Beyond Efficient Markets: Unveiling the Predictive Power of Short-Term Market Shocks*

How Short-Term Market Dynamics Forecast Future Risks

Raghav Bhatia

April 16, 2024

This study investigates the predictive power of short-term market shocks on future market volatility, specifically focusing on a two-month forecast horizon using the Standard & Poor's 500 index and the Volatility Index (VIX). By employing Discrete Haar Transform (DHT) for data analysis and constructing a Generalized Linear Model (GLM), we analyzed the relationship between current market returns and forward-looking volatility expectations. Our findings reveal a statistically significant correlation where negative market shocks are predictive of increased volatility, suggesting a robust challenge to the Efficient Market Hypothesis. This research provides insight for anticipating future market conditions, highlighting the need for further exploration into the behavioral biases that influence market dynamics.

Table of contents

*Code and data are available at: https://github.com/1raghav-bhatia/Spectral-Models.git

1 Introduction

In an era shaped by rapid shifts in market sentiment and extensive global information flows, understanding the dynamics between market shocks and future short-term market volatility expectations remains crucial for both investors and policymakers. This research investigates the predictive relationship between short-term market shocks, as measured by the residuals of market returns, and their impact on future short-term market volatility expectations, represented by the Volatility Index (VIX). By examining the lagged effects of these shocks, this study challenges the efficient markets hypothesis (Fama 1970), which asserts that current prices fully reflect all available information and thus, no amount of historical data can predict future movements.

The premise of this investigation is rooted in the observation that market participants often exhibit behavioral biases, such as the momentum effect (Jegadeesh and Titman 1993), where investors assume that current market conditions will persist into the future. This bias suggests that positive market returns, which indicate good current conditions, might lead to a decrease in expected future risk, as reflected by the VIX. Conversely, negative shocks might increase future risk aversion, leading to higher implied volatility. These behaviors challenge the expectations of the efficient markets hypothesis, indicating a potential disconnect between market participant behavior and market efficiency theories.

To explore this relationship, this study employs a generalized linear model (GLM) using detailed coefficients derived from Discrete Haar Transforms (Percival and Walden 2000) of both market returns and VIX data. The primary estimand in this study is the effect of short-term market return shocks on the future short-term volatility expectations as measured by the VIX, particularly focusing on a two-month lag. This approach not only allows for the isolation of short-term fluctuations but also aligns with sophisticated financial modeling techniques that account for non-linear dependencies and temporal dynamics in financial data.

This paper is structured to first detail the methods used for data collection and transformation, specifically focusing on the use of wavelet analysis to extract meaningful patterns from high-frequency financial data. Additionally, we construct a GLM model to showcase our methodology for analyzing this relationship. Following this, we present the results of our regression analysis, highlighting the significant predictive power of market shocks on future volatility. We conclude with a discussion on the implications of our findings for financial theory and practice, emphasizing how traditional models might need to adapt to incorporate behavioral biases and their effects on market dynamics.

By bridging the gap between theoretical finance and empirical evidence, this research contributes to a deeper understanding of market dynamics and offers valuable insights into the predictive relationships that might inform future trading strategies and risk management practices.

2 Data

2.1 Data Source and Preparation

This research utilizes publicly available financial data for the Standard & Poor's 500 Index (S&P 500) and the Chicago Board Options Exchange Volatility Index (VIX), sourced from Yahoo Finance. The choice of Yahoo Finance as a data source is driven by its comprehensive coverage and reliable historical financial data accessibility, which is crucial for the integrity of time-series analysis in financial research. The data covers a period from January 1993 to December 2023 for the S&P 500 and from March 1993 to February 2024 for the VIX.

The specific variables extracted from these datasets are the daily closing prices, which are essential for calculating monthly returns and analyzing market behavior over the study period. This selection is informed by the closing price's relevance in reflecting the final market consensus on value for each day, making it a critical indicator for financial analysis.

While alternative sources such as Google Finance or Bloomberg could provide similar data, Yahoo Finance was selected due to its ease of integration with the quantmod (Ryan and Ulrich 2020a) package in R (R Core Team 2023), which significantly simplifies the process of data fetching and preliminary handling. Furthermore, Yahoo Finance offers unrestricted access to historical data, unlike some other services that might require subscriptions.

