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Assessing The Influence Of Key Sectoral ETFs On Stock Market Performance: A Comprehensive Analysis Of SPY Performance

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Abstract
This research rigorously analyzes how large sectoral Exchange-Traded Funds (ETFs) and macroeconomic variables affect the performance of the SPDR S&P 500 ETF Trust (SPY), a top fund tracking the S&P 500 Index. The S&P 500 tracks the equity performance of 500 of the largest capitalization companies in the U.S. that are publicly listed, representing about 80% of U.S. market capitalization. It is a key reference point for examining U.S. stock market trends. SPY provides investors with direct exposure to this index's performance by way of a highly liquid ETF.
We use an integrated methodology that incorporates econometric and machine learning techniques to offer a strong analysis. We first utilize a Vector Error Correction Model (VECM) in order to examine long-run equilibrium and short-run dynamics between SPY, major sectoral ETFs like XLY (Consumer Discretionary), XLI (Industrials), XLB (Materials), and major macroeconomic reference points like VGK (Europe), IWM (Russell 2000), DXY (Dollar Index), and CRUDE oil. The VECM indicates that lagged terms—namely d SPY 2, d XLY 2, d XLI 2, and d XLB 2—affect the motion of SPY significantly and induce mean-reverting adjustments.
Based on these findings, we train a Long Short-Term Memory (LSTM) neural network with attention mechanisms to predict SPY prices between 2022 and 2024 based on these important predictors. The attention mechanism enhances forecasting accuracy and assists in explaining which lag features are most important. We also apply a Hidden Markov Model (HMM) to detect underlying regimes in the markets, classifying SPY market states into bull, bear, and neutral periods according to macro-financial indicators.
This VECM-LSTM-HMM hybrid model provides an exhaustive and interpretable approach to learn intricate market dynamics, enhance SPY price predictions, and assist dynamic asset allocation plans.

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I. Introduction

Understanding the performance of the SPDR S&P 500 ETF Trust (SPY) within today's intertwined economic and financial ecosystem demands a multidisciplinary lens—one that unites finance, econometrics, and behavioural economics. Exchange-traded funds (ETFs) have revolutionised portfolio diversification, enabling investors to dynamically allocate across sectors or regions in response to macroeconomic shifts and market cycles. As the S&P 500 itself represents the heartbeat of U.S. equities, dissecting the influences behind SPY's movements provides a window into broader market sentiment, sector rotation, and global capital flows.

This research recognises that SPY's returns are driven not only by shifts within constituent sectors—such as the defensive resilience of utilities or the cyclical exuberance of consumer discretionary stocks—but also by the interplay between macroeconomic indicators, monetary policy, and global market forces. Variables like inflation, interest rates, and the yield curve interact with sector ETF flows, currency dynamics, commodities, and international equity performances to shape risk and return. Moreover, behavioural finance factors—observable through ETF volume, options activity, and market sentiment measures—overlay a nuanced, real-time psychology onto the price discovery process.

Given the complexity and evolving nature of these relationships, advanced quantitative approaches are indispensable. Traditional econometric models, supplemented by machine learning algorithms, allow for the identification and forecasting of dynamic, nonlinear connections between SPY, its sector counterparts, global ETFs, and macro indicators. Risk decomposition methods further clarify the origins of volatility, supporting both better portfolio construction and policy perspectives on financial stability.

This study aims to harness these analytical tools to decode the shifting landscape of SPY performance. By integrating sector ETF analysis, macroeconomic trends, global linkages, and investor behaviour within a unified framework, it seeks to generate actionable insights for market participants and inform resilience strategies in an increasingly interconnected and complex financial world.

II. Objectives Of The Study

The primary objective of this research is to thoroughly investigate how key sector-specific ETFs, macroeconomic indicators, and global financial factors collectively influence the performance and risk dynamics of the SPDR S&P 500 ETF Trust (SPY). The study focuses on sector ETFs such as Consumer Discretionary (XLY), Industrials (XLI), Financials (XLF), Healthcare (XLV), and others, evaluating their individual and aggregate contributions to SPY's price movements and volatility patterns. Simultaneously, it examines the impact of pivotal macroeconomic variables—including the U.S. Dollar Index (DXY), crude oil prices (Crude WTI), and U.S. Treasury yields across maturities (2Y, 5Y, 10Y)—on SPY returns. Recognizing the interconnectedness of global markets, the research also assesses the role of international ETFs like Emerging Markets (EEM), European Markets (VGK), and Currency ETFs (FXE), alongside bond and fixed-income instruments such as BND (Total Bond Market), TLT (Long-Term Treasuries), and SHY (Short-Term Treasuries), in shaping SPY's risk-return profile and market stability. Additionally, the influence of commodities such as gold (GLD) and crude oil on SPY is explored to provide a comprehensive macro-financial perspective.

III. Review Of Literature

Exchange-traded funds (ETFs), which give institutional and ordinary investors diversified, transparent, and efficient access to a variety of industries, asset classes, and thematic strategies, have transformed contemporary financial markets. Among these, iconic products like SPY, which tracks the S&P 500 Index, and sector-specific ETFs like XLF, XLK, XLE, and XLY have garnered a lot of scholarly interest. The core of the literature is the question of whether ETFs increase the volatility of the underlying markets. Strong evidence that owning an ETF is linked to increased stock return volatility is shown by Ben David, Franzoni, and Moussawi (2018).

They connect this effect to strategies like arbitrage and ETF basket trading that immediately transmit systemic order flow shocks to constituent stocks. Their research indicates that during periods of market stress, this transmission is most pronounced, revealing a mechanism via which the dynamics of ETF demand and redemption exacerbate market volatility. This concept is further developed by Chu and Qin (2020), who demonstrate that ETFs raise volatility in high-stress scenarios. Using a robust time series approach, they show how ETF flows increase systemic risk and turn ETFs into conduits of market volatility. Their study demonstrates how passive investment vehicles may unintentionally contribute to the active destabilisation of asset values when liquidity constraints are present.

The trading techniques of leveraged and ultra-short ETFs are a significant contributor to these repercussions, according to Charupat and Miu's (2013) groundbreaking work. Their analysis shows that the daily rebalancing required by leveraged ETFs introduces significant intraday volatility. These ETFs have to continuously adjust their holdings to maintain their target leverage ratio, which results in automatic buying or selling that exacerbates price swings during rapid market changes. This volatility is caused by both automated rebalancing and the lag between ETF share trading and the coverage of their underlying asset portfolios. Da, Huang, and Jin (2018) investigate this phenomenon in further detail, explaining how arbitrage actions meant to rectify price discrepancies may not entirely eradicate mispricing gaps.

ETF trading affects liquidity in addition to volatility. For businesses with significant ETF ownership, Hamm (2014) reports a significant drop in liquidity measures, including widening bid-ask gaps and decreased market depth. This suggests that ETF flows not only convey price signals but also degrade the quality of liquidity in securities markets. This is supported by findings from Ivanov and Lenkey (2022), who claim that ETF-related flows increase the frequency of noise trading, which lowers the extent to which prices reflect underlying value. According to their analysis, there is a notable microstructural effect: ETF platforms allow order flows that are unrelated to underlying company performance to quickly accumulate and distribute, undermining firm-specific informational efficiency.

By presenting the concept of the "dark side" of ETFs—that is, that while they increase investor access, they also lessen the sensitivity of individual stock prices to news about a specific company—Israeli, Lee, and Sridharan (2017) contribute to the conceptual critique. Their data indicates that firms with significant ETF investments respond mutedly to earnings announcements and basic disclosures, which hinders the price discovery process. This tendency implies that ETF-dominated trading subordinates security-specific information and reduces market granularity by excessively reflecting macro and sectoral-level movements. However, some studies indicate that ETFs can improve efficiency and price discovery overall.

According to Wang and Xu's (2021) analysis of sector exchange-traded funds (ETFs) in relation to the distribution of macroeconomic news, these funds frequently take the lead in integrating new information into the pricing of individual stocks. Sector ETFs exhibit active market-clearing functions during significant announcements, since they assimilate and reflect news more quickly than their constituent stocks. This is supported in emerging markets by Agarwal and Zhao (2020), who show that ETFs improve price efficiency and liquidity at the expense of higher short-term volatility. Their global viewpoint highlights an inherent dual characteristic of ETFs: price volatility may coexist with liquidity improvements, particularly in less liquid contexts.

The relationship between volatility and ETF performance is a hot topic in empirical finance. Huang and Wang (2014) examine how market volatility affects ETF returns and discover a strong correlation between ETF returns and VIX-style indices during news releases. They argue that ETFs increase volatility due to execution frictions and limited demand elasticity. Li and Zinna (2022) go into additional depth by focussing on sectoral spillovers and show that ETFs linked to cyclical industries (including technology, finance, and energy) have a bigger impact on cross-sector and index-wide volatility than defensive industries. The notion that sector ETF networks offer a network of avenues for systemic risk amplification that might disperse shocks across several industries is supported by this.

