International Journal of Education Studies and Social Science Research

Volume: 01, Issue: 04 July - August 2026

ISSN 3139-4647

A MULTIVARIATE AUTOREGRESSIVE FRAMEWORK FOR ESTIMATING S & P 500 FUTURES

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Received: 31/07/2026 Accepted: 09/08/2026 Published: 15/08/2026

ABSTRACT

This study aims to model and estimate the behavior of S&P 500 index futures through an econometric framework that moves from multiple linear regression (OLS) to a first-order autoregressive specification AR (1). Using daily historical series for the period between May and June 2026—a period without precedent globally due to the United States–Iran conflict—the influence of West Texas Intermediate (WTI) crude oil and gold futures was analyzed as explanatory variables. The results of the baseline model indicate a moderate explanatory power ($R^2 = 0.632$), but with evidence of positive serial autocorrelation ($DW = 1.409$) that compromises the efficiency of the estimators. The transition to the AR (1) model proved essential, achieving a better fit ($R^2 = 0.666$) and, more importantly, correcting residual dependence by reaching a Durbin–Watson statistic of 2.164. The findings suggest that, based on the autoregressive model obtained to estimate the behavior of S&P 500 index futures, although the independent variables are statistically significant, the temporal persistence of the index itself is the determining factor for obtaining stochastically neutral residuals.

Keywords: Futures, S&P 500, Financial Forecasting.

1.0 INTRODUCTION

In the architecture of modern finance, stock index estimation constitutes the core of risk management and strategic asset allocation. The inherent volatility of global markets, exacerbated by energy supply shocks and fluctuations in reserve asset demand, requires models that go beyond simple univariate analysis. The ability to capture the interdependence between energy sectors and safe-haven assets is vital for mitigating systemic risks (Jackson & Pernoud, 2021). This analysis addresses the interconnection between WTI Crude Oil, Gold, and the S&P 500. The central issue lies in determining whether the futures price structure responds efficiently to exogenous variables or if it exhibits a temporal inertia that should be modeled using autoregressive components (Lee, 2025). This study aims not only for statistical accuracy but also for the validation of impulse transmission theories in a high-uncertainty environment.

1.1 General Objective

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Model and estimate the value of the S&P 500 futures using multiple linear regression and autoregressive models to quantify the predictive capacity of energy and safe-haven assets, ensuring robustness through econometric diagnostic tests.

1.2 Specific Objectives

1. To structure a historical database based on records from Investing.com (May-June 2026) for the variables S&P 500, WTI, and Gold (Investing.com, 2026).
2. To compare the technical performance of the Ordinary Least Squares (OLS) model with the AR (1) model, specifically evaluating the correction of serial autocorrelation.
3. To validate the assumptions of independence (Durbin-Watson), constant variance (Breusch-Pagan), and absence of multicollinearity (VIF) to ensure the integrity of statistical inferences.

2.0 THEORETICAL FRAMEWORK

2.1 Fundamentals of Market Efficiency and Asset Modeling

The architecture of contemporary financial theory and portfolio engineering is grounded in the Efficient Market Hypothesis (EMH). From a senior research perspective, EMH should not be understood merely as a descriptive postulate but as a normative framework and strategic reference point for asset modeling (Gabaix & Koijen, 2021). In this context, efficiency implies that the prices of financial instruments act as signals that incorporate, in an immediate, comprehensive, and unbiased manner, all available information. This fundamental premise drives the convergence of price toward intrinsic value, systematically eliminating pure arbitrage opportunities in a perfect competition environment (Kyle, 2019). For asset modeling, EMH establishes a standard of fair value upon which derivative valuation models and risk management strategies are built, assuming that any deviation from equilibrium is transient and caused by the arrival of new stochastic information (Bianchi, Angelini, Frezza & Pianese, 2025). However, a critical analysis from the econometrics of capital markets reveals that the immediate incorporation of information is often an idealization that omits real market frictions. These frictions—including limitations in liquidity depth, information asymmetries, transaction costs, and institutional restrictions on arbitrage—generate a dynamic in which price adjustments are not instantaneous but rather part of a continuous process (Buccheri, Corsi & Peluso, 2021).

The existence of these operational barriers justifies the imperative shift from linear and static models to multivariate and persistent approaches. Persistence, understood as the long-term memory in return and volatility time series, suggests that informational shocks have a temporal structure that simplistic models fail to capture. Therefore, the challenge is not to refute the EMH but to model short-term inefficiencies using multivariate tools that can isolate market noise from fundamental signals (Pradhan, Jena & Basel, 2026; Yaya et al., 2021). This inherent

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complexity in price formation demands that financial modeling abandon the unidimensional view of isolated assets. In a globalized financial ecosystem, macroeconomic variables, systemic liquidity, and agents' expectations interact in a nonlinear manner. The need to capture these interactions motivates the use of systems of equations and vector autoregressive models that recognize interdependence among different asset classes (Aste & Controzzini, 2025; Awiszus et al., 2023).

