variable when applied to unseen data. Unlike the traditional in-sample R-squared, it can take negative values, which occur when the model performs worse than a simple mean-based prediction. These metrics together provide insights into the reliability and effectiveness of the model in forecasting equity premia during both volatile and non-volatile phases. The detailed out-of-sample forecast results are presented in Table 4 in the Appendix.

In the volatile periods (Period 1, 3, and 5), the MAE and RMSE values are generally higher, reflecting a greater deviation between predicted and actual equity premia. Period 1 (Global Financial Crisis) exhibited the largest prediction errors, with a MAE of 0.2681 and RMSE of 0.3053, alongside a highly negative Prediction R-squared of –3.4479, indicating that the model performed significantly worse than a naive historical mean benchmark. Similarly, as seen in Table 4, Period 3 (Taper Tantrum) and Period 5 (COVID-19) also showed considerable errors, with Prediction R-squared values of –0.4460 and –0.6238, respectively. These results suggest that the model struggles to capture the extreme fluctuations and structural breaks that characterize volatile market environments.

In contrast, the non-volatile periods (Period 2, 4, and 6) demonstrated relatively better predictive performance. Period 2 (Post-GFC) had a MAE of 0.1830, RMSE of 0.2131, and a Prediction R-squared of –0.1057, reflecting an improvement over volatile periods, though still underperforming the benchmark. Period 4 (Post-Taper Tantrum) showed further reduction in error metrics, with a MAE of 0.1251 and RMSE of 0.1468, while Period 6 (Post-COVID Recovery) had a MAE of 0.2041 and RMSE of 0.2596. Although all three non-volatile periods still produced negative Prediction R-squared values, their lower error magnitudes compared to volatile phases indicate more consistent and less erratic forecasting outcomes.

These results offer key insights into the limitations and conditional effectiveness of the model. The high error rates and severely negative Prediction R-squared values during volatile periods suggest that dividend yield alone may be insufficient to predict equity premia when markets are undergoing shocks, disruptions, or heightened uncertainty. The model's inability to adapt to sharp price swings or regime changes may be due to the limited information content of dividend yield during such periods. On the other hand, the relatively lower errors observed in non-volatile periods indicate that the model performs less poorly when market dynamics are more stable. While predictive power remains weak overall, the results point toward a context-dependent model performance, with better relative outcomes when markets are calmer and structural patterns more intact.

Figure 2 in the appendix, comparing predicted versus actual equity premia for each of the periods, reveals a significant divergence across all periods, indicating that the model's predictions did not align well with observed market behavior. Overall, the model shows limited predictive power. The findings underscore the importance of market context in assessing the applicability of dividend yield as a predictor and point toward the need for further refinement to enhance the model's reliability across diverse market conditions.

4.2 Alternative Specifications

Additional model specifications were explored to test the robustness of the core findings. However, none of these variations impacted the conclusion. Across all models and time periods, dividend yield remained a statistically insignificant predictor of equity premia, even during non-volatile market phases. The out-of-sample results also remained consistent, with negative R-squared values and sizable forecast errors across all six periods. These findings reinforce the overall conclusion that dividend yield, as analyzed in this study, does not exhibit reliable predictive power in the Indian equity market, regardless of market volatility.

To strengthen the robustness of the findings and address concerns regarding the simplicity of the baseline model, an extended specification was introduced that incorporates sectoral equity returns as an additional explanatory variable. The rationale for this inclusion is that certain stock return movements may be influenced not solely by firm-specific fundamentals or dividend policy but also by broader sector-wide trends. By controlling for common sectoral shocks, the analysis aimed to isolate the marginal contribution of dividend yield more precisely. In this extended model, the dependent variable remains the equity premium for individual stocks, $(R_{s,t} - R_{f,t})$, while the independent variables include both the stock-specific dividend yield (DY_{t-1}) and the sectoral equity premium $(R_{si,t} - R_{f,t})$, where $R_{si,t}$ denotes the return of the sector to which the stock belongs over the relevant period.

