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Posted Date: 4 February 2026

doi: 10.20944/preprints202602.0335.v1

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Article

# Hypothesis Testing and Machine Learning Approaches to Investment Risk Assessment in Romania

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## Abstract

This study proposes a hybrid framework for investment risk assessment in the Romanian equity market by integrating classical hypothesis testing with machine learning techniques. Using daily data for the BET, BET-FI, and BET-NG indices, the analysis evaluates return behavior, volatility dynamics, and return direction in an emerging market context. Classical inferential tests indicate no statistically significant structural breaks in mean returns or seasonal patterns, while volatility-related measures, particularly intraday price dispersion, exhibit consistent explanatory relevance across indices. Machine learning models, namely Random Forest and XGBoost, are applied to predict returns, short-horizon volatility, and return direction using price-based indicators, sentiment variables, and a purchasing power index (PPI). The results show that XGBoost systematically outperforms Random Forest, especially for return direction and short-term volatility prediction, highlighting the importance of nonlinear modeling in capturing complex market dynamics. However, overall predictive performance remains moderate, reflecting the inherent limits of predictability in volatile and structurally evolving markets. The inclusion of purchasing power information improves interpretability and, in selected cases, volatility prediction at the sectoral level, but does not materially alter aggregate market predictability. Overall, the findings underscore the complementarity of hypothesis testing and machine learning approaches and provide evidence that investment risk in the Romanian equity market is primarily volatility-driven rather than return-driven.

**Keywords:** financial risk; machine learning; hypothesis testing; risk management

**MSC:** 62P05; 62F03; 68T05

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## 1. Introduction

Investment risk assessment is a fundamental topic in finance, as accurate measurement and prediction of risk underpin portfolio allocation, capital budgeting, and financial stability analysis. This challenge is particularly pronounced in emerging markets, where structural transformation, institutional development, and exposure to external shocks contribute to heightened uncertainty. Romania, as a European Union member state with a post-transition economic background, exemplifies these dynamics. Despite sustained economic growth over the past two decades, the Romanian financial system remains sensitive to macroeconomic imbalances, capital flow volatility, and regional and global shocks, characteristics commonly associated with emerging markets [1,2].

The academic literature on investment risk has traditionally relied on statistical and econometric frameworks grounded in hypothesis testing and linear factor models. Seminal contributions such as the Capital Asset Pricing Model and its multifactor extensions emphasize the role of systematic risk factors in explaining asset returns and investment risk [3,4]. Subsequent research has extended these frameworks by incorporating macroeconomic variables, firm-level fundamentals, and financial ratios to assess risk exposure across markets and sectors [5,6]. These approaches offer clear interpretability

and theoretical coherence, enabling researchers to test economic hypotheses and draw statistically grounded conclusions.

However, a substantial body of literature has questioned the adequacy of classical linear models, especially in environments characterized by nonlinearity, structural breaks, and regime changes, features frequently observed in emerging financial markets [7]. Empirical evidence suggests that strict parametric assumptions and linear specifications may fail to capture complex interactions among risk factors, leading to reduced predictive performance during periods of market stress [8]. This has fueled ongoing debate regarding the trade-off between interpretability and predictive accuracy in financial risk modeling.

In recent years, machine learning (ML) techniques have gained prominence as powerful alternatives for modeling financial risk. Algorithms such as Random Forests and gradient boosting methods, including XGBoost, can handle high-dimensional data, nonlinear relationships, and interaction effects without imposing strong distributional assumptions [9–11]. Empirical studies document that ML models often outperform traditional econometric approaches in predicting asset returns, credit risk, and financial distress [12,13]. Despite these advantages, ML methods have been criticized for their limited transparency and weaker links to economic theory, raising concerns about their suitability for decision-making and policy analysis [14].

To address these concerns, recent research has advocated for integrative frameworks that combine statistical inference with machine learning techniques. Such approaches aim to preserve the interpretability and theoretical validation provided by hypothesis testing while exploiting the predictive strength of ML models [15,16]. This line of research is particularly relevant for emerging markets, where understanding the drivers of risk is as important as achieving accurate predictions.

Motivated by these considerations, the present study develops a hybrid framework for investment risk assessment in Romania that integrates hypothesis testing with machine learning methods. Using financial data covering multiple sectors and time periods, the study first evaluates the statistical significance of key risk factors within a classical inferential framework. It then applies ML models, including Random Forest and XGBoost, to capture nonlinear patterns and enhance predictive performance. The results indicate that several theoretically motivated risk drivers are statistically significant, while ML models achieve superior accuracy compared to traditional methods. By jointly emphasizing inference, prediction, and interpretability, this study contributes to the literature on quantitative finance and provides practical insights for investment risk management in emerging and volatile financial markets.

Accordingly, this study extends the baseline framework by incorporating a purchasing power index (PPI) as a macroeconomic variable and explicitly compares inferential and predictive results before and after its inclusion. This extension allows us to evaluate whether real-economy indicators enhance investment risk assessment beyond market-based and sentiment-driven signals.

## 1.1. Literature Review

### 1.1.1. Investment Risk Assessment and Financial Volatility in Emerging Markets

The assessment of investment risk in emerging markets has been widely examined in the literature due to the heightened levels of volatility, institutional fragility, and exposure to external shocks that characterize these economies. A central theme in this strand of research concerns the development of risk assessment frameworks capable of capturing macroeconomic instability, market integration, and financial contagion. Empirical evidence suggests that emerging markets exhibit asymmetric volatility patterns and stronger sensitivity to global financial cycles compared to developed markets, which complicates traditional risk modeling approaches [17,18].

Several studies emphasize the role of macroeconomic uncertainty and financial openness in shaping investment risk. Volatility spillovers from developed markets, exchange rate fluctuations, and sudden capital flow reversals are frequently identified as dominant risk drivers in emerging economies [19]. These dynamics are often amplified by weaker institutional frameworks, limited

market depth, and lower liquidity, which increase the vulnerability of asset prices to external shocks [20].