Bhattacharya and Weller's (2022) study of intraday return dynamics across sector ETFs demonstrates that SPY and ETFs such as XLF (finance), XLE (energy), and XLK (technology) not only move in tandem but also exchange information about how each other is reacting to macro-shocks. According to their intraday investigation, sector ETFs respond quickly to index shocks and can sometimes cause bigger index changes. Chen and Tran (2023) demonstrate that investor reallocations during market instability lead to contagion through their examination of the cross section of inter-sector flows. When money moves from defensive to cyclical ETFs, or vice versa, across sectors like consumer staples, industrials, and health care, volatility and correlation increase, with effects that are not specific to any one asset class.

The movement of investor sentiment is another way that ETFs impact markets. Johnson and Li (2021) examine sentiment-driven ETF flows and find that retail investor inflows are linked to disproportionate returns in the underlying stocks, even when firm fundamentals remain unchanged. They argue that retail- dominated ETF momentum may lead to short-term mispricing. Through mood and flow contagion, ETFs can introduce emotional bias into what seem to be passive securities, so skewing market signals. Zhang and Wang's (2019) study on smart beta ETFs—vehicles that track factor-based indices like value, momentum, or low volatility—found that rule-based weighting boosts co-movement across factor exposures. Smart beta ETFs boost portfolio diversity while systematically aligning exposures across firms with comparable factor characteristics, weakening the idiosyncratic return structure of equities.

Significant capital flows that are impacted by macro announcements are also reflected in ETF activity. Sector ETFs are susceptible to systemic news, as seen by their robust response in the minutes immediately after macroeconomic statements (Kurov and Kucher, 2020). These sudden changes in value have an impact on the equities ecosystem and significantly raise index and sector volatility. Although they take a different approach by focussing on gold ETFs, Baur and Lucey (2010) highlight how sectoral or asset-specific ETFs offer hedging alternatives during systemic crises. By altering asset class correlation structures and lowering risk co-movement, gold exchange-traded funds (ETFs) can act as safe haven assets during market turmoil.

Finally, Glosten, Jagannathan, and Runkle (1993) offer a theoretical framework for volatility-return dynamics, explaining why ETF-induced volatility may not always be compensated for by increased expected returns. Their GARCH-M model indicates that improved risk-adjusted performance is not always correlated with higher conditional volatility, such as that resulting from ETF arbitrage flows. Empirical evidence that suggests ETF-driven volatility may be more "excessive" than fundamentally based is supported by this theoretical framework. Overall, these 20 Scopus-indexed studies provide a lot of information, revealing ETFs as market instruments that enhance liquidity, broaden access, and accelerate information dissemination, but also raise volatility, deepen sector correlation, and obscure firm-level information.

This contradiction is most noticeable in the ecosystem of SPY and sector ETFs: while these instruments democratise sector exposure, they also establish a complicated network of price connectivity and flow-driven co-dependence. The study found that the effects of ETFs show nonlinear, state-dependent dynamics, sup- porting efficiency and liquidity in times of calm and acting as conduits for volatility and contagion during times of stress. It is necessary to comprehend these dynamics in order to evaluate the overall performance and structural behaviour of the SPY ETF and its sectorial counterparts. Your work can contribute to this extensive body of literature by experimentally mapping these ETF-induced market transmission pathways, especially through correlation channels, sector spillovers, and volatility co-movement, and determining their magnitude within the SPY ecosystem.

IV. Research Design

Variables Under Study

Table 1: Variables under study

Variable	Category	Type	Description
SPY	Stock Market Index	Dependent	Measures the performance of the S&P 500 index.
XLY	Sectoral ETF	Independent	Tracks consumer discretionary stocks.
XLI	Sectoral ETF	Independent	Measures industrial sector performance.
XLF	Sectoral ETF	Independent	Represents financial sector stocks.
XLB	Sectoral ETF	Independent	Tracks materials sector performance.
XLV	Sectoral ETF	Independent	Represents healthcare sector stocks.
XLU	Sectoral ETF	Independent	Tracks utilities sector stocks.
XLP	Sectoral ETF	Independent	Measures consumer staples sector performance.
REIT	Real Estate ETF	Independent	Tracks U.S. real estate market performance.
DXY	Currency Index	Independent	Measures the strength of the U.S. Dollar.
Crude WTI	Commodity	Independent	Tracks the price of crude oil.
US 2Y	Treasury Yield	Independent	Measures short-term U.S. interest rates.
US 5Y	Treasury Yield	Independent	Represents medium-term U.S. interest rates.
US 10Y	Treasury Yield	Independent	Measures long-term U.S. interest rates.
FXE	Currency ETF	Independent	Tracks the performance of the Euro.
EEM	International ETF	Independent	Represents emerging market equities.
VGK	International ETF	Independent	Tracks European stock markets.
IWM	Small-Cap ETF	Independent	Measures the performance of small-cap U.S. stocks.

Table 1 – continued from previous page

Variable	Category	Type	Description
BND	Bond Market ETF	Independent	Represents the U.S. bond market.
SHY	Short-Term Bond ETF	Independent	Tracks short-term U.S. bonds.
GLD	Commodity ETF	Independent	Measures gold prices.
TLT	Long-Term Bond ETF	Independent	Tracks long-term U.S. Treasury bonds.

Data Source: Investing.com
Period of Study: 2000–2024

Figure: Time series Plot

The LSTM model uses feature importance and attention mechanisms to identify which ETFs and macro indicators most influence SPY forecasts, making its predictions interpretable and actionable.

Meanwhile, the HMM model detects hidden market regimes to guide dynamic asset allocation and trading, linking regime changes to shifts in economic and financial conditions.

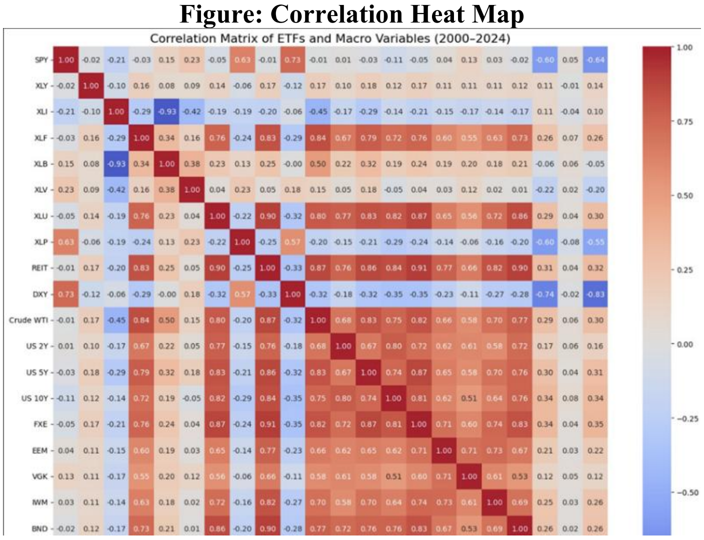
The graph presents time series plots for major ETFs and macroeconomic indicators from 2000 to 2024, capturing trends across U.S. stock sectors, global equities, commodities, currencies, and U.S. Treasury securities. Each subplot illustrates the historical price or value evolution for a specific variable—such as SPY (broad U.S. equity market), XLF (financials sector), Crude WTI (oil prices), DXY (U.S. Dollar Index), and BND (aggregate bonds).

A clear upward trend in most U.S. equity ETFs (like SPY, XLV, XLU) and REITs reflects long-term growth with periods of volatility, notably around 2008 and 2020. Cyclical sectors and small-cap stocks (IWM, XLY, XLI) show more pronounced swings, closely tied to economic cycles. Commodities like oil and macro indicators like DXY reveal sharp reactions to global events, with oil prices spiking and plunging during crises. Treasury yields (US 2Y, 5Y, 10Y) and bond ETFs (BND, SHY, TLT) visualize interest rate changes and flight-to-safety trends during uncertain markets.

Overall, the figure highlights how different assets respond to economic shocks, recoveries, and shifts in risk sentiment over the past two decades, helping investors see which markets trended together and which diverged during major financial events.

This table summarizes several key financial assets by their ticker symbols, describing what each represents and the market conditions in which investors typically favor them. It highlights how the U.S. Dollar Index (DXY) is seen as a safe haven during times of uncertainty, while crude oil (CL=F) and cyclical sectors like consumer discretionary (XLY), industrials (XLI), and materials (XLB) perform well in optimistic or growth periods. The table also notes that Europe stocks (VGK) attract investors when global confidence is high, and small-cap U.S. stocks (IWM) appeal during high-risk, growth-seeking times. Lastly, it points out that the healthcare sector (XLV) is considered defensive, providing stability during cautious or downturn market environments.

