

ADVANCED AND PIONEER RESEARCH IN SOCIAL, HUMAN AND ADMINISTRATIVE SCIENCES



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CONTENT

1. Chapter	5
Political Stability and Corruption Perceptions: Does the Relationship Differ Across Income Groups?	
<i>Bilal ORHAN</i>	
2. Chapter	33
The Impacts of Renewable Energy, Financial Development, Trade Openness, and Economic Growth on Income Distribution in Türkiye: Evidence from the ARDL Approach	
<i>Büşra HALİS ÖZTÜRK, Gülbahar ATASEVER</i>	
3. Chapter	57
A Three-Layered Enriching Artificial Learning Architecture for BIST 100 Forecasting via Traditional and AI-Based Methods – TRINET-FIN	
<i>Hüseyin İŞCAN, Ayşe DURGUN KAYGISIZ</i>	

Political Stability and Corruption Perceptions: Does the Relationship Differ Across Income Groups?

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ABSTRACT

This study examines whether the relationship between political stability and perceived public-sector corruption differs across countries' income groups and whether this relationship emerges with a time lag. The analysis is based on a balanced panel dataset covering 158 countries over the period 2012–2022. Countries are classified into high-, middle-, and low-income groups. The Corruption Perceptions Index (CPI), published by Transparency International, is used as the dependent variable, while the World Bank's Political Stability indicator is employed as the main explanatory variable. The empirical analysis employs a two-way fixed-effects model with Driscoll–Kraay robust standard errors as the baseline estimation method. Differences in coefficients across income groups are examined using a pooled interaction model, while the temporal dimension of the relationship is assessed using one-period lagged explanatory variables. The findings show that the coefficient on political stability is positive in all income groups in the baseline model, but statistical significance is observed only in the high-income group at the 10% level. Tests of coefficient equality indicate that the relationship does not differ statistically significantly across income groups. In contrast, the one-period lagged political stability coefficient is positive and statistically significant in all three income groups. While the direction of the baseline relationship is generally preserved across the robustness analyses, no statistically significant relationship is found in the first-difference model. Overall, the results indicate that the relationship between political stability and perceived corruption is particularly sensitive to the temporal dimension and model specification.

Keywords: Political Stability, Corruption Perceptions Index, Income Groups, Panel Data, Driscoll–Kraay

INTRODUCTION

Corruption is defined as the misuse of public power for private gain and is widely regarded as a fundamental governance problem with significant implications for the allocation of economic resources, the efficiency of public expenditures, and institutional performance. Practices such as bribery, embezzlement of public resources, irregularities in public procurement, and the use of public office for private interests can distort the functioning of market mechanisms by increasing uncertainty and transaction costs in economic decision-making processes. Corruption is therefore not merely a legal or ethical concern but also an important institutional determinant of economic development, investment decisions, and the efficient use of public resources. Mauro (1995) shows that corruption adversely affects economic

growth by reducing private investment, while Svensson (2005) emphasizes that corruption can divert resources from public programs, undermine the implementation of regulations, and weaken the efficient use of public resources. Similarly, Elbahnasawy and Revier (2012) show that corruption distorts resource allocation, reduces the efficiency of public expenditure, and slows economic growth. Understanding the level and determinants of corruption is therefore important not only for the design of anti-corruption policies but also for explaining economic development and institutional capacity.

However, because corruption is difficult to observe directly, cross-country comparative studies rely heavily on perception-based indicators. Among these measures, the Corruption Perceptions Index (CPI), published by Transparency International, is one of the most widely used indicators for measuring perceived public-sector corruption in a comparable manner across countries. The CPI is reported on a 0–100 scale, where 0 represents the highest and 100 the lowest perceived level of public-sector corruption. Accordingly, an increase in the CPI indicates a decline in perceived public-sector corruption. Early studies examining the determinants of corruption have also shown that political and institutional factors are closely associated with economic performance. In this context, political stability emerges as an important institutional factor that may influence the emergence and persistence of corruption in the public sector (Mauro, 1995; Treisman, 2000; Svensson, 2005).

The relationship between political stability and perceived corruption can be explained through channels such as the continuity of political and institutional arrangements, the functioning of oversight mechanisms, and the time horizon of political actors. In an environment characterized by greater political stability, governments, public institutions, and bureaucratic structures may operate in a more predictable and continuous manner, allowing oversight and accountability mechanisms to become institutionalized over time. From this perspective, political stability encompasses not only fewer government changes or lower levels of political conflict but also the capacity to enforce institutional rules, monitor the behavior of public officials, and sustain anti-corruption mechanisms. Political institutions may affect corruption primarily through political accountability, competition in public services, and incentive structures. The establishment of effective monitoring and sanctioning capacity may, in turn, increase the expected cost of corrupt behavior and thereby constrain such practices (Lederman et al., 2005).

Nevertheless, the theoretical relationship between political stability and corruption is neither unidirectional nor mechanical. Political stability may reduce the risk of public officials losing their positions, thereby creating a longer time horizon and potentially increasing the future returns to honest

behavior. At the same time, political actors who remain in power for extended periods may establish persistent ties between the public and private sectors and develop patronage relationships, thereby creating mechanisms that can increase opportunities for corruption. Political stability may therefore reduce perceived corruption by strengthening institutional continuity, oversight, and accountability, while simultaneously creating an environment conducive to the formation of entrenched political–economic relationships that may contribute to the institutionalization of corruption. This dual theoretical mechanism underscores the need to empirically examine the relationship between political stability and corruption (Treisman, 2000).

Another important issue in the empirical assessment of this relationship concerns the direction of causality. In addition to the possibility that political stability may affect corruption, high levels of corruption may also increase political instability through social unrest, institutional distrust, and political crises (Mauro, 1995; Treisman, 2000; Svensson, 2005). This suggests that simple correlations between political stability and corruption may provide insufficient information about the causal nature of the relationship. Accordingly, the key issue in the existing literature is not merely whether a relationship exists between political stability and corruption, but also under what conditions this relationship becomes stronger, weaker, or statistically insignificant.

At this point, heterogeneity associated with countries' level of economic development becomes particularly important. The inverse relationship between economic development and perceived corruption has been well documented in the literature. Treisman (2000) finds that perceived corruption is lower in more developed economies, while Serra (2006) and Elbahnasawy and Revier (2012) likewise provide evidence of an association between economic development and lower levels of corruption. However, whether the relationship between political stability and corruption varies across countries according to their income levels has received comparatively limited attention. Farzanegan and Witthuhn (2017) highlight the possibility that the political stability–corruption relationship is heterogeneous by showing that it varies according to country-specific conditions such as the size of the young population. Beju et al. (2024), while covering both developed and developing countries, examine heterogeneity primarily across geographical sub-samples. By contrast, the relationship between political stability and perceived public-sector corruption has not been sufficiently examined through a systematic comparison of high-, middle-, and low-income countries within a common empirical framework.

This research gap is important from both economic and institutional perspectives. Countries belonging to different income groups differ substantially in terms of public administrative capacity, the enforcement of

the rule of law, the effectiveness of judicial and oversight institutions, the professionalization of the bureaucracy, and the incentives faced by political actors. Accordingly, the same marginal change in political stability may not generate the same institutional consequences in a high-income country as in a middle- or low-income country. An average coefficient estimated from a global sample may therefore fail to fully capture the heterogeneous nature of the relationship across countries. Examining estimates by income group allows for a more detailed assessment of the extent to which the relationship between political stability and corruption varies across different economic and institutional contexts.

This study addresses this research gap by examining the relationship between political stability and perceived public-sector corruption using a balanced panel dataset covering 158 countries over the period 2012–2022. The dependent variable is Transparency International’s Corruption Perceptions Index (CPI), while the main explanatory variable is the Political Stability and Absence of Violence index. Country fixed effects are employed to control for unobserved country-specific characteristics that remain constant over time, while year fixed effects are included to account for global and common time shocks. Accordingly, the estimates rely primarily on changes occurring within countries over time rather than on persistent differences across countries. In addition, Driscoll–Kraay robust standard errors are employed to account for the potential effects of cross-sectional dependence and temporal dependence on standard error estimation in the panel data framework.

The primary research question of the study is whether the relationship between political stability and perceived public-sector corruption differs across high-, middle-, and low-income groups. The second research question is whether the effect of political stability materializes with a time lag rather than contemporaneously. To address this question, models incorporating a one-period lag of political stability are estimated in addition to the baseline specification, alongside robustness analyses based on alternative model specifications. In this way, the study moves beyond an exclusive focus on the average relationship between political stability and corruption by examining both heterogeneity across income groups and the temporal dimension of the relationship within a common empirical framework.

Within this framework, the study seeks to make two main contributions to the literature on the political stability–corruption relationship. First, it provides a systematic comparison of the relationship across high-, middle-, and low-income countries within a common empirical framework, thereby highlighting heterogeneity across income groups. Second, it considers the temporal dimension of the relationship by examining whether the role of political stability extends beyond contemporaneous associations and emerges with a lag. In doing so, the study contributes to the assessment of the role of political

stability in perceived public-sector corruption not only as an average relationship but also across different income levels and temporal dimensions.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and discusses the research gap. Section 3 presents the dataset, variables, and econometric methodology. Section 4 discusses the baseline estimates together with the heterogeneity, lagged models, and robustness analyses. The final section evaluates the findings and concludes the study.

LITERATURE REVIEW

The empirical literature addressing the determinants of corruption and the nexus between political stability and corruption has produced heterogeneous findings, largely reflecting differences in country samples, variable definitions, and econometric specifications. While several studies report that political stability is associated with lower levels of perceived corruption (Treisman, 2000; Lederman et al., 2005; Serra, 2006), Elbahnasawy and Revier (2012) find no statistically significant effect of political stability on corruption.

Other strands of the literature suggest that this relationship is contingent upon country-specific conditions, institutional configurations, or demographic structures. For instance, Farzanegan and Witthuhn (2017) demonstrate that the destabilizing effect of corruption depends heavily on the presence of a youth bulge, whereas Beju et al. (2024) identify a significant positive association between government destabilization risk and corruption. More recently, Al-Jabri et al. (2026) examine the relationship across 139 countries over the period 1984–2022, highlighting that this link varies systematically with both youth bulge dynamics and oil-export dependency. Taken together, these empirical contributions indicate that the relationship between political stability and corruption is neither unidirectional nor homogeneous.