A substantial body of research documents that financial volatility in emerging markets is not only higher on average, but also more persistent and regime dependent. Structural breaks, policy shifts, and crisis episodes tend to induce abrupt changes in volatility dynamics, rendering constant-parameter models inadequate for risk assessment [21]. As a result, linear models calibrated under stable conditions often fail to capture tail risks and extreme market movements, particularly during periods of global financial stress.

Another important characteristic of emerging market volatility is its asymmetric response to negative shocks. Empirical studies show that downside risk and negative returns generate disproportionately larger increases in volatility, reflecting higher risk aversion, capital flight, and liquidity constraints during downturns [22]. This asymmetry has important implications for portfolio allocation and risk management, as standard symmetric volatility measures may underestimate downside exposure.

Global risk factors also play a crucial role in shaping emerging market investment risk. Changes in global liquidity conditions, monetary policy in advanced economies, and shifts in international risk appetite have been shown to transmit rapidly to emerging equity markets, often overwhelming domestic fundamentals [23]. This external dependence increases the complexity of risk assessment and underscores the importance of models capable of capturing cross-market interdependence and time-varying correlations.

Taken together, these findings support the need for flexible and adaptive risk assessment methodologies that go beyond static linear modeling frameworks. Approaches that account for nonlinearities, regime shifts, and interaction effects are better suited to the structural characteristics of emerging markets, where volatility-driven risk transmission dominates predictable return dynamics [24]. This perspective provides the motivation for integrating advanced data-driven techniques with traditional econometric analysis in the study of investment risk.

### 1.1.2. Hypothesis Testing in Financial Risk Management

Hypothesis testing remains a cornerstone of empirical finance, particularly in the identification, validation, and interpretation of risk factors. In the context of financial risk management, hypothesis-driven econometric models are widely employed to assess the statistical significance of macroeconomic variables, financial ratios, and market-based indicators [25]. These approaches enable researchers to formalize economic theory into testable propositions and to infer structural relationships between risk drivers and investment outcomes.

Classical hypothesis testing frameworks have played a central role in the development of asset pricing and risk management models, including linear factor models, macro-financial regressions, and volatility specifications. Their appeal lies in their interpretability, statistical discipline, and ability to provide confidence intervals and significance measures that are directly linked to economic hypotheses [26]. As a result, such methods remain essential tools for policy analysis, regulatory assessment, and academic research.

Despite these advantages, a substantial body of literature documents important limitations of hypothesis testing in financial applications. Financial time series are often characterized by nonstationarity, heavy tails, volatility clustering, and structural breaks, which violate standard model assumptions and undermine the validity of classical inference [27]. In emerging markets in particular, frequent regime shifts driven by policy changes, external shocks, or financial crises increase the risk of model misspecification and unstable parameter estimates.

Another limitation arises from the reliance on linear functional forms. When relationships between risk factors and returns are nonlinear or state-dependent, hypothesis testing based on linear regressions may fail to detect economically meaningful effects or may produce misleading conclusions [28]. Empirical evidence suggests that risk exposures often vary across market regimes,

with different dynamics during tranquil periods and episodes of financial stress, further complicating inference based on constant-parameter models.

Moreover, hypothesis testing frameworks are primarily designed for inference rather than prediction. While statistical significance provides evidence of systematic relationships, it does not necessarily translate into strong out-of-sample predictive performance [29]. During periods of heightened financial stress, the predictive accuracy of linear hypothesis-driven models often deteriorates, as historical relationships break down and new risk channels emerge.

These limitations have motivated growing interest in complementary approaches that relax restrictive assumptions and allow for greater flexibility in capturing complex data-generating processes. Recent research emphasizes the need to integrate hypothesis testing with alternative modeling strategies that can accommodate nonlinearity, regime dependence, and high-dimensional information, while preserving interpretability and theoretical coherence [30]. This perspective underpins the motivation for combining classical inferential methods with machine learning techniques in modern financial risk management.

### 1.1.3. Machine Learning Methods in Financial Risk Prediction

Machine learning techniques have gained substantial traction as tools for financial risk prediction due to their ability to process large datasets and model complex relationships. Unlike traditional econometric models, machine learning algorithms are designed to optimize predictive performance by flexibly adapting to nonlinearities, interactions, and high-dimensional feature spaces. Empirical studies demonstrate that ensemble methods such as Random Forests and boosting algorithms are particularly effective in predicting financial risk indicators, default probabilities, and asset return distributions [31,32].

These methods are especially well suited for financial data, which are often noisy, nonstationary, and characterized by complex dependence structures. Tree-based ensemble models can accommodate nonlinear interactions among predictors without requiring strong distributional assumptions, making them attractive alternatives to linear regression frameworks in risk forecasting applications [33]. Their ability to handle large numbers of correlated predictors further enhances their appeal in modern financial environments where data availability has expanded rapidly.

Applications of machine learning in finance have grown significantly in recent years, spanning areas such as credit risk assessment, market risk forecasting, algorithmic trading, and systemic risk monitoring. Empirical evidence suggests that machine learning models frequently outperform traditional econometric approaches in out-of-sample prediction tasks, particularly when the underlying data-generating process is unstable or subject to regime shifts [34]. These performance gains are often attributed to the capacity of machine learning algorithms to exploit nonlinear patterns and time-varying relationships that are difficult to capture using fixed-parameter models.

Despite these advantages, the use of machine learning in financial risk management raises important methodological concerns. Overfitting remains a central challenge, especially in financial datasets where signal-to-noise ratios are low and structural breaks are frequent. Without careful model validation and regularization, machine learning models may achieve high in-sample accuracy while performing poorly out of sample [35]. This issue is particularly relevant in emerging markets, where shorter data histories and higher volatility exacerbate estimation risk.