This conceptual shift is fundamental: if markets were perfectly efficient in the strong sense, modeling persistence would lack predictive value. However, since real-world frictions distort the flow of information, it becomes necessary to employ specific valuation mechanisms that link present value with future expectations. The Cost of Carry model—which relates the current price to future financing and storage costs—serves as the key technical link in this framework (Wu & Xiong, 2025; Ederington et al., 2021).

2.2 Theory of Pricing in the Futures Market and the Cost of Carry Model

The determination of prices in the futures market represents one of the most rigorous processes in capital market theory, based on the parity between the spot value and the futures value. This relationship is not merely a subjective projection of upcoming prices, but a technical structure defined by the absence of arbitrage. The Cost of Carry model acts as the gravitational mechanism that links the current price of an asset with its agreed-upon price for a future date, integrating into a single metric the costs associated with the physical or financial possession of the asset during a specified period (Mondello, 2023; Poncet & Portait, 2022). This model is crucial because it enables the decomposition of price formation into tangible components, facilitating operational planning and the identification of disalignments that could indicate temporary inefficiencies or liquidity pressures (Liang, Yang & Han, 2024).

2.3 Analytical Breakdown of the Cost of Carry

The analytical breakdown of the Cost of Carry reveals an interconnected component structure that responds dynamically to macroeconomic conditions (Leistikow & Chen, 2019; Ernst & Häcker, 2025):

• **Financing Cost (Interest Rate):** Represents the opportunity cost of capital needed to acquire the asset in the spot market. In a developed capital markets environment, this component reflects the risk-free rate plus a liquidity premium. It is the factor that incorporates the time value of money within the futures curve; a change in monetary policy immediately alters this cost, shifting the maturity structure of derivative contracts.

• **Storage Costs:** Particularly relevant in the commodities market, this component includes logistical expenses, insurance, and maintenance costs to preserve the physical integrity of the asset. This cost is a function of the supply and demand for physical infrastructure, and its

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variability can lead to extreme situations of contango or backwardation, impacting the profitability of hedging strategies.

• **Inflation Expectations and Energy Variables:** Oil, as a fundamental macroeconomic variable, acts as a catalyst that redefines operational costs and price expectations throughout the economy. An increase in energy prices not only raises the direct storage costs but also filters through the supply chain, affecting inflation expectations. This shock alters the carry of the asset by modifying both the financing component and the projected operational costs of companies.

From a market theory perspective, the impact of oil is differentiated: while an energy price increase may represent a rise in the future value of a commodity producer's inventory, for an industrial consumer it signifies an erosion of margins that must be offset through derivative instruments. This mechanism of individual price formation is the first link in a chain of systemic interconnections (Qin, 2020). The dynamics of the Cost of Carry do not operate in a vacuum; fluctuations in crude oil prices or interest rates reverberate through equity and safe-haven markets, creating a network of correlations that define the overall risk structure (Dai & Wu, 2024).

2.4 Systemic Interconnection: WTI, S&P 500, and the Role of Gold

Modern institutional portfolio management requires a deep understanding of cross-asset correlations among energy assets, stock indices, and reserve assets. The interconnectedness of global markets implies that movements in the price of West Texas Intermediate (WTI) crude oil transcend the energy sector to become a leading indicator of production costs at the macroeconomic level (Kammoun & Belkhir, 2025).

As a critical input, oil exerts direct pressure on the cost structure of corporations comprising the S&P 500. Analytical evidence suggests a persistent negative correlation in this regard: a sustained increase in energy prices raises operating expenses and reduces net profit margins, ultimately leading to a contraction in market valuations in equities (Lu et al., 2024; Khan, Qureshi & Davidsen, 2020).

Facing this dynamic of cost pressure, gold emerges as a diversification component with an extremely sophisticated dual behavior. Traditionally, its role as a safe-haven or refuge asset is activated during periods of systemic uncertainty, geopolitical crises, or collapse in confidence in fiduciary assets (Triki & Maatoug, 2021). In these scenarios, gold disconnects from risk assets and acts as a store of value. However, in contexts of aggressive monetary expansion and excess liquidity, gold may show positive correlations with equities. This phenomenon occurs when an inundation of capital in financial markets erodes the relative value of currencies, driving up the prices of all real and financial assets simultaneously, prompting investors to reevaluate gold's effectiveness as a hedge during high liquidity phases (Gomis, Shi & Tan, 2022; Kumar, 2025).