The literature summary table compares selected empirical studies examining the determinants of corruption and the political stability–corruption nexus across sample coverage, observation period, methodology, and primary findings. While a substantial portion of the extant literature focuses on broad institutional and political determinants, relatively few studies directly investigate the directionality and conditional structure of the political stability–corruption relationship. Within this context, the present study contributes to the literature by evaluating this relationship across high-, middle-, and low-income country groups within a unified empirical

framework and by modeling its temporal dynamics using one-period lagged specifications.

Table 1. Selected Studies on the Determinants of Corruption and the Political Stability–Corruption Nexus

Author	Sample	Methodology	Key Finding
Mauro (1995)	58 countries, 1980–1983	OLS and 2SLS	Corruption lowers economic growth by reducing investment; conversely, enhancing bureaucratic efficiency significantly increases both investment and growth.
La Porta et al. (1999)	152 countries	OLS regression	Income levels and historical-institutional factors are strongly associated with the quality of government; ethnolinguistic fractionalization is generally associated with poorer government performance.
Ades & Di Tella (1999)	Cross-country	OLS, 2SLS, and fixed effects	Increased competition and reduced firm rents mitigate corruption, whereas rents generated from fuel and mineral exports heighten it.
Treisman (2000)	1980s–1990s	WLS and OLS	Economic development, Protestant tradition, long-standing democracy, and British colonial history are negatively associated with perceived corruption, whereas federal structures exhibit a positive association. Weaker evidence suggests trade openness also reduces corruption.
Fisman & Gatti (2002)	55 countries	Cross-sectional OLS and IV/2SLS	Fiscal decentralization is significantly and negatively associated with measured corruption; findings remain largely robust across alternative corruption indices and IV specifications.
Persson et al. (2003)	Approx. 80 democracies, 1990s	Cross-sectional and panel regressions; IV/2SLS sensitivity analyses	Larger electoral districts and candidate-based voting systems are associated with lower corruption, whereas the greater reliance on party-list voting corresponds to higher corruption levels.
Brunetti & Weder (2003)	125 countries, 1994–1998	OLS, IV/2SLS, and panel analyses	Press freedom is significantly associated with lower corruption; results remain highly robust across various metrics,

			sample specifications, and econometric methodologies.
Fredriksson & Svensson (2003)	63 countries in 1990	Cross-sectional OLS and 2SLS/IV	Corruption is negatively associated with the stringency of environmental policies, with this relationship being conditional on the degree of political instability.
Lederman et al. (2005)	146 countries, 1984–1999	Panel regressions; OLS and IV estimations	Democracy, parliamentary systems, political stability, and freedom of the press are associated with lower corruption; however, the effects of openness and legal tradition diminish once political institutions are controlled for.
Serra (2006)	62 developed and developing countries, 1990–1998	Extreme Bounds Analysis (EBA)	Economic development, long-standing democracy, political stability, Protestantism, and colonial heritage demonstrate a robust relationship with lower corruption, whereas other determinants prove sensitive to empirical specifications.
Elbahnasawy & Revier (2012)	150 countries, 1998–2005	Hausman-Taylor panel estimator	Institutional quality (rule of law, political stability) and per capita income reduce corruption. Conversely, government size, military expenditures, and natural resource abundance increase corruption levels.
Saha & Gounder (2013)	100 countries, 1995–2008	Panel Least Squares (PLS) and hierarchical polynomial regression; 2SLS sensitivity analysis	Identifies a non-linear relationship between income and perceived corruption: corruption may rise during low- and middle-income stages, but declines as economies reach advanced developmental stages.
Saha et al. (2014)	100 countries, 1995–2008	Two-way Fixed Effects model	Electoral democracy (political rights) alone is insufficient to curb corruption; rather, mature and comprehensive democracy supported by civil liberties, press freedom, and the rule of law significantly mitigates corruption.
Farzanegan & Witthuhn (2017)	100+ countries, 1984–2012	Two-way Fixed Effects, dynamic panel GMM (System GMM)	The destabilizing effect of corruption on political stability depends on demographic structures; in countries with a high share of youth and limited employment/educational opportunities,

			corruption substantially erodes political stability.
Khan & Farooq (2019)	28 developing countries, 2000–2014	Simultaneous Equations Model and 3SLS	Corruption and political instability exert a direct adverse effect on sustainable development. In turn, sustainable development acts to curb both corruption and political instability.
Beju et al. (2024)	Europe and Asia, 2014–2022	Pooled OLS, fixed/random effects, and dynamic panel GMM	Finds a positive and significant relationship between the risk of government destabilization and corruption; results remain robust across control variables and regional subsamples. Enhancing institutional quality and the political environment is decisive in curbing corruption.
Al-Jabri et al. (2026)	139 countries, 1984–2022	2SLS/IV; PCSE sensitivity analysis	Both corruption and youth bulges are positively associated with political instability. The youth bulge amplifies the destabilizing impact of corruption, particularly in oil-exporting economies.

DATA AND METHODOLOGY

Data and Variables

The relationship between political stability and perceived public-sector corruption is examined using a comparative panel-data approach for countries classified into high-income (High), middle-income (Middle), and low-income (Low) groups. The sample covers the period 2012–2022 and consists of 158 countries and 1,738 country-year observations. The High-income group includes 54 countries, the Middle-income group 84 countries, and the Low-income group 20 countries.

Table 2. Variable Definitions

Variable	Definition	Source
CPI	Corruption Perceptions Index, 0–100	Transparency International

PS	Political Stability percentile rank, 0–100	World Bank
lnGDPpc	ln(GDP per capita)	World Bank
Inflation	Inflation	World Bank
Unemployment	Unemployment	World Bank
FDI	Net FDI inflows / GDP	World Bank

Notes: The FDI variable is not log-transformed because it can take negative values. The baseline model uses CPI and PS in levels.

The CPI is an index ranging from 0 to 100, with higher scores corresponding to lower levels of perceived public-sector corruption. Transparency International states that, following its 2012 methodological update, CPI scores from 2012 onward are comparable over time (Transparency International).

The PS indicator is a measure of political stability reported by the World Bank’s Worldwide Governance Indicators in percentile-rank form on a 0–100 scale. A higher percentile rank corresponds to better governance outcomes (World Bank).

Descriptive Findings

Before proceeding to the econometric estimations, the distribution of the main variables across income groups is presented in Table 3. Table 3 reports the group means and standard deviations for the CPI, political stability (PS), the natural logarithm of GDP per capita (lnGDPpc), inflation, unemployment, and foreign direct investment (FDI).

Table 3. Descriptive Statistics of the Main Variables

Group	N	CPI	PS	lnGDPpc	Inflation	Unemployment	FDI
High	594	63.75 (16.03)	68.08 (19.97)	10.24 (0.64)	2.33 (2.93)	6.63 (4.24)	6.35 (29.56)
Middle	924	34.99 (10.04)	34.90 (19.50)	8.10 (0.73)	7.83 (23.26)	8.54 (6.31)	3.22 (4.60)

Group	N	CPI	PS	lnGDPpc	Inflation	Unempl oyment	FDI
Low	220	28.29 (9.30)	20.28 (15.68)	6.42 (0.32)	10.78 (28.78)	4.63 (3.63)	5.11 (8.96)

Note: Cells report means, with standard deviations in parentheses.

The descriptive statistics indicate substantial differences across income groups in both CPI and political stability. The High-income group has mean CPI and PS values of 63.75 and 68.08, respectively, compared with 34.99 and 34.90 for the Middle-income group and 28.29 and 20.28 for the Low-income group. Thus, the High-income group is characterized by both higher average CPI and higher average political stability. The control variables also differ across income groups. In particular, average inflation is higher in the Middle- and Low-income groups than in the High-income group, while lnGDPpc differs substantially across income groups, as expected.

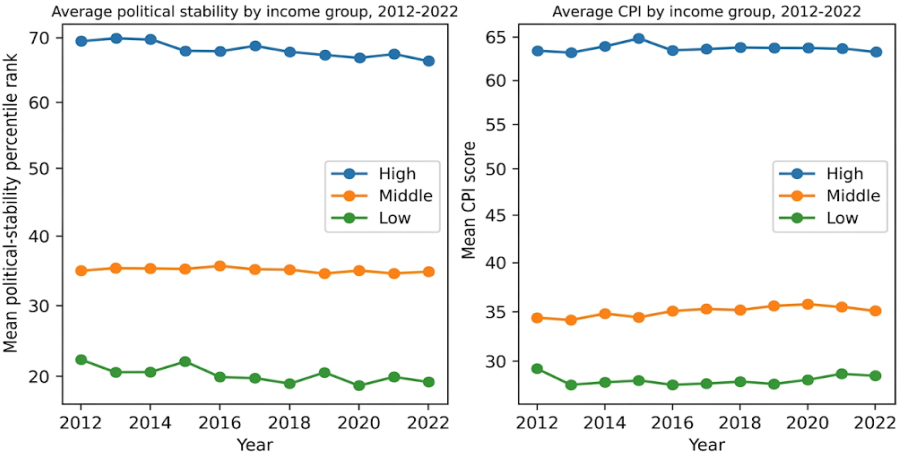


Figure 1. Average Political Stability and CPI by Income Group, 2012–2022

Figure 1 presents the evolution of average political stability and CPI across income groups over the 2012–2022 period. The left panel shows that average political stability remained in the range of approximately 66–70 for the High-income group, around 35 for the Middle-income group, and approximately 19–22 for the Low-income group. Although the High-income group experienced a relatively limited decline over the period, the differences across the three income groups were generally maintained. Political stability remained relatively stable in the Middle-income group, whereas the Low-income group exhibited somewhat greater year-to-year fluctuations.