Another widely discussed limitation relates to interpretability and economic plausibility. Many machine learning models operate as “black boxes,” offering limited insight into the economic mechanisms driving predictions. This lack of transparency complicates their use in policy analysis, regulatory contexts, and risk management decisions that require explainability and accountability [36]. As a result, purely predictive gains may be insufficient to justify their adoption in environments where understanding the sources of risk is as important as forecasting accuracy.

In response to these challenges, recent research increasingly advocates for hybrid modeling frameworks that combine machine learning methods with traditional statistical and econometric approaches. Such frameworks aim to preserve the interpretability and inferential strengths of

hypothesis testing while leveraging the predictive power of machine learning algorithms [37]. This integrative perspective is particularly relevant for financial risk assessment, where complex dynamics, nonlinearity, and structural change coexist with the need for economically meaningful interpretation.

#### 1.1.4. Empirical Evidence from Romania

Empirical studies focusing on Romania highlight distinct features of financial risk in transition and post-transition economies. Existing research indicates that Romanian financial markets exhibit sensitivity to both domestic macroeconomic conditions and external shocks originating from European and global markets [38]. This sensitivity reflects Romania's increasing financial integration within the European Union, combined with structural characteristics such as relatively low market depth, high concentration, and dependence on external capital flows. Despite a growing body of empirical work on Romanian financial markets, relatively few studies integrate advanced machine learning techniques into investment risk assessment. Existing research relies predominantly on econometric models, leaving a methodological gap regarding the application of hybrid statistical-machine learning frameworks [39].

Empirical studies document that financial volatility in Romania and other Central and Eastern European economies is closely linked to macroeconomic fundamentals, including fiscal conditions, monetary policy dynamics, and exchange rate movements, with domestic vulnerabilities often amplifying the transmission of external shocks to financial markets [40]. These findings are consistent with broader evidence from Central and Eastern European (CEE) economies, where macro-financial links remain strong.

Research also emphasizes the role of external spillovers in Romanian financial markets. Developments in euro area financial conditions, global liquidity cycles, and investor risk appetite have been shown to exert significant influence on Romanian asset prices and volatility. Empirical analyses indicate that global shocks are transmitted rapidly to the Romanian stock market, often amplifying domestic uncertainty during periods of international financial stress [41]. This exposure increases the complexity of risk assessment and underscores the importance of models capable of capturing cross-border interdependence.

Despite this growing body of empirical work, the methodological approaches applied to Romanian financial markets remain largely grounded in traditional econometric frameworks. Most studies rely on linear regression models, vector autoregressions, or volatility specifications to assess market dynamics and risk transmission. While these approaches provide valuable insights, they are often limited in their ability to capture nonlinear relationships, regime changes, and time-varying interactions that characterize financial markets in emerging European economies [42].

Only a limited number of studies have explored the use of advanced machine learning techniques in the context of Romanian financial risk assessment. As a result, there remains a methodological gap regarding the application of hybrid statistical-machine learning frameworks that integrate economic inference with data-driven prediction. Addressing this gap is particularly relevant given the volatility-prone nature of the Romanian equity market and its exposure to both domestic and external shocks.

This gap in the literature motivates the present study's focus on combining hypothesis testing with machine learning approaches for investment risk assessment in Romania. By jointly emphasizing interpretability and predictive performance, the proposed framework seeks to provide a more comprehensive understanding of investment risk dynamics in an emerging European market.

#### 1.1.5. Purchasing power, real economic conditions, and investment risk in emerging markets

In emerging markets, fluctuations in purchasing power often interact with labor market instability, fiscal policy adjustments, and external shocks, reinforcing real-financial feedback loops and amplifying investment risk [1,2]. Variations in real income conditions affect household

consumption, firms' revenue expectations, and aggregate demand, thereby influencing asset prices and market volatility through both demand-side and confidence channels.

A growing empirical literature documents that deteriorations in purchasing power are associated with heightened financial uncertainty and increased market volatility, particularly in economies where consumption smoothing mechanisms are limited. Declines in real income tend to weaken corporate earnings prospects and elevate default risk, which is rapidly reflected in equity prices and risk premia [43]. These effects are often more pronounced in emerging markets, where households and firms exhibit greater sensitivity to income shocks.

Purchasing power dynamics are also closely linked to fiscal and monetary policy conditions. Fiscal consolidation measures, changes in taxation, and adjustments in social transfers can have immediate effects on real disposable income, thereby influencing financial market sentiment and investment behavior. Empirical studies suggest that adverse real income shocks can amplify the transmission of macroeconomic policy uncertainty to financial markets, increasing volatility and downside risk [44].

External shocks further intensify these dynamics. In open emerging economies, global commodity price movements, inflationary pressures, and exchange rate fluctuations can significantly alter purchasing power, especially for import-dependent consumption baskets. Such shocks may generate feedback effects between the real economy and financial markets, magnifying investment risk during periods of global stress [45].

Despite its theoretical and empirical relevance, purchasing power is rarely incorporated explicitly into financial risk assessment models, which tend to focus on price-based indicators, returns, or volatility measures. As a result, the role of real income conditions in shaping market risk remains underexplored, particularly within data-driven and machine learning-based frameworks. Addressing this gap is important for understanding how real-economy fundamentals interact with financial market dynamics in emerging economies.

## 2. Materials and Methods

### 2.1. Data Description

The empirical analysis focuses on the Romanian stock market, using data from three major indices: BET (Bucharest Exchange Trading index), BET-FI (Financials), and BET-NG (Energy and Utilities). The study covers the period from 1 January 2019 to 1 January 2026, with daily observations for each index, where available, as the Bucharest Exchange does not operate daily. Data was obtained from the Bucharest Stock Exchange (BSE) database and includes the following variables:

- Date: Trading day;
- Price: Closing price of the index;
- Open, High, Low: Daily opening, highest, and lowest prices, respectively;
- Vol.: Trading volume (note: volume data was unavailable for the selected period);
- Change %: Daily percentage change of the closing price.

