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# A Mathematical Framework for Modeling Financial Resilience Through Regime Persistence: Change-Point Detection and Explainable Machine Learning

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**Abstract**

Financial markets exhibit complex nonlinear dynamics driven by interactions between firm-specific characteristics and macroeconomic conditions, requiring robust mathematical models capable of capturing structural changes and temporal heterogeneity. This study proposes an explainable machine learning framework that combines regime-switching analysis and predictive modeling to investigate the long-term resilience of firms listed in the BIST 100 Index. Structural breaks in monthly return and volatility series are first detected using the Pruned Exact Linear Time (PELT) algorithm, enabling the classification of firm trajectories into resilient and fragile market regimes. A Regime Persistence Score is then introduced to quantify the proportion of time each firm remains in the resilient state. This score serves as the response variable in a Random Forest model that evaluates the influence of firm-specific financial indicators and macroeconomic variables, including exchange rates, producer price inflation, and commercial loan interest rates. In addition, a forward-looking classification model estimates the probability that firms will transition into a fragile regime within the subsequent six months. The proposed framework achieves an AUC of 0.706 and demonstrates stable predictive performance under alternative regime definitions, penalty parameters, cost functions, and cross-validation strategies. Explainability analysis derived from Shapley Additive Explanations (SHAP) data shows book-to-market ratio and sensitivities to inflation and interest rate changes as the most important components of enduring resilience. The proposed methodology provides an interpretable mathematical framework for regime detection, nonlinear time-series modeling, and decision support in sustainable financial systems, offering practical value for risk assessment and resilience-oriented portfolio management.

**Keywords:** explainable machine learning; change-point detection; PELT algorithm; regime-switching analysis; financial time series; financial resilience; random forest; SHAP

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## 1. Introduction

Financial markets are complex systems shaped not only by firm-level performance indicators but also by macroeconomic conditions, monetary policies, financial stability factors, and global economic developments. Especially in emerging economies, capital markets may exhibit higher sensitivity to macroeconomic variables; factors such as inflation, interest rates, exchange rate movements, and credit costs can exert both direct and indirect effects on stock returns. Emerging markets are generally more exposed to macroeconomic uncertainty and external and domestic financial shocks, which may increase the sensitivity of stock markets to changing economic conditions. Empirical evidence also suggests that the effects of macroeconomic variables on stock returns may be asymmetric and nonlinear rather than constant across different economic environments [1]. In economies like Turkey, which experience high inflation, periodic exchange rate shocks, and intense financial volatility, the dynamic nature of these relationships becomes even more pronounced. Previous evidence from Turkey has also shown that the effects of macroeconomic variables on stock returns may change over time and exhibit asymmetric patterns [2].

The companies included in the Borsa Istanbul (BIST) 100 index represent the businesses with the highest market capitalization and trading volume in Turkey's capital markets. Therefore, identifying which macroeconomic factors influence the stock returns of BIST 100 companies, in what direction, and to what extent is of great importance for understanding investor behavior, developing portfolio management strategies, and analyzing financial risks. Evidence from the Turkish market indicates that foreign portfolio flows and monetary policy responses have significant effects on stock market performance, while foreign exchange rates, financial risk, and market volatility also play an important role in explaining market dynamics [3]. Furthermore, these relationships must be examined not only through linear effects but also within the framework of multidimensional and nonlinear interactions.

This study aims to examine the macroeconomic variables affecting the stock returns of companies listed on the BIST 100 using monthly data from the past twenty years. The study will evaluate firm-level indicators, such as stock returns, volatility, market capitalization, inflation-adjusted market capitalization, price-to-book ratio, and dividend yield, alongside macroeconomic indicators, including exchange rates, changes in the producer price index, commercial loan interest rate levels, and changes in interest rates. Additionally, sector-based classifications will be included in the model to account for sectoral differences. This approach is particularly relevant in the context of emerging markets, where macroeconomic conditions and financial factors can play a significant role in explaining stock market returns [4].

However, the existing literature largely focuses on estimating the effects of macroeconomic variables on stock returns and volatility, while comparatively less attention has been given to the dynamics of financial resilience, including the persistence of different financial states and the timing of transitions between them. Although nonlinear relationships and interactions among financial variables have increasingly been examined using machine learning approaches, the identification and interpretation of such complex patterns remain an important area of research. Recent evidence demonstrates that machine learning models can capture substantial nonlinearities and interaction effects in stock return prediction, highlighting their potential to identify relationships that may not be adequately represented by conventional linear approaches [5]. Furthermore, evidence from emerging markets shows that machine learning models allowing for nonlinearities and interactions can outperform conventional linear approaches in predicting stock returns [6]. Furthermore, through the original explainable artificial intelligence approach to be developed in this study, the goal is to go beyond existing XAI methods and provide a more detailed interpretation of the multi-layered effects between variables.

The growing use of complex machine learning algorithms in financial analysis has also increased the importance of model transparency and interpretability. Explainable artificial intelligence provides tools for investigating how and why complex machine learning models generate particular predictions and has become increasingly important in financial applications, where predictive performance alone may not be sufficient for decision-making. Recent reviews demonstrate the growing use of XAI in financial market analysis, portfolio management, risk management, and other financial decision-making processes [7]. Similarly, recent systematic evidence shows that XAI methods such as feature importance techniques and Shapley Additive Explanations (SHAP) are increasingly used to improve the interpretability and transparency of complex financial models [8].

In this regard, the study offers a multidisciplinary approach that integrates the fields of finance, econometrics, and artificial intelligence, aiming to produce significant findings for investors, portfolio managers, policymakers, and academic researchers. Particularly in emerging markets with high economic vulnerabilities, such as Turkey, analyzing the impact of macroeconomic variables on capital markets using explainable AI-based methods has the potential to fill a significant gap in the literature.

### *1.1. Research Question*

The central research question of this study can be formulated as follows:

"What is the effect of macroeconomic variables on the stock return performance of firms included in the BIST 100 index, and in what direction, magnitude, and interaction structures can these effects be identified using machine learning and explainable artificial intelligence methods?"

To make the scope of the research more analytical, sub-research questions can also be formulated:

1. What are the relative effects of variables such as inflation, interest rates, exchange rates, dividend yield, price-to-book ratio, and volatility on the stock returns of BIST 100 companies, and how do these effects vary across companies?
2. Are there meaningful differences in macroeconomic sensitivity, risk profile, and financial resilience among company clusters created using machine learning and deep learning methods?
3. Do firms that maintain their resilience over a larger portion of the sample period exhibit lower volatility and stronger downside protection during periods of crisis (the 2008 Global Financial Crisis, the pandemic) and in high-inflation environments? Furthermore, can the onset of a fragile regime be predicted in advance using firm-level and macroeconomic indicators?

### *1.2. Limitations of the Study*

This study has certain limitations. First, since the research covers only companies included in the BIST 100 index, the findings may not be directly generalizable to all companies traded on Borsa Istanbul or to markets in other countries. Furthermore, changes in the composition of the BIST 100 index over the past twenty years pose a significant constraint in terms of the continuity of firm-level data; firms with less than twelve months of continuous data were excluded from the panel. Although the monthly data set used in the study allows for the examination of long-term trends, short-term market reactions and high-frequency fluctuations fall outside the scope of the analysis. Furthermore, stock returns may be influenced by numerous factors not included in the model, such as political risks, global economic developments, investor psychology, and geopolitical factors. The high inflation, financial crises, and structural shocks experienced by the Turkish economy over the past twenty years may also have caused the relationships among the variables to change over time. Consistent with this, the results show that the accuracy of the forecasting model has declined in the more volatile and high-inflation years of the sample period compared to its calmer early years, indicating that forecasting performance is not constant throughout the sample period but varies over time.

### *1.3. Literature Review*

Studies examining the relationship between macroeconomic variables and firm performance generally focus on the effects of exchange rates, inflation, and interest rates on business performance. In this literature, it is observed that the impact of these variables varies depending on the country, sector, and time-period conditions.

A group of studies highlights the direct effects of macroeconomic variables on firm performance. For example, while Parab and Reddy [9] and Sreenu [10] identify a negative relationship between inflation and stock returns, they also show that interest rates, oil prices, and exchange rates can have positive effects. Similarly, Chiah et al. [11] demonstrate that exchange rate volatility has a negative effect on stock returns. It has been noted that, particularly in export-dependent economies, currency appreciation reduces companies' competitive strength, thereby lowering stock market performance. In contrast, Chiang and Chen [12] noted that there is a weak relationship between inflation and stock returns, while the energy sector serves as an exception, exhibiting a protective effect against inflation.

Another group of studies reveals that macroeconomic effects vary by country and sector. Ibrahimov et al. [13] found that firms in the chemical and plastics and manufacturing sectors performed better in terms of ROA compared to the core sector (food, beverages, and tobacco), while the energy and technology sectors did not demonstrate a statistically significant advantage. While identifying significant performance differences across sectors in the Turkish context, Rababa et al. [14] noted that economic policy uncertainty creates heterogeneous effects across sectors and that stock returns respond differently depending on the sector. They specifically noted that the financial sector is more sensitive to macroeconomic uncertainties. Şen et al. [15], on the other hand, demonstrate that long-term relationships exist between inflation, interest rates, and exchange rates in developing countries, though these relationships vary by country. Similarly, Wong [16] emphasizes that the relationship between exchange rates and stock prices becomes asymmetric during crisis periods.

There are also studies showing that the impact of macroeconomic variables becomes more pronounced during crisis periods. While Kusumahadi and Permana [17] draw attention to increased market volatility during the COVID-19 period, Li et al. [18] demonstrate that inflation shocks became the primary determinant of stock volatility in the post-pandemic period. Kayani et al. [19], on the other hand, demonstrate that there was a strong return spillover across U.S. sectors during the COVID-19 period, with the finance and industrial sectors playing a risk-spreading role, while the energy and technology sectors acted as risk-takers.

However, some studies highlight the need to evaluate firm-level characteristics in conjunction with macroeconomic effects. Charalampakis et al. [20] emphasize the impact of firm size and internationalization on performance, while Nguyen and Nguyen [21] demonstrate that board size may be a determinant of financial performance. Yusuf et al. [22], on the other hand, state that macroeconomic variables create indirect effects, particularly under fixed exchange rate regimes.

Overall, the literature reveals that the impact of macroeconomic variables on firm performance is neither unidirectional nor homogeneous; rather, it varies depending on factors such as country, sector, firm characteristics, and crisis periods. Although the

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existing literature has comprehensively examined the relationship between macroeconomic variables and stock returns, it is observed that this relationship is mostly addressed either solely within the framework of macroeconomic indicators or using limited firm-level variables. Particularly in the context of emerging markets, it is noteworthy that studies evaluating both macroeconomic volatility and firm-specific factors together are limited.