The right panel of Figure 1 presents the average CPI by income group. CPI remained approximately within the 63–65 range in the High-income group and exhibited a relatively stable pattern throughout the period. In the Middle-income group, CPI fluctuated between approximately 34 and 36, while the Low-income group remained around 28 and consistently below the other two groups. Overall, the figure indicates that the most pronounced differences arise across income-group levels, whereas within-group changes over time are comparatively limited.

These findings indicate substantial differences across income groups in both CPI and political stability, while within-group changes over time remain relatively limited. It is therefore important to account for unobserved, time-invariant differences across countries in the empirical analysis. Accordingly, the subsequent analysis employs a two-way fixed-effects model that controls for country-specific fixed effects and common time shocks.

Econometric Model

Because unobserved and time-invariant country characteristics may be correlated with the explanatory variables in panel-data settings, the baseline estimation employs a two-way fixed-effects model that jointly incorporates country and year fixed effects. This approach controls for time-invariant differences across countries and estimates the relationship primarily from within-country variation over time (Wooldridge, 2010).

$$CPI_{it} = \beta_0 + \beta_1 PS_{it} + \beta_2 \ln GDP_{it} + \beta_3 INF_{it} + \beta_4 UNEMP_{it} + \beta_5 FDI_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Here, i denotes the country and t denotes the year; α_i represents country fixed effects, λ_t represents year fixed effects, and ε_{it} denotes the error term. The coefficient β_1 captures the conditional relationship between political stability and CPI after controlling for the other variables and fixed effects. Since higher CPI values correspond to lower perceived public-sector corruption, a positive β_1 indicates that higher political stability is associated with higher CPI and, consequently, lower perceived corruption. This interpretation does not constitute a causal claim.

Model Selection and Diagnostic Tests

The necessity of country fixed effects was assessed using an F-test of the joint null hypothesis that the country-specific effects are equal to zero. The tests are strongly significant in all three income groups ($p < 0.001$), supporting the use of country fixed effects rather than a pooled model. Year fixed effects are not jointly statistically significant in any of the three subsamples. Nevertheless, year fixed effects are retained in the baseline specification to control for global and regional shocks common to the 2012–2022 period.

Three aspects of the error structure were examined in the diagnostic analysis. The Wooldridge test for serial correlation in panel data, the groupwise heteroskedasticity test, and the Pesaran CD test were applied to assess serial correlation, groupwise heteroskedasticity, and cross-sectional dependence, respectively (Drukker, 2003; Pesaran, 2021).

The diagnostic results indicate that country fixed effects should be retained and that standard errors should not be calculated under the conventional assumptions of homoskedasticity and serial independence. Accordingly, the two-way fixed-effects specification is retained in the baseline estimations, while standard errors are corrected using the Driscoll–Kraay method. The approach of Driscoll and Kraay (1998) provides robust covariance estimates when panel error terms may exhibit both serial dependence and cross-sectional dependence. A bandwidth/lag parameter of 2 is used in the baseline estimations. PCSE estimates are additionally employed as an alternative inference and robustness specification using the same country and year fixed effects represented by dummy variables (Beck & Katz, 1995).

Multicollinearity among the explanatory variables was also examined using variance inflation factors (VIFs). In the High-income group, the VIF values for PS and lnGDPpc are 15.29 and 19.96, respectively, which are higher than those observed in the other groups. The corresponding values are 4.62 and 6.38 for the Middle-income group and 2.91 and 4.65 for the Low-income group. These results suggest that particular caution is warranted when disentangling political stability from economic development in the High-income group. Accordingly, robustness specifications using alternative measures of economic development are treated as complementary analyses to the baseline model.

Coefficient Heterogeneity Across Income Groups

To assess whether the relationship between political stability and CPI differs across income groups, coefficient equality is tested directly rather than comparing the p-values of the subsample estimates. The Low-income group is specified as the reference category, and interactions between PS and the Middle- and High-income group indicators are introduced. Because of country fixed effects, the time-invariant level effects of income-group membership are not estimated separately; instead, differences in the slope coefficients are identified through the interactions between PS and the income-group indicators.

$$CPI_{it} = \beta_0 + \beta_1 PS_{it} + \delta_1(PS_{it} \times Middle_i) + \delta_2(PS_{it} \times High_i) + \gamma' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In this model, the PS slope for the Low-income group is β_1 , while the slopes for the Middle- and High-income groups are $\beta_1 + \delta_1$ and $\beta_1 + \delta_2$, respectively. The main test of the heterogeneity hypothesis is based on the

joint Wald test of $\delta_1 = \delta_2 = 0$, while pairwise comparisons across groups are also conducted. This approach avoids the incorrect inference that coefficients differ simply because one group coefficient is statistically significant while another is not.

One-Period Lagged Political Stability Model

Because the CPI is a perception-based indicator, changes in political and institutional conditions may not be fully reflected in assessments within the same year. Therefore, a second specification is estimated using one-period lagged values of the explanatory variables.

$$CPI_{it} = \beta_0 + \beta_1 PS_{i,t-1} + \beta_2 \ln GDP_{i,t-1} + \beta_3 INF_{i,t-1} + \beta_4 UNEMP_{i,t-1} + \beta_5 FDI_{i,t-1} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3)$$

This model examines the relationship between the previous period's level of PS and the current period's CPI. Although the use of lagged explanatory variables strengthens temporal ordering, it does not by itself eliminate reverse causality, omitted-variable bias, or simultaneity. Therefore, the results from the lagged specification are interpreted as supporting evidence regarding the timing of the relationship rather than as causal effects.

Robustness Analyses

A series of robustness analyses is conducted to assess the sensitivity of the baseline results to alternative model specifications. First, a dynamic fixed-effects model is estimated to account for the high persistence of CPI. In this specification, the one-period lag of the dependent variable is added to the set of explanatory variables.

$$CPI_{it} = \rho CPI_{i,t-1} + \beta_1 PS_{it} + \gamma' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (4)$$

Because the dynamic FE model may be subject to finite-TT dynamic panel bias in panels with a short time dimension, this specification is treated only as a robustness analysis rather than as the baseline model (Nickell, 1981). Given that $T=11$, strong causal conclusions are not drawn from the dynamic model.

Second, a first-difference model is employed to directly examine short-run within-country changes:

$$\Delta CPI_{it} = \beta_1 \Delta PS_{it} + \gamma' \Delta X_{it} + \Delta \varepsilon_{it} \quad (5)$$

This specification eliminates time-invariant country characteristics through first differencing and provides an alternative within-country specification to the level model. The statistical insignificance of the first-difference model is interpreted as limiting the evidence for a strong relationship in annual changes. However, this result is not treated as a direct test of a competing hypothesis against the baseline model (Wooldridge, 2010).

Third, PCSE estimates are employed as an alternative to Driscoll–Kraay inference.

Fourth, sensitivity to the measurement of economic development is assessed using alternative specifications that replace $\ln\text{GDPpc}$ with HDI, education indicators, and life expectancy. Additional specifications include a model with winsorized FDI to examine the influence of extreme FDI observations, a model excluding the FDI control to assess its role, and a log-CPI model to evaluate sensitivity to the transformation of the dependent variable.

Overall, the empirical strategy addresses three main questions through complementary specifications. First, the two-way fixed-effects model examines the conditional relationship between political stability and CPI; second, the pooled interaction model directly tests differences in slopes across income groups; and third, the one-period lagged model examines the temporal relationship between political stability and CPI in the subsequent period. Based on the diagnostic tests, the main inference is conducted using Driscoll–Kraay robust standard errors, while dynamic, first-difference, PCSE, and alternative variable/sample specifications are employed for robustness assessment. Across all models, the estimated relationships are interpreted as correlational or conditional associations; fixed effects, lagged specifications, and robustness analyses do not by themselves provide causal identification, and the results are therefore not interpreted as establishing strong causal effects.

FINDINGS

Baseline Estimation Results

The baseline model is estimated using two-way fixed effects with Driscoll–Kraay robust standard errors. Table 4 presents the coefficient estimates for the three income groups jointly. The coefficient on PS is positive in all three groups. In the High-income group, the coefficient is 0.0437 and statistically significant at the 10% level ($p=0.092$). In the Middle-income group, the coefficient is 0.0132 ($p=0.542$), while in the Low-income group it is 0.0298 ($p=0.207$); neither is statistically significant. Thus, although the estimated coefficient is positive across all three groups in the baseline level specification, statistical support is limited to the High-income group. Given that higher CPI values correspond to lower perceived corruption, the positive PS coefficient indicates a positive conditional relationship between political stability and CPI. This relationship should not be interpreted as a causal effect.

Table 4. Baseline Two-Way Fixed-Effects Estimates with Driscoll–Kraay Standard Errors

Variable	High	Middle	Low
PS	0.0437* (0.0259)	0.0132 (0.0216)	0.0298 (0.0236)
lnGDPpc	6.2367*** (2.0024)	6.0678*** (0.4767)	0.9258 (2.8543)
Inflation	-0.0242 (0.0480)	0.0009 (0.0028)	0.0207*** (0.0057)
Unemployment	-0.0289 (0.0419)	0.1452*** (0.0191)	-0.2388 (0.1701)
FDI	0.0118** (0.0051)	-0.0126 (0.0156)	0.1085*** (0.0292)

Note: Values in parentheses are standard errors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The numbers of observations for the High-, Middle-, and Low-income groups are $N=594$, $N=924$, and $N=220$, respectively; the corresponding within R^2 values are 0.055, 0.029, and 0.122.

Regarding the control variables, lnGDPpc is strongly positive in the High- and Middle-income groups, with coefficients of 6.237 ($p=0.002$) and 6.068 ($p<0.001$), respectively. In the Low-income group, the coefficient on lnGDPpc is 0.926 and statistically insignificant ($p=0.746$). Inflation is positive and statistically significant only in the Low-income group (0.0207; $p<0.001$). Unemployment is positive and highly significant in the Middle-income group (0.1452; <0.001), but is not statistically significant in the High- and Low-income groups. FDI is positive and statistically significant in the High-income group (0.0118; $p=0.020$), negative and insignificant in the Middle-income group (-0.0126; $p=0.418$), and positive and statistically significant in the Low-income group (0.1085; $p<0.001$). These control-variable estimates should be regarded as supporting findings rather than as the primary focus of the study.