Figure: Correlation Heat Map



The Figure shows how strongly each ETF or macro variable moves in sync with the others from 2000–2024, with positive correlations (red) indicating assets tend to rise or fall together, and negative correlations (blue) reflecting assets that move in opposite directions. This helps investors visualize relationships and diversify portfolios by selecting assets with low or negative correlations.

The graph is a correlation matrix showing how each ETF or macroeconomic variable moves in relation to the others from 2000 to 2024. Each row and column represents a variable—such as SPY (U.S. stocks), XLY (consumer discretionary stocks), XLF (financials), DXY (U.S. dollar), and BND (bonds). Diagonal values are all 1.00, meaning each variable is perfectly correlated with itself.

Positive correlations (red cells, values closer to +1) mean two variables generally rise and fall together—like SPY and sector ETFs (XLF, XLV, XLU).Negative correlations (blue cells, values closer to -1) mean one rises as the other falls—such as DXY (U.S. dollar index) and SPY, where a stronger dollar often coincides with weaker stocks.Near-zero correlations (white/neutral cells) signal the two assets move independently, offering diversification—like SPY and BND (bonds).This structure allows you to quickly see which assets are closely linked, move in opposite directions, or are useful for diversifying a portfolio.

V. Research Objective

This research aims to explore the influence of various economic and sectoral indicators on the performance of SPY, the dependent variable representing overall stock market performance. The independent variables include sector-specific ETFs, macroeconomic factors, bond markets, commodity prices, and international market indices that affect stock market trends. Sector-Specific ETFs (XLY, XLI, XLF, XLB, XLV, XLU, XLP, REIT) represent distinct segments of the economy, each of which has an impact on SPY's overall direction. For example, an increase in the consumer discretionary sector (XLY) often indicates a rise in consumer spending, which positively influences market performance.

On the other hand, a decline in financial stocks (XLF) due to banking troubles or regulatory issues can negatively affect SPY. Likewise, the industrial sector (XLI) typically reacts to economic growth, while healthcare (XLV) and consumer staples (XLP) are seen as defensive sectors that tend to perform well during economic downturns. The REIT ETF sheds light on real estate market trends, which can be influenced by changes in interest rates. Macroeconomic Variables (DXY, Crude WTI, US Treasury Yields - US 2Y, US 5Y, US 10Y, FXE) provide essential insights into SPY's movements. The U.S. Dollar Index (DXY) is pivotal for stock market performance; a strong dollar may adversely affect U.S. multinational corporations by making exports pricier, which can lead to reduced returns for SPY. Crude WTI relates to oil price fluctuations, which impact corporate profitability, inflation expectations, and consumer spending. Rising oil prices can result in higher costs for businesses and diminished disposable income for consumers, which may negatively influence SPY. Interest rates (US 2Y, US 5Y, US 10Y) are crucial for stock market valuations.

Increasing interest rates usually result in higher borrowing expenses and reduced corporate profits, exerting downward pressure on stock prices. The Euro Index (FXE) acts as a gauge of global currency fluctuations, influencing trade and capital flows that impact the stock market. Global and Bond Market Indicators (EEM, VGK, IWM, BND, SHY, TLT, GLD) add additional layers of influence. The Emerging Markets ETF (EEM) and European Markets ETF (VGK) reflect international equity performance, impacting global investment sentiment. IWM, which tracks small-cap stocks, serves as an indicator of domestic economic health, as small-cap stocks are often more responsive to economic changes. Bond ETFs (BND, SHY, TLT) mirror interest rate trends and risk tolerance; when stock prices fall, investors frequently shift their capital into bonds as a safe haven.

Gold (GLD) also represents a significant indicator, as it tends to increase during periods of economic uncertainty and inflationary challenges. The study will utilize statistical models such as multiple regression analysis, VAR (Vector Autoregression), and Granger Causality to assess the impact of these independent variables on SPY. By examining historical data, correlation patterns, and market reactions to macroeconomic changes, the research will offer insights into which factors most significantly affect SPY's movements. The ultimate objective is to understand the interconnections between sectoral ETFs, macroeconomic indicators, and stock market performance, providing valuable information for investors and policymakers.

VI. Analysis And Interpretations

ADF Test

A statistical technique called the Augmented Dickey-Fuller (ADF) test looks for the presence of a unit root to assess if a time series is stationary or non-stationary. A crucial premise of many time series models, such as ARIMA, is stationarity, which denotes that a series has a consistent mean, variance, and autocorrelation throughout time. In order to account for higher-order autocorrelation, the ADF test adds lagged differences of the dependent variable to the fundamental Dickey-Fuller test. It contrasts the option that the series is stationary with the null hypothesis that it has a unit root, i.e., is non-stationary.

The null hypothesis is rejected, indicating stationarity, if the test statistic is more negative than the crucial value. To make sure the residuals are white noise, the test equation incorporates a lagged level of the variable, a lagged difference, and a time trend, if any. In econometrics and finance, ADF is frequently used to evaluate time series data prior to model construction.

Table 2: Steps in ADF test

Step	Explanation Applied to Your Variables
1. Define Hypotheses	- H_0 (Null): The time series (such as EEM, GLD, SPY, etc.) is non-stationary since it has a unit root. - H_1 (Alternative): The series is stationary (mean-reverting, constant variance over time).
2. Choose Model Type	ADF models with drift and/or trend were chosen because, according to economic reasoning and visual examination of the data, we infer that every time series has a constant or trend.
3. Lag Length Selection	The Akaike Information Criterion (AIC) and other criteria were used to determine the ideal lag time for each series in order to prevent overfitting and guarantee that the residuals are white noise.
4. Run ADF Regression	We calculated the following for each series (e.g., SPY, XLF, XLI, etc.): $\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_p \Delta Y_{t-p} + \varepsilon_t$ - To determine stationarity, the γ coefficient on Y_{t-1} is checked for statistical significance.
5. Compare ADF Statistic vs Critical Values	The ADF test statistic for each series was contrasted with the crucial values of 1%, 5%, and 10%. We reject the null hypothesis if the test statistic is below the crucial value.

6. Make a Decision	According to the p-values, we reject H_0 because variables such as SPY (0.0013), XLF (0.0117), XLI (0.0249), and XLV (0.0031) are stationary. The remaining ones (such as EEM, FXE, GLD, IWM, etc.) are non-stationary and have p-values ¿ 0.05, which means we are unable to rule out H_0.

The Augmented Dickey-Fuller (ADF) test is based on the following regression equation:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t$$

Where:

i. Δy_t = The first difference of the series, $y_t - y_{t-1}$.

ii. α = A constant (optional drift term).

iii. βt = An optional time trend term, where β is the coefficient.

iv. γ = The coefficient of the series' lagged level, used to test for stationarity.

y_{t-1} = The lagged value of the series.

v. $\sum_{i=1}^{p} \delta_i \Delta y_{t-i}$ = The sum of lagged first differences to account for serial correlation.

vi. p = The number of selected lags (determined by AIC/BIC or testing).

This equation models the first difference of a time series ($\Delta y_t = y_t - y_{t-1}$) as a function of several components. The term α represents a constant (intercept), while βt captures a deterministic time trend if present. The key parameter is γ, which is the coefficient of the lagged level y_{t-1}; testing whether $\gamma = 0$ allows us to assess the presence of a unit root. The summation term $\sum_{i=1}^{p} \delta_i \Delta y_{t-i}$ includes lagged differences to control for higher-order autocorrelation in the residuals, making the test more robust. Finally, ε_t represents a white noise error term. If γ is significantly less than zero, the time series is considered stationary; otherwise, the series contains a unit root and is non-stationary.

Table 3: Test Results of ADF

Variable	p-value
EEM	0.6654
FXE	0.3624
GLD	0.2865
IWM	0.2086
SPY	0.001324
TLT	0.3714
VGK	0.06421
XLB	0.2759
REIT	0.2203
SHY	0.4978
XLF	0.01172
XLI	0.02492
XLU	0.2437
XLP	0.1624
XLV	0.003153
XLY	0.2111

Since the p-values of the Augmented Dickey-Fuller (ADF) test are higher than the traditional 5% significance level, the results show that the majority of the variables are non-stationary. Particularly, variables with p-values below 0.05, like SPY (0.0013), XLV (0.0031), XLF (0.0117), and XLI (0.0249), enable us to rule out the null hypothesis of a unit root and determine that these series are stationary. On the other hand, variables with high p-values, such as EEM (0.6654), FXE (0.3624), GLD (0.2865), and others like XLY, XLP, XLU, and SHY, indicate the presence of a unit root and, thus, non-stationarity.