Although this approach offered some insights, it was not comprehensively explored due to data limitations, as most sectoral indices have been introduced only in the past 10–12 years. This meant that sectoral data was unavailable for earlier periods considered in this study, such as the Global Financial Crisis and Taper Tantrum. For the periods where sectoral indices were available, their inclusion improved the R^2 values slightly, indicating better explanatory power. However, this adjustment had minimal impact on the dividend yield coefficient, which retained its sign and general magnitude. Importantly, the interpretation of its significance across market conditions did not change. The additional variable, the sectoral equity premium, did not significantly improve model fit in most periods.

A further specification was tested by incorporating firm size as an additional explanatory variable. Size was measured as the natural logarithm of market capitalization at the start of each 6-month period, allowing the model to capture potential systematic differences in returns between relatively smaller and larger large-cap firms within the NIFTY 50. The extended regression takes the form:

$$R_{s,t} - R_{f,t} = \alpha + \gamma \cdot DY_{t-1} + \delta \cdot \ln(\text{Size}_{t-1})$$

The results, reported in Table 5 of the Appendix, show that including size improves explanatory power across nearly all sub-periods, with the increase being especially notable during the COVID and Post-COVID phases (e.g., R^2 rising from 2.88% to 12.33% and from 1.4% to 17.17%, respectively). The estimated size coefficients are generally negative, suggesting that smaller large-cap firms outperformed their larger peers, particularly in volatile and recovery phases. While the dividend yield coefficient broadly retains its sign and magnitude, its contribution weakens once size is controlled for. Overall, this extended specification highlights that dividend yield alone provides limited predictive content, and that firm size captures a greater share of the cross-sectional variation in excess returns.

In addition, the out-of-sample analysis was re-run using a 12-month prior period as the training window instead of the immediate 6-month prior period to ensure consistency across financial quarters and control for seasonal factors. For example, for the March–August 2020 COVID-19 volatile period, data from March–August 2019 were used for training. This adjustment, however, did not improve the model's predictive power, as the predicted equity premia continued to deviate significantly from actual values.

Given these outcomes, and to maintain focus and clarity in the presentation of results, the extended regressions are not shown in the main output tables. Across all specifications, dividend yield does not emerge as a statistically significant predictor of returns in either volatile or non-volatile periods. The inclusion of sectoral equity premia and alternative training windows provided little change in results, while the addition of firm size improved model fit but did not alter the insignificance of dividend yield. Taken together, these findings suggest that although explanatory power can be marginally enhanced by incorporating controls such as firm size, dividend yield itself does not exhibit reliable predictive power in the Indian equity market across different conditions.

5 Limitations and Directions for Future Research

This study offers key insights into the predictive role of dividend yield in explaining equity premia across different market volatility regimes in the Indian equity market. Although the findings contribute meaningfully to the literature, several limitations suggest directions for future research.

The cross-sectional sample consists of 18 consistently listed NIFTY 50 firms. While modest in size, this sample prioritizes consistency, quality, and comparability across periods, mitigating survivorship bias and stock turnover effects. This choice is supported by similar emerging market studies such as Serra (2003), Fama and French (1988), and Sehgal and Garg (2016) that favor stable, representative samples over larger but less consistent data sets. The relatively small sample size also reflects inherent data constraints common to developing markets, where long-term, high-quality firm-level data and sectoral indices are less widely available or standardized than in developed markets.

The regression models are intentionally parsimonious, focusing primarily on dividend yield. To strengthen robustness, additional specifications were also tested with sectoral indices and firm size. These checks revealed that dividend yield's predictive power remained weak, while firm size contributed more meaningfully to cross-sectional return variation in certain phases. The core approach nonetheless prioritizes isolating dividend yield's role across regimes, ensuring the clarity and interpretability of the model. The observed limited out-of-sample predictive accuracy is consistent with the findings of Goyal and Welch (2003), who documented the inherent instability of valuation ratios in financial time series forecasting, especially in emerging markets.