The data retrieval and initial processing were conducted using the quantmod package in R, which is instrumental for financial modeling and time series analysis due to its capabilities in fetching and handling various financial data formats.

2.2 Data Cleaning and Transformation

Once retrieved, the data was cleaned and transformed into monthly returns to average out the minor fluctuations in day-to-day returns and to capture the significant monthly trends that highlight short-term market fluctuations. This transformation was facilitated by converting daily data into monthly data points, specifically extracting closing prices and calculating the monthly returns. The transformation process employed the xts (Ryan and Ulrich 2020b) library in R.

Table 1: S&P 500 Monthly Returns and VIX Monthly Values

S&P 500 Monthly Returns (%)	VIX Index Values
1.04	-0.88
1.85	8.12
-2.57	-17.92
2.25	4.09
0.08	1.02
-0.53	9.19

2.3 Detailed Analysis of Short-Term Market and VIX Fluctuations

To understand the relationship between short-term market fluctuations and future short-term volatility expectations as represented by the VIX, the analysis began with fitting an ARIMA (AutoRegressive Integrated Moving Average) model to the S&P 500 return data. The ARIMA model is utilized to forecast future values based on past values of a time series and its lags. In this context, the residuals from the ARIMA model—representing unexpected values or shocks in the market—were of particular interest. These residuals signify deviations from the expected trend and cyclical components, effectively isolating the pure shock elements in the market returns, which are crucial for understanding reactionary market behaviors.

2.3.1 ARIMA Model for Market Returns

The ARIMA model was chosen for its ability to model various types of time series with trends and seasonalities effectively. By analyzing the residuals, we can identify the short-term shocks in market returns, which are not explained by the model's fitted values. These shocks are essential for analyzing how unexpected changes in market returns might influence future market conditions. Figure 1 provides the fitted values for market return.

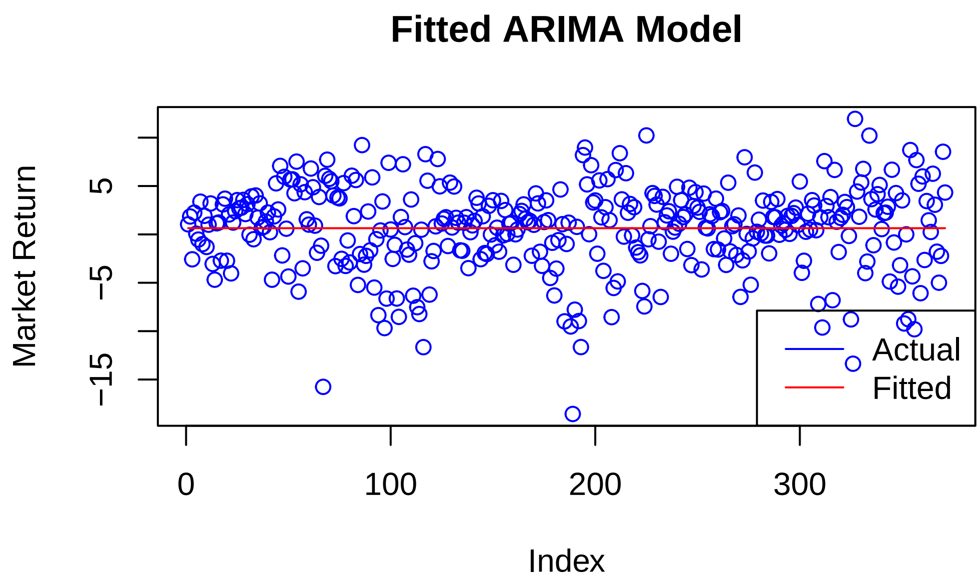

Figure 1: Fitted Values of the Arima Model

2.3.2 Discrete Haar Transform for Decomposition

For both the market return shocks and the VIX data, a Discrete Haar Transform (DHT) was applied to further analyze these time series. The DHT is particularly suited for this analysis because it decomposes the time series data into levels of detail that correspond to different time scales. In our case, the focus is on capturing fluctuations that span up to 2 months, aligning with our definition of short-term fluctuations. We use the 'wavethresh' (Nason 2020) and 'wavelets' (Aldrich 2020) package for this.