For an investor, these observations translate into critical strategic implications for portfolio design and Value at Risk (VaR) management (Sunchalin et al., 2019; Živkov et al., 2022):

• **Hedging Strategies**: The negative correlation between WTI and the S&P 500 enables the implementation of cross-hedging strategies. A equity portfolio highly sensitive to energy costs can mitigate its exposure through long positions in crude futures, offsetting losses in corporate margins with gains in the commodities sector.

• **VaR Adjustments During Liquidity Periods:** During phases of monetary expansion, the loss of the traditional negative correlation between gold and equities increases the portfolio's VaR, as diversification becomes less effective against systemic shocks that impact global liquidity. Therefore, the manager must adjust hedging ratios to compensate for this increase in asset covariance.

• **Monitoring Production Costs:** Using WTI as a leading indicator allows analysts to anticipate changes in corporate profit expectations before they are reflected in quarterly reports, enabling tactical rebalancing of the portfolio toward less energy-intensive sectors.

However, the implementation of these hedging and arbitrage strategies cannot be based on qualitative intuitions. The validity of these correlation relationships must be confirmed through rigorous statistical analysis. The observed interconnectedness between WTI, the S&P 500, and gold is only actionable if it can be demonstrated that it is not a product of chance or model misspecification, which inevitably leads us to the necessity of a robust econometric framework (Zaman, 2025).

2.5 Econometric Architecture and Validation of Regression Models

The validation of any financial theory, no matter how elegant, resides in the integrity of its empirical verification. In the econometrics of capital markets, the Ordinary Least Squares (OLS) model is the fundamental tool for estimating the functional relationships between variables. However, the explanatory power of OLS strictly depends on the fulfillment of Gauss-Markov classical assumptions to produce the best linear unbiased estimators (BLUE). These include linearity in parameters, the existence of a random sample, and the absence of perfect multicollinearity among explanatory variables. Additionally, homoscedasticity and the lack of autocorrelation in errors are assumed, ensuring efficiency and unbiasedness (Hansen, 2022; Baissa & Rainey, 2020).

For estimators to be the best linear unbiased estimators (BLUE), the model residuals must constitute "white noise." White noise implies that the errors are independent, identically distributed random variables with zero mean and constant variance. If the residuals contain

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systematic information or predictable patterns, this indicates that the model has failed to capture some essential market dynamics, invalidating the inferences and investment strategies derived from it (Francq & Zakoian, 2019; Moews, Herrmann & Ibikunle, 2019). Financial persistence, characteristic of price and return series, often violates the independence assumption, generating autocorrelation phenomena that distort the variance of the estimators. To ensure the robustness of the analysis, a rigorous set of diagnostic tests must be employed (Morosan et al., 2025; Mursalov et al., 2025):

- Durbin-Watson (DW) and Serial Dependence.

This test is the primary critical filter for identifying the presence of first-order autocorrelation in the residuals. In an ideal market efficiency environment, errors from one period should not provide information about errors in the following period. The Durbin-Watson statistic operates within a range of 0 to 4, where a value of 2.00 indicates optimal independence or absence of serial dependence. Significant deviations toward 0 suggest positive autocorrelation (persistence), while deviations toward 4 indicate negative autocorrelation (Kumar, 2023). From an efficiency perspective, a DW value far from 2.00 suggests the existence of uncaptured information patterns, implying that the model is inefficient and that conclusions about the relationship—for example, between oil and stocks—could be biased by data inertia.

- Breusch-Pagan and Variance Stability.

Heteroscedasticity, or the constancy of the variance of errors, is vital for the reliability of statistical significance tests. The Breusch-Pagan test is used to detect heteroscedasticity, a very common phenomenon in finance where volatility tends to cluster. If the variance of the errors is not constant, the standard errors calculated by Ordinary Least Squares (OLS) are incorrect, invalidating t-tests and confidence intervals (Osho & Oloyede, 2024). Practically, this means we might erroneously conclude that the price of gold has a significant impact on the S&P 500 when, in reality, this significance is an artifact of uncontrolled volatility in the model. Therefore, the Breusch-Pagan diagnostic acts as a safeguard against spurious conclusions in highly turbulent market environments.

- Variance Inflation Factor (VIF) and Multicollinearity.