Studies conducted specifically on Turkey generally analyze the impact of variables such as inflation, interest rates, and exchange rates on the market in a one-dimensional manner; they do not sufficiently account for firm-level heterogeneity. Furthermore, the number of empirical studies that simultaneously address variables such as stock returns, volatility, dividend yield, and market value within the same model is quite limited.

### *1.4. Research Gap*

Although the relationship between macroeconomic variables and stock returns has been extensively examined in the literature, a significant portion of existing studies either focus solely on macroeconomic indicators or consider firm-level variables only to a limited extent. Particularly in the context of emerging markets, the number of studies that evaluate macroeconomic volatility and firm-specific indicators together within the same model is quite limited. Furthermore, current measures of regime persistence in finance are predominantly based on parametric regime switching or duration models. To our knowledge, a model-independent measure that directly derives persistence from non-parametric change point segmentation and correlates this with out-of-sample estimation has not yet been developed.

In the literature specific to Turkey, it is notable that studies primarily address the effects of macroeconomic variables such as inflation, interest rates, and exchange rates on the market in a one-dimensional manner, while examining cross-sectoral heterogeneity and firm-level differences to a limited extent. Furthermore, it is evident that there is a lack of empirical studies that analyze firm performance indicators—such as stock returns, volatility, market value, price-to-book ratio, and dividend yield—within a comprehensive framework.

However, despite the increasing use of machine learning and explainable artificial intelligence methods in financial market analysis in the literature, studies that interpret the effects of macroeconomic variables on stock returns using long-term panel data specific to BIST 100 firms through explainable artificial intelligence techniques such as SHAP are quite limited. In particular, there is a lack of comprehensive studies that examine nonlinear relationships among variables, sector-specific differences, and dynamic effects during crisis periods within the same model framework. This study aims to fill this gap by presenting a comprehensive analysis based on machine learning and explainable artificial intelligence that evaluates macroeconomic indicators alongside firm-level financial variables.

This study offers three key contributions. First, it reconceptualizes financial resilience, defining and measuring its temporal continuity through a firm-level Regime Persistence Score instead of statically characterizing resilience at a single point in time. Thus, continuity itself becomes the object of measurement, explanation, and prediction. Second, unlike regime duration measurements derived from parametric generative models such as Markov transitional resilience durations or hazard-based duration models, which assume a fixed number of states and a specific transition structure, our persistence measurement is obtained through nonparametric changepoint detection. Therefore, it does not introduce distributional or transitional structure assumptions, which helps ensure resilience against misidentification of the regime-generating process. Third, the developed framework integrates leakage into a unified pipeline that links non-parametric segmentation to a prospective, out of sample early warning target and an explainable persistence attribution. To our knowledge, this integration has not been previously established for changepoint-based resilience measurements.

## 2. Theoretical Section

Stock returns in financial markets are shaped by the interaction of macroeconomic conditions, market risks, and investor expectations. While macroeconomic factors such as inflation, interest rates, and exchange rates directly affect asset prices, volatility and market interconnectivity determine the propagation of these effects within the financial system. Therefore, it is crucial to evaluate both traditional asset pricing theories and modern data analytics and machine learning approaches together when explaining and forecasting stock returns.

### 2.1. *The Effects of Macroeconomic Factors and Monetary Policies on Stock Markets*

Macroeconomic factors and monetary policies are among the key elements that shape the functioning of financial markets and investor behavior. Changes in economic indicators such as inflation, interest rates, and exchange rates play a decisive role in the formation of stock prices by affecting companies' cash flows, cost of capital, and future return expectations. In this context, monetary policy decisions, the credibility of central banks, and the market implications of macroeconomic shocks are of critical importance for understanding the risk–return dynamics of stock markets.

#### 2.1.1. Inflation Dynamics and Return Expectations

In macroeconomic theory, inflation dynamics are one of the fundamental mechanisms shaping stock market pricing behavior and investors' forward-looking return expectations. Since the prices of financial assets such as stocks reflect the present value of future cash flows, both cash flow forecasts and discount rates are highly sensitive to macroeconomic uncertainties. Existing empirical evidence indicates that macroeconomic uncertainty can affect stock market performance in a nonlinear manner, with the magnitude of these effects varying across different economic and financial conditions. The negative effect of uncertainty-related shocks on stock market returns may become stronger as the level of economic policy uncertainty increases, while the sensitivity of stock markets to such shocks may differ across countries and between crisis and non-crisis periods [23].

The impact of inflation dynamics on equity risk premiums (ERP) also exhibits significant variations depending on the length of the investment horizon. Within an analytical framework developed using the Quadratic Gaussian asset pricing model, the relationship between equity risk premiums across different investment horizons and inflation has been disentangled. According to this model, short-horizon equity risk premiums are primarily associated with the volatility of inflation, whereas long-horizon risk premiums exhibit a much stronger theoretical link with the trend components of inflation [24].

On the other hand, the effects of inflation on specific market indices are subject to regional variations. Studies examining Islamic stock indices in India and China using the GARCH-MIDAS approach indicate that the impact of the CPI on long-term market volatility varies from country to country. While the effect of inflation indicators on long-term volatility was found to be insignificant in the Indian market, it was determined to have a marginally significant yet negative effect in the Chinese market [25].

#### 2.1.2. Interaction Between Interest Rates and the Cost of Capital

Interest rates, which determine the cost of capital, are the most powerful macroeconomic tool for discounting corporate profitability, and this directly impacts market volatility. Empirical analyses examining the interaction between Islamic and traditional stock markets have identified a very strong positive correlation between short-term interest rates and long-term volatility in stock markets. This finding demonstrates that investors adopt mainstream traditional interest rates as a decision-making indicator even when directing their investments in alternative and specific markets. In line with Campbell's theoretical conclusions, it has been confirmed that rising interest rates increase firms' cost of capital, which in turn leads to a decline in firm values, thereby amplifying market fluctuations and volatility [25].

Another dimension of macroeconomic instability is how this volatility is transmitted from international to local markets. Panel data analyses examining the role of uncertainties in national macroeconomic factors on the volatility spillover from global markets to Islamic equity markets indicate that interest rates serve as a critical filter in this transmission. Based on projections for emerging Islamic stock markets, it has been documented that interest rate volatility has a statistically significant negative effect on global volatility spillover [26].

#### 2.1.3. Exchange Rates and the Global Dollar Effect

In global capital markets, exchange rates—particularly the strength of the U.S. dollar—serve as a key barometer of international risk appetite. The concept of the "dollar return multiplier" introduced in the literature, clearly demonstrates that stock returns denominated in dollars act as an amplified and reinforced version of returns denominated in local currency. A broad-based U.S. dollar index has been proven to be an extremely suitable global factor for explaining return performance and risk premiums in emerging markets. An appreciation of the U.S. dollar implies a decline in economic risk capital for portfolio investors and drives them to reduce their holdings in emerging stock markets [27].

This dynamic link between exchange rates and stock returns reveals much deeper transition regimes when examined using nonlinear asymmetric methods such as the Panel Smooth Transition Regression (PSTR) model. In developed markets, it has been found that high interest rate differentials (relative to the U.S.) significantly amplify the negative impact of exchange rate fluctuations on stock performance, consistent with carry-trade mechanisms. In emerging economies, however, for exchange rate depreciation to meaningfully reduce stock returns, inflation differentials must exceed a critical threshold, which demonstrates that exchange rate shocks become destructive under conditions of macroeconomic instability [28].

#### 2.1.4. Monetary Policy Shocks and Financial Markets

Central banks' monetary policy decisions and unexpected shocks in these decisions cause immediate asset repricing in stock markets. Studies that distinguish the effects of traditional (interest rates) and non-traditional (balance sheet size) monetary policy shocks on U.S. stock returns using a structural VAR model clearly reveal the nature of the market response. It is estimated that an expansionary shock reducing long-term interest rates by 25 basis points increases stock returns by 0.57% over a 5-week period under traditional monetary policy, whereas under non-traditional policy conditions, this increase reaches 2%. Furthermore, it has been statistically proven that the interest rate channel plays a primary role in the transmission mechanism of policy shocks to the market, rather than the bank credit channel [29].

In another analysis that supports these findings with a historical and broader timeline, U.S. economic cycles between 1982 and 2022 were examined. It has been documented that a positive shock in the S&P 500 index signals a significant increase in investors' financial income, and that this wealth effect directly stimulates national consumption and investment—the two main components of GDP. Within the framework of the Efficient Market Hypothesis (EMH), it was found to be consistent with the theoretical framework that announcements regarding monetary policy and unexpected shocks create an immediate and direct downward or upward momentum in stock prices [30].

#### 2.1.5. Central Bank Credibility and Market Volatility

Beyond the monetary policies implemented by central banks, their level of institutional credibility and transparency serves as a psychological anchor for market participants, helping to counteract panic-driven volatility. A study covering the period from 1998 to 2022 and analyzing macroeconomic data from 45 OECD countries found that central bank credibility directly and significantly reduces volatility in stock market returns. Panel regression results indicate that high credibility keeps market expectations grounded in rationality, while economic growth also has a volatility-reducing effect on the stock market. On the other hand, it has been noted that fluctuations in money market interest rates, high turnover ratios in the stock market, and periods of financial crisis act as amplifiers that exacerbate market volatility [31]. This environment of transparency, necessary for markets to respond rationally to applied penalties and incentives, is of critical importance in controlling the magnitude of negative financial shocks that surprises in monetary policy could cause [30].

### *2.2. Volatility, Risk, and Market Interconnectedness*

In financial markets, risk and volatility do not stem solely from factors specific to individual firms but are also shaped by interactions between markets and the transmission mechanisms of global shocks. Particularly with the increase in financial integration, uncertainty and risk factors emerging in one market can rapidly spread to others, thereby making interconnectivity structures a significant factor in investment decisions. In this context, examining idiosyncratic risks, global volatility spillovers, and the interactions between commodity and equity markets contributes to a more comprehensive understanding of the sources of financial risk and market dynamics.

#### 2.2.1. Idiosyncratic Risk and Network Structures

Idiosyncratic risk—which cannot be explained by general market movements and is specific to a particular asset—forms the core of the systemic structure when examined through modern financial network theories. A network analysis study conducted on the Istanbul Stock Exchange constructed a fully connected stock network based on idiosyncratic volatility correlations. Analyses using eigenvector centrality on this structure revealed that idiosyncratic volatility and trading volume are positively correlated with network centrality. Empirical findings obtained through Granger causality tests have demonstrated that shocks in the average idiosyncratic volatility of stocks with high centrality can significantly predict both the idiosyncratic volatility and market beta of stocks with low centrality [32].