Future research could extend this framework by incorporating sector-specific indices to capture industry-level variations, leveraging more comprehensive sectoral data as it becomes available. Additional firm-level controls, such as profitability, leverage, or liquidity measures, may also build on the role of size highlighted in this study. Advanced modeling techniques, such as rolling window regressions, time-varying parameter models, or machine learning methods, may uncover nonlinearities and structural shifts beyond the reach of traditional OLS models. Larger datasets and longer time series could also enhance out-of-sample forecasting power through improved model flexibility and conditioning on macroeconomic states.

Finally, the study's focus on the Indian equity market, with its distinct institutional and regulatory characteristics, limits direct generalization to developed markets. Comparative analyses across emerging and developed markets, and examinations of structural events such as the 2016 demonetization or changes in dividend taxation policy, would enrich understanding of dividend yield in diverse contexts.

In summary, this study's methodological choices—period-specific regressions, a consistent cross-sectional sample, and focused modeling—reflect a considered balance between theoretical rigor, data limitations typical of developing markets, and interpretability. The robustness checks with size and sectoral indices further strengthen these conclusions, while also pointing to new avenues for inquiry. These decisions ensure robust insights into the regime-dependent relationship between dividend yield and equity returns, laying a foundation for broader future inquiries.

6 Conclusion

This study finds that dividend yield exhibits limited predictive power for equity premia during both volatile and non-volatile periods in the Indian equity market. Out-of-sample results consistently showed substantial divergence between predicted and actual equity premia, as evidenced by high MAE and RMSE values. Additionally, negative Prediction R-squared values across all periods underscore the model's poor goodness-of-fit and limited forecasting ability.

Despite its traditional role as a valuation metric, dividend yield did not demonstrate statistically significant predictive capability in any market regime. The consistently insignificant p-values and coefficients suggest that volatility alone does not enhance the explanatory power of dividend yield.

The inclusion of sectoral indices as control variables had minimal effect. While R-squared values improved marginally in certain periods, these gains did not translate into meaningful improvements in out-of-sample performance. Similarly, including firm size as an additional explanatory variable improved in-sample fit in some periods, particularly during COVID and Post-COVID phases, but dividend yield remained insignificant and predictive gains in out-of-sample performance were limited.

Several plausible explanations may account for these results. During volatile periods, investors often shift their focus from firm-level fundamentals to broader concerns—such as macroeconomic uncertainty, liquidity risk, and global sentiment—rendering dividend yield less relevant. Moreover, the use of six-month intervals may have limited the metric's effectiveness, as dividend yield typically operates as a long-term valuation indicator. Additionally, the high visibility of NIFTY 50 stocks may lead to rapid information absorption, consistent with semi-strong form market efficiency, leaving limited scope for yield-based anomalies. Finally, the Indian market's structural evolution—marked by regulatory reforms, sectoral reclassifications, and data inconsistencies—may have introduced further noise into the model.

While these explanations are not conclusive, they offer plausible insight into the model's poor performance across different regimes. Overall, the findings suggest that dividend yield—while theoretically appealing—has limited standalone predictive power in the modern Indian equity context. The robustness checks with sectoral indices and firm size confirm that controlling for additional factors may improve model fit, but do not change the central conclusion regarding dividend yield. These results highlight the importance of considering investor behavior, market structure, and regime dynamics when applying fundamental indicators in empirical finance. Future research should explore the integration of macroeconomic variables, longer forecasting horizons, and machine learning–based approaches to better capture the complexity of return predictability.

7 Use of Generative AI and AI-assisted tools

During the preparation of my thesis, I used ChatGPT to improve the clarity and structure of certain sections and to assist with fixing LaTeX errors that I could not resolve myself.