In multivariate models attempting to explain the stock market using multiple macroeconomic indicators (such as WTI, gold, and interest rates), multicollinearity poses a risk. VIF is the technical tool used to determine whether independent variables are so highly correlated that it becomes impossible to isolate each variable's individual effect on the dependent variable (Kyriazos & Poga, 2023). A high VIF indicates that the variance of the coefficients is artificially inflated, which reduces model precision and complicates the interpretation of which factor is truly driving stock index returns. A low VIF guarantees that the hedging strategy is

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based on distinct factors rather than statistical redundancy, which could collapse if market regimes change.

In summary, econometric architecture is not merely an academic exercise but a necessary technical audit for financial survival. Robust validation—ensuring white noise and passing DW, Breusch-Pagan, and VIF tests—is what allows us to transform theoretical observations about the cost of carry and asset interconnection into legitimate, mathematically grounded conclusions. Only through this statistical rigor can we ensure that valuation models reflect the operational reality of markets and are not just stochastic coincidences in historical data. The integration of capital theory with econometric validation sets the standard of excellence for decision-making in global financial markets (Rasyid, 2024; Keswani, Puri & Jha, 2024).

3.0 METHODOLOGY

The methodological design explained below transforms data into financial intelligence through a process of statistical refinement.

Here is the translation of the provided section:

3.1 Model Specification

Daily data corresponding to the period between May 18 and June 16, 2026, were used. It is important to note that while the Ordinary Least Squares (OLS) model employs the full sample of 22 observations ($n = 22$), the AR(1) autoregressive model uses only 21 observations ($n = 21$) due to the loss of the first observation necessary to incorporate the lagged variable S&P 500 ($t-1$).

1. Multivariate Model (OLS):
2. Autoregressive Model AR (1):

3.2 Validation Procedure

The validation of the models was conducted through residual analysis. To assess the presence of heteroscedasticity, the Breusch-Pagan test was applied. This test involves estimating an auxiliary regression using the squared residuals as the dependent variable and calculating the "$n \times R^2$" statistic, where R^2 is the coefficient of determination of that regression. Subsequently, this statistic was compared with the critical value from the Chi-square (χ^2) distribution to determine if there was evidence of heteroscedasticity in the residuals.

Fundamentals of Estimation In the architecture of modern financial econometrics, Modeling equity assets requires a deep understanding of macroeconomic interdependencies and market microstructure. This analysis is situated within the time horizon of May to June 2026, a period during which the convergence between safe-haven assets and energy variables determines the

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volatility of the S&P 500. The relationship between Gold, WTI Crude Oil, and the benchmark index is not merely correlational but indicative of inflation expectations, operational costs, and global capital flows.

For this study, variables have been rigorously defined within a window of daily data observation:

- Dependent Variable (Y): S&P 500 futures, capturing the market's aggregate expectation.
- Independent Variables (X): WTI Crude Oil futures (proxy for supply pressures and input costs) and gold futures (indicator of risk aversion and inflation hedging).

From a strategic perspective, the use of futures data rather than spot prices is fundamental: futures incorporate stochastic memory and more efficiently discount risk premiums and interest rate expectations. This methodology enables a transition from descriptive analysis toward operational forecasting capacity in complex capital markets.

3.3 Multiple Linear Regression Model (Normal Model)

The initial stage of the analysis involves specifying a multiple linear regression model using Ordinary Least Squares (OLS). This approach establishes the baseline to identify the direct sensitivity of S&P 500 futures to shocks in commodities, assuming the estimators are unbiased under ideal conditions.

• Diagnostic statistics for this initial model reveal considerable statistical strength: • Explanatory Power: The model achieves an R^2 of 0.633, indicating that 63.3% of the index's variance is captured by the selected predictors. The adjusted R^2 (0.594) confirms that including these variables provides meaningful explanatory value, avoiding overfitting. • Global Significance: With an F-significance of 7.35 x 10^(-5), the model demonstrates a statistical discrimination capacity well above that of a simple mean model, allowing rejection of the null hypothesis of zero coefficients with confidence exceeding 99%.

Table 1: Normal Model Coefficients (OLS)

Variable	Coefficient	Standard Error	t-Statistic	P-value
Intercept	6396.34	368.43	17.36	0.0000
Crude Oil WTI	-9.99	1.86	-5.38	0.0000
Gold Futures	0.46	0.10	4.65	0.0002

Source: Author's own elaboration based on the results of the econometric estimations.

The analysis of the coefficients provides key information for interpreting the model: the negative elasticity with WTI (-9.99) reflects how an increase in energy costs erodes the margins of S&P 500 corporations. Meanwhile, the coefficient for Gold (0.46) suggests an asset revaluation dynamic; in the context of 2026, the appreciation of the precious metal does not indicate panic but rather a liquidity expansion that nominally increases the value of equities.