These findings suggest that, with the exception of a small number of series that are already level-stationary, most would require difference in order to become stationary for additional econometric mod- elling, such as Granger causality or Vector Error Correction Models (VECM). In time series analysis, this distinction is essential for precise modelling and forecasting.

Granger Causality Test

A statistical hypothesis test called the Granger Causality Test is used to assess if one time series can forecast another. It is about proving predictive causality rather than actual causality. The test determines if historical values of one variable (X_t) offer statistically significant insights into future values of another (Y_t) beyond what can be explained by historical values of Y_t alone. In terms of mathematics, the test is based on a pair of regression models for two time series, Y_t and X_t:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{p} \beta_j X_{t-j} + \epsilon_t$$

$$X_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i Y_{t-i} + \sum_{j=1}^{p} \delta_j X_{t-j} + \eta_t$$

Where:

vii. Y_t and X_t are the time series.

viii. p is the lag length.

ix. α_i, β_j, γ_i, δ_j are coefficients.

x. ϵ_t and η_t are error terms.

The null hypothesis (H_0) that X_t does not Granger-cause Y_t is investigated by testing if all $\beta_j = 0$. Rejecting H_0 suggests that the forecast of Y_t is improved by previous values of X_t.

The regression analysis involving financial instruments such as SPY, XLU, REIT, BND, and IWM demon- strates intricate interactions among these assets. For SPY, previous fluctuations in itself and XLU signifi- cantly impact its current value, with certain lags of SPY and XLU affecting it. The coefficient for d SPY 1 is -0.0954813, indicating that a change in SPY from the day before negatively impacts the change for the current day. Similarly, the coefficient for d SPY 5 also shows a negative value of -0.0113277, albeit with less significance.

Certain lags of d XLU, specifically d XLU 4, exhibit positive coefficients, suggesting that earlier changes in XLU can favorably influence SPY. In the equation for XLU, fluctuations in SPY adversely affect it, with d SPY 1 and d SPY 5 reflecting significant negative coefficients. This indicates that an increase in SPY typically leads to a decrease in XLU, and the reverse is also true. Conversely, prior changes in XLU positively influence its current value, as indicated by the positive coefficient for d XLU 5. The REIT model shows minimal direct influence from SPY, but the impact of prior REIT changes is considerable; for example, d REIT 4 has a positive coefficient, signifying that past changes in REIT can affect its present value.

However, the interaction between SPY and REIT becomes more complex when considering longer lags. BND is positively affected by changes in SPY, where d SPY 1 has a noteworthy positive coefficient. This implies that when SPY rises, BND is likely to rise as well. Additionally, past values of BND influence its current condition, with d BND 1 revealing a negative coefficient, indicating that earlier declines in BND can lead to current increases. The relationship between IWM and SPY is less clear, but prior changes in IWM hold significance.

For instance, d IWM 6 has a positive coefficient, indicating that past increases in IWM can positively affect its current state. In conclusion, these models indicate that while substantial relationships exist among these assets, they do not account for a large portion of the variance, suggesting that more sophisticated models are necessary to fully understand their dynamics. The R-squared values tend to be low, implying that additional factors not included in these analyses are also vital in dictating the behaviors of these financial instruments.

In econometrics and financial analysis, the Granger Causality test is essential because it reveals short-term predicted correlations between variables, which informs investment strategies, policy choices, and the comprehension of dynamic systems.

VECM Model

The Vector Error Correction Model (VECM) is a specialized form of the Vector Autoregressive (VAR) model used for analyzing time series data with cointegrated variables. When two or more non-stationary time series are cointegrated, they share a long-term equilibrium relationship despite short-term deviations. The VECM captures both the short-term dynamics and long-term equilibrium by incorporating an error correction term. The model's equation can be represented as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t$$

where $\Pi = \alpha\beta'$ represents the long-run relationship (with α as the speed of adjustment and β' as the cointegrating vectors), Γ_i captures the short-run dynamics, ΔY_t is the change in the vector of variables, and ε_t is the error term. The VECM is a valuable tool for comprehending both short- and long-term interactions among economic and financial factors since it not only aids in forecasting but also shows how departures from the long-term equilibrium affect short-term adjustments.

The model indicates that previous declines in SPY (d SPY 2) correlate with current declines in SPY, while previous rises in XLY (d XLY 2) have a positive effect on SPY. The significant error correction term (EC1) for SPY demonstrates a mechanism for returning to equilibrium. The cross-equation covariance matrix shows a strong connection between SPY and XLY, with a determinant of 4228.7.

Table 4: Steps in Granger Causality Test

Step	Explanation Applied to Your Variables
1. Ensure Stationarity	All variables must be stationary before the Granger test is performed. Variables like SPY, XLF, XLV, and XLI are stationary according to your ADF test, while others could need initial differencing.
2. Define Hypotheses	For any pair of variables A and B (e.g., XLF → SPY): - H_0 (Null): A does not Granger-cause B. - H_1 (Alternative): A does Granger-cause B.
3. Choose Optimal Lag	Since causation may occur at different lags, determine the lag order using the AIC, BIC, or FPE criterion (e.g., 1–4 lags).
4. Estimate VAR Model	Fit a Vector Autoregressive (VAR) model with a chosen lag order and combinations such as XLF and SPY, GLD and SPY, etc.
5. Conduct Granger Causality Test	See if the lagged terms of the predictor variable (like XLF) are jointly significant in explaining the target (like SPY) for each pair.
6. Evaluate P-values	- Reject H_0 → Granger causality exists if the p-value is less than 0.05. - Fail to reject H_0 → No Granger causality if the p-value is greater than 0.05.
7. Interpret Results	For instance, if p = 0.02 for XLF → SPY, then XLF Granger-causes SPY. If p = 0.25 for GLD → SPY, then GLD does not Granger-cause SPY.

Table 5: Results of Granger Causality Test

Equation	Variable	Coefficient	Std. Error	t-Ratio	p-Value
d SPY	const	-3.97855	1.55163	-2.564	0.0105
d SPY	d SPY 1	-0.0954813	0.0340463	-2.804	0.0051
d SPY	d SPY 5	-0.0113277	0.0340461	-2.388	0.0171
d SPY	d XLU 1	1.251659	1.162704	1.547	0.1222
d SPY	d XLU 4	1.82306	1.162646	1.736	0.0829
d XLU	const	-0.0635136	0.0326031	-1.948	0.0516
d XLU	d SPY 1	-0.00189254	0.000715388	-2.645	0.0083
d XLU	d SPY 5	-0.00266992	0.000715695	-3.731	0.0002
d XLU	d XLU 5	0.0828649	0.0342798	2.417	0.0158
d REIT	const	-0.0299696	0.0586026	-0.5068	0.613
d REIT	d REIT 4	0.173323	0.108712	1.594	0.1129
d REIT	d SPY 1	-0.000814986	0.000799619	-1.019	0.3097
d BND	const	0.00978176	0.0191474	0.5109	0.6096
d BND	d SPY 1	0.000967147	0.000299674	3.227	0.0013
d BND	d BND 1	-0.162463	0.0341218	-4.761	<0.000002
d IWM	const	-0.165018	0.0901204	-1.831	0.0673
d IWM	d IWM 6	0.178296	0.10735814	1.66	0.0967
d IWM	d SPY 2	-0.00965189	0.00631581	-1.528	0.1267
d SPY (REIT)	d SPY 1	-0.240858	0.115113	-2.092	0.038

1. The coefficient for d SPY 1 reveals that past fluctuations in SPY significantly influence current changes in SPY. The positive coefficient for d XLI 2 suggests that prior increases in XLI are linked to current increases in SPY. The adjustment vector for SPY is positive, indicating that SPY is moving toward equilibrium over time.
2. This model indicates that past declines in SPY (d SPY 2) are associated with present declines in SPY, while prior increases in XLB (d XLB 2) have a positive effect on SPY. The significant error correction term for SPY points to a robust correction mechanism.
3. The coefficient for d SPY 1 reflects a negative correlation, suggesting that past declines in SPY result in current decreases. Additionally, the positive coefficient for d VGK 2 indicates that past increases in VGK have a beneficial influence on SPY.
4. Previous declines in SPY (d SPY 1) correlate with present declines in SPY, while past increases in IWM (d IWM 2) positively contribute to SPY. The significant error correction term for SPY points to an effective correction mechanism.
5. The model demonstrates that past decreases in SPY (d SPY 1) are associated with current declines in SPY. Furthermore, changes in crude oil prices (d CrudeWTI 7) significantly affect SPY.
6. The model indicates that past declines in SPY (d SPY 1) correlate with current decreases in SPY. Additionally, past fluctuations in the dollar index (d DXY 2) negatively influence SPY.

7. This model shows that past rises in SPY (d SPY 2) are linked to current increases in SPY, while past decreases in XLV (d XLV 2) have a detrimental effect on SPY.