The transformation process through DHT breaks down the original time series into a series of approximations and details. The approximations represent the smoothed-out trends, while the details capture the finer nuances of the data at various intervals. For this study, the first level detail coefficients (Detail 1) were extracted, as they represent the highest resolution of short-term fluctuations accessible from the transform, corresponding to a bi-monthly frequency. This choice aligns with our interest in understanding the immediate impacts within a two-month period, considered a critical timeframe for reactive market behaviors.

2.3.3 Decomposition of Residuals and VIX

Similarly, the VIX data underwent DHT to isolate its short-term components. By focusing on the same level of detail as the market returns, we ensure a consistent basis for comparison. The Detail 1 coefficients given in Figure 2 from the VIX transformation provide a mirrored view of how volatility expectations, as captured by the VIX, respond in the short term, potentially influenced by the market shocks identified from the S&P 500 residuals. The 'ggplot2' (Wickham 2023) and 'gridExtra' (Auguié 2023) packages were used to create the tables.

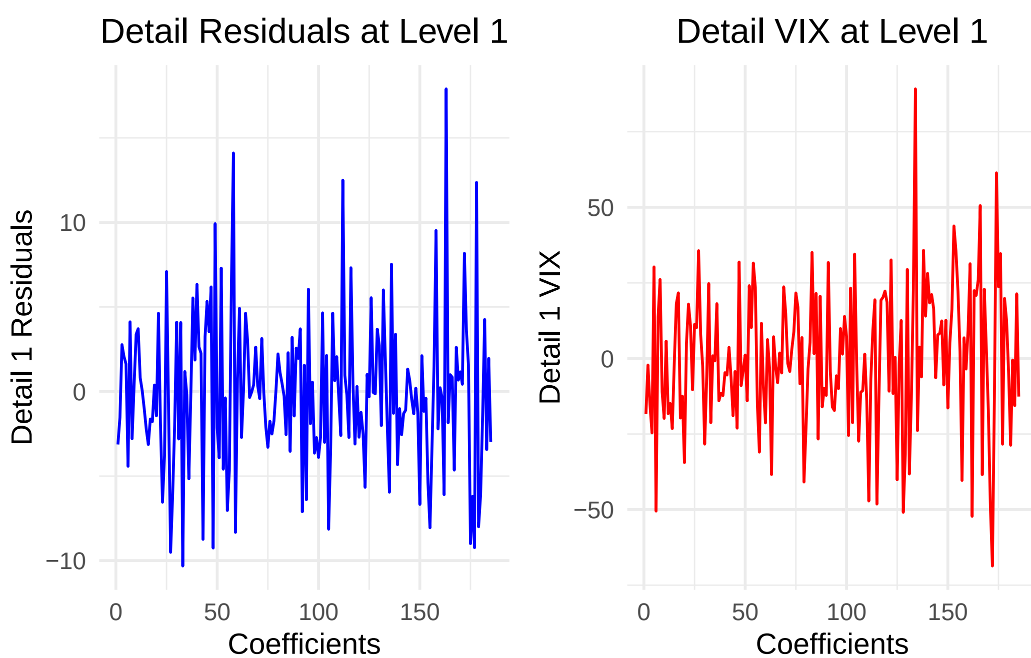

Figure 2: Short Term Fluctuations in Market Shocks and VIX

This detailed decomposition allows us to trace the direct and immediate impacts of market shocks on future volatility expectations, offering insights into the behavioral dynamics of market participants. The analysis of these coefficients in the next section is aimed at exploring whether short-term shocks in the market have a predictive power over short-term shifts in volatility expectations, challenging the conventional wisdom suggested by the efficient market hypothesis.

2.4 Measurement of Short-Term Market Fluctuations and Volatility Expectations

2.4.1 Quantifying Short-Term Market Fluctuations

Short-term market fluctuations in the S&P 500 index are fundamental indicators of transient market behaviors that can provide insights into investor sentiment and market dynamics. These fluctuations are measured using the monthly returns derived from daily closing prices sourced from Yahoo Finance. The transformation from raw daily prices to monthly returns involves calculating the percentage change in closing prices at the end of each month. This approach smooths out day-to-day volatility, focusing on significant monthly changes which better represent short-term market trends.