3.4 First-Order Autoregressive Model AR(1)

Despite fitting a normal model, financial series often exhibit stochastic inertia. To refine the estimation and correct for bias due to omitted variables, a First-Order Autoregressive Model AR (1) has been implemented, incorporating the lag of the S&P 500 (T-1) as an explanatory variable. By integrating temporal persistence, the model's efficiency improves significantly:

- **Model Fit:** The R^2 increases to 0.666, enhancing forecast accuracy.
- **Persistence (Lagged S&P):** The coefficient of 0.288 indicates that the market possesses a "memory," where nearly 29% of the current price is conditioned by the previous closing.

Table 2: AR (1) Model Coefficients

Variable	Coefficient	Standard Error	t-Statistic	P-value
Intercept	4510.84	1216.78	3.71	0.0018
S&P 500 (T-1)	0.288	0.176	1.64	0.1200
Crude Oil WTI	-8.00	2.44	-3.28	0.0044
Gold Futures	0.354	0.116	3.05	0.0073

Source: Author's own elaboration based on the results of the econometric estimations.

Strategic Interpretation: A key finding is the change in sensitivity to oil, which shifts from -9.99 to -8.00. This reduction indicates that a portion of the negative impact originally attributed to WTI was, in fact, due to downward inertia inherent in the market itself. This adjustment is essential as it prevents the overestimation of energy risk.

Model Validation Part I: Autocorrelation and Durbin-Watson Test

To ensure that our estimators are the most efficient (BLUE - Best Linear Unbiased Estimator), it is imperative that the residuals do not exhibit autocorrelation. The presence of temporal dependence would invalidate the reliability of the standard errors. Using the Durbin-Watson (DW) statistic, we evaluate the independence of the errors in both specifications:

Table 3: Autocorrelation Diagnostic (Durbin–Watson Test)

Model	Calculated DW Value	Residual Status
Normal Model	1.409	Moderate positive autocorrelation

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Model	Calculated DW Value	Residual Status
AR(1) Model	2.164	No autocorrelation (Optimal)

Source: Author's own elaboration based on the results of the econometric estimations.

The transition to the AR (1) model shifts the DW statistic toward the neutral zone (~2.0), eliminating residual correlation. This ensures that the information captured by the model is purely stochastic ("white noise"), allowing for valid statistical inference.

Model Validation Part II: Homoscedasticity and Breusch-Pagan Test

Homoscedasticity, or constant variance of errors, is a prerequisite for the validity of hypothesis tests. Unstable variance (heteroscedasticity) would compromise the accuracy of the obtained p-values. We applied the Breusch-Pagan test, analyzing the regression of squared residuals (Pj):

- Calculated Statistic (n X R^2): 0.283
- Critical Value (Chi-Square with 2 degrees of freedom): 5.99
- P-value of the Test: 0.884

Since $0.283 < 5.99$ and the p-value is significantly higher than 0.05, the null hypothesis of homoscedasticity is accepted. The stability of the residual variance confirms the structural robustness of our model.

Model Validation Part III: Multicollinearity and Variance Inflation Factor (VIF)

Finally, we assess the risk of redundancy among predictors. A high correlation between Gold and WTI could artificially inflate the variance of their coefficients, making it difficult to isolate their individual effects. It is essential to note that, according to the auxiliary regression data, the R^2 for the intercorrelation among independent variables is 0.319. Based on this value, we calculated the VIF (Variance Inflation Factor).:

A VIF of 1.468 (well below the critical threshold of 10) ensures that there is no multicollinearity conflict. The absence of redundancy allows for full confidence in the individual significance of each predictor and its ability to produce a robust forecast.

3.5 Conclusions and Price Projection

The rigor of the statistical validation confirms that the AR (1) model satisfies the Gauss-Markov assumptions, positioning it as the BLUE estimator (Best Linear Unbiased Estimator) for forecasting the future of the S&P 500. The combination of external factors (commodities) and the market's own inertia provides a highly reliable decision-making framework.

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3.6 Practical Application: Next Day Forecast

Using the closing values as of June 16, 2026, the estimation equation for the following day is specified as follows:

By substituting the current market values, with information as of May 16, 2026:

- Intercept: 4510.84
- S&P 500 (T-1): 7603.50
- WTI Futures: 76.80
- Gold Futures: 4359.51

Therefore, the operational conclusion is as follows: The model projects a future S&P 500 price of 7,633.25 for the upcoming session. This result underscores the importance of monitoring market inertia and gold resilience. The methodology presented here not only predicts price levels but also provides a critical sensitivity metric for risk management in portfolios with high equity exposure.