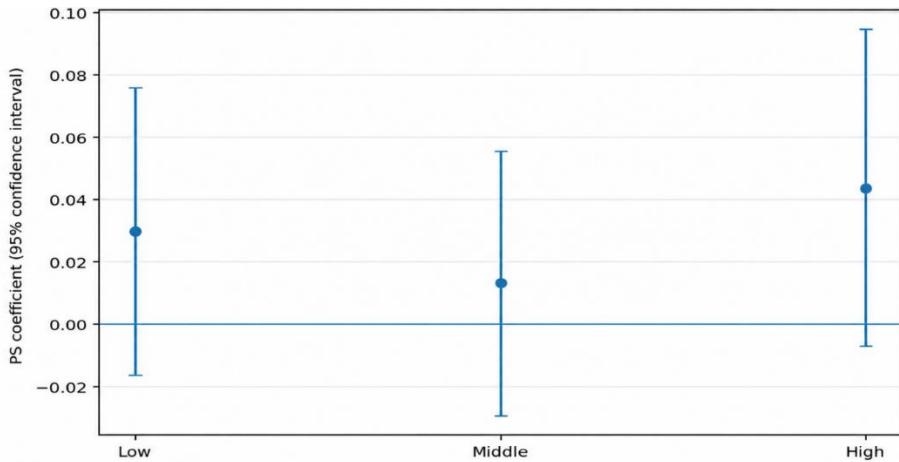


Figure 2. Political Stability Coefficients and 95% Confidence Intervals in the Baseline Model

Note: Point estimates represent the PS coefficients reported in Table 6. Confidence intervals are calculated using Driscoll–Kraay standard errors.

Figure 2 shows that the estimated coefficient on political stability is positive in all three income groups. The coefficient is largest for the High-income group, followed by the Low- and Middle-income groups. However, the 95% confidence intervals include zero for all three groups, indicating that none of the coefficients is statistically significant at the 5% level. The statistical evidence for the High-income group is therefore limited to the 10% significance level reported in Table 4.

Differences in Coefficients Across Income Groups

The fact that the estimated PS coefficients appear to differ in magnitude across the three groups does not, by itself, establish that the coefficients are statistically different. Therefore, a pooled interaction model is employed, with the Low-income group specified as the reference category, and the PS×Middle and PS×High interaction terms are directly tested. Table 5 reports the resulting group-specific PS slopes and pairwise contrasts.

Table 5. Pooled Interaction Model: Income-Group-Specific PS Slopes and Pairwise Differences

<i>Panel A. Income-Group-Specific PS Slopes</i>			
Group	PS Slope	SE	p
Low	0.0495	0.0213	0.020
Middle	0.0144	0.0205	0.480
High	0.0514	0.0250	0.040
<i>Panel B. Pairwise Differences in PS Coefficients Across Income Groups</i>			
Contrast	Difference	SE	p
Low-Middle	0.0350	0.0307	0.255
Low-High	-0.0019	0.0344	0.956
Middle-High	-0.0369	0.0443	0.404

Note: The Low-income group is the reference category. Pairwise contrasts in Panel B are based on Wald-type comparisons.

The PS slope is estimated at 0.0495 ($p=0.020$) for the Low-income group, 0.0144 ($p=0.480$) for the Middle-income group, and 0.0514 ($p=0.040$) for the High-income group. However, the joint test of the interaction terms yields $\chi^2=1.32$ with $p=0.517$. The pairwise comparisons likewise produce p -values of 0.255 for Low–Middle, 0.956 for Low–High, and 0.404 for Middle–High. Therefore, there is no statistical evidence that the coefficients differ across income groups. This result also demonstrates empirically that differences in statistical significance across subsamples should not be interpreted directly as evidence of heterogeneous effects.

Results from the One-Period Lagged Model

Given that the CPI is a perception-based indicator, changes in political stability conditions may not be fully reflected in assessments within the same year. Accordingly, an alternative estimation is conducted using one-period lagged values of all explanatory variables. Table 6 shows that the coefficient

on L1.PS is positive and statistically significant in all three income groups. The coefficient is 0.0802 ($p<0.001$) in the High-income group, 0.0398 ($p=0.035$) in the Middle-income group, and 0.0439 ($p=0.003$) in the Low-income group. Thus, in contrast to the more limited statistical support in the baseline level specification, the one-period lagged specification indicates a positive conditional relationship between lagged political stability and current-period CPI across all three income groups.

Table 6. Estimation Results with One-Period Lagged Explanatory Variables

Variable	High	Middle	Low
L1.PS	0.0802*** (0.0202)	0.0398** (0.0188)	0.0439*** (0.0148)
L1.lnGDPpc	5.5473** (2.4580)	5.4704*** (1.0512)	1.7611 (1.6888)
L1.Inflation	-0.0750 (0.0731)	0.0020 (0.0013)	0.0179*** (0.0056)
L1.Unemployment	0.0852* (0.0458)	0.1242*** (0.0276)	-0.5590*** (0.1999)
L1.FDI	0.0093** (0.0043)	-0.0227 (0.0183)	0.1041*** (0.0251)

Note: Values in parentheses are standard errors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

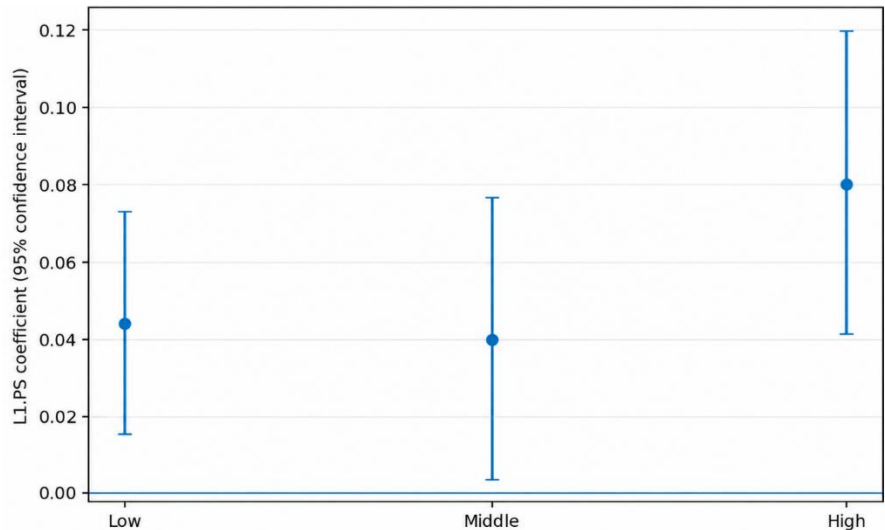


Figure 3. One-Period Lagged PS Coefficients and 95% Confidence Intervals

Note: The coefficients are obtained from models in which all explanatory variables are lagged by one period.

In the lagged model, lnGDPpc is also positive and statistically significant in the High- and Middle-income groups, with coefficients of 5.547 ($p=0.024$) and 5.470 ($p<0.001$), respectively, while the coefficient for the Low-income group is 1.761 and statistically insignificant ($p=0.297$). The unemployment coefficient is positive and marginally significant at the 10% level in the High-income group (0.0852; $p=0.063$), positive and highly significant in the Middle-income group (0.1242; $p<0.001$), and negative and statistically significant in the Low-income group (-0.5590; $p=0.005$). Inflation is statistically insignificant in the High- and Middle-income groups but is positive and significant in the Low-income group (0.0179; $p=0.001$). FDI is positive and statistically significant in the High-income group (0.0093; $p=0.029$), negative and insignificant in the Middle-income group (-0.0227; $p=0.213$), and positive and highly significant in the Low-income group (0.1041; $p<0.001$).

Table 7. Lagged Interaction Model: Income-Group-Specific L1.PS Slopes and Pairwise Differences

<i>Panel A. Income-Group-Specific L1.PS Slopes</i>			
Group	L1.PS Slope	SE	p
Low	0.0633	0.0168	<0.001
Middle	0.0440	0.0166	0.008
High	0.0917	0.0187	<0.001
<i>Panel B. Pairwise Differences in Lagged PS Coefficients</i>			
Contrast	Difference	SE	p
Low-Middle	0.0192	0.0246	0.434
Low-High	-0.0284	0.0294	0.334
Middle-High	-0.0477	0.0327	0.145

Note: The Low-income group is the reference category. Pairwise contrasts in Panel B are based on Wald-type comparisons.

According to Table 7, coefficient differences are likewise not statistically supported in the lagged pooled interaction model. The group-specific lagged slopes are 0.0633 ($p < 0.001$) for Low, 0.0440 ($p = 0.008$) for Middle, and 0.0917 ($p < 0.001$) for High, while all pairwise differences are statistically insignificant ($p = 0.434$, 0.334, and 0.145, respectively). Thus, although the lagged relationship is observed in all three income groups, there is no statistical evidence that the magnitude of this relationship differs across income groups.

Robustness Analyses

A series of robustness analyses is conducted to assess the sensitivity of the baseline results to alternative temporal, estimation, and modeling choices. These analyses are not treated as replacements for the baseline model but rather as complementary assessments of how the relationship between political stability and CPI changes under alternative model assumptions.

In the dynamic fixed-effects model, the coefficient on the one-period lagged dependent variable, L1.CPI, is 0.705, 0.703, and 0.640 for the High-, Middle-, and Low-income groups, respectively, and is statistically significant in all three groups ($p < 0.001$). This result indicates a high degree of persistence in the CPI measure. After controlling for L1.CPI, the PS coefficients are 0.0438 ($p < 0.001$), 0.0265 ($p = 0.012$), and 0.0307 ($p = 0.008$) for the High-, Middle-, and Low-income groups, respectively. However, given the relatively short time dimension of only 11 years, dynamic fixed-effects estimates may be subject to finite-TT bias. The results are therefore interpreted as complementary robustness evidence rather than as substitutes for the baseline model (Nickell, 1981).