The ARIMA (AutoRegressive Integrated Moving Average) model plays a pivotal role in this analysis by fitting these monthly returns to forecast future values and, crucially, to extract the residuals. In econometrics, residuals from such models represent the unexpected component of returns, which can be interpreted as the short-term shocks or the novel information arriving in the market during that month. These residuals are what we define as the "short-term market fluctuations." By focusing on residuals, we directly measure the impact of new information on market behavior, excluding the predictable component based on past data.

2.4.2 Measuring Future Short-Term Volatility Expectations

Future short-term volatility expectations are captured through the VIX index, often referred to as the market's "fear gauge." The VIX index is designed to measure the stock market's expectation of volatility over the coming 30 days, computed from the option prices of the S&P 500 index. For our analysis, similar to the S&P 500 data, we sourced daily VIX data from Yahoo Finance, which we then processed into monthly averages to align with our market return data.

To specifically measure future expectations as influenced by current market conditions, we applied the Discrete Haar Transform (DHT) to both the residuals of the S&P 500 returns and the VIX data. The DHT helps in decomposing these time series into various levels of detail, reflecting different time scales of volatility. The first level detail coefficients from this transformation represent the highest frequency components available in our monthly data, corresponding to movements within a two-month window. These coefficients capture the essence of rapid changes in volatility and are used to represent the short-term future volatility expectations.

2.4.3 Methodological Justification and Application

The choice of the ARIMA model for analyzing S&P 500 returns and the application of DHT on both S&P 500 and VIX indices are rooted in financial econometrics, where the objective is to distill raw financial data into actionable insights about underlying market behaviors. This measurement approach ensures that our study accurately reflects the transient phenomena occurring in the financial markets and how they translate into entries in our dataset. By capturing and quantifying these short-term dynamics, we can explore their predictive power on future market conditions.

In summary, our measurement techniques are meticulously designed to transform high-frequency financial market data into a structured format that captures essential dynamics at a monthly frequency. This enables a rigorous examination of the relationship between short-term market shocks and future volatility expectations, providing a robust framework for understanding and forecasting market behavior.

3 Model

3.1 Theoretical Foundation

This study employs a generalized linear model (GLM) to explore the predictive relationship between short-term market return fluctuations and future market volatility expectations as measured by the VIX, lagged by two months. The use of a GLM is particularly advantageous in this context due to its ability to model linear relationships even with data exhibiting volatility clustering—a common characteristic in financial time series.

Our hypothesis posits that present short-term market fluctuations, specifically those within a two-month cycle, can provide predictive insights into the market's volatility expectations for the subsequent two months. This investigation into the lagged effects of market returns on perceived future risks is critical for understanding market dynamics that may not adhere strictly to the principles of the efficient market hypothesis. The hypothesis is rooted in the belief that current market conditions, through their short-term fluctuations, exert a measurable influence on the risk perceptions and volatility expectations that are embodied in the VIX two months later.

3.2 Model Specifications

The model employed in this analysis explores the predictive relationship between short-term market return fluctuations and future market volatility expectations. The model is specified as follows:

$$
\begin{aligned}
y_i &\sim \mathcal{N}(\mu_i, \sigma^2) \\
\mu_i &= \beta_0 + \beta_1 \times \text{Market Shock}_i \\
\beta_0 &\sim \mathcal{N}(0, 10) \\
\beta_1 &\sim \mathcal{N}(0, 10) \\
\sigma &\sim \text{Exponential}(1)
\end{aligned}
$$

Where:

- y_i denotes the VIX detail coefficients, modeled as normally distributed with mean μ_i and variance σ^2.
- Market Shock_i represents the detailed coefficients of market returns, treated as the independent variable influencing the VIX.
- β_0 and β_1 are the intercept and slope of the linear regression model respectively.
- $\mathcal{N}(0, 10)$ indicates that the priors for the regression coefficients are normally distributed with mean 0 and standard deviation 10, reflecting no strong prior beliefs about the magnitude of these parameters.
- Exponential(1) suggests that the prior variance σ^2 of the VIX detailed coefficients is modeled with an exponential distribution, emphasizing the variability in volatility predictions.

This precise mathematical representation facilitates a detailed analysis of the factors that potentially influence market behavior over short intervals. The next section will delve into the justifications for this model's framework, elucidating the theoretical foundations and empirical evidence that support its relevance and effectiveness in analyzing financial market dynamics.