4.0 RESULTS

The quantitative results demonstrate the technical superiority of the autoregressive approach in capturing market reality.

Table 4: Statistics of Model 1: Multiple Linear Regression

Variable	Coefficient	Standard Error	t-Statistic	P-value
Intercept	6396.34	368.43	17.36	4.10×10^{-13}
Crude Oil WTI	-9.99	1.85	-5.37	3.44×10^{-5}
Gold Futures	0.458	0.098	4.65	1.73×10^{-4}

Model Statistic	Value
R^2	0.632
Observations	22
Durbin–Watson (DW)	1.409
F-statistic Significance	7.35×10^{-5}

Source: Author's own elaboration based on the results of the econometric estimations.

Table 5: Statistics of Model 2: AR (1) Autoregressive Model

Variable	Coefficient	Standard Error	t-Statistic	P-value
Intercept	4510.84	1216.78	3.71	0.0017
S&P 500 (T-1)	0.288	0.176	1.63	0.1199

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Variable	Coefficient	Standard Error	t-Statistic	P-value
Crude Oil WTI	-8.00	2.44	-3.27	0.0044
Gold Futures	0.354	0.116	3.04	0.0072

Model Statistic	Value
R^2	0.666
Observations	21
Durbin–Watson (DW)	2.164

Source: Author's own elaboration based on the results of the econometric estimations.

4.1 Analysis of Impact and Economic Relevance

The AR (1) model reveals that WTI maintains a robust negative relationship (-8.00), confirming the influence of energy costs. Gold has a coefficient of 0.354; however, from a research perspective, its low economic elasticity should be highlighted. With the index trading near 7,500 points, a one-unit increase in gold barely impacts the S&P 500 by 0.004%, suggesting that, although statistically significant, gold's relevance for high-frequency arbitrage is marginal in this period.

4.2 Robustness Diagnosis

The primary justification for the AR (1) model does not lie in the marginal increase in R^2 (from 0.63 to 0.66), but in the significant correction of autocorrelation. Model 1 showed a Durbin-Watson (DW) value of 1.409, indicating positive serial dependence that invalidated the t-test efficiency. The AR (1) model increased the DW to 2.164, reaching the ideal residual independence range. Additionally, the Breusch-Pagan test yielded a value of 0.2836 (below the critical 5.99 threshold), confirming homoscedasticity. The Variance Inflation Factor (VIF) of 1.46 rules out multicollinearity issues, validating coefficient stability.

5.0 CONCLUSION AND DISCUSSION

According to the analysis in this research, it is concluded that the AR (1) model is the optimal specification for short-term estimation of S&P 500 futures. The inclusion of the lag of the index neutralizes market inertia, allowing macroeconomic variables (WTI and Gold) to be estimated without bias from serial autocorrelation. Despite the statistical robustness, 33.4% of the variance remains unexplained, which is consistent with the Efficient Markets Hypothesis and the presence of unpredictable stochastic shocks. A limitation acknowledged is the sample size; therefore, future research should incorporate treasury bond returns (T-bills) and extend the time horizon to capture broader monetary policy cycles, among other guidelines.