The dataset provides daily observations (where available) for each index, allowing separate analyses for the overall market (BET), the financial sector (BET-FI), and the energy and utilities sector (BET-NG). Although volume data are missing, the dataset remains suitable for evaluating returns, volatility, and price-based risk measures.

For subsequent analysis, the daily percentage change ("Change %") is used as the main variable of interest, serving as the dependent variable in both the hypothesis testing framework and machine learning models (Random Forest and XGBoost). This approach enables the study to capture sector-specific dynamics and to examine risk patterns across different segments of the Romanian market.

To capture real income conditions, a purchasing power index (PPI) was incorporated into the dataset. The PPI reflects changes in household purchasing capacity and is obtained from official national statistical sources. The index is available at monthly frequency and serves as a proxy for real-economy conditions affecting consumption and investment behavior.

## 2.2. Hypothesis Testing Framework

To assess the statistical significance of risk factors in the Romanian stock market, we employ a classical hypothesis testing framework using daily returns from the BET, BET-FI, and BET-NG indices over the period 1 January 2019 to 1 January 2026. The dependent variable is the daily percentage change of the closing index price, denoted as  $R_t$ .

The objective of this framework is twofold: first, to evaluate whether price-based volatility indicators significantly explain daily returns; and second, to examine whether real-economy conditions, proxied by a purchasing power index, provide additional explanatory power beyond financial market variables.

### 2.2.1. Risk Indicators

Several risk indicators are constructed from the raw price data:

- Intraday Range ( $IR_t$ ): A proxy for daily volatility, calculated as the normalized difference between the daily high and low prices relative to the opening price:

$$IR_t = \frac{High_t - Low_t}{Open_t}.$$

- Scaled High Price ( $H_{scaled}$ ): Daily high prices scaled by the mean high over the sample period to account for level effects:

$$SH_t = \frac{High_t}{High}.$$

- Purchasing Power Index ( $PPI_t$ ), a macroeconomic indicator reflecting real income and consumption capacity. The index is observed at monthly frequency and is lagged and carried forward to daily frequency to ensure information availability and to avoid look-ahead bias;

- Return Direction: A categorical variable indicating whether daily returns are positive ("Up") or negative ("Down").

### 2.2.2. Statistical Tests

We implement multiple hypothesis tests to explore patterns in the daily returns and evaluate the relevance of the constructed risk indicators:

- Two-sample t-test: To examine whether mean returns differ between two time periods (pre-2020 vs post-2020), under the null hypothesis  $H_0: \mu_{pre} = \mu_{post}$ ;
- One-way ANOVA: To test whether mean daily returns differ across months ( $H_0: \mu_1 = \mu_2 = \dots = \mu_{12}$ ), assessing potential seasonal effects;
- Chi-square test of independence: To evaluate the association between return direction (Up / Down) and volatility level (High / Low, defined by a median split of intraday range), under the null hypothesis of independence;
- Regression-based hypothesis testing: Ordinary least squares (OLS) regression models are estimated to test whether the constructed risk factors statistically explain daily returns:

$$R_t = \beta_0 + \beta_1 IR_t + \beta_2 (High_t - Low_t) + \epsilon_t,$$

where  $\epsilon_t$  is a normally distributed error term. Significance of coefficients is evaluated using standard t-tests, while overall model fit is assessed via R-squared and F-statistics.

All computations are performed in Python (v3.10) using pandas, NumPy, SciPy, and statsmodels libraries. Regression results are documented for interpretability, enabling identification of key drivers of daily returns in the Romanian stock market.

## 2.3. Machine Learning Models

To capture nonlinear relationships and interactions among risk factors, we employ supervised machine learning methods, specifically Random Forest (RF) and XGBoost (Extreme Gradient Boosting), applied separately to regression and classification tasks.

### 2.3.1. Problem Definition

Let  $P_t$  denote the closing price of an index at day  $t$ , and let  $r_t$  denote the logarithmic return:

$$r_t = \ln \frac{P_t}{P_{t-1}}.$$

The input feature matrix  $X$  includes the following:

1. Price-based features:

$$\{P_t, P_{t-1}, P_{t-7}, P_{t-14}\},$$

where  $P_{t-\tau}$  are lagged prices corresponding to 1-, 7-, and 14-day lags, capturing short- and medium-term trends;

2. Volatility indicators: rolling standard deviations of returns over 7 and 14 days:

$$\sigma_{7d,t} = \sqrt{\frac{1}{7} \sum_{i=0}^6 (r_{t-i} - \bar{r}_{t-7:t})^2}, \quad \sigma_{14d,t} = \sqrt{\frac{1}{14} \sum_{i=0}^{13} (r_{t-i} - \bar{r}_{t-14:t})^2},$$

where  $\bar{r}_{t-k:t}$  denotes the mean return over the corresponding window;

3. Date-based features:

$$\text{Year}_t, \text{Month}_t, \text{Day}_t, \text{DayOfWeek}_t.$$

These encode potential seasonal or calendar effects.

4. Sentiment features:

$$S_t^{\text{polarity}}, S_t^{\text{volume}}$$

Derived from market sentiment data, where missing values are imputed with zeros. These features reflect investor mood and trading activity. Target variables:

- Regression: daily returns ( $r_t$ ) and rolling volatility ( $\sigma_{7d,t}$ ,  $\sigma_{14d,t}$ );
- Classification: return direction:

$$y_t^{(c)} = \begin{cases} 1 & r_t > 0 \\ 0 & r_t \leq 0 \end{cases}.$$

5. Macroeconomic feature:

Purchasing Power Index ( $PPI_t$ ), reflecting real income conditions and lagged to ensure contemporaneous availability of information.

### 2.3.2. Random Forest Models

A Random Forest model consists of an ensemble of  $M$  decision trees  $\{T_m(X)\}_{m=1}^M$ .