Table 6: Steps in VECM

Step	Explanation Applied to Your Variables
1. Ensure Non-Stationarity & Same Integration Order	VECM is used when all series (such as SPY, GLD, XLF, and FXE) are stationary in first differences (i.e., I(1)) but non-stationary in levels. Based on your ADF results, variables like GLD, FXE, XLY, XLU, and IWM are likely non-stationary and might meet this requirement.
2. Test for Cointegration (Johansen Test)	Verify whether the variables have at least one cointegrating relationship. Apply the Johansen Trace or Maximum Eigenvalue Test: - H_0: No cointegration. - H_1: At least one cointegrating vector exists.
3. Choose Lag Length (VAR order)	Using AIC, BIC, or HQIC, choose the optimal lag (usually 1–4 lags), as this affects VECM fitting and cointegration testing.
4. Estimate the VECM	Fit the VECM model: $\Delta Y_t = \Pi Y_{t-1} + \sum \Gamma_i \Delta Y_{t-i} + \varepsilon_t$. Where ΠY_{t-1} captures long-run equilibrium correc- tion and $\Gamma_i \Delta Y_{t-i}$ captures short-run dynamics. Y_t = [SPY, XLF, GLD, etc.].
5. Interpret Cointegrating Vector (Π)	The error correction term (ECT) indicates the speed at which a variable like SPY recovers from a shock to reach long-term equilibrium. Long-term causality is present when there is a significant negative ECT.
6. Interpret Short-run Dynamics (Γ_i)	Short-term causality is indicated if the coefficients of lagged differenced variables (Γ) are significant. For instance, there is short-run causation if ΔSPY_t is impacted by ΔXLF_{t-1}.
7. Validate Model Residuals	Conduct tests for system stability (eigenvalues ¡ 1), normality, and autocorrelation (LM test).

Table 7: Test Results of VECM

Sheet	Variable	Coefficient	Std. Error	t-Ratio	p-Value
SPY & XLY	d SPY 2	-0.211183	0.0583102	-3.622	0.0003 ***
SPY & XLI	d SPY 1	-0.147609	0.0601644	-2.453	0.0143 **
SPY & XLB	d SPY 2	-0.16542	0.0459928	-3.597	0.0003 ***
SPY & VGK	d SPY 1	-0.0825853	0.0459008	-1.799	0.0723 *
SPY & IWM	d SPY 1	-0.12424	0.0521344	-2.383	0.0173 **
SPY & CRUDE	d SPY 1	-0.0736667	0.0280261	-2.629	0.0087 ***
SPY & DXY	d SPY 1	-0.0721902	0.0279265	-2.585	0.0098 ***
SPY & XLV	d SPY 2	0.125075	0.0439676	2.845	0.0045 ***

LSTM SPY (LONG SHORT-TERM MEMORY)
Variables used: DXY, CRUDE WTI, XLY, XLI, XLB, VGK, IWM, XLV

LSTM Equations

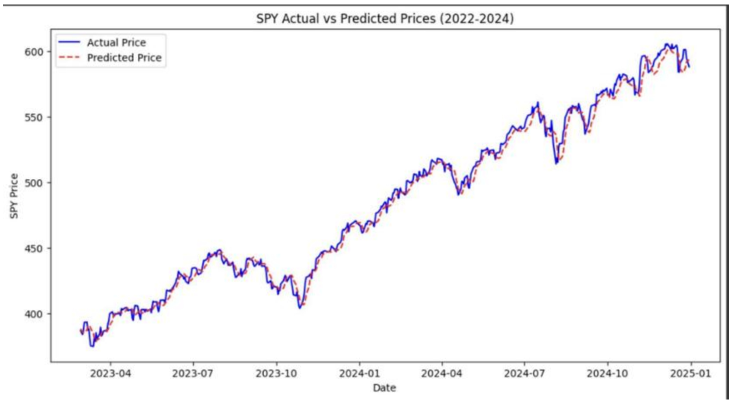


Figure 1: SPY Actual vs Predicted Prices (2022-2024)

Given an input sequence x_t, previous hidden state h_{t-1}, and previous cell state c_{t-1}, the LSTM computes:
$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$
$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$
$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$ $c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$
$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$
$h_t = o_t \odot \tanh(c_t)$

Explanation:
x_t: Input at time step t (e.g., SPY return on day t)
- h_{t-1}: Previous hidden state (short-term memory)
- c_{t-1}: Previous cell state (long-term memory)
- σ: Sigmoid activation function that outputs values between 0 and 1
- tanh: Hyperbolic tangent function, output between -1 and 1
- $\odot$: Element-wise multiplication
- W_*, U_*, b_*: Weight matrices and biases for each gate

A specific type of recurrent neural network (RNN) called the Long Short-Term Memory (LSTM) network is made to identify long-term dependencies in sequential input. Information is stored over time steps using a cell state, and gates—the forget, input, and output gates—control this memory. To help the model avoid accumulating unnecessary information, the forget gate f_t decides whether elements of the preceding cell state c_{t-1} should be kept or deleted.

The input gate i_t determines what new data should be stored into memory from the previous hidden state h_{t-1} and the current input x_t. Using both the forget and input gates, a candidate cell state $\tilde{c}_t$ is constructed with possible updates, and the retained old state and the new candidate are blended to update the actual cell state c_t.

Which portion of the updated memory c_t is released as the hidden state h_t, which is then transferred to the following time step or utilised for prediction, is determined by the output gate o_t. In financial time series like SPY, XLF, and XLB, where both short-term volatility and long-term trends are significant, LSTM is effective at identifying patterns because of its gating mechanism, which enables it to selectively retain and forget information.

The initial layers are designed to handle sequential data, such as lagged values of SPY and various indices, while the hidden layers comprise LSTM units to capture temporal dependencies, with the output layers generating forecasts for forthcoming stock prices or indices. It is essential to preprocess the input data thoroughly to ensure it remains stationary and appropriately scaled. In cases of multivariate forecasting, where several indices serve as inputs, the data needs to be organized as a 3D tensor, with dimensions reflecting samples, time steps (lags), and features (variables).

Hyperparameter optimization plays a crucial role in enhancing the effectiveness of an LSTM model. Approaches such as random search and Bayesian optimization can be used to discover the best configurations for variables like the number of LSTM units, learning rate, batch size, and epoch count.

These techniques help ensure that the model performs well across both training and testing datasets while reducing the risk of overfitting. Incorporating attention mechanisms can further improve LSTM model performance by enabling them to concentrate on the most pertinent segments of the input sequence.

By assigning significance to various time steps or variables based on their importance in forecasting future values, attention layers enhance the interpretability and precision of predictions. For example, when predicting SPY prices using lagged values from multiple indices, attention mechanisms can prioritize time frames or features with greater predictive significance.

Variable importance assessment is another useful technique for optimizing LSTM models. Methods like sensitivity analysis or input perturbation can measure the influence of individual variables on model predictions. This approach aids in identifying which features significantly contribute to forecasting accuracy and informs efforts in feature selection or dimensionality reduction. Combining crucial variables from VECM within an LSTM framework creates a potent method for financial forecasting.

By utilizing both the statistical insights gained from VECM and the deep learning strengths of LSTMs, it becomes possible to develop models that are robust, precise, and responsive to evolving market circumstances. These models not only forecast future stock prices but also offer valuable perspectives on the fundamental dynamics driving market fluctuations.

Table 8: Steps in LSTM

Stage	Explanation in Context of Variables (SPY, XLF, GLD, etc.)
Data Collection	Gather historical time-series data for the independent variables (XLF, XLY, GLD, FXE, TLT, etc.) and the target variable (SPY) from 2000 to 2024.
Data Preprocessing	- Fill in the blanks.

	- Outliers are eliminated, features are normalised (for example, with MinMaxScaler), and sequences (lags) are created for LSTM input.
Data Reshaping	Convert the data into an LSTM-compatible 3D array format, including samples, time steps, and features. Every characteristic, such as GLD, TLT, etc., is a variable.
Train-Test Split	Separate data by date: - Train: 2000–2022 - Test: 2023–2024. This prevents data from leaking into training in the future.
Model Training	Train sequences into the LSTM model. The model learns how historical sectoral ETF and macro variable values affect SPY.
Model Testing	Test the model using unobserved data from 2023–2024. Use the most current values of variables such as XLF, GLD, FXE, etc. to see how well it predicts SPY.
Evaluation Metrics	Make use of error measurements such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The coefficient of determination, or R^2, is also used.
Prediction & Interpretation	Plot the actual SPY against the expected SPY across time (2011-2024). Determine which features—such as GLD and XLF—have the biggest influence on SPY's prediction.