In addition to quantitative data, content analysis of companies' verbal and written communications to the public has emerged as an important method for determining idiosyncratic risk. An innovative study investigating the impact of companies' Environmental, Social, and Governance (ESG) sensitivity on idiosyncratic volatility (IVOL) in the Turkish stock market utilized the text-mining-based FinBERT-ESG model. It was found that the Positive ESG Index (PESGIN), derived from corporate disclosures, reduces firm-specific risk and volatility by eliminating information asymmetry through transparent and optimistic communication. Conversely, the Enhanced Negative Polarity Index (ANPI), which measures investor sensitivity to negative ESG statements, was found to exhibit a positive correlation with IVOL in full alignment with the overreaction hypothesis and to intensify risk perception among investors [33].

#### 2.2.2. Global Volatility Spillovers and Interconnectedness

The increasing integration of financial markets on the international stage creates conditions for volatility in one market to spread instantly to others (spillover). In a study examining volatility interconnectivity in European stock markets, a large-scale network estimation was conducted using the daily return volatilities of 645 large-scale firms operating in 35 different countries. The primary objective of the study was to determine, among the driving forces of interconnectivity in international financial networks, whether the country in which a firm is listed or the industrial sector in which it operates holds greater weight [34].

Global volatility and market connectivity are profoundly shaken not only by economic factors but also by geopolitical shocks. A study that analyzed the U.S. stock market by dividing it into various portfolios based on market capitalization investigated how geopolitical threats (GPT) and crises alter capital flows. It has been demonstrated that during periods of high geopolitical crisis, investors exhibit a "flight-to-quality" behavior by shifting toward large-cap and prime-cap stock portfolios, and that these portfolios respond positively to crises, providing investors with extra returns. Stocks of small and medium-sized companies remain completely unresponsive during such crisis periods, and the view in traditional literature that "small companies provide high premiums" is completely reversed under geopolitical shocks, turning large-cap companies into a "safe haven" [35].

Volatility transmission mechanisms can also be mapped using the asymmetric dynamic conditional correlation (ADCC) method from developed to emerging markets. It has been found that national macroeconomic instabilities in exchange rates and inflation rates positively and statistically significantly increase the spread of return volatility (volatility spillover) from the global market to emerging Islamic equity markets [26].

#### 2.2.3. Interaction Between Commodity Markets and Stock Markets

In resource-based economies, fluctuations in commodity markets rank among the most critical external factors influencing stock performance. In a study analyzing data from the Saudi Stock Exchange (TASI) between 2000 and 2022, the significant impact of crude oil and gold returns on index performance was examined. Findings obtained using traditional econometric models and deep learning techniques confirmed that global oil prices exert a statistically very strong and positive asymmetric effect on TASI stock returns [36]. It is known that stock performance is exposed to commodity shocks not only in oil-exporting countries but also in developed markets. Recent cross-country evidence demonstrates that oil price volatility can have a significant negative effect on stock market returns, while economic policy uncertainty can amplify this adverse relationship. Moreover, these effects are nonlinear and vary according to the prevailing economic and financial conditions [23].

### *2.3. Asset Pricing and Forecasting Approaches*

While asset pricing theories seek to explain which risk factors determine the expected returns of financial assets, evolving financial markets demonstrate that these relationships can change over time. Increasing market integration and the growing complexity of investor behavior have led to the growing importance of context-dependent and multi-factor approaches alongside traditional pricing models. In recent years, machine learning methods have become a significant area of research in predicting stock returns and understanding asset pricing processes, thanks to their ability to analyze nonlinear relationships and high-dimensional data structures.

#### 2.3.1. Market Integration and State-Dependent Pricing Models

The dynamic nature of integration in global capital markets necessitates that asset pricing models incorporate state-dependent transition probabilities rather than fixed parameters. In a study examining the integration of emerging stock markets with the U.S. market, a State-Dependent International CAPM model based on Time-Varying Transition Probabilities (TVTP) was used for partially integrated markets. The analyses revealed a common trend: during transitions from low-volatility (bull) states to high-volatility (bear) states, the explanatory power of both U.S.-sourced risk factors (S&P 500, effective exchange rate) and local risk variables (illiquidity ratio, dividend yield) in explaining returns decreased significantly. Furthermore, it has been demonstrated that most emerging markets are highly sensitive to signals from the U.S. stock market (S&P 500), particularly during periods of economic growth, and that the most critical factor determining this level of sensitivity is the exchange rate regime adopted by the country [37].

Mathematical frameworks presented as alternatives to traditional CAPM derivatives are also revolutionizing the pricing of market expectations. A Quadratic Gaussian-based asset pricing model has been formulated to examine the term structure of equity risk premiums (ERP) in environments dominated by low interest rates. To analytically solve the expected dividend growth component within this complex nonlinear structure, an approximate analytical expression was developed. Its accuracy was validated through simulation results, enabling the effective calculation of the interaction between equity risk premiums and inflation dynamics across both long- and short-term investment horizons [28].

#### 2.3.2. Machine Learning Approaches in Stock Return Forecasting

The increasingly complex structure of financial markets has led to the active use of artificial intelligence and machine learning algorithms in forecasting stock returns, moving beyond traditional statistical methods. A study utilizing approximately four decades of stock market data from 71 countries worldwide tested 87 different macroeconomic and market-based features using various algorithms such as Random Forests, Artificial Neural Networks, and Elastic Net. Variable importance analysis derived from the models clearly documented that cross-country return differences are primarily explained by a handful of critical predictors, such as long-term reversal, momentum, earnings yield, and market capitalization. On the other hand, it was concluded that traditionally highly regarded country risk metrics play a rather weak role in predictive power, and that as capital mobility restrictions decrease, the predictability of returns in small and unintegrated markets gradually disappears [38].

Another innovative application area of machine learning is Natural Language Processing (NLP) methods used to extract sentiment analysis from unstructured text data. The FinBERT-ESG deep learning architecture, designed to read and interpret company reports and ESG (Environmental, Social, Governance) disclosures, has enabled the creation of robust indices for predicting firms' idiosyncratic stock volatility (IVOL) [33].

In another analysis comparing machine learning with traditional econometric models in a hybrid manner, the capabilities of the Long Short-Term Memory (LSTM) artificial neural network model were compared with those of the GARCH family of models. It was found that the LSTM model is by far the most effective method in capturing nonlinear complex volatility patterns and in machine learning-based forecasts. However, it was observed that econometric models such as GJR-GARCH still yield the best results in standard return projections and the distribution of traditional shocks; the theoretical validity of integrating these two approaches to create a synergistic advantage in investment strategies has been confirmed [36].

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## 3. Methodology

The empirical analysis is based on a monthly panel dataset covering a twenty-year period ($T$ = 240 months per firm) for the 100 firms that make up the BIST 100 index. The complete dataset used for the analysis is available in the Supplementary Materials as Supplementary Dataset S1. Companies with less than twelve months of continuous data were removed from the panel prior to the analysis, and missing observations resulting from index entries and exits were addressed during the preprocessing stage, ensuring that each company in the final panel was observed for the full 240-month window. Firm-level variables (monthly stock returns, volatility, market capitalization, inflation-adjusted market capitalization, book-to-market ratio, and dividend yield) and macroeconomic variables (exchange rate, change in the producer price index, and level and change in commercial loan interest rates) were standardized using a robust scaling procedure prior to modeling. Information regarding the variables of data parameters used in the model is provided in Appendix A.

In this study, firm-level financial resilience is treated not as a static, one-time classification, but as a dynamic process that can change over the sample period. The methodology consists of three stages. First, structural change points in each firm's return and volatility series are identified. Second, the periods between consecutive change points are classified as "Resilient" or "Fragile", and a firm-level "Regime Persistence Score"—summarizing the proportion of each firm's history spent in a resilient state—is calculated. Third, the structural determinants of this persistence are identified, and a forward-looking classifier that predicts the emergence of fragility is developed. The sensitivity of the results to a range of methodological choices is assessed in "Sensitivity Analyses." The overall structure of the study is given in Figure 1.

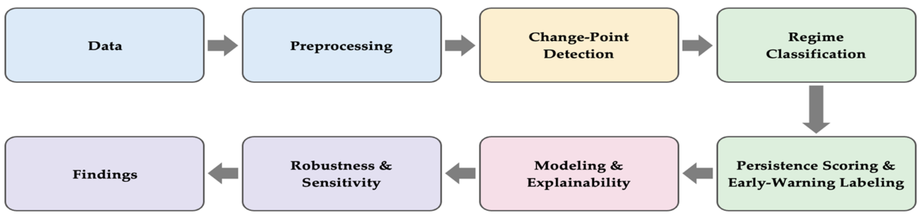


**Figure 1.** Overview of the research procedure.

### *3.1. Identifying Change Points*

The empirical analysis is based on monthly data from the 100 firms comprising the BIST 100 index throughout the 2004–2024 period and includes 24.000 firm/month observations. Firm level data and macroeconomic series were obtained from The Central Bank of the Republic of Türkiye "https://www.tcmb.gov.tr/ (accessed on 10 August 2026)" and BIST data store "https://datastore.borsaistanbul.com/ (accessed on 10 August 2026)". Since the composition of the BIST 100 index changed over the 20-year period, firms with less than 12 months of continuous data were excluded from the dataset. Remaining missing observations resulting from index entries and exits were addressed during preprocessing using a forward matching and assignment procedure, ensuring that each firm in the final panel was observed throughout the entire 240-month window. All variables were standardized using RobustScaler v1.9.

For each firm, a bivariate time series consisting of monthly stock returns and volatility over a period of $T$ = 240 months (20 years) was analyzed. The Pruned Exact Linear Time (PELT) algorithm was used to identify the time points at which firm behavior changed in a statistically significant manner. PELT is a dynamic programming approach that minimizes the total cost (Equation (1)).

$$\min_{m,\tau_1<\tau_2<\cdots<\tau_m}\left[\sum\nolimits_{i=0}^{m} C\left(y_{(\tau_{i+1}):\tau_{i+1}}\right) + \beta\cdot m\right] \tag{1}$$

Here, $m$ denotes the number of change points identified, $\tau_1$, $\tau_2$, ..., $\tau_m$ denote the time indices of the change points, $C(\cdot)$ denotes the segment cost function and $\beta$ denotes the penalty parameter. As the segment cost function, a radial basis function (RBF) kernel was used, which can capture nonlinear distributional changes without requiring a parametric assumption. The PELT algorithm solves this minimization problem exactly, rather than approximately, with O($T$) time complexity.

The penalty parameter, defined as $\beta$ = 1, yields an average of 6.96 change points per firm ($\sigma$ = 3.18). This indicates that a structural break occurred approximately every three years over the 20-year period. This frequency of disruption is consistent with the major macro-financial shocks observed during the analysis period (2008 global financial crisis, COVID-19 pandemic, and high inflation period). The impact of this parameter selection on the final findings was also analyzed separately under Section 3.6.6.