- Regression prediction is the average of individual tree predictions:

$$\hat{y}^{(r)} = \frac{1}{M} \sum_{m=1}^M T_m(X);$$

- Classification prediction is based on majority voting across trees:

$$\hat{y}^{(c)} = \text{mode}\{T_m(X)\}_{m=1}^M.$$

Each tree is trained on a bootstrap sample of the data, and at each split, a random subset of features is considered, which reduces correlation among trees and improves generalization.

Hyperparameters include  $M = 800$  trees, maximum depth 20, and minimum samples per split / leaf as set in the code.

### 2.3.3. XGBoost Models

XGBoost implements an additive gradient boosting model. Let  $\{f_m(X)\}_{m=1}^M$  denote the sequence of regression trees. The predicted value at iteration  $m$  is:

$$\hat{y}_t^{(r)} = \sum_{m=1}^M f_m(X_t), f_m \in \mathcal{F},$$

where  $\mathcal{F}$  is the space of regression trees. Each tree is fit to minimize a regularized objective function:

$$\mathcal{L}^{(r)} = \sum_{t=1}^n \ell(y_t^{(r)}, \hat{y}_t^{(r)}) + \sum_{m=1}^M \Omega(f_m), \Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2,$$

where  $\ell$  is the squared error loss for regression,  $T$  is the number of leaves,  $w_j$  is the score of leaf  $j$ , and  $\gamma, \lambda$  are regularization parameters. For classification,  $\ell$  is replaced with the logistic loss.

### 2.3.4. Model Training and Evaluation

The dataset is split chronologically into training (80%) and testing (20%) sets. Regression models predict log returns and volatility; classification models predict return direction. The evaluation metrics are:

- Regression: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE),  $R^2$ ;
- Classification: Accuracy, Precision, Recall, F1-score, ROC-AUC.

The metrics were analyzed before and after the inclusion of PPI, to compare the results.

This ML framework allows sector-specific risk prediction across BET, BET-FI, and BET-NG, complementing classical hypothesis testing and enabling the exploration of complex nonlinear patterns in Romanian financial markets.

## 3. Results

### 3.1. Hypothesis Testing Results

The hypothesis testing framework was applied separately to the BET, BET-FI, and BET-NG indices to evaluate the statistical significance of key risk factors and market behavior patterns. Across all indices, classical inferential tests reveal a consistent absence of structural shifts in mean returns, coupled with a strong relationship between volatility and return direction.

For the BET index, the two-sample t-test comparing mean daily returns before and after 2020 yields a t-statistic of  $-0.656$  with a p-value of  $0.512$ , indicating no statistically significant difference between the two periods. Similarly, the one-way ANOVA testing for monthly seasonality produces an F-statistic of  $0.261$  ( $p = 0.992$ ), suggesting that average returns do not vary significantly across calendar months. In contrast, the Chi-square test reveals a strong association between return direction and volatility level ( $\chi^2 = 13.947$ ,  $p = 0.0002$ ), indicating that periods of elevated intraday volatility are more frequently associated with negative return realizations.

Regression-based hypothesis testing further confirms the relevance of volatility as a risk driver. Ordinary least squares estimation shows that the intraday range exerts a statistically significant negative effect on daily returns, while the scaled high price does not reach conventional significance levels. Although the model explains only a modest fraction of return variation ( $R^2 = 0.051$ ), the results

are consistent with the well-documented difficulty of explaining daily returns using linear contemporaneous predictors.

**Table 1.** Hypothesis testing results for BET.

Predictor	Coefficient	Standard Error	t	P> t
Intercept	0.2894	0.063	4.607	0.000
Intraday Range	-25.384	2.216	-11.455	0.000
High (scaled)	3.878e-06	4.64e-06	0.836	0.403

For the BET-FI index, inferential tests similarly indicate no statistically significant differences in mean returns across subperiods ( $t = 1.530$ ,  $p = 0.127$ ) or months ( $F = 0.859$ ,  $p = 0.581$ ). However, the Chi-square test again points to a significant dependence between return direction and volatility ( $\chi^2 = 6.978$ ,  $p = 0.0083$ ). Regression results show a statistically significant negative coefficient for intraday range, confirming that higher short-term volatility is associated with lower daily returns in the financial sector. The explanatory power of the model remains low ( $R^2 = 0.011$ ), reflecting the noisy nature of high-frequency financial data.

**Table 2.** Hypothesis testing results for BET-FI.

Predictor	Coefficient	Standard Error	t	P> t
Intercept	0.0248	0.118	0.211	0.833
Intraday Range	-10.143	2.468	-4.110	0.000
High (scaled)	0.0036	0.002	1.675	0.094

For the BET-NG index, neither the t-test nor the ANOVA indicates significant temporal variation in mean returns. Nevertheless, volatility once again plays a key role: the Chi-square test reveals a significant relationship between return direction and volatility ( $\chi^2 = 12.955$ ,  $p = 0.0003$ ). In contrast to the other indices, regression coefficients for intraday range and scaled high price are not statistically significant, and the model explains virtually none of the variation in returns ( $R^2 = 0.002$ ), suggesting that return dynamics in the energy sector are less well captured by simple price-based indicators.

**Table 3.** Hypothesis testing results for BET-NG.

Predictor	Coefficient	Standard Error	t	P> t
Intercept	0.1134	0.041	2.777	0.006
Intraday Range	6.482e-06	3.87e-06	1.673	0.094
High (scaled)	-8.124e-07	6.26e-07	-1.298	0.194

Overall, the hypothesis testing results consistently indicate that investment risk in the Romanian equity market is not driven by systematic shifts in expected returns, but rather by volatility-related dynamics that influence return direction and short-term market behavior.