REFERENCES

1. Aste, T., & Controzzini, D. (2025). Multivariate network modeling: A novel approach to corporate bond pricing. Data-Driven Modelling, 1, 67–99. https://doi.org/10.1142/S3029101125500024
2. Awiszus, K., Knispel, T., Penner, I., Svindland, G., Voß, A., & Weber, S. (2023). Modeling and pricing cyber insurance: Idiosyncratic, systematic, and systemic risks. European Actuarial Journal, 13(1), 1-53. https://link.springer.com/article/10.1007/s13385-023-00341-9
3. Baissa, D. K., & Rainey, C. (2020). When BLUE is not best: non-normal errors and the linear model. Political Science Research and Methods, 8(1), 136-148. DOI: https://doi.org/10.1017/psrm.2018.34
4. Bianchi, S., Angelini, D., Frezza, M., & Pianese, A. (2025). From fair price to fair volatility: Towards an Efficiency-Consistent Definition of Financial Risk. arXiv preprint arXiv:2508.11649. https://arxiv.org/abs/2508.11649
5. Buccheri, G., Corsi, F., & Peluso, S. (2021). High-frequency lead-lag effects and cross-asset linkages: a multi-asset lagged adjustment model. Journal of Business & Economic Statistics, 39(3), 605-621. https://www.tandfonline.com/doi/abs/10.1080/07350015.2019.1697699
6. Dai, Z., & Wu, T. (2024). The impact of oil shocks on systemic risk of the commodity markets. Journal of Systems Science and Complexity, 37(6), 2697-2720. https://link.springer.com/article/10.1007/s11424-024-3224-y
7. Ederington, L. H., Fernando, C. S., Holland, K. V., Lee, T. K., & Linn, S. C. (2021). Dynamics of arbitrage. Journal of Financial and Quantitative Analysis, 56(4), 1350-1380. https://doi.org/10.1017/S0022109020000204
8. Ernst, D., & Häcker, J. (2025). Fundamentals and Pricing of Futures. In Derivatives: Options and Futures (pp. 45-54). Cham: Springer Nature Switzerland. https://link.springer.com/chapter/10.1007/978-3-031-85822-2_3
9. Francq, C., & Zakoian, J. M. (2019). GARCH models: structure, statistical inference and financial applications. John Wiley & Sons. https://ideas.repec.org/p/hal/journl/hal-05430939.html
10. Gabaix, X., & Koijen, R. S. (2021). In search of the origins of financial fluctuations: The inelastic markets hypothesis (No. w28967). National Bureau of Economic Research. https://www.nber.org/papers/w28967
11. Gomis-Porqueras, P., Shi, S., & Tan, D. (2022). Gold as a financial instrument. Journal of Commodity Markets, 27, 100218. https://www.sciencedirect.com/science/article/abs/pii/S2405851321000519
12. Hansen, B. E. (2022). A modern Gauss–Markov theorem. Econometrica, 90(3), 1283-1294. https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA19255
13. Investing.com. (2026). World financial markets. https://www.investing.com/markets/
14. Jackson, M. O., & Pernoud, A. (2021). Systemic risk in financial networks: A survey. Annual Review of Economics, 13, 171-202.

https://www.annualreviews.org/content/journals/10.1146/annurev-economics-083120-111540
15. Kammoun Masmoudi, W., & Belkhir, N. (2025). Cross-asset dynamics: the interplay of oil, gas, wheat, and emerging market stock index in diversified portfolios. Cogent Business & Management, 12(1), 2549508. https://www.tandfonline.com/doi/full/10.1080/23311975.2025.2549508
16. Keswani, S., Puri, V., & Jha, R. (2024). Relationship among macroeconomic factors and stock prices: cointegration approach from the Indian stock market. Cogent Economics & Finance, 12(1), 2355017. https://www.tandfonline.com/doi/full/10.1080/23322039.2024.2355017
17. Khan, A., Qureshi, M. A., & Davidsen, P. I. (2020). How do oil prices and investments impact the dynamics of firm value?. System dynamics review, 36(1), 74-100. https://onlinelibrary.wiley.com/doi/full/10.1002/sdr.1649
18. Kumar, K. (2023). Autocorrelation and heteroscedasticity in regression analysis. Journal of Business and Social Sciences, 5(1), 9-20. https://nepjol.info/index.php/jbss/article/view/72442
19. Kumar, K. (2025). Cross-Asset Correlation Shifts in Crisis Periods: A Framework for Portfolio Hedging. Journal of Data Analysis and Critical Management, 1(01), 40-51. https://jdacm.com/index.php/jdacm/article/view/58
20. Kyle, A. S. (2019). Market structure, information, futures markets, and price formation. In International agricultural trade (pp. 45-64). CRC Press. https://www.taylorfrancis.com/chapters/edit/10.1201/9780429050169-3/market-structure-information-futures-markets-price-formation-albert-kyle
21. Kyriazos, T. and Poga, M. (2023) Dealing with Multicollinearity in Factor Analysis: The Problem, Detections, and Solutions. Open Journal of Statistics, 13, 404-424. https://doi.org/10.4236/ojs.2023.133020
22. Liang, J., Yang, D., & Han, Q. (2024). Tail risk aversion and backwardation of index futures. Quantitative Finance, 24(3-4), 387-407. https://doi.org/10.1080/14697688.2024.2330612
23. Lee, L. (2025). Price as a Construct of Time: the Temporal Structure of Contemporary Markets. Available at SSRN 6223338. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=6223338
24. Leistikow, D., & Chen, R. R. (2019). Carry cost rate regimes and futures hedge ratio variation. Journal of Risk and Financial Management, 12(2), 78. https://www.mdpi.com/1911-8074/12/2/78
25. Lu, Q., Umair, M., Qin, Z., & Ullah, M. (2024). Exploring the nexus of oil price shocks: Impacts on financial dynamics and carbon emissions in the crude oil industry. Energy, 312, 133415. https://www.sciencedirect.com/science/article/abs/pii/S0360544224031918
26. Moews, B., Herrmann, J. M., & Ibikunle, G. (2019). Lagged correlation-based deep learning for directional trend change prediction in financial time series. Expert Systems

with Applications, 120, 197-206. https://www.sciencedirect.com/science/article/abs/pii/S0957417418307474