In the first-difference model, the coefficient on ΔPS is estimated at -0.0096 ($p = 0.258$) for the High-income group, 0.0079 ($p = 0.607$) for the Middle-income group, and 0.0112 ($p = 0.584$) for the Low-income group. None of these coefficients is statistically significant. This result indicates that the first-difference specification based on annual within-country changes provides no statistical support for a significant relationship between political stability and CPI. Accordingly, caution is warranted in interpreting the positive coefficients in the baseline level models as short-run causal effects.

Table 8. Evolution of PS Coefficients across Baseline, Lagged, and Robustness Specifications

Specification	High	Middle	Low
Main FE–DK	0.0437*	0.0132	0.0298
Lagged PS	0.0802***	0.0398**	0.0439***
Dynamic FE	0.0438***	0.0265**	0.0307***
First Difference	-0.0096	0.0079	0.0112
PCSE	0.0437*	0.0132	0.0298
Alternative development controls	0.054–0.057	0.023–0.023	0.011–0.038
FDI sensitivity	0.045–0.049*	0.014	0.023–0.042

Note: The table reports PS coefficients. The baseline FE–DK model uses Driscoll–Kraay robust standard errors. The Lagged PS, Dynamic FE, and First Difference rows report the coefficients on L1.PS, PS conditional on L1.CPI, and Δ PS, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Ranges reported for alternative specifications represent the estimated ranges of the corresponding PS coefficients.

Table 8 summarizes the behavior of the PS coefficient across the baseline and alternative specifications. In the baseline FE–DK estimates, the coefficients are positive in all three income groups. In the one-period lagged specification, the L1.PS coefficients are again positive and statistically significant in all three groups. In the dynamic FE model, the sign of the PS coefficient remains positive and statistically significant across all income groups after controlling for lagged CPI. By contrast, the first-difference model yields no statistically significant PS coefficient when annual changes are considered. Taken together, the level, lagged, dynamic, and differenced specifications indicate that the statistical support for the relationship between political stability and CPI is sensitive to the model specification and is more limited when focusing on short-run within-country changes.

The sign of the PS coefficient is generally preserved across alternative control-variable and model specifications. In the High-income group, replacing $\ln$ GDPpc with HDI, education indicators, and life expectancy yields PS

coefficients of 0.0537 ($p=0.027$), 0.0540 ($p=0.023$), and 0.0566 ($p=0.019$), respectively, providing stronger statistical support than in the baseline model. In the Middle-income group, the PS coefficients remain within the range of 0.0226–0.0233 but are statistically insignificant when alternative development indicators are used. In the Low-income group, the PS coefficients remain statistically insignificant in the specifications using HDI and life expectancy; however, when FDI is excluded from the model, the coefficient rises to 0.0415 and becomes statistically significant ($p=0.026$). This result suggests that the estimated PS coefficient, particularly in the Low-income group, may be more sensitive to the choice of control variables and the specification of FDI.

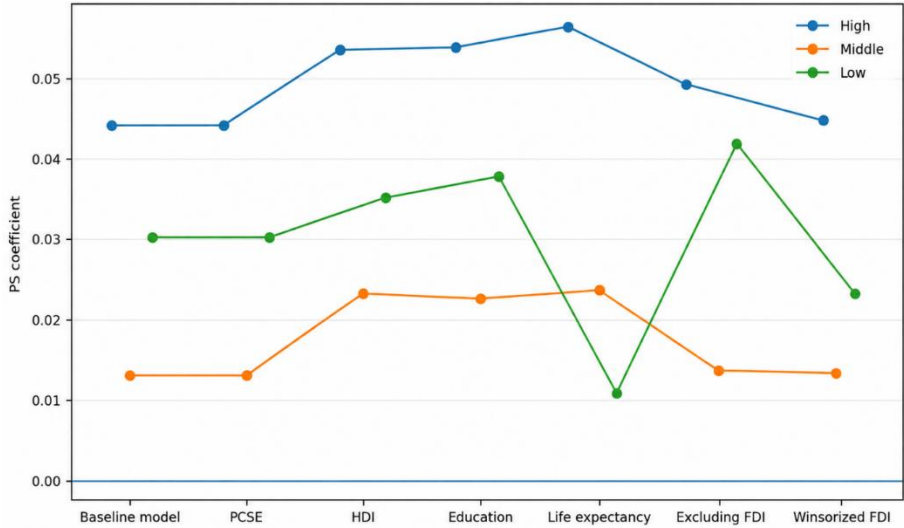


Figure 4. Sensitivity of PS Coefficients to Alternative Specifications

Note: The figure is intended solely for visual comparison; the dependent-variable scale differs in the log-CPI specification.

The PCSE estimates likewise do not alter the direction of the baseline relationship. The PS coefficients are 0.0437 ($p=0.059$), 0.0132 ($p=0.525$), and 0.0298 ($p=0.197$) for the High-, Middle-, and Low-income groups, respectively. Thus, the signs of the baseline coefficients are preserved under an alternative inference approach. However, because PCSE and Driscoll–Kraay rely on different assumptions regarding the error structure, these results should be regarded not as validation tests of one another but as complementary robustness evidence.

CONCLUSION

This study examines the relationship between political stability and perceived public-sector corruption across high-, middle-, and low-income countries using a balanced panel of 158 countries over the period 2012–2022. The empirical strategy combines two-way fixed-effects estimations with Driscoll–Kraay robust standard errors, pooled interaction models to formally assess coefficient heterogeneity across income groups, one-period lagged specifications to examine the temporal dimension of the relationship, and a set of robustness analyses. The analysis is motivated by the possibility that the relationship between political stability and perceived corruption may differ across economic contexts and may not be fully captured by contemporaneous associations.

Taken together, the findings point to a relationship between political stability and perceived public-sector corruption that is positive in sign across the income groups considered, but whose statistical strength depends on the temporal and econometric specification. The contemporaneous level model offers limited support, whereas the lagged specification yields statistically significant positive associations across all three groups. At the same time, the absence of statistically significant cross-group coefficient differences indicates that the data do not provide sufficient evidence of systematic income-group heterogeneity in the slope of the relationship. The first-difference results further suggest that the association is less pronounced when the analysis focuses exclusively on short-run annual changes within countries. These patterns imply that the relationship is better characterized as a persistent and temporally distributed association than as a simple contemporaneous relationship.

From a broader perspective, the findings contribute to the literature by bringing together two dimensions that have often been considered separately: heterogeneity across income groups and the temporal dimension of the political stability–corruption nexus. Rather than assuming that the relationship is necessarily homogeneous or immediate, the results show that its empirical manifestation depends on how the relevant variation is measured and over what time horizon it is considered. This is particularly relevant for cross-country research on institutional outcomes, where substantial differences in levels may coexist with relatively limited within-country variation over time.

Several limitations should nevertheless be acknowledged. First, the CPI is a perception-based measure and therefore captures perceived rather than directly observed corruption. Second, despite the use of country and year fixed effects, Driscoll–Kraay standard errors, lagged specifications, and multiple

robustness checks, the empirical design does not provide a fully exogenous source of variation in political stability. The results should therefore not be interpreted as establishing strong causal effects. Third, the relatively short time dimension limits the scope for dynamic panel estimation and makes short-run within-country relationships difficult to identify precisely.

Overall, the study finds that political stability and perceived public-sector corruption are positively associated in the expected direction, with the strongest and most consistent statistical evidence emerging when political stability is allowed to operate with a one-period lag. However, the evidence does not indicate statistically significant differences in this relationship across high-, middle-, and low-income groups. The main implication of the analysis is therefore not that income level fundamentally changes the direction of the relationship, but that the empirical strength of the association is sensitive to temporal specification and to the type of within-country variation used for identification.

REFERENCES

- Ades, A., & Di Tella, R. (1999). Rents, competition, and corruption. *American economic review*, 89(4), 982-993.
- Al-Jabri, N., Saha, S., Campbell, N., & Gillani, A. A. (2025). Does Corruption Trigger Political Instability? Evidence on the Role of Demographics and Social Cohesion1. *Economic Modelling*, 107456.
- Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American political science review*, 89(3), 634-647.
- Beju, D. G., Ciupac-Ulici, M. L., & Bresfelean, V. P. (2024). Political stability and corruption nexus: an international perspective on European and Asian countries. *The Journal of Risk Finance*, 25(3), 422-442.
- Brunetti, A., & Weder, B. (2003). A free press is bad news for corruption. *Journal of Public economics*, 87(7-8), 1801-1824.
- Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, 80(4), 549-560.
- Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The stata journal*, 3(2), 168-177.
- Elbahnasawy, N. G., & Revier, C. F. (2012). The determinants of corruption: Cross-country-panel-data analysis. *The Developing Economies*, 50(4), 311-333.

Farzanegan, M. R., & Witthuhn, S. (2017). Corruption and political stability: Does the youth bulge matter?. *European Journal of Political Economy*, 49, 47-70.

Fisman, R., & Gatti, R. (2002). Decentralization and corruption: evidence across countries. *Journal of public economics*, 83(3), 325-345.

Fredriksson, P. G., & Svensson, J. (2003). Political instability, corruption and policy formation: the case of environmental policy. *Journal of public economics*, 87(7-8), 1383-1405.

Khan, R. E. A., & Farooq, S. (2019). Corruption, political instability and sustainable development: The interlinkages. *Journal of Quantitative Methods*, 3(1), 57-84.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (1999). The quality of government. *Journal of Law, Economics, and organization*, 15(1), 222-279.

Lederman, D., Loayza, N. V., & Soares, R. R. (2005). Accountability and corruption: Political institutions matter. *Economics & politics*, 17(1), 1-35.

Mauro, P. (1995). Corruption and Growth,' *Quarterly Journal of Economics*, VoL 110, pp. 681-712., 1997. *The Effects of Corruption on Growth, Investment and Government Expenditure A Cross — Country Analysis*, "Corruption and the Global Economy", 83-107.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, 1417-1426.

Persson, T., Tabellini, G., & Trebbi, F. (2003). Electoral rules and corruption. *journal of the European Economic Association*, 1(4), 958-989.