3.3 Model Justification

This model seeks to quantify the extent to which short-term shocks in market returns can forecast volatility outlooks two months ahead. Given the financial market's complexity and the intricacies involved in volatility forecasting, the decision to focus on a two-month horizon stems from previous studies indicating significant correlations within this timeframe. The choice of a linear model is supported by preliminary analyses suggesting a linear trend in the changes of VIX levels following shifts in market returns.

The variables' quantitative properties, such as their distribution and scale, were thoroughly assessed to ensure that the GLM's assumptions of linearity, independence, and homoscedasticity are reasonably satisfied. The model incorporates normal priors for the regression coefficients, reflecting a belief in the absence of extreme effects unless supported by the data.

3.4 Model Implementation and Diagnostics

The model was implemented using the rstanarm (Goodrich et al. 2023) package, which facilitates Bayesian inference, providing a robust framework for parameter estimation and model uncertainty.

Parameter estimation was approached from a Bayesian perspective, enabling the incorporation of prior knowledge and direct probability statements about the parameters. Diagnostics from the GLM included checks for multicollinearity, leverage points, and influence measures, facilitated by standard diagnostic plots and summary statistics produced during the fitting process. These diagnostics help ensure the model's appropriateness and the reliability of the inferences drawn from the analysis.

4 Results

4.1 Overview

This section presents the findings from the regression analysis conducted to explore the relationship between short-term market fluctuations and future market volatility expectations, specifically looking at a two-month horizon. The analysis centers around the lagged impact of market returns on the VIX index, interpreted as a proxy for market risk perception. Various lags, ranging from no lag up to four months, were examined to pinpoint the timing and strength of this relationship.

4.2 Detailed Regression Outcomes

The regression model provided robust results that articulate the dynamic relationship between market returns and subsequent volatility expectations. Here are the summarized outcomes of the regression:

- Intercept: -0.044
- Market Shock Detailed Coefficients Coefficient: -0.561
- Number of Observations: 185
- Adjusted R-squared: 0.467
- Log Likelihood: -440.738
- Expected Log Pointwise Predictive Density (ELPD): -444.7
- Standard Error of ELPD: 17.8
- Leave-One-Out Information Criterion (LOOIC): 889.5
- Standard Error of LOOIC: 35.7
- Watanabe-Akaike Information Criterion (WAIC): 889.5
- Root Mean Square Error (RMSE): 2.61