27. Mondello, E. (2023). Futures, Forwards, and swaps. In Applied fundamentals in finance: portfolio management and investments (pp. 451-477). Wiesbaden: Springer Fachmedien Wiesbaden. https://link.springer.com/chapter/10.1007/978-3-658-41021-6_13
28. Morosan-Danila, L., Grigoras-Ichim, C. E., Jeflea, F. V., Filipeanu, D., & Tugui, A. (2025). Assessing the sustainability of construction companies in the digital context: an econometric approach based on financial, social, and environmental indicators. Sustainability, 17(10), 4744. https://www.mdpi.com/2071-1050/17/10/4744
29. Mursalov, M., Niemi, O., Kolomiiets, S., & Trofimenko, D. (2025). Determinants of Financial Stability in Banks: The Impact of Key Regulatory Financial Indicators. Financial Markets, Institutions and Risks, 9(2), 123-134. https://armgpublishing.com/journals/fmir/volume-9-issue-2/article-6/
30. Osho, G. S., & Oloyede, B. (2024). A generalized autoregressive conditional heteroscedasticity garch for forecasting and modeling crude oil price volatility. The Journal of Applied Business and Economics, 26(6), 39-53. https://www.proquest.com/openview/2751287ba39a5735d070086a9ab5eba9/1?pq-origsite=gscholar&cbl=38282
31. Poncet, P., & Portait, R. (2022). Futures and Forwards. In Capital Market Finance: An Introduction to Primitive Assets, Derivatives, Portfolio Management and Risk (pp. 311-352). Cham: Springer International Publishing. https://link.springer.com/chapter/10.1007/978-3-030-84600-8_9
32. Pradhan, A. A., Jena, S., & Basel, S. (2026). A Multidimensional Approach To the Measurement and Classification of Stock Market Inefficiency Across Economies. Computational Economics, 1-27. https://link.springer.com/article/10.1007/s10614-026-11315-w
33. Qin, X. (2020). Oil shocks and financial systemic stress: International evidence. Energy Economics, 92, 104945. https://www.sciencedirect.com/science/article/abs/pii/S0140988320302851
34. Rasyid, A. (2024). The Art and Science of Financial Econometrics: Applications, Challenges, and Future Directions. Advances in Economics & Financial Studies, 2(1), 44-52. https://doi.org/10.60079/aefs.v2i1.287
35. Sunchalin, A. M., Kochkarov, R. A., Levchenko, K. G., Kochkarov, A. A., & Ivanyuk, V. A. (2019). Methods of risk management in portfolio theory. Revista Espacios, 40(16), 25. https://www.revistaespacios.com/a19v40n16/19401625.html
36. Triki, M. B., & Maatoug, A. B. (2021). The Gold market as a safe haven against the stock market uncertainty: Evidence from geopolitical risk. Resources Policy, 70, 101872. https://www.sciencedirect.com/science/article/abs/pii/S030142072030903X
37. Wu, X., & Xiong, Y. (2025). A fractal market perspective on improving futures pricing and optimizing cash-and-carry arbitrage strategies. Quantitative Finance and

Volume: 01, Issue: 04 July - August 2026

ISSN 3139-4647

Economics, 9(4), 713. https://www.aimspress.com/aimspress-data/qfe/2025/4/PDF/QFE-09-04-025.pdf

38. Yaya, O. S., Ogbonna, A. E., Mudida, R., & Abu, N. (2021). Market efficiency and volatility persistence of cryptocurrency during pre-and post-crash periods of Bitcoin: Evidence based on fractional integration. International Journal of Finance & Economics, 26(1), 1318-1335. https://onlinelibrary.wiley.com/doi/abs/10.1002/ijfe.1851
39. Zaman, K. (2025). A new metric for spuriousness detection in linear models. Latest Developments Econometrics, 104, 12023-12031. https://zenodo.org/records/15563736
40. Živkov, D., Manić, S., Đurašković, J., & Gajić-Glamočlija, M. (2022). Oil hedging with a multivariate semiparametric value-at-risk portfolio. Borsa Istanbul Review, 22(6), 1118-1131. https://www.sciencedirect.com/science/article/pii/S2214845022000576