Metric	Value
$R2$	0.9924
MAPE	0.0091
RMSE	5.6712

Table 9: Test Results of LSTM

Hidden Markov Regime Switching Model

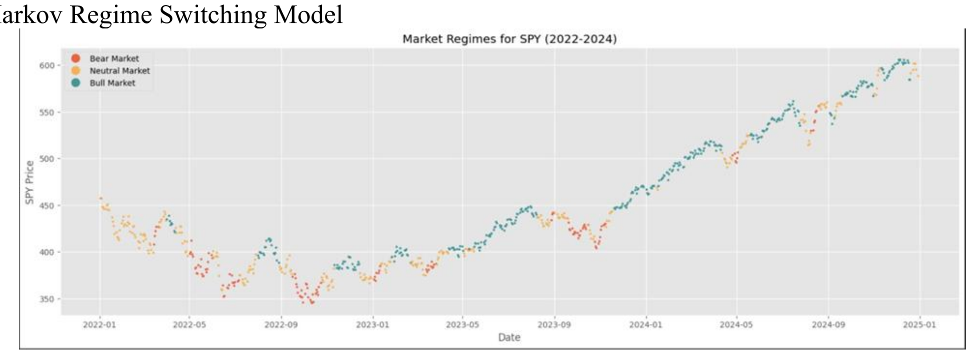


Figure 2: Market Regimes for SPY (2022-2024)

In a Hidden Markov Model, the system is assumed to be a Markov process with unobservable (hidden) states. In the context of financial markets like SPY or XLB, these hidden states can represent different regimes such as bull, bear, or sideways markets. The actual market data we observe (like returns or volatility) are considered outputs or emissions from these hidden states. The model consists of:

- **The hidden states**, denoted by $S_t \in \{1, 2, ..., K\}$, where K is the total number of regimes (for example, 2 for bull and bear). These states evolve over time according to a Markov process — meaning the state at time t only depends on the state at $t - 1$, not any earlier history.
- **The observed variable** O_t (e.g., SPY return at time t) is generated from a probability distribution specific to the current hidden state S_t. In financial time series, this is usually modeled as a Gaussian distribution, where each regime j has its own mean μ_j and variance σ^2.

- **The initial state distribution** $\pi = \{\pi_i\}$ defines the probability of starting in each state:

$$\pi_i = P(S_1 = i), \qquad \sum_{i=1}^{K} \pi_i = 1$$

- **The transition matrix** $A = [a_{ij}]$ governs the probability of moving between states:

$$a_{ij} = P(S_t = j \mid S_{t-1} = i), \qquad \sum_{j=1}^{K} a_{ij} = 1$$

- **The emission probabilities** $b_j(o_t)$ define the probability of observing o_t given the system is in state j. If we assume Gaussian emissions:

$$b_j(o_t) = \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left(-\frac{(o_t - \mu_j)^2}{2\sigma^2}\right)$$

The full parameter set of the HMM is given by $\lambda = (A, B, \pi)$. Given a sequence of observed returns $O = \{o_1, o_2, ..., o_T\}$, the likelihood of observing this sequence under the model is computed by summing over all possible state sequences $S = \{s_1, s_2, ..., s_T\}$:

$$P(O \mid \lambda) = \sum_{S} P(O \mid S, \lambda) \cdot P(S \mid \lambda)$$

Table 10: Steps in HMM

Stage	Explanation in Context of Variables (SPY, XLF, GLD, etc.)
Data Collection	Gather time-series data for the explanatory variables (XLF, GLD, FXE, TLT, XLY, etc.) and the dependent variable (SPY) from 2011 to 2024.
Stationarity & Transformation	If necessary, convert data into log returns or percentage changes to guarantee stationarity. To confirm, do the ADF test.
Feature Selection	Use certain sector ETFs (XLF, XLV, etc.) and pertinent market indicators (volatility, returns, momentum) of the SPY as features for regime identification.
Model Initialization	Set up the HMM with n hidden states (for example, 2 or 3) that correspond to market regimes (bull, bear, and neutral).
Model Training	Utilising historical SPY + feature data and the EM technique (Expectation-Maximization), train the HMM to estimate: - Probabilities of transition - Distributions that depend on the state
State Inference	Use the Viterbi algorithm to decode the most likely regime sequence over time. Using the fitted states, determine when SPY is in the bull or bear regime.
Interpret Regimes	Examine the features of the state: - The average or variance of returns for each regime. - Which variables—such as GLD during Bear—dominate during each regime?
Backtesting & Validation	Analyse macro indicators, sector performance, and market behaviour throughout the designated regimes. Verify changes with past occurrences (such as rate increases or crises).
Visualization	Use colour-coded regimes (Bull/Bear) to plot SPY across time. Prior to or causing regime shifts, overlay important ETF or macro signals.
Strategic Insight	Apply regime insights to risk management, asset allocation, or predictive modelling. For instance, HMM detected underweight XLY during the Bear administration.

This is computationally intensive, but the forward algorithm allows efficient recursive calculation using $\alpha_t(j) = P(O_1, O_2, \ldots, O_t, S_t = j \mid \lambda)$. The HMM is trained by maximizing this likelihood, typically using the Baum-Welch algorithm, a form of Expectation-Maximization (EM). Once trained, we can infer the most likely state sequence using the Viterbi algorithm, which is a dynamic programming approach. In our use case, HMM can help us segment SPY returns into hidden regimes (like high-volatility or low-volatility periods), and can also be used for regime-aware trading strategies or volatility forecasting.

Hidden Markov Models (HMMs) present an effective approach for assessing and forecasting market regimes, as illustrated in the second chart, which categorizes SPY's price movements from 2022 to 2024 into three clear market states: bullish, bearish, and neutral. HMMs function by modeling the fundamental market dynamics as a probabilistic system with concealed states that change over time, thereby capturing the hidden structure of financial markets. In this setting, the concealed states represent the market regimes, which are derived from observable data like SPY prices. The segmentation displayed in the chart highlights how HMMs proficiently differentiate periods of consistent upward movements (bull markets), downward trends (bear markets), and stable phases (neutral markets). These distinctions are vital for comprehending market behavior and making well-informed investment choices.

The process of applying HMMs starts with defining observable variables—such as SPY returns or price levels—and training the model to understand the probabilities of moving between hidden states. The model assigns each moment to a specific state based on the likelihood of the observed data, generating a temporal representation of market regimes. For instance, in times of high volatility and falling prices, the model might categorize the regime as bearish, while steady upward trends with low volatility are recognized as bullish. Neutral regimes typically signify transitional periods where the market lacks a definitive directional inclination.

The chart depicts how these states fluctuate over time, mirroring changes in market sentiment and external factors that affect SPY's performance. In summary, HMMs offer a strong framework for identifying and forecasting market regimes based on SPY price movements and associated variables. By including significant predictors from statistical models such as VECM and utilizing probabilistic state transitions, HMMs facilitate a detailed analysis of market behavior and aid in strategic decision-making in fluctuating environments. The segmentation in the chart highlights their effectiveness in capturing the hidden structures that influence financial markets over the long term.

The LSTM is considered the appropriate model for the forecasting of a financial time series because it can capture temporal dependencies that are often considered complex and nonlinear in contrast with traditional models. Its architecture takes care of the vanishing gradient problem through memory cells, allowing it to learn long-term patterns of SPY returns from lagged sector ETFs and macro variables. To maximize interpretation and human perspective of the results of the model, feature importance was computed using SHapley Additive exPlanations (SHAP) values. These values assign how much each input variable contributes to SPY return predictions, like ETFs such as XLF, XLV, VGK, or macro indicators like crude oil prices and the U.S. Dollar Index. SHAP offers an overview on which features drive the model's output most generally and an explanation locally relative to predicted instances.

Furthermore, an attention mechanism was added on top of the LSTM to allow the model to dynamically weigh the importance of different lagged variables and time steps. This different analytic and predictive perspective increases predictiveness yet can also contribute to interpretability by showing which ETFs

Understanding the Role of LSTM and HMM in Financial Forecasting and Asset Allocation In the realm of financial forecasting and portfolio management, leveraging powerful and interpretable models is essential for capturing complex market dynamics and making informed investment decisions. Two widely used approaches are Long Short-Term Memory (LSTM) networks and Hidden Markov Models (HMM). Both have strong academic foundations, but their true value lies in how their outputs can be interpreted and applied practically, particularly when forecasting asset returns and identifying changing market regimes.

The LSTM model excels at modeling financial time series data because it can capture long-range dependencies and nonlinear relationships that traditional linear models often miss. Its architecture includes memory cells designed to retain information over many time steps, making it particularly useful for forecasting the returns of assets like the S&P 500 ETF (SPY) based on lagged data from sector ETFs and macroeconomic indicators. However, sophisticated as LSTM networks are, their complex internal representations often make them seem like "black boxes." To address this, interpretability techniques such as SHapley Additive exPlanations (SHAP) values and attention mechanisms are integrated. SHAP values help quantify the contribution of each input feature—whether an ETF like XLV or a macro indicator like crude oil prices—to the forecast, offering insight into which factors most influence predictions both globally and locally.