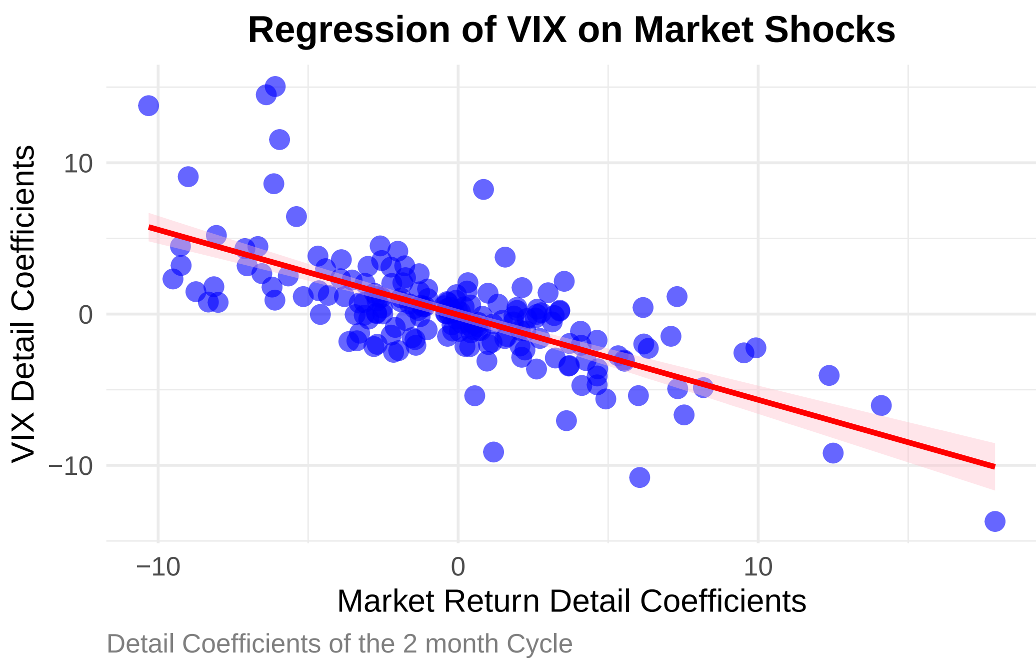

Figure 3: **?(caption)**

The model's negative slope coefficient for Market Shock Detailed Coefficients (-0.561) suggests a strong inverse relationship between market returns and future volatility expectations. Specifically, this indicates that positive shocks in market returns lead to a decrease in volatility expectations two months later, reflecting reduced risk aversion among investors. Conversely, negative market shocks result in increased volatility expectations, indicating heightened risk aversion. This dynamic is crucial for understanding investor behavior and market sentiment shifts.

The Adjusted R-squared value of 0.467 implies that approximately 46.7% of the variability in future volatility expectations can be explained by the current market return shocks, underlining the significant predictive power of short-term market movements on future risk perceptions.

4.3 Regression Model Performance

We can analyze the regression model's performance by lagging the VIX coefficients in order to find the time period that has the strongest effect of market fluctuations. The regression model's performance across different lags is quantitatively summarized by R-squared values, which indicate the proportion of variance in the dependent variable (VIX index detail coefficients) that is predictable from the independent variable (market return detail coefficients). Figure 1 below illustrates the progression of R-squared values across different lags:

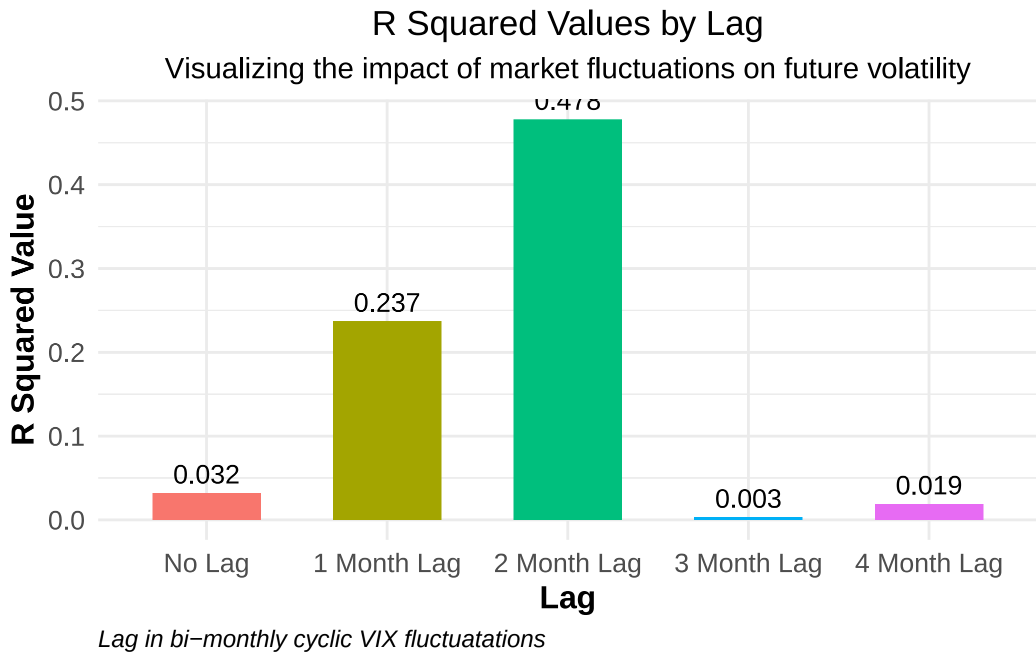

Figure 4: **?(caption)**

Figure 4 clearly shows that the influence of market fluctuations on future volatility perceptions peaks significantly at a two-month lag with an R-squared value of 0.478, indicating a strong predictive relationship at this point. This peak suggests that the market's response to shocks is most predictive of volatility perceptions two months later, before diminishing in influence.

5 Discussion Section

5.1 Overview of Research and Insights

In this study, we've conducted a detailed analysis of how short-term market shocks influence future market volatility expectations, particularly looking two months ahead. Our results indicate a statistically significant relationship where current market shocks predict future volatility, as evidenced by changes in the VIX index, a popular measure of market risk and investor sentiment.