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical economics*, 60(1), 13-50.

Saha, S., & Gounder, R. (2013). Corruption and economic development nexus: Variations across income levels in a non-linear framework. *Economic Modelling*, 31, 70-79.

Saha, S., Gounder, R., Campbell, N., & Su, J. J. (2014). Democracy and corruption: A complex relationship. *Crime, law and social change*, 61(3), 287-308.

Serra, D. (2006). Empirical determinants of corruption: A sensitivity analysis. *Public Choice*, 126(1), 225-256.

Svensson, J. (2005). Eight questions about corruption. *Journal of economic perspectives*, 19(3), 19-42.

Transparency International. (n.d.). *Transparency International*. Retrieved October 3, 2026, from <https://www.transparency.org/en>

Treisman, D. (2000). The causes of corruption: a cross-national study. *Journal of public economics*, 76(3), 399-457.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data* (Vol. 108, No. 2, pp. 245-254). Cambridge, MA: MIT press.

World Bank. (n.d.). *The World Bank*. Retrieved October 3, 2026, from <https://www.worldbank.org>

The Impacts of Renewable Energy, Financial Development, Trade Openness, and Economic Growth on Income Distribution in Türkiye: Evidence from the ARDL Approach

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ABSTRACT

Income distribution, or the way in which the entire revenue produced in an economy is divided among people, households, or factors of production, reflects both individual productivity and the equity of the social system. Income distribution is affected by a broad range of economic, social, demographic, and political forces. Social wellbeing is shaped by these elements that impact income distribution through both long-term structural changes and short-term economic volatility. In this context, income distribution is a crucial indicator demonstrating how fairly economic welfare is shared among different social segments. This study was prepared to determine the effects of financial development, economic growth, renewable energy use, and trade openness on income distribution in Türkiye during the period 1990-2021. According to the ARDL model estimation results, in the long run, only financial development has a corrective effect on income distribution. Therefore, more effective use of financial transmission mechanisms is necessary to improve income distribution. It is concluded that increases in economic growth alone are not sufficient in the long run. In addition, FMOLS, DOLS, and CCR analyses were performed as robustness checks. In the long term, only the positive impact of financial development on income distribution was confirmed.

Keywords - Gini Coefficient, Financial Development, Trade Openness, Renewable Energy, ARDL, Türkiye

1. INTRODUCTION

Distribution of income is an issue that faces all economies. The equity of its distribution matters not only for social justice but also for economic stability and the viability of the growth process. On the other hand, in its political and social ramifications, growing income inequality undermines political stability, social cohesion, democratic participation and the well-functioning of democratic institutions (Adam ve Alzuman, 2024; Ağırkaya, 2022), all of which turns income distribution into the consideration of a key aggregate macroeconomic indicator. In Türkiye, the income distribution has a significant relationship with economic growth, employment, financial development and social welfare policies. Although per capita income in Türkiye has grown over time, it is not clear if this has led to a more equitable distribution of national income.

When the gains from economic growth are not shared equally across society, income disparities may widen across regions and social groups (Ağırkaya, 2022; Akar, 2010). This situation raises questions about the relationship between economic growth and income inequality. In this context, financial development and trade openness are two important factors affecting income distribution. An inclusive financial system can improve access to

credit and financial resources for lower-income groups, while trade openness may influence income distribution by changing production structures and increasing the economy's exposure to international markets.

The income growth distribution is affected by energy consumption and its link with economic growth. As a rule, production and economic activity at large raises the demand for energy. While Ağırkaya (2022) contends that renewable energy investments in Türkiye contribute to sustainable economic growth with reduced external energy dependency. Nevertheless, the poor are hit harder by rising energy prices, and this can also increase income inequality, particularly in (energy) importing countries, e.g. Türkiye (Akar, 2010). Hence, it is imperative to analyze macroeconomic determinants of the income distribution in order to know how welfare is distributed in the course of economic expansions. Among the determinants are GDP per capita. When production income is unevenly shared between capital and labor, then growth's contribution to social welfare is attenuated. In levels, the differences in productivity between industry, service and agriculture in Türkiye bring about the existence of persistent wage differentials and as a result, income disparities. In this sense, the sectoral disparities might pose a challenge to achieving long-run equity, whereas sector-based credit policy and general financial deepening may ease income disparities and facilitate sustainable economic growth.

While a great deal of the research has focused on the determinants of income distribution in various countries, the evidence for Türkiye is not so abundant. In order to fill the gap, this paper explores the impact of financial development, trade openness, renewable energy consumption and GDP per capita on income inequality in Türkiye. The Gini index is used to measure income inequality with yearly data during the period 1990–2021. The short-run and long-run dynamics among the variables are tested by ARDL bounds testing approach, and robustness checks are performed by FMOLS, DOLS and CCR estimators. Therefore, the present work has the objective of adding new text and further policy recommendations for ensuring a more even income distribution.

The rest of this paper is organized as follows: The following section describes the notion and quantification of income distribution, elaborates on its major determinants, and reviews the income distribution patterns in Türkiye. Section 2 describes the data, the econometric model, and the methodology. Section 3 contains a discussion of the empirical results and their implications. The last section concludes by summarizing the main findings, offering policy implications, and a future research agenda.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1.The Concept of Income Distribution

Income distribution is broadly understood as the way in which the entire revenue produced in an economy is divided among people, households, or factors of production. The idea of income distribution is intrinsically linked to social fairness, equal opportunity, social cohesiveness, and political stability. Accordingly, income distribution is seen as a development indicator and social policy instrument in addition to being a statistical criterion in economic analyses (Akar, 2010; Akı, 2021). Income distribution is generally examined through two main dimensions: functional income distribution and personal income distribution. Here, wage, interest, rent, and profit rates offer crucial hints on the economic structure's class and production relations. Personal income distribution refers to how total income is allocated among individuals and households and therefore provides a direct indication of income disparities within society.

In previous extensive research, the question of how income distribution changes, particularly with the industrialization process, was addressed in conjunction with economic growth theories (Akı, 2021; Alev vd., 2025). While classical economists view income distribution as a natural consequence of factors of production, modern economic approaches conceptualize income inequality as a critical problem for social welfare and economic stability, with increasing imbalances in income distribution reported to decrease consumption demand and long-term economic growth, while increasing social unrest.

2.2.Methods for Measuring Income Distribution

The degree, direction, and time changes in income inequality are measured using income distribution measurement methods both on the micro level (individuals or households) and on the macro level (income structure of national economies). The main purpose of measuring income distribution is to objectively demonstrate how total income is distributed among different social segments and to develop corresponding policies for income equity (Ayhan ve İnancılı, 2022; Aydın vd., 2014). One of the most widely used and fundamental statistical measures here is the Gini coefficient, a numerical measure of how well a nation's total income is distributed among its citizens or households. The income inequality is generally measured by Gini coefficient which is derived from Lorenz curve and Lorenz curve shows how uniformly or skewly income is distributed among the population (Baş ve Sertkaya, 2021; Bayar, 2023). The value of the coefficient lies between zero and one. Zero means income is distributed equal among people and it is known as perfect equality while the closer value to one, the more major income inequality. The Lorenz curve is a graph that plots the cumulative income share against the cumulative population share, and the distance

between the line of perfect equality and the Lorenz curve serves as a measure of the extent of income inequality. Income inequality becomes more severe when the Lorenz curve diverges more from the line of equality (Bayar, 2023; Bezen, 2022). Consequently, the Gini coefficient is a valuable instrument to compare patterns of income distribution between the countries and over time (Aydın vd., 2014).

Income share ratios, indicating the share of income accrues to a certain percentage of the population, is another means to assess the income distribution. The population is commonly broken up into percentiles or quintiles, for example the bottom 20 percent, second 20 percent, and so on, up to the top 20 percent. These ratios are useful in showing how income is spread throughout the population. Yet another advanced method to measure income inequality is the Atkinson index (Barbaros vd., 2018; Baş ve Sertkaya, 2021). Yet another advanced method to measure income inequality is the Atkinson index (Barbaros vd., 2018; Baş ve Sertkaya, 2021).

2.3.Factors Affecting Income Distribution

Factors affecting income distribution emerge as a result of the complex interaction of economic, social, demographic, and political elements. Economic factors include technological developments, growth rates, capital accumulation, and employment structure, while social factors relate to cultural norms, education levels, and gender roles. Demographic factors address variables such as migration, population growth rates, and age, while political factors include determinants such as public expenditures, tax policies, and institutional arrangements that affect income distribution. The structure of production processes, job possibilities, public policies, and the operation of social institutions also influence how income is distributed across people and households in an economy. Through both short-term economic fluctuations and long-term structural changes, these elements influence the degree of social welfare. One of the most important elements here is the quality of economic growth. While the general level of wellbeing rises with rapid economic expansion, the rise is not always distributed equally among social groups (Blomme ve Héricourt, 2025; Bostan ve Ravanoğlu, 2019). With the growth of capital-intensive sectors, the labor income shares declines. Conversely, with the expansion of labor-intensive industries, more people in society can profit from higher wages. Recent shifts in the Turkish economy's production structure, particularly the expansion of the service sector, have led to sector-based disparities in income distribution (Bostan ve Ravanoğlu, 2019).

2.4.Income Distribution in Türkiye

Income distribution in Türkiye has long been shaped by the economic growth process, structural transformations, regional development disparities, and social policy implementations. Since the early days of the Republic, state-led development policies focused on increasing the rate of economic growth,

rather than ensuring income equity, thus making income inequality a persistent problem (Keskin, 2022; Koç, 2021). Owing to higher trade density and industrialization, the Marmara, Central Anatolia, and Aegean regions account for a larger share of the country's income. In the Eastern and Southeastern regions, income distribution is more unbalanced due to inadequate infrastructure, low education levels, and low employment rates. Regional imbalances can be considered one of the main reasons for income inequality in Türkiye.