After using this tool/service, I reviewed and edited the content as needed and take full responsibility for the content of my thesis.

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APPENDICES

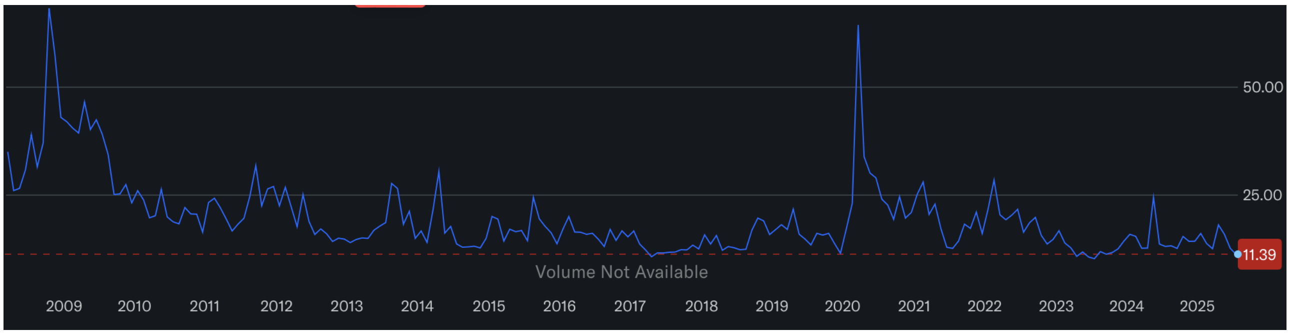
Tables and Figures

Table 1: Selected NIFTY 50 Stocks for Analysis

S. No.	Stock Name
1	Asian Paints Ltd
2	Bharat Petroleum Corporation Ltd (BPCL)
3	Cipla Ltd
4	Dr. Reddy's Laboratories Ltd
5	HCL Technologies Ltd
6	Hindustan Unilever Ltd
7	Hero MotoCorp Ltd
8	ITC Ltd
9	Infosys Ltd
10	Larsen and Toubro Ltd
11	Mahindra and Mahindra Ltd
12	Maruti Suzuki India Ltd
13	NTPC Ltd
14	Power Grid Corporation of India Ltd
15	Reliance Industries Ltd
16	Tata Consultancy Services Ltd (TCS)
17	Tata Steel Ltd
18	UltraTech Cement Ltd

Note: The 18 selected stocks are from the NIFTY 50 index, chosen for consistent size, longevity, and the payment of annual dividends from 2007 to 2022. Each stock was part of the index during at least two of the identified volatile periods.

Figure 1: Nifty-50 VIX Chart



Note: The India VIX (Volatility Index) reflects the market's expectation of near-term volatility in the NIFTY 50 index, derived from options pricing. This chart presents the daily India VIX levels from 2008 to 2025. Following widely accepted financial industry practice and NSE guidelines, periods with VIX values above 20 are typically classified as volatile, while those below 15 are considered stable.

Table 2: Descriptive Statistics Across Periods

Periods	**Period 1**	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**Period 6**
Mean R_s (%)	-29.0	23.3	11.7	2.1	21.5	15.2
Median R_s (%)	-29.4	24.1	10.2	2.3	12.0	12.8
Sdev. R_s	14.9	20.8	16.0	13.0	26.5	20.5
Mean DY (%)	5.4	5.5	6.6	5.3	4.3	5.9
Median DY (%)	2.6	3.4	3.5	2.5	2.1	1.6
Sdev. DY	7.8	6.7	9.4	7.8	8.1	10.4
Rf Rate (% p.a.)	8.5	7.8	8.0	7.8	6.0	7.2
Nifty50 Return (%)	-44.8	15.2	0.5	-7.4	2.3	6.9

Note: The table shows the mean returns(Rs), median returns, standard deviation of the returns, average dividend yield, median dividend yield and standard deviation of the dividend yields of all 18 stocks considered for this research, for all the 6 periods. Period 1 (May to October 2008), Period 2 (May to October 2010), Period 3 (April to September 2013), Period 4 (April to September 2015), Period 5 (March to August 2020), Period 6 (March to August 2022). The table also shows the nifty 50 returns and the annualized average risk-free rates, during each of the periods.