### 3.2. Machine Learning Results

Machine learning models were applied to the BET, BET-FI, and BET-NG indices to predict daily returns, short-term volatility (7-day and 14-day horizons), and return direction. Random Forest and XGBoost models were estimated using identical feature sets. Performance is reported both **before** and **after** the inclusion of the Purchasing Power Index, allowing an assessment of the incremental contribution of real-economy information.

Before PPI inclusion, XGBoost substantially outperforms Random Forest in return prediction ( $R^2 = 0.193$  vs.  $0.026$ ) and achieves positive explanatory power for both 7-day and 14-day volatility, whereas Random Forest yields negative  $R^2$  values for volatility forecasts. This indicates that gradient boosting is better able to exploit nonlinear interactions among lagged prices, volatility indicators, and sentiment features.

**Table 4.** BET-FI Random Forest vs. XGBoost return, volatility (7d) and volatility (14d) before PPI.

Random Forest	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.013795	0.00776	0.025803
	Volatility (7d)	0.010017	0.005017	-0.051318
	Volatility (14d)	0.009518	0.004855	-0.066428
XGBoost	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.012552	0.00716	0.193472
	Volatility (7d)	0.009636	0.004911	0.02723
	Volatility (14d)	0.008973	0.004603	0.052114

After PPI inclusion, XGBoost return predictability declines slightly ( $R^2 = 0.177$ ), while volatility predictability deteriorates at both horizons. In contrast, Random Forest performance remains largely unchanged. These results suggest that, for the financial sector, purchasing power information does not materially enhance short-term volatility forecasting and may introduce additional noise when combined with high-frequency financial predictors.

**Table 5.** BET-FI Random Forest vs. XGBoost return, volatility (7d) and volatility (14d) after PPI.

Random Forest	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.013788	0.007783	0.026741
	Volatility (7d)	0.010074	0.00502	-0.06327
	Volatility (14d)	0.00958	0.004873	-0.08051
XGBoost	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.012682	0.007087	0.176557
	Volatility (7d)	0.00976	0.004966	0.001935
	Volatility (14d)	0.00912	0.004681	0.020757

In classification tasks, XGBoost consistently achieves higher accuracy and ROC-AUC than Random Forest, both before and after PPI inclusion. However, Random Forest displays higher recall, indicating a tendency to classify a larger share of positive-return days at the expense of precision. This highlights a fundamental trade-off between sensitivity and overall classification quality.

**Table 6.** BET-FI Random Forest vs. XGBoost direction before PPI.

Model	Direction	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest		0.5128	0.4577	0.7987	0.5819	0.5891
XGBoost		0.6125	0.5461	0.5168	0.531	0.6906

**Table 7.** BET-FI Random Forest vs. XGBoost direction after PPI.

Model	Direction	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest		0.49	0.45	0.906	0.6013	0.621
XGBoost		0.6154	0.5522	0.4966	0.523	0.6765

For the energy sector, XGBoost again outperforms Random Forest in predicting daily returns and 7-day volatility, both before and after PPI inclusion. Notably, 7-day volatility predictability remains relatively strong after incorporating PPI ( $R^2 \approx 0.20$ ), suggesting that real-economy conditions may be more relevant for short-term risk dynamics in energy-related stocks.

At the 14-day horizon, however, volatility predictability deteriorates for both models, with negative  $R^2$  values indicating that longer-term volatility is difficult to forecast using the available feature set. This result points to the presence of latent macroeconomic or global commodity-related factors not captured by the model.

**Table 8.** BET-NG Random Forest vs. XGBoost return, volatility (7d) and volatility (14d) before PPI.

Random Forest	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.01469	0.009435	-0.150164
	Volatility (7d)	0.009	0.006276	-0.248638
	Volatility (14d)	0.008312	0.005672	-0.194686
XGBoost	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.012888	0.00808	0.114712
	Volatility (7d)	0.007217	0.004959	0.197051
	Volatility (14d)	0.007937	0.005193	-0.089393

**Table 9.** BET-NG Random Forest vs. XGBoost return, volatility (7d) and volatility (14d) after PPI.

Random Forest	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.014214	0.008934	-0.07682
	Volatility (7d)	0.0085	0.005844	-0.11369
	Volatility (14d)	0.00804	0.005301	-0.11771
XGBoost	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.012846	0.008254	0.120467
	Volatility (7d)	0.007206	0.004767	0.199597
	Volatility (14d)	0.007838	0.005386	-0.06244

Directional classification results again favor XGBoost in terms of overall accuracy and F1-score, while Random Forest exhibits more balanced precision–recall profiles. The inclusion of PPI leads to modest changes in classification performance, suggesting that purchasing power has a limited but non-negligible effect on return direction in the energy sector.

**Table 10.** BET-NG Random Forest vs. XGBoost direction before PPI.

Model	Direction	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest		0.5556	0.5862	0.2048	0.3036	0.6009
XGBoost		0.6325	0.6667	0.4458	0.5343	0.652

**Table 11.** BET-NG Random Forest vs. XGBoost direction after PPI.

Model	Direction	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest		0.5755	0.562	0.4639	0.5083	0.6087
XGBoost		0.604	0.6195	0.4217	0.5018	0.65

For the aggregate market index, both machine learning models struggle with volatility prediction, particularly at longer horizons. Highly negative R<sup>2</sup> values for 7-day and 14-day volatility indicate that neither Random Forest nor XGBoost can meaningfully outperform naive benchmarks in forecasting aggregate market volatility. This likely reflects the heterogeneous composition of the index and the dominance of unobserved macro-financial shocks.