In Türkiye, income distribution is closely related to the employment structure, regional development disparities, the tax system, the quality of economic growth, and the effectiveness of social policy measures. Gini, P80/P20 ratio, income share by percentile, Palma ratio, and household income decile are the measures that have been used to track changes and examine the degree of income inequality at the country level (Lang, 2016; Makhdum vd., 2022). In the Turkish case, these indicators suggest that income inequality has remained a structural problem despite periods of economic growth. According to the Household Income and Living Conditions Survey published periodically by the Turkish Statistical Institute, the Gini coefficient fluctuated between 0.44 and 0.39 from the early 2000s to the mid-2010s.

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The Gini coefficient also contributes to the enlightenment about the macroeconomic correlates of income inequality. While the growth of the economy may lower the coefficient in some cases but high inflation, high unemployment and high exchange rate volatility deteriorate the income distribution. In Türkiye, the rise of the Gini coefficient in the aftermath of the

pandemic, and following the economic crisis of 2018, points to worsening income distribution (Mahiroğulları, 2021; Mucuk ve Uysal, 2009).

2.5.The Relationship Between Income Distribution and the Gini Coefficient

The relationship between the Gini coefficient and income distribution provides a fundamental analytical framework for measuring whether income is fairly distributed among individuals and households. The Gini coefficient converts the level of income inequality into a numerical indicator, thus enabling a concrete assessment of the relationship between income equity and economic growth. Furthermore, the Gini coefficient reveals not only the general state of income distribution, but also shows its changes over time (Cevizli, 2013; Coşkun vd., 2015).

The connection between macroeconomic success and income distribution may also be seen by interpreting the Gini coefficient from an economic standpoint. An increase in the Gini coefficient means that money is concentrated in higher-income groups, while low-income groups receive a smaller portion of total income. This limits the consumption expenditures of low-income persons by lowering their aggregate demand level (Coşkun vd., 2015; Çiftçi, 2022). The durability of economic growth in countries with a more equal distribution of income is enhanced because domestic demand is more evenly spread. On the other hand, a low rate of demand adversely affects employment and output, generating fluctuations in the economic growth process. Therefore, the Gini ratio also reflects the quality of economic growth (Çiftçi, 2022; Çiftçi ve Yıldız, 2015) and captures social welfare. The level of social well-being is determined by how money is distributed among social groupings as well as per capita income. A skewed distribution of income within society also means low-income people have more difficulty obtaining basic services such as shelter, health care, and education, which negatively impacts the development of human capital and productivity. In this vein, Blomme and Héricourt (2025) in an analysis on the middle-income groups, income inequality and current account imbalances surprisingly revealed that income inequality and macroeconomic instability are deeply intertwined, and that current account deficits become more fragile in middle-income countries. Therefore, a large value of the Gini means the social well-being is undermined not only from an economic welfare perspective but also from a social welfare perspective. In the long run, since the income distribution deteriorates, poverty turns permanent, thus stifling social mobility and deepening social stratification (Çiftçi ve Yıldız, 2015; Destek vd., 2020).

2.6.The Relationship Between Financial Development and Income Distribution

A very crucial part of processes of economic growth is the relationship between financial development and income distribution. Financial

development is described as the size, the efficiency, the accessibility and the richness of a country's financial system, and the level of development of this system directly affects the equality and direction in the distribution of income. With the latest debates signaling potential nonlinear relationship (Siddique ve Lee, 2024; Kavya ve Shijin, 2020), the impact of financial development on disparity could be dependent on a nation's general economic and financial growth stage. Yet financial market access is often restricted to the rich early on in development, possibly reinforcing income inequality. In contrast, mature economies tend to be more successful in narrowing such disparity through enhanced financial inclusion (Thornton ve Tommaso, 2019). Furthermore, governments are increasingly interested in examining the impacts that financial sector policies have on economic growth and its distribution across different income classes (Nguyen vd., 2019). Although some argue that further financial development with banking and financial markets as its main components can bring about higher levels of income inequality, there is also evidence that suggests financial development could lead to a reduction in income inequality by increasing the access to financial services, which itself, can incentivize low income households to invest in asset accumulation, entrepreneurship and education (Hordofa, 2023). On the whole, existing evidence points towards a positive relationship between the expansion of the financial sector and wealth inequality, especially so for developed nations (Siddique ve Lee, 2024).

Although there are differing views on how financial development affects income distribution, it can generally be said that this effect is closely linked to economic growth and the policies pursued (Bittencourt vd., 2019; Altunbaş ve Thornton, 2019). In a comparison of Türkiye with the BRICKS countries in terms of the effect of financial development on economic growth, Makhdom vd. (2022) found that the effect of financial development on growth differs according to a nation's institutional capabilities. By promoting capital accumulation, directing savings into investments, and guaranteeing effective resource allocation, the financial system boosts economic growth. In a different study, Durgun (2024) discovered an uneven correlation between growth and financial development in Türkiye between 1990 and 2023, suggesting that growth promotes income equity. The primary way through which financial development influences income distribution is via financial intermediation activities. Financial intermediaries serve to increase economic activity by facilitating the transfer of resources between people and businesses (Eker, 2021; Emin 2021). Credit is easier to obtain in established financial systems, and small and medium-sized businesses can boost output and create jobs. Large portions of society can thus make more money, which improves wealth distribution (Emin, 2021; Ertaş, 2019). Conversely, capital accumulation is concentrated in high-income segments while low-income people stay outside the financial system in economies where financial access is restricted to specific groups.

2.7.The Relationship Between Energy Consumption and Income Distribution

While energy consumption and income distribution are critical to sustainability of social welfare, economic growth, and production efficiency, thorough analyses of income inequality, wealth redistribution, and the dynamics of renewable and non-renewable energy use are largely lacking in the literature. Despite the evidence showing how a fair income distribution would significantly reduce home energy usage (Acheampong vd., 2023), the impact of income redistribution on the demand for renewable and non-renewable energy is not taken into consideration. It is well known that low-income households generally prefer fossil fuels, which are more affordable but less environmentally sustainable. However, the impact of economic inequality on the adoption of renewable energy technologies has not yet been sufficiently addressed in the literature. The notion that income inequality can degrade the environment by hindering environmental quality and energy equity poses a significant challenge. Initiatives aimed at increasing employment, targeted training programs, and redistributive policies such as progressive taxation are considered important tools for reducing environmental degradation and promoting equitable access to resources (Ofori vd., 2024). Concurrently, wealth inequality significantly contributes to the increase in environmental variables such as CO₂ emissions and accelerating the transition to clean energy and implementing more equitable socioeconomic models are crucial for achieving sustainable development goals (Hacıımamoğlu vd., 2025). Since energy is a determinant of both industrial production and household living standards, and a fundamental production input in modern economies, institutional structures play a crucial role in environmental protection and ensuring renewable energy consumption. Accordingly, in an analysis of the impact of per capita income and household size on energy consumption on the regional level in Türkiye, Koç (2021) found that energy demand rises with income levels and that home size influences energy efficiency. Energy access is also directly impacted by the quality of life and involvement of various societal groups in economic activities (Karabulut, 2006; Karış ve Ayla, 2018). In an earlier study conducted between 1990 and 2020, Ayhan ve İnançlı (2022) concluded that energy consumption indirectly affects inequality through economic growth.

The impact of energy use on income distribution is primarily shaped by the structure of production and consumption. Increases in energy costs cause low-income households to allocate most of their expenditures to energy, thereby weakening income equity. In macroeconomic terms, this causes income disparities to become permanent and energy-based production opportunities to be distributed regionally unequally. Indeed, one of the key factors in ensuring income equity is a balanced development of energy infrastructure across the country.

2.8.The Relationship Between Trade Openness and Income Distribution

The impact of trade openness on income distribution has been a longstanding subject of debate in the development and international economics literature. Theoretical perspectives on this relationship vary according to countries' structural characteristics and stages of economic development, leading to different interpretations of its distributional effects. Classical trade theory, particularly "the Heckscher–Ohlin model and the Stolper–Samuelson theorem", suggests that trade openness contributes to reducing income inequality in developing economies (Stolper ve Samuelson, 1941). Within this framework, international trade increases the demand for production factors in which countries possess a relative abundance.

The relatively large share of unskilled labor in developing economies, combined with trade liberalization, gives rise to the expectation that wages for this segment may increase relative to capital income. For this reason, it is believed that trade liberalization can improve income distribution by reducing income inequality. This optimistic view of globalization is also supported by Dollar and Kraay (2004). The authors argue that economic growth has accelerated in developing economies that are more strongly integrated into global markets and have embraced trade liberalization; they contend that this process has contributed to the reduction of poverty and income inequality. However, current debates on globalization and a growing body of empirical evidence are prompting a reevaluation of these traditional views. In particular, it is understood that the assumptions underlying the Stolper-Samuelson theorem may not hold to the same extent for every country and period. For this reason, some researchers argue that the transformation of global production networks, technological advancements, and rising demand for a skilled workforce-combined with trade liberalization-could increase income inequality in developing countries. In their comprehensive assessment of the relationship between globalization and income inequality, Goldberg and Pavcnik (2007) emphasize that empirical findings often do not align with traditional theoretical expectations. They point to the effects of skill-biased technological change as one of the main reasons for this. As developing countries open up further to trade and import more technology-intensive capital goods, the demand for a skilled workforce may increase. This process could lead to a widening wage gap between skilled and unskilled workers and weaken the position of unskilled workers in the labor market. Meschi and Vivarelli (2009) also note that trade between high-income developed countries and middle-income developing countries may increase income inequality in developing countries. According to the authors, skill-based technologies spread through international trade are widening income disparities across sectors, thereby deepening income inequality. This situation limits the effects

of income redistribution and leads to a less balanced income distribution than predicted by traditional trade theories.