Table 3: In Sample Univariate Regressions

Period	α **(Intercept)**	γ **(DY coeff.)**	R^2 **(%)**
Period 1 (GFC)	-0.337 (0.045)	0.085 (0.479)	0.2
Period 2 (Post-GFC Non-Volatile)	0.158 (0.065)	0.67 (0.758)	4.6
Period 3 (Taper Tantrum)	0.079 (0.048)	-0.02 (0.427)	0.014
Period 4 (Post-Taper Non-Volatile)	-0.021 (0.039)	0.057 (0.418)	0.12
Period 5 (COVID)	0.161 (0.072)	0.557 (0.809)	2.88
Period 6 (Post-COVID Non-Volatile)	0.129 (0.057)	-0.234 (0.49)	1.4

Note: The table shows the results of the following univariate regression: $R_s - R_f = \alpha + \gamma \cdot \mathrm{DY}$
The first row of each regression is the coefficient, the second line (in the brackets) is its standard error.

Table 4: Out-of-Sample Performance

Period	**Root Mean Square Error (RMSE) (%)**	**Mean Absolute Error (MAE) (%)**
Period 1 (GFC)	37.84	34.32
Period 2 (Post-GFC Non-Volatile)	17.99	15.30
Period 3 (Taper Tantrum)	39.53	26.69
Period 4 (Post-Taper Non-Volatile)	26.68	17.55
Period 5 (COVID)	59.91	40.84
Period 6 (Post-COVID Non-Volatile)	24.95	18.68

Note: The table shows the RMSE and MAE values for each of the six periods in order to analyze whether to evaluate the predictive accuracy of the model.