### 3.2. Durability Score and Regime Classification

The defined change points divide each firm's time series into successive sub-segments; accordingly, a total of 796 segments have been identified across 100 firms. The average return ($\overline{r_s}$) and volatility ($\overline{v_s}$) values were calculated for each $s$ segment and standardized across all segments (Equation (2)).

$$Z_r(s) = \frac{\overline{r_s} - \mu_r}{\sigma_r}, \quad Z_v(s) = \frac{\overline{v_s} - \mu_v}{\sigma_v} \tag{2}$$

In Equation (2), the parameters $\mu_r$ and $\sigma_r$ represent the mean and standard deviation of the average return across all segments, while the variables $\mu_v$ and $\sigma_v$ represent the mean and standard deviation of the average volatility. The Resilience Score at the segment level is defined as the difference between the standardized return and volatility (Equation (3)).

$$R(s) = Z_r(s) - Z_v(s) \tag{3}$$

Segments that satisfy the condition $R(s) \geq 0$ are classified as "Resilient" while those that satisfy the condition $R(s) < 0$ are classified as "Fragile" The sensitivity of this threshold value is further examined in Section 3.6.1.

### 3.3. Regime Sustainability Score

For each firm, a Regime Persistence Score was calculated to indicate what proportion of the observation period was spent in the Stable regime (Equation (4)).

$$P_i = \frac{\sum_{s\in S_i,\ Regime(s)=Resilient} L(s)}{\sum_{s\in S_i} L(s)} \tag{4}$$

$S_i$ denotes the set of segments belonging to firm $i$, and $L(s)$ denotes the length of segment $s$ in months. $P_i$ takes values in the interval [0, 1] and measures the persistence of the firm's resilience over the observation period. Unlike static clustering approaches, this score treats resilience as a time-sensitive and continuous measure.

### 3.4. Structural Factors Explaining Persistence

To identify the structural factors explaining the Regime Persistence Score, a set of explanatory variables was constructed at the firm level: average market value, book-to-market ratio, dividend yield, industry identity, and measures indicating the firm's sensitivity to macroeconomic shocks (correlation coefficients between firm returns and exchange rates, changes in the PPI, and interest rates). Using these variables, a Random Forest regression model was developed to estimate the Regime Persistence Score.

Since average volatility is already used in the calculation of the Resilience Score, it was excluded from the set of explanatory variables to avoid circular inference. Due to the limited sample size ($n$ = 100 firms), model performance was evaluated using 5-fold cross-validation rather than a single train-test split.

### 3.5. Forward-Looking Early Warning Model

The predictive component of the study is based on predicting, using the information available at time $t$, whether a firm will enter a Fragile regime within the next $h$ months. The Early Warning Label is defined as follows:

$$E_{i,t}^{(h)} = \mathbb{1}[\exists \tau \in \{t+1, \ldots, t+h\} : Regime(i, \tau) = Fragile] \tag{5}$$

In Equation (5), where the Early Warning Label is defined, 1[·] denotes the indicator function, and $h$ represents the lookahead horizon (in months). In the baseline scenario, $h$ = 6 months was used, and the robustness of this choice was also tested for $h \in \{3, 12\}$ (Sections 3.6 and 4.2.2). The model was constructed as a Random Forest classifier that predicts this label based on 11 observable variables at time $t$ (monthly return, volatility, market value, book-to-market ratio, dividend yield, and macroeconomic variables) (Equation (6)) In evaluating the model, a chronological rather than random train-test split was used to prevent future information from leaking into the training process (data leakage): the first 180 months (15 years) were designated as the training set, and the last 60 months (5 years) as the test set. Multi-fold versions of this evaluation scheme are discussed in Section 3.6.2.

$$\widehat{E_{i,t}^{(h)}} = f_{RF}(x_{i,t}),\ f_{RF} : \mathbb{R}^{11} \longrightarrow [0, 1] \tag{6}$$

The temporal sequencing of the process is as follows: first, change points are identified and segments are labeled as Robust or Fragile. These labels are used solely to generate the Early Warning target $E^{(h)}{}_{i,t}$, and the classifier is then trained to predict this target using only concurrent, observable data from month $t$ as features. Therefore, regime labels function as a target generation tool and are never used as predictive inputs.

### 3.6. Sensitivity Analysis

To assess the sensitivity of the proposed method to its key parameters (PELT penalty parameter and cost function, regime threshold, prediction horizon, and class weighting), the following six analyses were conducted.

#### 3.6.1. Regime Threshold Sensitivity

To evaluate the effect of the zero threshold defined in Section 3.2 on the results, the entire analysis pipeline (segmentation, labeling, persistence scoring, and early warning modeling) was repeated for three different threshold values ($\tau \in \{-0.1; 0; 0.1\}$) (Equation (7)).

$$Regime(s) = \begin{cases} Resilient & R(s) \geq \tau \\ Fragile & R(s) < \tau \end{cases} \tag{7}$$

In addition, to assess the possibility that binary classification might impose an artificial sharpness on a continuous score, a three-category alternative was also tested, in which segments close to the threshold were assigned to a separate category (Equation (8)). The results of these analyses are detailed in Sections 4.3.1 and 4.3.2.

$$Regime(s) = \begin{cases} Resilient & R(s) \geq 0.1 \\ Neutral & -0.1 < R(s) < 0.1 \\ Fragile & R(s) \leq -0.1 \end{cases} \quad (8)$$

### 3.6.2. Time-Based Cross-Validation

To eliminate the possibility of periodic bias arising from a single train-test split, two multi-fold, chronological validation approaches based on expanding windows and sliding windows were applied. In the expanding window approach, the training set is gradually expanded with each fold, while in the sliding window approach, the training set is kept at a fixed volume (120 months) and shifted chronologically forward. The quadruple mean AUC and standard deviation results for the two validation schemes are reported under Section 4.3.3.

### 3.6.3. Class Weighting and Calibration

The effect of the class weighting parameter (class_weight) on performance is discussed in Section 4.3.4 by comparing unweighted, balanced, and manual weight options. In addition, the reliability of the probabilities predicted by the model was examined using the calibration curve and the Brier score (Section 4.3.5).

### 3.6.4. Historical Additional Variables

The basic early warning model uses only the observable variables at time $t$. To enhance the model's predictive power, three additional variables reflecting the firm's regime history have been defined. The duration in the regime refers to the number of months the firm has spent in its current regime (Equation (9)). In the expression $d_{i,t}$, $i$ denotes firm $i$, and $t$ denotes the month; $d_{i,t}$ represents the duration that firm $i$ has spent in the regime in month $t$, *start*(*segment*(*i*,*t*)) indicates the month in which the segment in which firm $i$ is located in month $t$ begins. One has been added to the value obtained from the inclusive count.

$$d_{i,t} = t - start(segment(i,t)) + 1 \quad (9)$$

The breakpoint counter represents the cumulative number of regime changes that have occurred up to time $t$, while the volatility trend shows the change in volatility over the last three months. (Equations (10) and (11), respectively.) In Equation (10), $k_{i,t}$ denotes the cumulative number of regime change points that occurred strictly before month $t$ for firm $i$; $\tau_j$ denotes the time index of the $j$-th regime change point identified for firm $i$ using the PELT algorithm; and the expression $\{\tau_j : \tau_j\} < t$ denotes the set of all regime change points that occurred before time $t$. The $|\cdot|$ notation on the set denotes the number of elements in that set—that is, the total number of regime changes the firm has undergone up to time $t$. In Equation (11), $\Delta V_{i,t}$ represents the change in firm $i$'s volatility between month $t-3$ and month $t$; $V_{i,t}$ and $V_{i,t-3}$ denote the firm's volatility values at months $t$ and $t-3$, respectively. A positive value indicates that volatility has increased, while a negative value indicates that it has decreased; in other words, this is not a level signal but a directional/momentum signal.

$$k_{i,t} = \left|\{\tau_j : \tau_j\} < t\right| \quad (10)$$

$$\Delta V_{i,t} = V_{i,t} - V_{i,t-3} \quad (11)$$

The model performance obtained by adding these three variables is reported in Section 4.2.4.

### 3.6.5. Comparison with Alternative Classifiers

To evaluate the performance difference of the Random Forest model compared to simpler alternatives, penalized logistic regression and gradient boosting classifiers were also trained using the same set of variables and the same time-based split (Section 4.2.3).

### 3.6.6. PELT Penalty Parameter and Cost Function Sensitivity

To evaluate the effect of the PELT algorithm's penalty parameter ($\beta \in \{0.5; 1; 2\}$) and the choice of cost function (RBF and Normal) on the results, the entire analysis was rerun for six different combinations. The Normal cost function assumes that the data within a segment follows a Gaussian distribution and detects changes in the mean and covariance based on log-likelihood (Equation (12)). Here, $(y_{a:b})$ represents the (Return, Volatility) sub-series between months $a$ and $b$, i.e., $a$ candidate segment; $\hat{\mu}$ and $\hat{\sum}$ denote, respectively, the sample mean vector and the covariance matrix of the observations within this segment; $|\hat{\sum}|$ represents the determinant of the covariance matrix (a measure of the segment's overall dispersion). Considering that the RBF and Normal cost functions operate on different numerical scales, the results were evaluated separately for each cost function (Section 4.3.6).

$$C_{normal}(y_{a:b}) = \sum_{t=a}^{b}\left[(y_t - \hat{\mu})^T \widehat{\sum^{-1}} (y_t - \hat{\mu}) + log\left|\hat{\sum}\right|\right] \tag{12}$$

## 4. Results

### *4.1. Regime Detection and Persistence*

#### 4.1.1. Findings on the Change Point and Regime Identification

Figure 2 shows the change points identified based on the company with the highest average market capitalization in each sector. The number of change points identified per company ranges from 1 to 14, with an average of 6.96 ($\sigma$ = 3.18).