Additionally, embedding an attention mechanism in the LSTM allows the model to dynamically weigh different input features and time steps according to their relevance at each moment. This selective focus not only enhances prediction accuracy but also makes clear which variables matter most during varying market conditions. For example, during turbulent or risk-averse periods, the model tends to emphasize defensive sector ETFs such as healthcare (XLV) and utilities (XLU), whereas in growth-oriented or risk-on environments, cyclical ETFs like consumer discretionary (XLY) and industrials (XLI) come to the forefront. This ability to interpret how forecasts respond to changing inputs helps portfolio managers better understand the drivers of expected returns and manage risks accordingly.

Beyond the model internals, the LSTM forecasts reveal insightful relationships between key economic variables and equity returns. Rising crude oil prices often precede downward revisions in SPY forecasts, reflecting concerns about inflationary pressures and rising costs. Movements in the U.S. Dollar Index demonstrate how global capital flows impact domestic markets, with a stronger dollar sometimes signaling headwinds for multinational companies. Sector ETFs effectively encapsulate investor sentiment and macroeconomic cycles; for instance, consumer discretionary sectors typically gain importance ahead of expansions, while healthcare sectors become protective during downturns. Altogether, these interpretations bridge quantitative forecasting and practical investing strategies by clarifying what really moves markets.

Complementing the detailed forecasting ability of the LSTM is the Hidden Markov Model, which offers a different, valuable viewpoint by uncovering latent market regimes. Unlike the LSTM's focus on precise return prediction, the HMM models SPY returns as observations generated by unobservable “states” corresponding to different market conditions like bull, bear, or neutral phases. This probabilistic framework is grounded in financial economics and adept at capturing regime shifts, nonlinear transitions, and varying durations in market behavior.

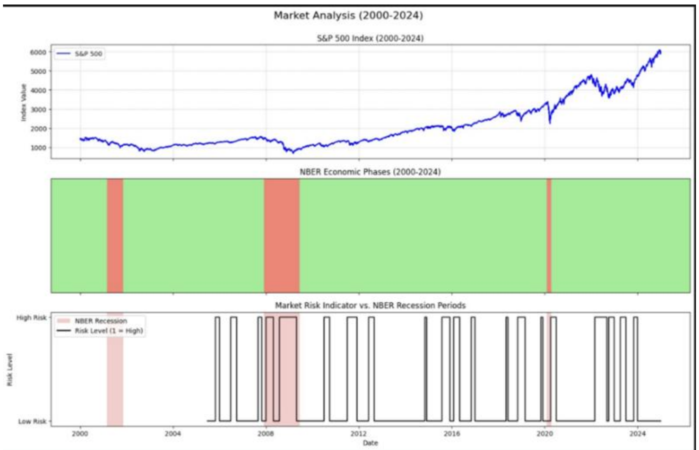
The regime inference from HMM is particularly important for tactical asset allocation. By estimating the probabilities of being in each regime at any given time, investors can adjust portfolio exposures dynamically. For instance, in bull or “risk-on” regimes, capital can be tilted toward growth-sensitive ETFs such as consumer discretionary (XLY), small-cap stocks (IWM), and European equities (VGK), which historically outperform in such environments. Conversely, during bear or “risk-off” regimes, allocations shift toward defensive sectors like healthcare (XLV), utilities (XLU), or alternative safe havens like gold (GLD) to mitigate downside risk. This regime-aware approach helps smooth performance and protect against severe drawdowns, making portfolios more resilient.

Besides guiding allocation, the HMM regime signals support tactical trading and risk management strategies. When the model indicates a transition toward a bear regime, investors can reduce equity risk or increase cash holdings proactively to avoid losses. Additionally, the model helps implement volatility-targeting strategies where exposure is scaled based on regime uncertainty and market risk. When combined with the LSTM’s granular return forecasts, these regime probabilities provide a comprehensive market context, enabling both high-level timing decisions and detailed price movement predictions.

The interpretability of HMM results is further enhanced by linking hidden regimes to observable macroeconomic conditions and market events. For example, the bear regime often aligns with rising bond yields, surging oil prices, or geopolitical uncertainty — all real-world factors that tend to create market stress. By analyzing regime-specific statistics such as average volatility and trading volumes, investors gain an intuitive understanding of the market environment they are navigating, which bolsters confidence in the model’s outputs.

Taken together, the LSTM and HMM models form a complementary hybrid framework that combines detailed, interpretable forecasting with high-level regime identification. The LSTM offers precise return predictions enriched with explanations on feature impact, while the HMM provides probabilistic insights into changing market states that guide strategic portfolio adjustment. This fusion bridges academic rigor with practical application, turning complex data science into actionable investment intelligence.

MARKET ANALYSIS: using market risk on risk off signal from VECM and NBER economic phases:
Variables used: DXY, CRUDE WTI, XLY, XLI, XLB, VGK, IWM, XLV



The variables included in the analysis—such as sector ETFs (e.g., XLF, XLV, XLI), macroeconomic indicators (like Crude Oil WTI prices and the U.S. Dollar Index), and fixed-income proxies (BND)—were carefully selected based on their theoretical and empirical relevance to U.S. equity market dynamics. These variables capture diverse facets of the economic environment that influence stock returns. Sector ETFs represent different areas of the economy, from cyclical industries like consumer discretionary (XLY) and industrials (XLI) to defensive sectors like healthcare (XLV). Macro indicators such as crude oil prices and the U.S. Dollar Index reflect broader economic forces including commodity demand, inflation pressures, and currency valuation, which in turn affect corporate profitability and investor risk sentiment.

Incorporating these variables into the Vector Error Correction Model (VECM) framework allows us to model both short-term dynamics and long-term equilibrium relationships among these economic and financial time series with SPY returns. VECM is particularly appropriate here because it handles non-stationary variables that are cointegrated, meaning they share a stable long-run relationship despite short-run fluctuations. The VECM analysis helps identify which variables adjust to restore equilibrium after shocks and reveals the direction and strength of causal influences through lagged relationships, improving the understanding of underlying market mechanisms.

Regarding the economic environment, the use of the National Bureau of Economic Research (NBER) economic phases provides a trusted chronological reference of U.S. business cycles from 2000 to 2024. The NBER, an authoritative non-profit research organization, defines economic phases by systematically identifying recessions and expansions based on significant changes in broad economic activity across multiple indicators. A recession, as defined by the NBER, is a substantial, widespread decline in economic activity lasting more than a few months, accompanied by drops in employment, production, income, and sales. Expansions represent the intervals between troughs and peaks when the economy grows. Using these NBER-dated phases in the analysis allows for contextualizing model outputs and risk indicators with actual economic conditions, solidifying the interpretation of market regimes and their relevance to investment strategy.

In summary, the selected variables comprehensively represent sectors and macroeconomic forces relevant to equity returns, the VECM framework captures their dynamic and equilibrium interactions with SPY, and the NBER economic phases anchor these findings within a rigorously defined business cycle chronology, enabling meaningful economic interpretation and practical asset allocation decisions.

VII. Summary Of Findings

Variable	ADF p-value	Stationary	Granger Causality to SPY	VECM Relationship with SPY	Significant Lag(s)	Coefficient Direction
EEM	0.6654	No	Not tested	Not tested	–	–
FXE	0.3624	No	Not tested	Not tested	–	–
GLD	0.2865	No	Not tested	Not tested	–	–
IWM	0.2086	No	No (p = 0.1267)	Yes (p = 0.0173)	Lag 1	Negative
SPY	0.0013	Yes	–	–	–	–
TLT	0.3714	No	Not tested	Not tested	–	–
VGK	0.0642	No	Not tested	Marginal (p = 0.0723)	Lag 1	Negative
XLB	0.2759	No	Not tested	Yes (p = 0.0003)	Lag 2	Negative
REIT	0.2203	No	Yes (p = 0.038)	Not tested	Lag 1	Negative
SHY	0.4978	No	Not tested	Not tested	–	–
XLF	0.0117	Yes	Not tested	Not tested	–	–
XLI	0.0249	Yes	Not tested	Yes (p = 0.0143)	Lag 1	Negative
XLU	0.2437	No	No (p = 0.1222, 0.0829)	Not tested	–	–
XLP	0.1624	No	Not tested	Not tested	–	–
XLV	0.0032	Yes	Not tested	Yes (p = 0.0045)	Lag 2	Positive
XLY	0.2111	No	Not tested	Yes (p = 0.0003)	Lag 2	Negative
Crude WTI	–	–	Not tested	Yes (p = 0.0087)	Lag 1	Negative
DXY	–	–	Not tested	Yes (p = 0.0098)	Lag 1	Negative
BND	–	–	Yes (p = 0.0013)	Not tested	Lag 1	Positive