Table 5: In Sample Univariate Regressions with Firm Size

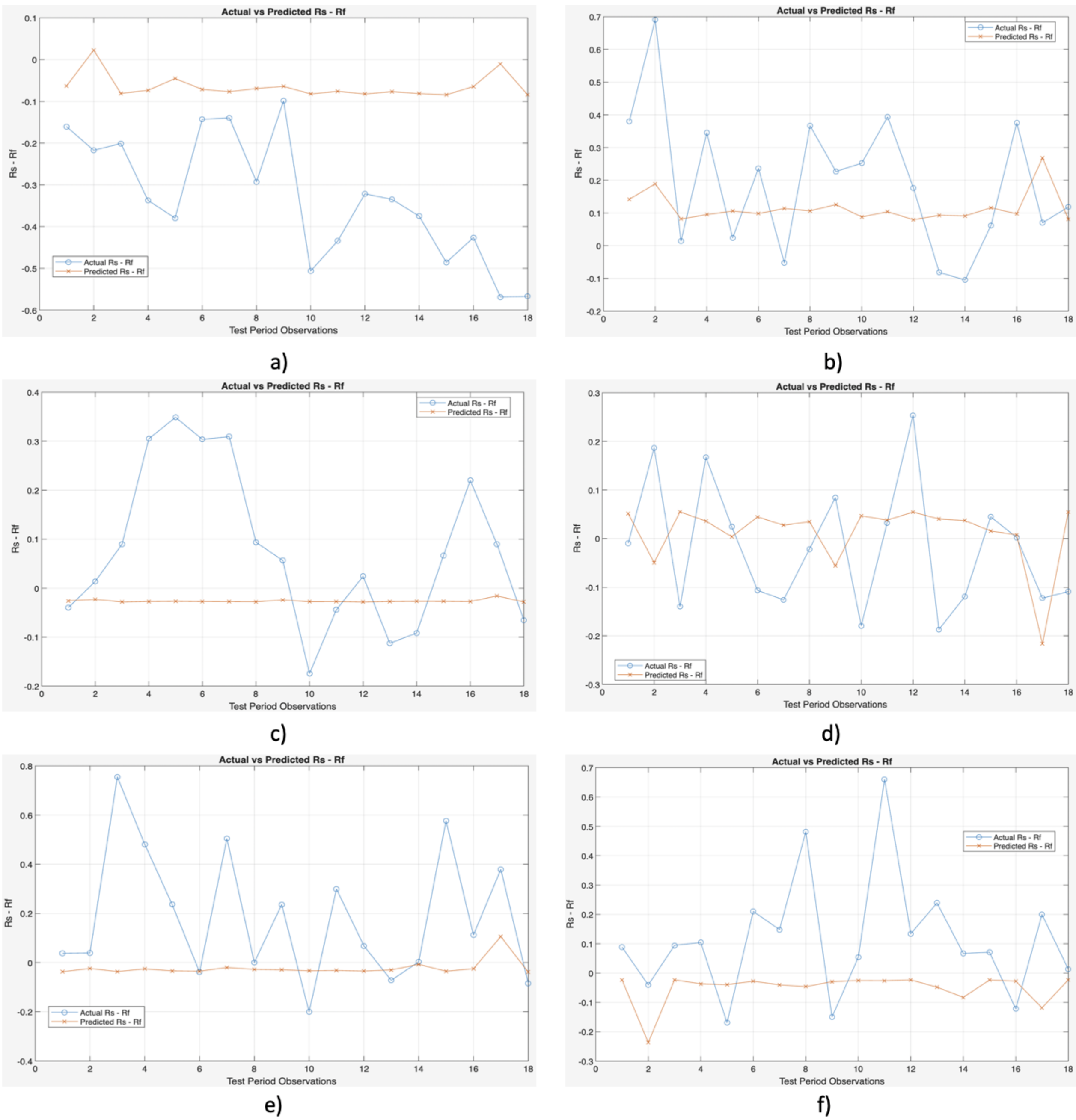
Period	α **(Intercept)**	γ **(DY coeff.)**	δ **(Size coeff.)**	R^2 **(%)**
Period 1 (GFC)	0.332	0.034	-0.025	3.34
	(0.959)	(0.492)	(0.036)	
Period 2 (Post-GFC Non-Volatile)	1.379	0.638	-0.045	8.47
	(1.533)	(0.768)	(0.057)	
Period 3 (Taper Tantrum)	0.220	-0.031	-0.005	0.076
	(1.462)	(0.454)	(0.053)	
Period 4 (Post-Taper Non-Volatile)	-0.560	0.106	0.019	1.18
	(1.344)	(0.446)	(0.048)	
Period 5 (COVID)	2.663	0.212	-0.089	12.33
	(1.969)	(0.838)	(0.070)	
Period 6 (Post-COVID Non-Volatile)	2.639	-0.526	-0.088	17.17
	(1.486)	(0.495)	(0.052)	

Note: To provide an additional robustness check, the regression includes firm Size as an extra explanatory variable. Size is measured as the natural logarithm of market capitalization (market cap) at the start of each 6-month period, capturing potential differences in returns between larger and smaller large-cap firms within the NIFTY 50. The regression specification is:

$$R_s - R_f = \alpha + \gamma \cdot \mathrm{DY} + \delta \cdot \ln(\mathrm{Size})$$

The first row of each regression shows the coefficient, and the second row (in brackets) shows its standard error.

Figure 2: Actual Vs. Predicted Equity Premia



Note: The figures show the actual vs predicted equity premia (Rs − Rf), using out-of-sample forecasting. The blue lines show the actual, and the orange line shows the predicted. The figure a) is for period 1, b) for period 2, c) for period 3, d) for period 4, e) for period 5, and f) for period 6. As seen, the predictions are way off, hence the prediction power of the model is poor.