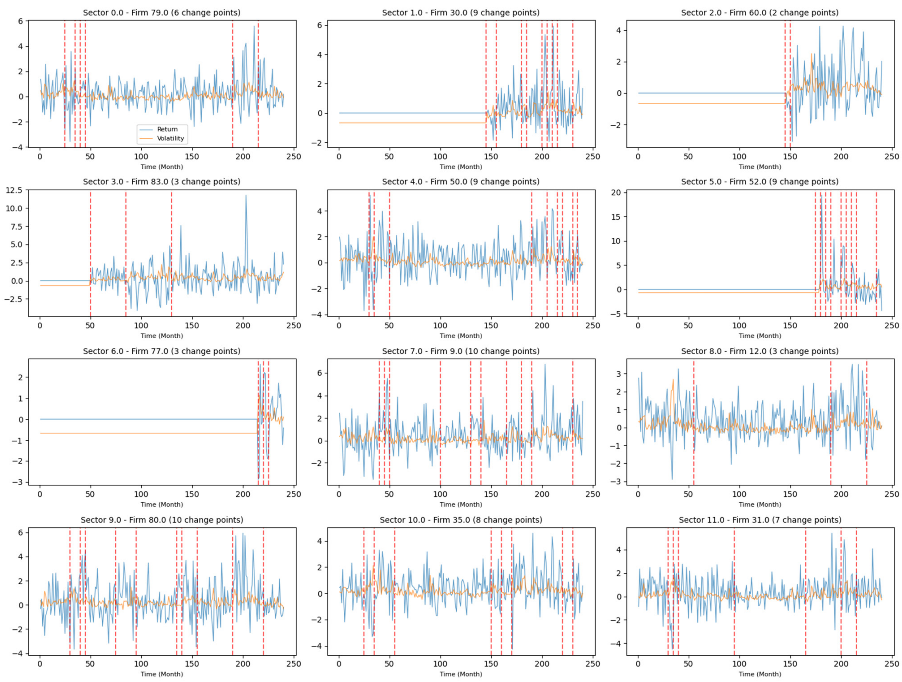


**Figure 2.** Based on the firm with the highest average market capitalization in each sector, the change points (dashed lines) identified in the return and volatility series of these firms.

Figure 3 shows the regime distribution over time for the top 10 firms based on the Regime Persistence Score. The green areas represent periods classified as Resilient, while the red areas represent periods classified as Fragile; the gray line represents the firm's monthly return to provide context. The $x$-axis shows the time index (months), and the title of each panel indicates the relevant firm's Regime Persistence Score ($P$). While Resilient and Fragile segments are roughly equally distributed in terms of the number of segments (400 and 396, respectively), Resilient periods are significantly longer in terms of the number of months (16.315 and 7.685 months, respectively). This finding suggests that periods of stability exhibit relatively higher persistence, while periods of fragility, although appearing similar in number, are shorter in duration.

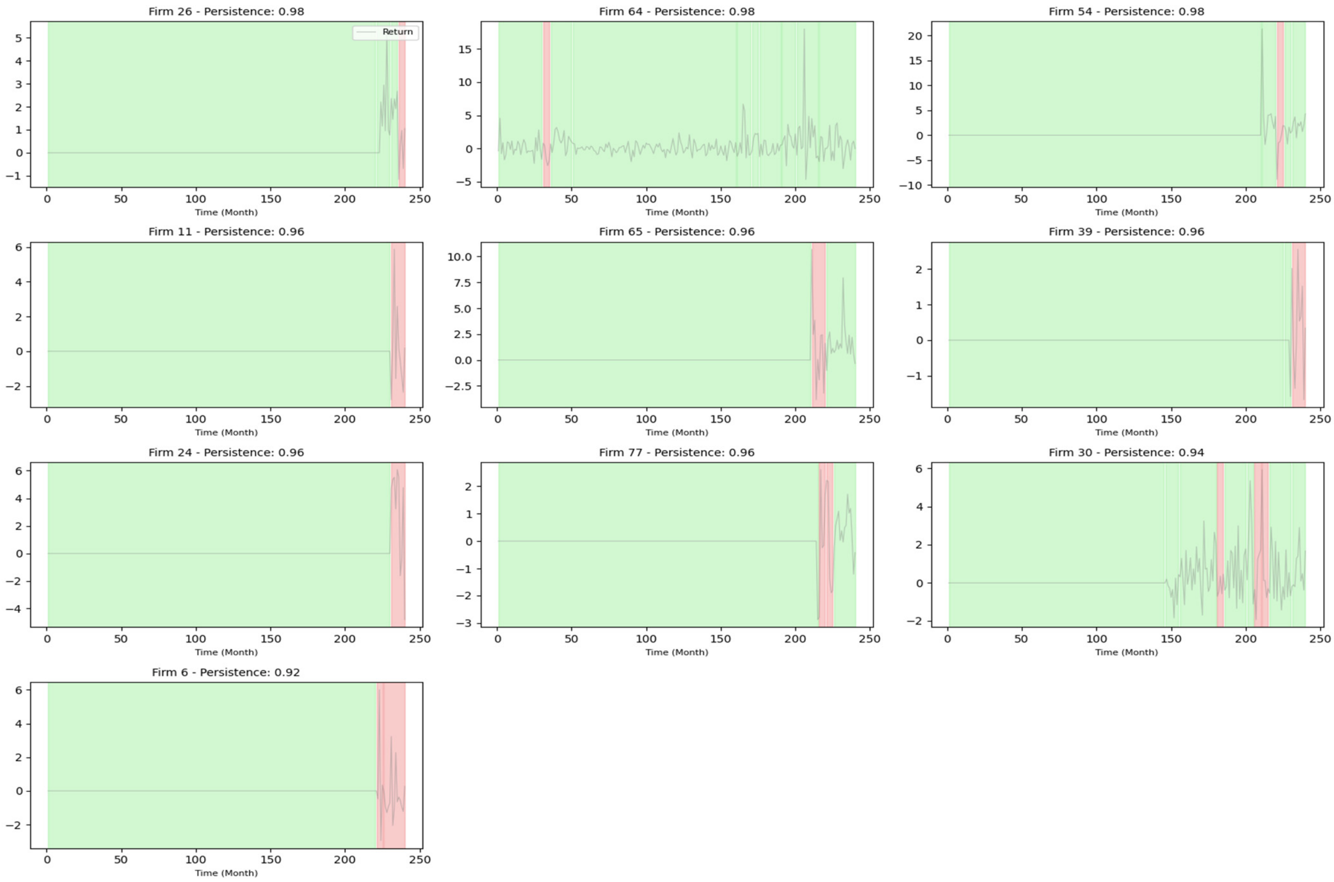


**Figure 3.** The resilient (green) and vulnerable (red) periods over time for the 10 companies with the highest Regime Stability Scores.

Table 1 shows the distribution of segment lengths. Resilient segments are significantly longer on average (mean = 40.8 months, median = 20) than fragile segments (mean = 19.4 months, median = 15 months). This indicates that resilient periods tend to persist once they occur, while fragile periods tend to be shorter.

**Table 1.** Descriptive statistics for robust and fragile segment lengths (in months).

| Regime | Segments ($n$) | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Resilient | 400 | 40.79 | 20.0 | 53.92 | 5 | 230 |
| Fragile | 396 | 19.41 | 15.0 | 17.56 | 5 | 110 |

#### 4.1.2. Distribution and External Validation of the Regime Persistence Score

Descriptive statistics regarding the Regime Retention Score, calculated for 100 firms, are presented in Table 2. The average score is 0.680, indicating that the firms in the sample spent an average of 68% of their observation periods in the Stable regime. The median value (0.750) being higher than the mean indicates that the distribution exhibits a left-skewed structure. This situation shows that a small number of firms with low persistence scores (minimum 0.021) in the sample pulled the overall mean down, but the majority of firms maintained a high level of persistence around the median. The relatively wide interquartile range (Q3 − Q1 = 0.854 − 0.583 = 0.271) indicates a significant heterogeneity among firms regarding the persistence of resilience. The fact that the score is distributed across almost the entire theoretical range (0.02–0.98) confirms that the Regime Persistence Score is a variable with high information content and the capacity to differentiate between firms.

**Table 2.** Descriptive statistics of the Regime Persistence Score ($n$ = 100).

| Statistics | Value |
|---|---|
| Average | 0.680 |
| Standard Deviation | 0.243 |
| Minimum | 0.021 |
| 1. quarter (Q1) | 0.583 |
| Median | 0.750 |
| 3. quarter (Q3) | 0.854 |
| Maximum | 0.979 |

To demonstrate that the resilient and fragile segments are economically meaningful, rather than as an additional process of robustness classification, they were compared with two independent risk measures not used in the construction of R(s). These were the maximum decline and downward bias metrics. The robust segments exhibited significantly lower maximum decline (median 2.10/5.14; Mann–Whitney $p < 10^{-44}$) and lower downward bias (median 0.98/1.52; $p < 10^{-36}$) (Table 3). Since R(s) is a conceptually standardized reward-risk comparison, it was found to be consistent with the logic of the Sharpe ratio, which penalizes return with volatility. These results confirm that segments labeled as robust are also more robust under independent, economically based criteria.

**Table 3.** External validation of the resilience classification against independent risk measures.

| Independent Measure | Resilient (Median) | Fragile (Median) | Mann–Whitney $p$ |
|---|---|---|---|
| Maximum drawdown | 2.10 | 5.14 | $<10^{-44}$ |
| Downside deviation | 0.98 | 1.52 | $<10^{-36}$ |

#### 4.1.3. Factors Explaining Longevity

The Random Forest regression model, evaluated with 5-fold cross-validation, reached an average $R^2$ value of 0.391 (sigma = 0.069). Since the volatility variable, which carries cyclical risk, has been excluded, this value shows the explanatory power of independent firm characteristics. The book-to-market ratio (0.181), sensitivity to changes in PPI (0.178), and sensitivity to changes in interest rates (0.175) are the three strongest predictors. These three variables, with their close significance values, present a balanced explanatory structure where no single parameter is dominant. Dividend yield (0.154) and exchange rate sensitivity (0.123) follow closely behind this trio. Average market value (0.073), sector (0.067), and interest rate sensitivity (0.050) contribute relatively more significantly to the model. The current distribution suggests that the persistence of firm resilience depends not on a single parameter, but rather on the combined effect of valuation (book-to-market), macroeconomic sensitivity (PPI, interest rates, exchange rates), and dividend policy (Figure 4).