**Table 12.** BET Random Forest vs. XGBoost return, volatility (7d) and volatility (14d) before PPI.

Random Forest	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.008559	0.006261	-0.200652
	Volatility (7d)	0.012927	0.011263	-8.406296
	Volatility (14d)	0.012163	0.01051	-10.823135
XGBoost	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.008719	0.006209	-0.245992
	Volatility (7d)	0.010733	0.00882	-5.48462
	Volatility (14d)	0.010858	0.008608	-8.422544

**Table 13.** BET Random Forest vs. XGBoost return, volatility (7d) and volatility (14d) after PPI.

Random Forest	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.00861	0.006306	-0.21497
	Volatility (7d)	0.012861	0.011151	-8.31139
	Volatility (14d)	0.012276	0.010539	-11.0431
XGBoost	Predictor	RMSE	MAE	R <sup>2</sup>
	Results	0.008553	0.006086	-0.19888
	Volatility (7d)	0.010254	0.008496	-4.91844
	Volatility (14d)	0.010976	0.008768	-8.62794

Return predictability remains weak for both models, with slightly better performance for XGBoost before PPI inclusion and marginal deterioration after PPI inclusion. In classification tasks, XGBoost consistently outperforms Random Forest in terms of accuracy and ROC-AUC, although Random Forest again exhibits higher recall.

**Table 14.** BET Random Forest vs. XGBoost direction before PPI.

Model	Direction	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest		0.5331	0.5091	0.7029	0.5905	0.5266
XGBoost		0.6072	0.6503	0.3891	0.4869	0.6403

**Table 15.** BET Random Forest vs. XGBoost direction after PPI.

Model	Direction	Accuracy	Precision	Recall	F1	ROC-AUC
Random Forest		0.5251	0.5027	0.7824	0.6121	0.536
XGBoost		0.5972	0.6319	0.3808	0.4752	0.637

Across all indices and tasks, XGBoost consistently outperforms Random Forest in regression settings, particularly for return and short-horizon volatility prediction. This reflects the ability of gradient boosting to model nonlinearities and interaction effects more efficiently. Random Forest models, while robust, tend to average out predictive signals, leading to weaker performance in noisy financial environments.

Negative out-of-sample R<sup>2</sup> values observed for volatility forecasts, especially at longer horizons, indicate that volatility dynamics are highly unstable and influenced by latent factors not captured by historical prices, sentiment, or purchasing power alone. These results underscore the inherent limits of short-term risk prediction in emerging markets.

Overall, the machine learning evidence suggests that non-linear models provide incremental predictive gains over classical approaches, particularly for sector-specific indices and directional classification tasks. The inclusion of purchasing power information improves interpretability and, in selected cases, short-term volatility prediction, but does not fundamentally alter the low predictability of aggregate market returns.

#### 4. Discussion

This study examined the dynamics of returns, volatility, and return direction in the Romanian stock market using a hybrid framework that integrates classical hypothesis testing with machine learning techniques. The empirical findings offer insights into the nature of investment risk in an emerging European market and carry implications for both academic research and practical risk management.

A central finding across all three indices is the absence of statistically significant differences in mean returns before and after 2020. Despite the substantial uncertainty introduced by the COVID-19 pandemic and subsequent global disruptions, the Romanian equity market did not exhibit a persistent structural break in expected returns. This suggests that adjustment to external shocks

occurred primarily through volatility channels rather than sustained shifts in average returns, a pattern consistent with research on financial globalization in emerging markets [1,2].

The lack of detectable seasonal effects further supports this interpretation. The Efficient Market Hypothesis predicts that predictable calendar anomalies weaken as markets deepen and information processing improves [3]. Although Romania remains classified as an emerging market, its growing integration into European and global financial systems may explain the absence of exploitable seasonality, consistent with findings from other increasingly integrated emerging economies [17].

In contrast to the stability of mean returns, chi-square tests consistently reveal a statistically significant association between return direction and intraday volatility across all indices. This finding positions volatility as a key determinant of short-term market behavior, particularly in shaping the likelihood of negative return realizations. The pattern aligns with established stylized facts of financial returns, including volatility clustering and asymmetric responses to adverse shocks [8].

Regression results reinforce this conclusion. For the BET and BET-FI indices, intraday range emerges as a statistically significant explanatory variable with a negative coefficient, indicating that heightened short-term volatility accompanies lower daily returns. This relationship is consistent with risk-based asset pricing theories, where increased uncertainty raises required risk compensation and can trigger short-term sell-offs [3,4]. The insignificance of the scaled high-price variable across specifications suggests that price levels alone inadequately explain return dynamics, supporting the relevance of volatility-focused risk frameworks over simple price-based models.

The low explanatory power of the linear regressions ( $R^2$  ranging from 0.2% to 5.1%) reflects the intrinsic limitations of linear models applied to daily financial returns. Such results are typical in financial econometrics, where return series are dominated by noise, nonlinear dependencies, and regime shifts [20,21]. These limitations motivate the complementary use of machine learning techniques capable of capturing more complex interactions.

The machine learning results reveal systematic differences across indices and modeling approaches. XGBoost consistently outperforms Random Forest across regression tasks, achieving positive out-of-sample  $R^2$  values for BET-FI (approximately 0.18–0.19) and BET-NG (approximately 0.11–0.12) returns. These results indicate that gradient boosting methods are better suited to capturing nonlinear relationships and interaction effects in sector-specific indices, consistent with literature demonstrating the advantages of boosting algorithms in financial forecasting [10–12].

Random Forest models generally yield near-zero or negative  $R^2$  values, particularly for volatility prediction. This outcome suggests that while Random Forests offer robustness, they may struggle in environments characterized by rapid regime changes and highly volatile dynamics [9]. The negative  $R^2$  values observed, indicating performance worse than a naive historical mean forecast, underscore the difficulty of volatility prediction in noisy, non-stationary financial environments.

The particularly weak performance for the aggregate BET index, especially at longer volatility horizons, suggests that market-wide volatility is driven by latent macroeconomic and global factors not fully captured by the available feature set. This interpretation aligns with regime-switching and macro-financial models that emphasize the dominant role of external shocks and global risk cycles in shaping aggregate market volatility [7,18].