5.2 Psychological Bias and Market Participant Behavior

Our analysis supports the hypothesis that current market shocks significantly influence future market volatility expectations. Specifically, a positive shock in market returns tends to decrease future volatility expectations, suggesting that investors expect positive trends to continue, thereby reducing their demand for risk protection. Conversely, a negative shock increases volatility expectations, indicative of heightened risk aversion. This behavior underscores a psychological bias among market participants where current conditions are expected to persist into the future, a phenomenon often referred to as the "momentum effect" in financial economics. Such findings challenge the Efficient Market Hypothesis (EMH), which posits that current prices reflect all available information, making it impossible to predict future prices based on past or present data.

5.3 The Role of the Efficient Markets Hypothesis

Our analysis challenges the Efficient Market Hypothesis (EMH), which asserts that current prices fully reflect all available information, making it impossible to predict future prices based on past data. However, our findings reveal an anomaly where past and present market conditions do have predictive power over future volatility. This suggests inefficiencies in the market where informed investors might exploit these insights to adjust their risk management strategies. For example, an investor who anticipates an increase in volatility two months ahead based on current negative shocks could strategically invest in risk management instruments like options or futures. When the anticipated increase in volatility materializes, the demand for these instruments rises, potentially allowing the investor to sell at a profit. Conversely, if a positive shock is observed, the investor might take a contrary position, anticipating a decrease in volatility.

5.4 Implications for Risk Management

The ability to anticipate future volatility based on current market conditions can significantly impact risk management strategies. Investors can use these insights to better time their entries and exits in risk management instruments, optimizing their investment returns by capitalizing on predicted fluctuations in market volatility. This proactive approach to risk management, based on predictive insights from market shocks, offers a strategic advantage in navigating the options and futures markets.

5.5 Weaknesses and Limitations

While our study provides crucial insights, it has several limitations:

- We rely solely on the VIX to measure volatility, which might not capture all aspects of market risk.
- The assumption of linearity in the relationship between market shocks and changes in volatility might not hold under all market conditions, potentially oversimplifying the dynamics involved.

The two-month forecast horizon, while significant, limits our understanding of how longer or shorter periods might behave, which could vary considerably. Additional weaknesses include potential data anomalies and the exclusion of other macroeconomic factors that could influence volatility.

5.6 Future Research Directions

Future research could explore the predictive power of different market indicators alongside the VIX, incorporating macroeconomic variables to deepen our understanding of volatility drivers. Investigating different time scales, such as 2-4 months or 4-8 months, and even long-term business cycle fluctuations lasting years, could provide a more comprehensive view of market dynamics. Employing nonlinear models or machine learning techniques could also enhance the accuracy of volatility predictions.

6 Conclusion

This research underscores the significance of understanding psychological biases in financial markets, highlighting how short-term market shocks can influence investor behavior and future market conditions over a two-month horizon. Despite the foundational principles of the EMH, our study reveals potential inefficiencies that could be exploited to manage risk more effectively, suggesting that current market shocks do have a discernible impact on future volatility expectations.

References

Aldrich, Eric. 2020. *Wavelets: Functions for Computing Wavelet Filters, Wavelet Transforms and Multiresolution Analyses*. https://CRAN.R-project.org/package=wavelets.

Auguié, Baptiste. 2023. *gridExtra: Miscellaneous Functions for "Grid" Graphics*.

Fama, Eugene F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25 (2): 383–417.

Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2023. *Rstanarm: Bayesian Applied Regression Modeling via Stan*. https://mc-stan.org/rstanarm.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48 (1): 65–91.

Nason, G. P. 2020. *Wavethresh: Wavelets Statistics and Transforms*. https://CRAN.R-project.org/package=wavethresh.

Percival, Donald B., and Andrew T. Walden. 2000. *Wavelet Methods for Time Series Analysis*. Cambridge University Press.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Ryan, Jeffrey A., and Joshua M. Ulrich. 2020a. *Quantmod: Quantitative Financial Modelling Framework*. https://CRAN.R-project.org/package=quantmod.

———. 2020b. *Xts: eXtensible Time Series*. https://CRAN.R-project.org/package=xts.

Wickham, Hadley. 2023. *Ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics*. https://ggplot2.tidyverse.org.