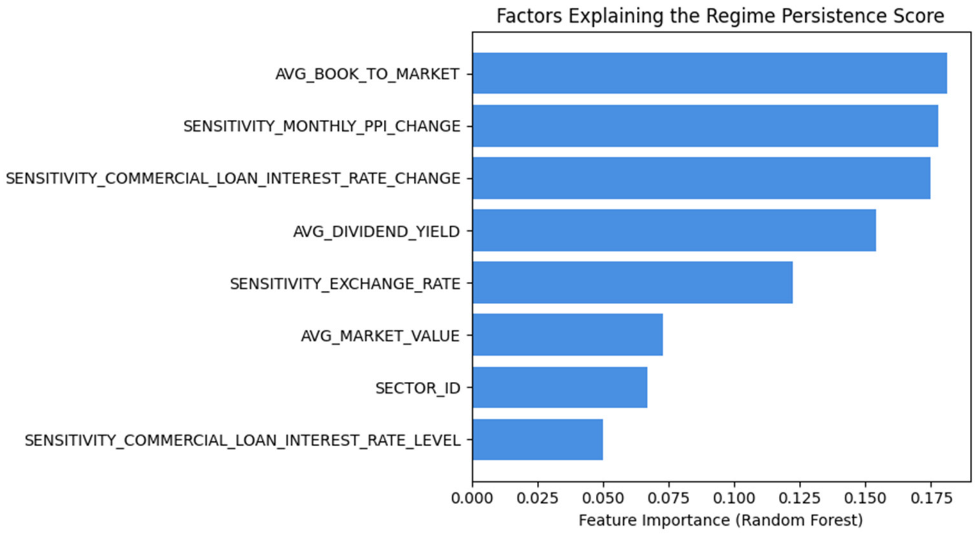


**Figure 4.** Relative Importance of Factors Explaining the Regimen Persistence Score (Random Forest).

### *4.2. Early Warning Prediction*

#### 4.2.1. Early Warning Model Performance

The performance metrics of the early warning model trained within a six-month prediction horizon ($h$ = 6) in the time-based test set (last 5 years) were: Accuracy = 0.617, F1 = 0.645, and AUC = 0.706 (Table 4). The Accuracy metric reveals that the model's predictions for both Resilient and Fragile classes are 61.7% accurate. However, due to the uneven distribution of classes in the test set (the share of Fragile months increasing to 56.9%), the Accuracy value alone is not considered sufficient to evaluate model performance. The F1-Score provides a more balanced assessment, particularly in terms of accurately identifying the Fragile class. The model's value of 0.645 indicates that this class was identified with a reasonable level of accuracy. The Area Under the ROC Curve (AUC), a threshold-independent discrimination metric, represents the model's capacity to distinguish a randomly selected Fragile observation from a Robust observation with a higher probability. The achieved value of 0.706 is significantly above the random guess level (AUC = 0.50), indicating that the model has significant predictive power.

**Table 4.** Performance results of the test set for the early warning model.

| **Metric** | **Value (Test Set, $h$ = 6)** |
|---|---|
| Accuracy | 0.617 |
| F1-Score | 0.645 |
| AUC | 0.706 |

Figure 5 illustrates the roles of variables in predictions for the early warning model ($h$ = 6 months; positive class: transition to fragile regime within the next six months) through SHAP values. The position on the horizontal axis indicates the contribution of the relevant variable to the model output in either the increasing (right) or decreasing (left) direction; the color coding symbolizes the relative level of the variable value (pink: high, blue: low). Variables are ranked according to their mean absolute contribution levels.

Volatility is the most significant variable, with high and low levels consistently correlated with positive and negative SHAP values, respectively Dividend yield and commercial loan interest rate stand out as secondary determinants. The more complex distribution patterns observed in these variables indicate that their effects are partly dependent on their interactions with other variables. The contributions of the other variables remain relatively limited. In our study, the SHAP-based explainability analysis of the early warning model is presented in two stages. This section shows the basic model, and Section 4.2.4 shows the expanded model supported by historical data.

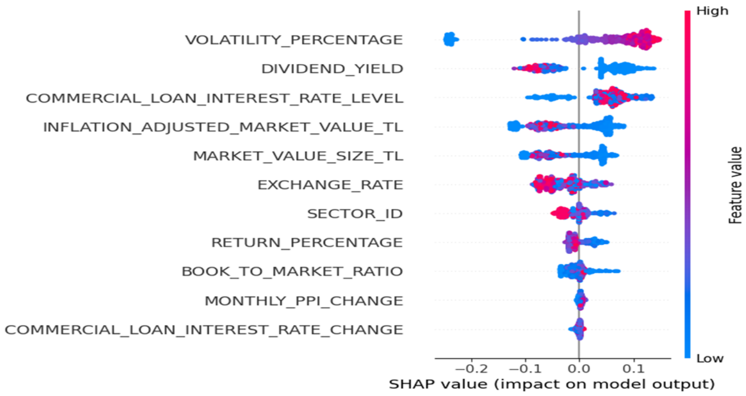


**Figure 5.** Early warning model SHAP summary chart (positive class: transition to fragile regime within a 6-month horizon).

### 4.2.2. Forecast Horizon Sensitivity

Table 5 presents a comparative analysis of the early warning model's performance results across three ($h$ = 3), six ($h$ = 6), and twelve-month ($h$ = 12) forecast horizons. The results indicate that the model performance is not significantly affected by the chosen forecast horizon. The fact that the AUC values remain in a narrow band between 0.695 and 0.710 shows that the base scenario with h = 6 months is not random and that the model offers robust forecasting capacity across different timeframes. Accuracy shows a slight downward trend as the horizon lengthens (from 0.624 to 0.615), whereas the F1-Score increases as the horizon lengthens (from 0.637 to 0.671); this opposite trend can be attributed to the increasing proportion of the positive class (Fragile) in the sample at longer horizons and indicates that the F1-Score is a more informative metric than Accuracy in the face of this imbalance. Overall, the stability of the AUC across horizons supports the notion that the model's predictive power is not an artifact specific to a particular time interval, but rather can be generalized to different prediction windows.

**Table 5.** Model performance across different forecast horizons.

| Horizon (Month) | Accuracy | F1 | AUC |
|---|---|---|---|
| 3 | 0.624 | 0.637 | 0.710 |
| 6 | 0.617 | 0.645 | 0.706 |
| 12 | 0.615 | 0.671 | 0.695 |

### 4.2.3. Early Warning Model and Alternative Classifiers Results

Table 6 presents the comparative performance of the early warning model against penalized logistic regression and gradient boosting classifiers, which were trained on the same set of variables and the same time-based segmentation. The results show that penalized logistic regression outperforms the other two model families on each of the metrics: Accuracy (0.691), F1-Score (0.740), and AUC (0.741). The Random Forest model ranks second with an AUC of 0.706, while the gradient boosting classifier exhibits the lowest performance (AUC = 0.696) among the three models examined. This finding indicates that tree-based methods, which have the capacity to model nonlinear relationships, do not provide additional explanatory power compared to a simpler, linear classifier in the current dataset. This finding suggests that the relationship between the explanatory variables and fragility is approximately linear in the log-odds (logit) scale. However, this is not true for probability itself, due to the nonlinearity of the logistic link. The comparative advantage of the regularized logistic model therefore reflects a predominantly monotonic log-odds structure rather than linearity in probability. In this context, tree-based models may exhibit a limited tendency toward overfitting in out-of-sample generalization. Reporting this finding as is methodologically significant in that it demonstrates that simpler models may exhibit stronger generalization performance than more complex models under certain conditions.

**Table 6.** Comparative performance results of Random Forest, penalized logistic regression, and gradient boosting classifiers using the same set of variables and under time-based discrimination.

| Model | Accuracy | F1 | AUC |
|---|---|---|---|
| Penalized Logistic Regression | 0.691 | 0.740 | 0.741 |
| Gradient Boosting | 0.601 | 0.571 | 0.696 |
| Random Forest | 0.617 | 0.645 | 0.706 |

Table 7 shows the standardized coefficients of the penalized logistic regression. Volatility appears to have by far the strongest effect. Furthermore, an increase of one standard deviation increases the probability of entering a fragile regime by more than five times (OR = 5.28). A higher book value/market value ratio (OR = 2.35) and a higher commercial loan interest rate level (OR = 1.70) also significantly increase the risk of fragility, consistent with distress risk and cost of capital channels. Conversely, a higher dividend yield (OR = 0.68), a stronger exchange rate position (OR = 0.80), and higher concurrent returns (OR = 0.86) reduce the risk of fragility (all $p < 0.001$). These aspects are economically intuitive and consistent with the reported SHAP-based ranking for the Random Forest model.

**Table 7.** Standardized penalized logistic regression coefficients for the six-month fragility-transition model.

| Variable | Coef. | Std. Err. | $z$ | $p$ | Odds Ratio |
|---|---|---|---|---|---|
| Volatility | 1.664 | 0.029 | 57.59 | <0.001 | 5.28 |
| Book-to-Market | 0.855 | 0.090 | 9.52 | <0.001 | 2.35 |
| Loan Rate Level | 0.532 | 0.022 | 24.00 | <0.001 | 1.70 |
| PPI Change | 0.086 | 0.026 | 3.36 | <0.001 | 1.09 |
| Loan Rate Change | −0.092 | 0.024 | −3.93 | <0.001 | 0.91 |
| Return | −0.153 | 0.020 | −7.73 | <0.001 | 0.86 |
| Sector | −0.200 | 0.022 | −9.30 | <0.001 | 0.82 |
| Exchange Rate | −0.218 | 0.024 | −9.20 | <0.001 | 0.80 |
| Dividend Yield | −0.389 | 0.025 | −15.36 | <0.001 | 0.68 |

#### 4.2.4. The Contribution of Past-Based Variables

Table 8 presents a comparison of the performance between the basic early warning model (which includes only variables observable at time $t$) and the extended model, to which dwell time, break count, and the 3-month volatility trend have been added. The inclusion of the expanded model resulted in a significant increase in the F1-Score (from

0.644 to 0.730). This increase indicates a marked improvement in the model's sensitivity, particularly in identifying the Fragile class. Similarly, the Accuracy rate climbed from 0.616 to 0.669, while the AUC value showed a limited but positive increase from 0.706 to 0.708. The finding in question; It reveals meaningful information about not only the current situation of a company, but also the duration of its stay in the current regime, the frequency of regime switching in the past, and the recent volatility trend in terms of fragility risk. The significant improvement in the F1 score, in particular, demonstrates that history-dependent variables have added critical context to the model. The model now considers not only the immediate situation but also how the firm arrived at that situation.

**Table 8.** The contribution of regime duration, breakout counter, and volatility trend variables to the model: A comparison of basic and extended models.

| **Model** | **Accuracy** | **F1** | **AUC** |
|---|---|---|---|
| Basic Model (variables at time t only) | 0.616 | 0.644 | 0.706 |
| Extended Model (+Dwell Time. Break Count. Vol. Trend) | 0.669 | 0.730 | 0.708 |

Figure 6 presents the SHAP ranking of the extended model obtained by adding three historical variables (time spent in the regime, break counter, and volatility trend). Compared to Figure 4 of the basic model, volatility, dividend yield, and commercial loan interest rate remain the three most influential variables. This indicates that adding new variables does not disrupt the existing explanatory structure. However, a significant shift in the ranking of variables is noteworthy. The variable representing the duration of stay in the regime ranked sixth among the 14 variables. This parameter, which surpassed some key variables such as inflation-adjusted market value, made a significant contribution to the overall explanatory structure of the model. The breakout counter and volatility trend are positioned at the lower levels in the ranking. While the contribution levels of the relevant variables are limited, they exhibit a significant and non-zero effect. This comparison shows that the information structure provided by the historical variables is not homogeneous. Whereas the duration of stay in the regime offers an independent and meaningful signal regarding the firm's position in the current regime, the contribution of the number of breaks and volatility trend to the model remains relatively limited. The findings confirm that not only a firm's current situation but also the time it has spent in that situation is a significant predictor of vulnerability risk. When the two SHAP analyses in Figures 4 and 5 are taken together, it can be seen that volatility, dividend yield, and interest rate level remain the dominant predictors in both the basic and extended models. Waiting time, however, emerges as the most informative variable among the newly added historical variables, confirming that the model's forecasting logic is stable and interpretable, rather than relying on newly introduced features.