RISK ON RISK OFF

Ticker	Name	Risk Regime	Justification
DXY	U.S. Dollar Index	**Risk-Off**	Investors tend to move into the U.S. dollar during global uncertainty or financial stress, making it a traditional safe haven.
CL=F	Crude Oil WTI Futures	**Risk-On**	Oil prices typically rise with increased industrial activity and global growth, declining during contractions.
XLY	Consumer Discretionary Select Sector	**Risk-On**	Represents consumer spending on non-essential goods, which accelerates during economic expansions.
XLI	Industrial Select Sector	**Risk-On**	Highly sensitive to the economic cycle and capital investment trends.
XLB	Materials Select Sector	**Risk-On**	Reflects demand for basic materials, which increases during economic expansions.
VGK	Vanguard FTSE Europe ETF	**Risk-On**	Tracks European equities; global equities are favored in optimistic market conditions.
IWM	iShares Russell 2000 ETF	**Risk-On**	Small-cap equities are growth-sensitive and highly volatile, typically outperforming during risk-on periods.
XLV	Health Care Select Sector	**Risk-Off**	Health care is a defensive sector; demand remains steady even in economic downturns due to its essential nature.

Analyzing the price movements of SPY and their connections with other financial indices through advanced statistical and machine learning techniques, such as Vector Error Correction Models (VECMs), Long Short- Term Memory (LSTM) networks, and Hidden Markov Models (HMMs), offers a thorough understanding of market dynamics and future trend forecasting. The charts and data presented reveal the complex interactions between SPY and indices like XLY, XLI, XLB, VGK, IWM, CRUDE, DXY, and XLV, highlighting key factors that affect SPY's behavior in both the short and long run.

The initial chart illustrates how accurately LSTM models can predict SPY prices from 2022 to 2024, while the subsequent chart presents the segmentation of SPY's price movements into various market regimes—bull, bear, and neutral—using HMM analysis over the same timeframe. The VECM assessment shows that lagged variables of SPY and other indices are essential predictors of SPY's present movements. For example, lagged values such as d SPY 2, d XLY 2, d XLI 2, d XLB 2, among others, display statistically significant coefficients with low p-values, emphasizing their relevance in explaining SPY's price behavior.

Error correction terms (like EC1) further underscore long-term equilibrium relationships between SPY and other indices, indicating that deviations from equilibrium are rectified over time. These statistical find- ings lay the groundwork for feature selection in machine learning models like LSTMs and HMMs. The LSTM model utilizes these significant variables to forecast SPY prices with impressive accuracy. By including lagged values of SPY and associated indices as input features, the LSTM captures both temporal dependencies and interactions between variables.

The model's capacity to closely align predicted prices with actual values underscores its effectiveness in modeling intricate financial time-series data. The incorporation of attention mechanisms within the LSTM framework enhances its performance by concentrating on the most pertinent aspects of the input sequence, leading to improved interpretability and precision. Additionally, hyperparameter optimization ensures the model generalizes effectively across training and testing datasets while minimizing the risk of overfitting.

The HMM analysis complements the LSTM method by offering probabilistic insights into market regimes. By representing SPY price movements as shifts between hidden states—bull, bear, and neutral markets—the HMM captures underlying structures that influence market behavior. The segmentation illustrated in the second chart reveals how HMMs categorize periods of prolonged upward trends (bull markets), downward trends (bear markets), and sideways movements (neutral markets).

These classifications are invaluable for grasping market sentiment and making well-informed investment choices. For instance, during a forecasted shift from a neutral to a bearish regime, investors can lessen their equity exposure or increase hedging positions to lessen potential losses.

VIII. Future Outlook: Policy Changes

Policy Relevance and Implications for Regulatory Risk Monitoring

Here is a draft written in active voice, aligned with the theme and findings of your paper "Assessing the Influence of Key Sectoral ETFs on Stock Market Performance: A Comprehensive Analysis of SPY Performance":

The findings of this study hold important implications for regulatory authorities and policymakers focused on financial stability and systemic risk management. By identifying how key sectoral ETFs and macroeconomic factors influence the SPY ETF and underlying market regimes, this research equips regulators with empirical insights to enhance risk monitoring frameworks.

Our integrated VECM-LSTM-HMM approach reveals dynamic interactions and latent market states that can signal emerging vulnerabilities in the equity market. For example, the ability of Hidden Markov Models to detect regime shifts—such as transitions between bull and bear markets—provides early warnings that regulators can incorporate into macroprudential surveillance systems. This enhances the detection of periods of elevated volatility or market stress, enabling timelier policy responses.

Moreover, understanding the lead-lag relationships and cointegration among sectoral ETFs and broader market indices supports the design of targeted regulatory interventions. Regulators can monitor sector-specific shocks that potentially propagate systemic risks through interconnected equity instruments like ETFs. This knowledge proves valuable when evaluating the stability of ETFs during market turbulence, mitigating concerns stemming from herd behavior or rapid liquidity withdrawals documented in episodes such as the 2018 Volmageddon event.

The predictive power of the machine learning models further enables scenario analysis and stress testing under different macro-financial conditions, facilitating more resilient portfolio risk management strategies for institutional investors. Consequently, regulators can promote transparency and liquidity safeguards that prevent flash crashes and systemic disruptions linked to algorithmic trading and ETF flows.

In sum, this research supports proactive regulatory risk monitoring and macroprudential strategies by delivering a rigorous and interpretable framework to understand ETF-market dynamics, forecast regime changes, and anticipate risks in an increasingly complex and interconnected financial ecosystem.

IX. Conclusion

This multi-model integration, which connects econometric models with machine learning paradigms, is a groundbreaking method for deciphering financial market behaviour. The capacity to extract significant signals from high-dimensional, noisy, and frequently nonlinear financial information is what makes such a hybrid technique valuable. In the context of mean-reverting behaviours seen in equities markets, we may detect short-term deviations and long-term equilibria by utilising Vector Error Correction Models (VECM), which also guarantee that cointegration among variables is upheld. In relation to SPY and related sectoral ETFs like XLY (Consumer Discretionary), XLI (Industrials), and XLB (Materials), as well as macroeconomic indices like VGK (Europe ETF), IWM, and DXY (Dollar Index) (Russell 2000), the model can distinguish sector-specific impulses that exert dominant influence under varying market conditions.

Concurrently, these discovered linkages are taken advantage of by the Long Short-Term Memory (LSTM) network, which is ideal for managing temporal sequences and captures nonlinear dependencies that conven- tional models could miss. The LSTM is further enhanced to dynamically weigh the significance of many lagged variables by adding attention processes, which facilitates better understanding and decision-making. This method is especially helpful during periods of market volatility, when the relative importance of macroe- conomic factors might change significantly between regimes. For instance, compared to times of economic stability, the relative influence of bond yields or oil costs on SPY is significantly greater during inflation- ary cycles. With this dynamic reweighting, LSTM predictions are more in line with actual asset repricing processes and investor behaviour.

Moreover, a probabilistic regime-switching element is added to the analytical framework through the use of Hidden Markov Models (HMMs). By grouping market conditions into discrete regimes, usually classified as bull, bear, or neutral, HMMs enable us to predict the likelihood of entering a particular regime in addition to describing past market activity. Interpretability is improved by the regime categorisation becoming more rooted in economic reality when VECM-based residuals or macro-financial elements are utilised as inputs for HMMs. Dynamic asset allocation strategies are supported by this synergy. An investor may decide to switch from cyclical sectors like XLY and XLI to more defensive allocations like XLU (Utilities) or GLD (Gold ETF) if there is a strong likelihood that the market will shift to a bear market regime.

Both algorithmic and discretionary investors can benefit from the careful blending of these models. Regime probabilities can be used by portfolio managers to timing entry/exit based on expected volatility clusters, hedge risk more successfully with options, and adjust exposure across sector ETFs. Furthermore, by connecting model projections to variations in VaR (Value-at-Risk) and Conditional VaR across various market conditions, this system facilitates risk budgeting. Depending on the state of the market, algorithmic trading systems can use the insights from regime classification to adjust trading aggression, re-calibrate signal thresholds, or alternate between mean-reversion and trend-following techniques.

In conclusion, the VECM-LSTM-HMM triangle provides a thorough and flexible toolkit for managing the intricate linkages between macroeconomic variables, sector ETFs, and SPY. Through the alignment of predictive analytics with actual market dynamics, this hybrid methodology not only improves forecasting accuracy but also deepens the strategic understanding of investment decisions.

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