Directional classification results provide more encouraging evidence of short-term predictability. XGBoost achieves classification accuracy between 60% and 63% across indices, with ROC-AUC values exceeding 0.64 in most cases. These metrics indicate moderate but economically meaningful predictive power compared to Random Forest models, which often perform close to random classification. The superior performance of XGBoost supports the hypothesis that nonlinear models can exploit subtle patterns in price-based and sentiment-derived features that remain undetectable within linear frameworks [12,14].

Nevertheless, the modest magnitude of these metrics suggests that Romanian equity markets remain largely weak-form efficient. While short-term directional signals exist, they are insufficient to generate persistent arbitrage opportunities, a balance between limited predictability and substantial uncertainty characteristic of emerging markets transitioning toward greater efficiency [1,17].

An important contribution of this study lies in its sectoral perspective. Financial sector stocks (BET-FI) exhibit comparatively higher return predictability, potentially reflecting the systematic influence of monetary policy expectations and credit conditions [6,25]. Energy sector stocks (BET-NG), while highly volatile, show stronger links between volatility and return direction, consistent with sensitivity to global commodity prices and external demand shocks. The aggregate BET index proves the most difficult to model, particularly for volatility forecasting, suggesting that sectoral diversification introduces heterogeneity that obscures exploitable signals at the market-wide level [19].

From a theoretical standpoint, these findings reinforce the limitations of single-factor and linear asset pricing models in emerging markets, lending support to multifactor and nonlinear approaches [4,5,12]. Empirically, the results corroborate the view that volatility, rather than mean returns, constitutes the primary channel through which risk manifests in globalized emerging markets [1,2].

From a practical perspective, the evidence suggests that machine learning models, particularly gradient boosting, can enhance short-term risk assessment and directional forecasting when applied appropriately. However, the moderate predictive gains also caution against overreliance on algorithmic strategies in markets characterized by structural instability. Machine learning outputs should therefore complement, rather than replace, economic reasoning and traditional risk management frameworks [7,18].

The inclusion of a purchasing power index produces mixed effects across indices and prediction targets. For BET-FI, PPI inclusion slightly reduces return predictability and substantially weakens volatility prediction, potentially reflecting the frequency mismatch between monthly macroeconomic observations and daily financial dynamics. For BET-NG, the effects are marginally positive, suggesting that real-economy conditions may be more relevant for energy-sector risk where demand fundamentals exert greater influence.

These results indicate that purchasing power information improves interpretability by connecting financial market dynamics to real-economy conditions, but does not fundamentally enhance short-term predictability when combined with high-frequency price-based features. The finding aligns with broader evidence that macroeconomic variables operate at different frequencies than daily market movements, limiting their utility for short-horizon forecasting while remaining relevant for understanding medium-term risk dynamics [43,44].

## 5. Conclusions

This study developed a hybrid framework for investment risk assessment in the Romanian equity market, integrating classical hypothesis testing with machine learning techniques. The analysis of the BET, BET-FI, and BET-NG indices yields several findings with implications for both academic research and practical risk management.

First, investment risk in the Romanian equity market manifests primarily through volatility dynamics rather than systematic shifts in expected returns. Neither structural breaks in mean returns nor seasonal patterns display robust statistical significance, while volatility-related measures, particularly intraday price dispersion, consistently exhibit explanatory and predictive relevance. This pattern suggests that emerging market risk transmission occurs episodically through uncertainty channels rather than through stable return premia.

Second, the results reveal substantial sectoral heterogeneity. Financial sector stocks exhibit stronger and more stable sensitivity to volatility fluctuations, while energy sector dynamics appear more influenced by external factors that generate predictable short-term volatility patterns. The aggregate market index proves the most challenging to model, likely reflecting the heterogeneous composition that obscures sector-specific signals. These findings underscore the importance of sector-specific analysis and caution against treating aggregate indices as homogeneous risk environments.

Third, gradient boosting models consistently outperform Random Forests across prediction tasks, particularly in directional forecasting and short-horizon volatility estimation. This advantage reflects the capacity of XGBoost to capture nonlinear relationships and interaction effects that

ensemble averaging approaches fail to exploit. At the same time, the generally modest out-of-sample performance reinforces the inherent limits of predictability in emerging markets characterized by structural instability and evolving information environments.

Fourth, the inclusion of purchasing power information improves interpretability by linking financial market behavior to real-economy conditions but does not materially enhance aggregate predictability. The mixed effects across sectors suggest that macroeconomic indicators operate at different frequencies than daily price dynamics, limiting their utility for short-horizon forecasting while potentially remaining relevant for medium-term risk assessment.

Finally, the findings illustrate the value of integrating hypothesis-driven econometric analysis with data-driven machine learning methods. Classical inference provides interpretability and theoretical grounding, while machine learning enhances predictive flexibility by relaxing restrictive functional assumptions. Their joint application yields a more comprehensive framework for risk assessment than either approach alone.

This study has several limitations. The feature set excludes potentially relevant macroeconomic variables such as inflation rates, interest rate differentials, and global risk indices, which may improve longer-horizon volatility forecasting. Additionally, the models assume stable parameters across the sample period; incorporating regime-switching mechanisms could better capture the state-dependent dynamics evident in aggregate volatility. Finally, while XGBoost outperforms Random Forest, its complex ensemble structure limits economic interpretability [36].

Future work could address these gaps by integrating broader macro-financial indicators, applying regime-aware architectures, or using explainability techniques such as SHAP values. Comparative analysis with other Central and Eastern European markets would also help situate Romania's efficiency and integration within the regional context.

Overall, this study contributes to the literature by providing sector-level evidence from Romania and demonstrating how hybrid modeling strategies can improve risk assessment without overstating predictability. The results suggest that practical investment risk management in emerging markets should prioritize volatility monitoring over return forecasting, adopt sector-specific modeling approaches, and combine algorithmic insights with economic judgment. Future research may extend this framework by incorporating additional macro-financial indicators, regime-aware learning models, or cross-market comparisons to further refine understanding of risk dynamics in emerging financial systems.

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