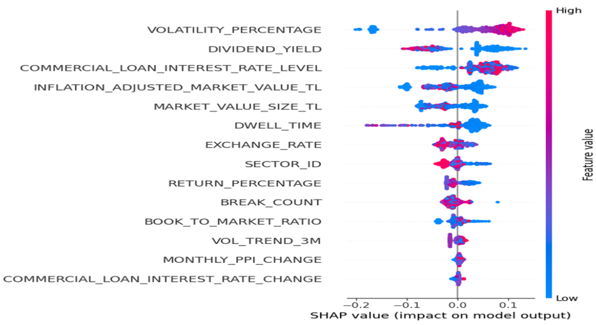


**Figure 6.** SHAP summary plot for the extended early warning model created by incorporating historical variables (duration in the regime, change point counter, and 3-month volatility trend) (positive class: transition to the Fragile regime within the next six months).

## 4.3. Robustness and Sensitivity Analyses

### 4.3.1. Threshold Sensivity Analysis

Table 9 evaluates the effect of the zero threshold on the results. Accordingly, the model performances for three different scenarios where the Robustness Score threshold is set as $\tau \in \{-0.1; 0; 0.1\}$ are presented. The findings indicate that changes in the threshold parameter have a marginal impact on performance indicators. Indeed, the AUC metric fluctuates within a narrow band from 0.716 at $\tau = -0.1$ to 0.698 at $\tau = 0.1$, while the F1-Score exhibits a stable structure in the 0.654–0.658 range. Stretching the threshold value negatively ($\tau = -0.1$) allows more segments to be included in the Resilient class, creating a slight increase in the AUC value. On the other hand, by shifting the threshold in the positive direction ($\tau = 0.1$), the classification criterion becomes stricter and a limited regression is recorded in the AUC metric. This finding demonstrates that the baseline scenario $\tau = 0$ is not an arbitrary choice. Rather, the model exhibits consistent performance under alternative threshold values within a reasonable range. In addition, it is noteworthy that firms' rankings based on Regime Resistance Scores maintain a strong correlation across alternative thresholds. This demonstrates that threshold preference does not significantly alter not only model performance but also the firm resilience ranking, which is the main outcome of the study.

**Table 9.** Results of the sensitivity analysis regarding the effect of the regime threshold value ($\tau$) on the performance of the early warning model.

| $\tau$ | Accuracy | F1 | AUC |
|---|---|---|---|
| −0.1 | 0.647 | 0.654 | 0.716 |
| 0 | 0.617 | 0.645 | 0.706 |
| 0.1 | 0.611 | 0.658 | 0.698 |

### 4.3.2. Results of the Three-Category Classification

According to the three-tier classification structure (Resilient under the condition $R(s) \geq 0.1$, Fragile under the condition $R(s) \leq -0.1$, and Neutral otherwise), 93 out of the 796 segments examined (11.7%) are located in the neutral category. This corresponds to 2720 out of 24,000 firm-months (11.3%). The early warning model trained within this framework achieved an AUC of 0.716, showing no performance loss compared to the binary classification structure (AUC of 0.706).

### 4.3.3. Time-Based Cross-Validation and Leakage-Free Robustness

Table 10 presents the AUC values calculated based on four chronological folds, according to the expanding window and sliding window cross-validation approaches. A parallel pattern is evident across both schemes. The AUC metric is at high levels in the first two folds (approximately 0.90 and 0.86, respectively), while it declines significantly to approximately 0.73 in the third and fourth folds. The AUC values calculated using the four-fold average are 0.808 ($\pm$0.086) for the expanding window approach and 0.809 ($\pm$0.087) for the sliding window approach. These results indicate a significant difference between the two schemes. This significant performance divergence observed across multiples of the sample indicates that the model's predictive ability does not exhibit a stationary structure throughout the entire sample period. The decline in performance in recent multiples parallels a significant increase in the fragile month rate (from 28.5% to 56.9%). This trend confirms that the model's predictive power has decreased to a limited extent in the recent period, characterized by macroeconomic fluctuations and high inflation. This finding suggests that a single average AUC metric may not fully reflect the overall performance of the model. Therefore, presenting fold-based findings is necessary to transparently demonstrate the temporal performance fluctuations of the model.

**Table 10.** AUC values for the early warning model across four chronological folds under expanding-window and sliding-window schemes.

| Folding | Expanding Window AUC | Sliding Window AUC |
|---|---|---|
| 1 | 0.901 | 0.901 |
| 2 | 0.861 | 0.864 |
| 3 | 0.734 | 0.738 |
| 4 | 0.735 | 0.731 |
| Mean ± Standard Deviation | 0.808 ± 0.086 | 0.809 ± 0.087 |

A potential concern is that change points and regime labels are observed throughout the entire 240-month series before the temporal training-test split. This could, in principle, cause future information to influence past labels. Regime labels were used only as a targeting tool. The classifier at month $t$ uses only concurrent, observable data at month $t$ as a feature. To directly test for forward bias, the entire pipeline was re-estimated where change point detection and standardization were performed only within the training window (first 180 months) and the resulting regime limits were spread across the test period. The out-of-sample AUC value obtained under this strictly causal procedure is 0.717, which is not significantly different from, or even slightly higher than, the 0.706 obtained in the main specification (Table 11). If forward information had significantly inflated performance, removing this information would have reduced the AUC value. The fact that this value did not decrease confirms that the reported results are not an example of information leakage.

**Table 11.** Leakage free robustness check. Segmentation and standardization estimated only on the training window.

| Specification | Accuracy | F1 | AUC |
|---|---|---|---|
| Main (full-series segmentation) | 0.617 | 0.645 | 0.706 |
| Leakage-free (training-window-only) | 0.571 | 0.589 | 0.717 |

#### 4.3.4. Class Weighting Sensitivity

Table 12 presents the performance metrics of the Random Forest algorithm under three different class weighting scenarios (unweighted, balanced, and a custom ratio of {0:1, 1:2}). Brier Score, which is based on the mean square error between the probabilities predicted by the model and the actual situations, is an important calibration metric. The fact that the metric in question remains at low levels confirms that the reliability level of probability estimates is high. The results indicate that the class weighting strategy creates a trade-off between different performance metrics. The unweighted setting achieves the highest AUC (0.728) but has the lowest F1-Score (0.603); in contrast, balanced weighting offers a significantly higher F1-Score (0.645) at the cost of a slight decrease in AUC (0.706). The custom weight ratio ({0:1, 1:2}) exhibits intermediate performance between these two settings (AUC = 0.710, F1 = 0.642). Upon examining the Brier Scores, it is observed that the balanced and specific weighting settings (0.219 and 0.218, respectively) produce marginally better-calibrated probabilities compared to the unweighted setting (0.227). When these findings are evaluated as a whole, it becomes clear that class weighting does not provide a one-sided improvement; rather, it involves a clear trade-off between overall discriminative power (AUC) and the balanced detection of the minority class (F1), and that this trade-off must be evaluated based on the model's intended use (for example, whether overall ranking performance or balanced classification is prioritized).

**Table 12.** Results of the sensitivity analysis on the effect of the class weighting setting on the performance of the early warning model and probability calibration.

| Class Weight | Accuracy | F1 | AUC | Brier Score |
|---|---|---|---|---|
| Weightless | 0.626 | 0.603 | 0.728 | 0.227 |
| Balanced | 0.617 | 0.645 | 0.706 | 0.219 |
| Special {0:1, 1:2} | 0.622 | 0.642 | 0.710 | 0.218 |

4.3.5. Calibration Analysis

Figure 7 presents calibration curves for balanced (class_weight = balanced) and unweighted (class_weight = None) settings to evaluate the reliability of the probabilities predicted by the early warning model. The horizontal axis shows the average predicted value for observations in the test set grouped according to their predicted probability intervals; the vertical axis shows the actual observed proportion of positive (Fragile) results in these groups. The dashed diagonal line represents the perfect calibration reference, where the predicted probabilities and the observed rates are in perfect agreement. The fact that both configurations closely follow the diagonal reference line confirms that the probability estimates produced by the model are consistent and reliable. However, both curves show limited deviations from the reference line in the mid-probability range (approximately 0.4–0.6). This finding confirms that the model is capable of generating over/underconfident probability estimates in this range. When comparing Brier Scores, it was found that the balanced configuration (0.219) provided marginally superior calibrated probability estimates compared to the unweighted scenario (0.227). Taken as a whole, the findings suggest that the probability estimates produced by the model are reasonably reliable but fall somewhat short of perfect calibration; this suggests that it would be more appropriate to interpret the model's outputs as a relative risk indicator rather than as point estimates.

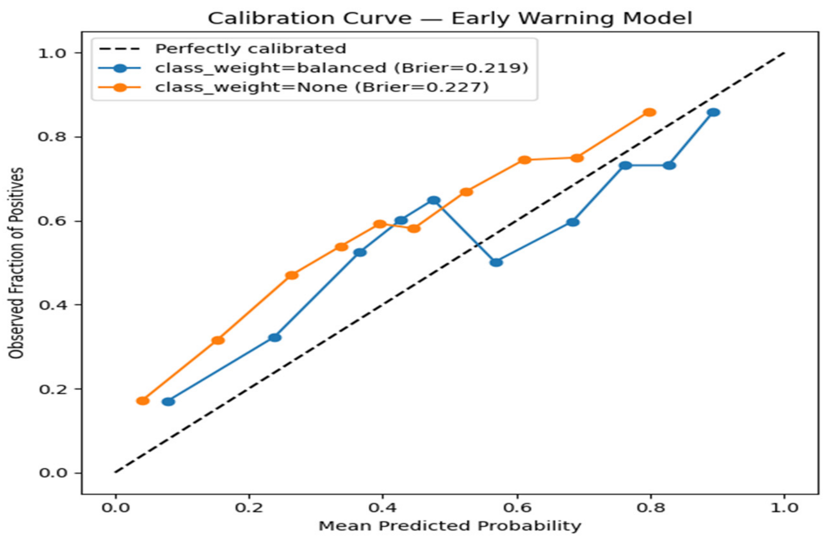


**Figure 7.** Calibration curves of the early warning model under two weighting settings (balanced and unweighted).

4.3.6. Effect of PELT Penalty Parameter and Cost Function

Table 13 presents the segmentation density and model performance results obtained for six combinations of penalty-cost functions. In the RBF cost function, as the penalty parameter $\beta$ increases, the average number of change points per firm decreases significantly (from 17.68 for $\beta = 0.5$ to 1.70 for $\beta = 2$), accompanied by a slight increase in AUC (from 0.684 to 0.739). In the normal cost function, however, the number of change points remains at a much higher level compared to the RBF (in the range of 28–31) and exhibits a relatively insensitive trend to increases in the penalty parameter. This confirms that the sensitivity of the two cost functions to the penalty parameter is shaped at different scales. The most striking result among the findings is that the AUC value falls within the 0.68–0.74 range for all six combinations evaluated. In other words, the model demonstrates significantly better performance than chance-based estimation (AUC = 0.50). This finding confirms that the early warning model's predictive performance is not overly sensitive to the penalty parameter or cost function preference in the PELT algorithm. This reveals that the main output of the study (the persistence and predictability of robustness) is not merely an artificial state created by specific methodological choices. However, the divergence in segmentation intensity between the two cost functions suggests that when evaluating the findings, the β values should not be directly compared between the functions; rather, it is more accurate to consider each cost function within its own scale.

**Table 13.** Sensitivity analysis findings regarding the effect of PELT penalty parameter ($\beta$) and cost function preference (RBF, Normal) on segmentation density and early warning model performance.

| Cost Function | $\beta$ | Average Change-Even Point (per Company) | AUC |
|---|---|---|---|
| RBF | 0.5 | 17.68 | 0.684 |
| RBF | 1 | 6.96 | 0.706 |
| RBF | 2 | 1.70 | 0.739 |
| Normal | 0.5 | 30.65 | 0.733 |
| Normal | 1 | 29.73 | 0.728 |
| Normal | 2 | 27.84 | 0.726 |

## 5. Discussion

The findings of this study demonstrate that the financial resilience of BIST 100 firms is not fixed. Instead, it evolves over time, and resilience levels differ significantly from one firm to another. The Regime Persistence Score, which spans almost the entire theoretical range of 0.02 to 0.98, suggests that firms do not share a uniform structure regarding resilience persistence. Conversely, they demonstrate a substantial degree of heterogeneity. This aligns with existing research that highlights how macroeconomic factors affect firm performance differently based on country, sector, and specific firm traits (Ibrahimov et al., 2025 [13]; Rababa et al., 2022 [14]). However, this study stands out by illustrating this diversity through a measure of persistence over time, rather than through static groupings.

When examining the factors explaining persistence, the book-to-market ratio and sensitivity to changes in PPI and interest rates stand out as the strongest determinants. This aligns perfectly with the theoretical framework that argues for the critical role of inflation and interest rate dynamics on stock performance. Kikuchi (2026) [24] associates short-term risk premiums with inflation volatility, while Agarwal (2026) [25] emphasizes the impact of interest rates on the cost of capital. The findings in this literature are quite consistent with the sensitivity trends we obtained in our study. This study not only focuses on correlation but also demonstrates how and to what extent these sensitivities shape the longevity of firm resilience. This approach sets it apart from the existing literature.

The most significant methodological outcome of the study is that penalized logistic regression yields more successful results than complex models such as Random Forest and Gradient Boosting in the early warning task. This result refutes the assumption that complex models in machine learning will always yield superior performance. Rather than treating the Random Forest as the single principal model, we therefore frame the early warning analysis as a model comparison. The regularized linear model is the strongest predictive model, while the Random Forest, together with SHAP, serves the explanatory role of attributing persistence to firm characteristics. The superior out of sample performance of the regularized model indicates that the relationship between the explanatory factors and fragility is approximately linear in the log-odds scale. This finding, which shows that the complexity of financial forecasting models is not directly proportional to performance, is consistent with current studies in the literature [38]. This result reflects that in low dimensional, high noise financial environments where variance control is more important than the benefit of modeling high-order interactions, simpler regulated models may offer stronger generalization capacity.

The most significant finding of this research was obtained through time-based cross-validation analyses. However, it is imperative to exercise caution when interpreting this result. The model's predictive performance is not constant over time. During the calmer initial periods of the sample, the AUC produces high values in the 0.86–0.90 range. Nevertheless, in recent years, characterized by high inflation and interest rate dynamics, the model performance has dropped to 0.73. This result shows that the structural shocks experienced in the Turkish economy over the last twenty years (high inflation, exchange rate volatility, and crises) can alter the relationships between variables over time. This empirically confirms the fundamental assumption presented under the Section 1.2. The findings are indirectly consistent with the literature arguing that central bank credibility reduces market volatility [31]. These results suggest that an uncertain monetary policy climate can not only cause market fluctuations but also weaken the performance of models aimed at predicting these dynamics. When evaluated within the framework of the research questions, the findings show that the impact of macroeconomic factors on the performance of BIST 100 companies is not homogeneous. This effect is both differentiated among firms and exhibits a dynamic structure over time. Companies with a consistently resilient structure appear to offer greater protection during periods of crisis and high inflation. Furthermore, this indicates that such vulnerabilities can be predicted with a reasonable degree of accuracy. From a sustainable finance perspective, this last result is of particular importance. Firm sustainability cannot be limited solely to current performance; the permanence and predictability of this performance also become a fundamental element of the definition.

The findings of this study should be evaluated within certain limitations. Since the analysis covers only BIST 100 companies and a single emerging market context, the generalizability of the findings to different market structures may be limited. Furthermore, the time-dependent variability of predictive performance indicates that static validation may not fully reflect the model's real-world success. Therefore, when such a system is integrated into the operational process, periodic retraining and continuous performance monitoring become unavoidable. At this stage, two additional limitations should be highlighted. First, the 240-month continuous coverage requirement means the sample must include firms that remained in the index (or returned to the index) during the period, which leads to survival bias. Our findings should be read as applicable to firms consistently listed on the BIST 100, and future studies should utilize unbalanced panels with explicit entry/exit (delisting) modeling. Second, while our leak-free robustness check shows that regime labeling does not inflate forecasting performance, the framework's reliance on retrospectively identified change points means that real-time implementation will require online change point detection. We also identify this as a key area for future research.

## 6. Conclusions

This research employs a dynamic approach to evaluating the financial resilience of firms traded on the BIST 100. The study proposes an explainable, AI-based, and integrated model that evaluates this resilience based on its persistence over time. The proposed approach integrates PELT with change point identification, Regime Persistence Score, and a forward-looking early warning mechanism. Unlike previous studies based on static clustering, this structure simultaneously analyzes firms' resilience persistence and the predictability of this situation.

The results show that there are significant differences in the persistence of resilience among firms, and this is fundamentally based on book-to-market ratio, inflation, and interest rate sensitivity. Furthermore, transitions to fragile regimes can be predicted consistently and with acceptable accuracy (AUC = 0.706) under comprehensive robustness checks. A critical point is that the model's success is not homogeneous across the sample and declines during periods of high inflation. This fluctuation should be carefully considered both in evaluating the results and in potential practical applications.

The study offers a very concrete practical takeaway for investors and portfolio managers. Focusing solely on short-term performance indicators is insufficient when selecting companies; it is essential to also consider how sustainable that resilience is. The research findings offer a critical perspective for policymakers. The findings reveal that macroeconomic stability, particularly inflation and interest rates, shapes not only firm performance but also the predictability of that performance. The proposed hybrid XAI framework ensures that such decisions are made on a transparent and interpretable basis through a SHAP-focused explainability layer.

Several prominent research directions can be suggested for future studies. First, applying the proposed framework to different emerging or developed markets would be valuable for testing the generalizability of the findings. Additionally, directly incorporating Environmental, Social, and Governance (ESG) indicators into the model could further strengthen the study's empirical link to sustainability. Finally, the development of adaptive retraining schemes aimed at reducing the model's performance variability over time emerges as another important direction for future research.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/math14183353/s1, Dataset S1: The complete dataset used for the analysis.

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## Appendix A

The table shows the definitions, units, conversions, and time fits for each variable used in the analysis. The Time Alignment column indicates whether each variable was actually known at month t (and therefore acceptable as a predictor in the early warning model) and whether it was calculated over the entire sample for descriptive purposes only or used solely as a predictive target.

| Variable | Definition | Unit | Transformation | Time Alignment |
|---|---|---|---|---|
| COMPANY_ID | Firm identifier | categorical | — | Fixed |
| SECTOR_ID | Sector identifier (12 sectors) | categorical | — | Fixed |
| YEAR, MONTH | Calendar year/month | date | — | Known at t |
| TIME_INDEX | Sequential time index (1–240) | index | Firm-wise cumulative count | Known at t |
| RETURN_PERCENTAGE | Monthly stock return | % (scaled) | RobustScaler | End of month t |
| VOLATILITY_PERCENTAGE | Monthly return volatility | % (scaled) | RobustScaler | End of month t |
| MARKET_VALUE_SIZE_TL | Market capitalization | TRY (scaled) | RobustScaler | End of month t |
| INFLATION_ADJUSTED_ MARKET_VALUE_TL | Inflation-adjusted market capitalization | TRY (scaled) | RobustScaler | End of month t |
| BOOK_TO_MARKET_RATIO | Book value/market value | ratio | RobustScaler | End of month t |
| DIVIDEND_YIELD | Dividend yield | % | RobustScaler | End of month t |
| EXCHANGE_RATE | Exchange rate (macroeconomic) | level | RobustScaler | End of month t |
| MONTHLY_PPI_CHANGE | Monthly producer price index change (macroeconomic) | % | RobustScaler | See publication-lag note |
| COMMERCIAL_LOAN_ INTEREST_RATE_LEVEL | Commercial loan interest rate level (macroeconomic) | % | RobustScaler | End of month t |
| COMMERCIAL_LOAN_ INTEREST_RATE_CHANGE | Monthly commercial loan interest rate change (macroeconomic) | % | RobustScaler | End of month t |
| CURRENT_REGIME | Current regime label (derived) | Resilient/Fragile | Section 3.4 | Known at t (computed from past data) |
| EARLY_WARNING_LABEL | Enters a Fragile regime within the next h months (derived) | 0/1 | Section 4.2.1 | Target variable only—realized in the future |
| RESILIENCE_ PERSISTENCE_SCORE | Firm-level Regime Persistence Score (derived) | [0, 1] | Section 3.5 | Full-sample; descriptive use only |
| SENSITIVITY | Correlation between firm return and a macroeconomic variable (derived) | [−1, 1] | Section 3.6 | Full-sample; explanatory model only |

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