Empirical studies conducted in the context of the Turkish economy reveal that the relationship between trade and income distribution is complex and multidimensional. In their study covering the 2013–2023 period, Alev vd. (2025) state that the effect of foreign trade on income distribution does not manifest directly or linearly; rather, this effect is shaped primarily through transformations in the structure of production and sectoral adjustment processes. These findings suggest that market integration does not necessarily imply more equal income distribution. The impact of trade on income distribution depends, among other things, on the technological content of exports and the skill level of the labour force. In addition, when the inflow of foreign capital (and other macroeconomic variables) are considered, the connection between trade openness and income inequality is further complicated. In this context, Kariş and Ayla (2018) examined the relationship between foreign direct investment inflows and the trade gap in Turkey using econometric methods. The study emphasizes that the trade gap is closely linked to international investment flows. When trade expansion occurs through capital-intensive foreign investment or production structures dependent on imports, labor's share of national income may remain limited. This situation, in turn, can lead to structural imbalances in the distribution of wealth. Overall, the ultimate impact of trade openness on income distribution remains an empirical issue, the outcome of which is largely contingent upon a country's industrial policies, labor market institutions, and institutional capacity.

3.RESEARCH METHODOLOGY

3.1.Data and Variables Explanation

This study investigates the impact of financial development, renewable energy use, economic growth, and trade openness on income inequality in Türkiye during the period 1990-2021. The Autoregressive Distributed Lag (ARDL) Approach was used in these process. In addition, it was conducted as robustness checks though Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegration Regression (CCR) analyses.

As seen in Table 1, as dependent variable GINI coefficient (GINI), as independent variables are financial development (FD), GDP per capita (GDP), trade openness (TRD), and renewable nergy use (REC) are included in the model. All variables are in logarithmic form. The GINI coefficient was obtained from Destek et al. (2020), and TUIK website, FD variable provided from the IMF website, REC, GDP, and TRD variables obtained from the WDI database.

Table 1: Data, Information and Source

Variables	Description	Unit and Information	Source
GINI	Income Inequality	GINI coefficient	SWIID (Solt, 2016)
FD	Financial development	Financial system deposits to GDP for Türkiye	IMF
GDP	GDP per capita	GDP per capita (constant 2015 US\$)	WDI
TRD	Trade openness	Trade (% of GDP)	WDI
REC	Energy use	Renewable energy use (% of total final energy use)	WDI

Figure 1 shows the trend of the variables in the model over time. Accordingly, it is seen that income distribution has the greatest improvement during the period of 2012-2016. Throughout the entire period, financial development and trade openness followed an upward trend, albeit with fluctuations. Economic growth was negative during the periods of the 1994, 2001, and 2008 economic crises. Renewable energy consumption was included in the analysis to determine the link between income distribution and sustainability. Renewable energy consumption has shown a stable trend since 2007.

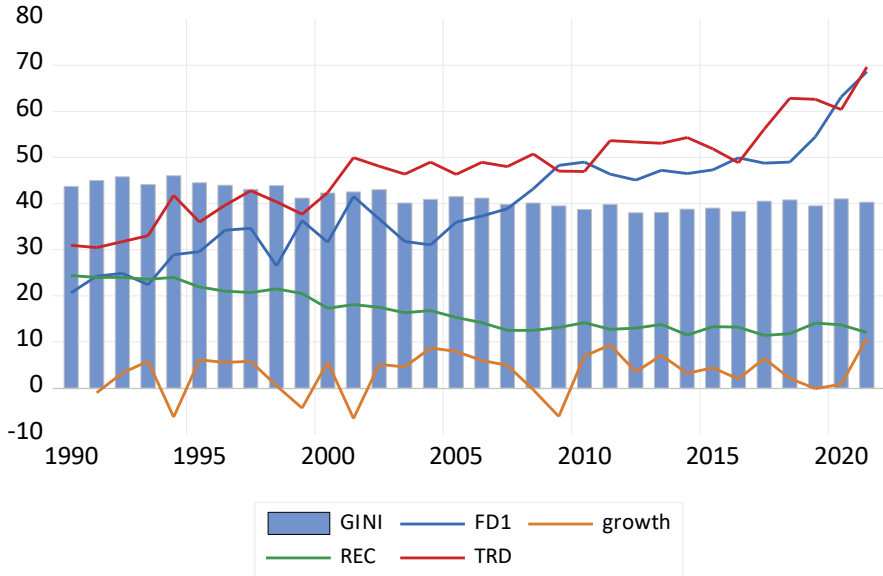


Figure 1: All Variables Path Ways in the over Time

Table 2 introduces the descriptive statistics of the variables. According to the Jarque-Bera (JB) test results, all variables have a normal distribution. Therefore, the ARDL approach can be considered appropriate as a symmetric analysis.

Table 2: Descriptive Statistics

	lnGINI	lnFD	lnGDP	lnTRD	lnREC
Mean	3.7219	3.6426	8.9633	3.8368	2.7816
Median	3.7124	3.6397	8.9584	3.8726	2.6905
Maximum	3.8286	4.2278	9.5230	4.2429	3.1946
Minimum	3.6376	3.0281	8.5437	3.4169	2.4336
Std. Dev.	0.0555	0.2962	0.3096	0.2088	0.2578
Skewness	0.3123	-0.2233	0.2610	-0.3806	0.3407
Kurtosis	2.0067	2.4111	1.6931	2.6491	1.6430
Jarque-Bera	1.8358	0.7283	2.6406	0.9369	3.0744
Probability	0.3994	0.6948	0.2671	0.6260	0.2150
Observations	32	32	32	32	32

3.2. Estimation Procedures

The income distribution model for Türkiye is as follows Eq. (1):

$$\ln GINI_t = \delta_0 + \delta_1 \ln FD_t + \delta_2 \ln REC + \delta_3 \ln GDP_t + \delta_4 \ln TRD_t + \varepsilon_t \quad (1)$$

where t refers time dimension, δ is coefficient of the variables, ε is error term. The short- and long-term effects of the variables were examined in this work using the Autoregressive Distributed Lag (ARDL) approach, which was established by Pesaran and Shin (1995) and Pesaran vd. (2001). Accordingly, the cointegration between the variables was examined and the short-term and long-term coefficients of the variables were determined. The ARDL model is formulated as follows Eq. (2).

$$\begin{aligned} \Delta \ln GINI_t = & \delta_0 + \sum_{i=1}^n \delta_{1,i} \Delta \ln GINI_{t-i} + \sum_{i=0}^n \delta_{2,i} \Delta \ln FD_{t-i} + \sum_{i=0}^n \delta_{3,i} \Delta \ln REC_{t-i} \\ & + \sum_{i=0}^n \delta_{4,i} \Delta \ln GDP_{t-i} + \sum_{i=0}^n \delta_{5,i} \Delta \ln TRD_{t-i} + \theta_1 \ln GINI_{t-1} \\ & + \theta_2 \ln FD_{t-1} + \theta_3 \ln REC_{t-1} + \theta_4 \ln GDP_{t-1} + \theta_5 \ln TRD_{t-1} \\ & + \mu_t \end{aligned} \quad (2)$$

Short-term effects are reflected in the coefficients of the first-differenced variables. The long-term relationship's null hypothesis is described as follows:

Hypothesis H_0 : $\theta_0 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = 0$ (there is no long-run relationship)

Hypothesis H₁: $\theta_0 \neq \theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq 0$ (there is a long-run relationship)

The null hypothesis that there is no cointegration cannot be rejected when the F-statistics are below the lower bound critical value. Nevertheless, the null hypothesis that there is no cointegration is rejected when the F-statistics exceed the upper bound critical value at least at the 10% significance level (Handayani vd., 2022).

If there is cointegration between variables, long-run ARDL estimation is performed in Eq. (3).

$$\begin{aligned} & \ln GINI_t \\ &= \delta_0 + \sum_{i=1}^p \delta_{1,i} \ln GINI_{t-i} + \sum_{i=0}^q \delta_{2,i} \ln FD_{t-i} + \sum_{i=0}^r \delta_{3,i} \ln REC_{t-i} + \sum_{i=0}^s \delta_{4,i} \ln GDP_{t-i} \\ &+ \sum_{i=0}^t \delta_{5,i} \ln TRD_{t-i} \\ &+ \rho_t \end{aligned} \quad (3)$$

where p, q, r, s , and t are optimal lag length.

Finally, the error correction model are created for short-run coefficients of the variables. This is shown in Eq. (4).

$$\begin{aligned} \ln GINI_t = & \delta_0 + \sum_{i=1}^p \delta_{1,i} \Delta \ln GINI_{t-i} + \sum_{i=0}^q \delta_{2,i} \Delta \ln FD_{t-i} + \sum_{i=0}^r \delta_{3,i} \Delta \ln REC_{t-i} \\ & + \sum_{i=0}^s \delta_{4,i} \Delta \ln GDP_{t-i} + \sum_{i=0}^t \delta_{5,i} \Delta \ln TRD_{t-i} + \phi ECM_{t-1} \\ & + \tau_t \end{aligned} \quad (4)$$

where the coefficients ϕ shows the speed of adjustment of ECM_{t-1} , which is error-correction term. These coefficients are interpreted when they are negative and significant (Destek vd., 2020).

In addition to ARDL analysis it was conducted the robustness checks. For this, advanced econometric methods that are frequently used to predict long-term relationships between non-stationary variables include FMOLS by Phillips and Hansen (1990), DOLS developed by Stock and Watson (1993), and CCR developed by Park (1992).

3.3. Empirical Results

Firstly, VIF values were generated for the model to determine whether there was multicollinearity among the variables. Since the VIF values in Table 3 are less than 10, this confirms that there is no multicollinearity among the variables.

Table 3: VIF Results

	VIF	1/VIF
lnGDP	7.60	0.1315
lnTRD	7.24	0.1382
lnFD	7.22	0.1384
lnREC	6.19	0.1615
Mean VIF	7.06	

Table 4 displays the outcomes of unit root testing using the ARDL approach. It shows the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests for the variables. As a result, all variables are stationary at the I(1). Accordingly, the ARDL technique, which allows for different levels of variable stationarity or all variables at stationary at I(1), can be used.

Table 4: Unit Root Test Results

ADF			PP	
	level	first difference	level	first difference
lnGINI	-1.4486	-8.6659***	-1.4390	-9.6977***
lnFD	-0.6382	-8.1728***	-1.0340	-12.4563***
lnREC	-1.6198	-6.4368***	-1.1703	-7.1201***
lnGDP	0.6005	-5.4412***	1.8312	-5.9456***
lnTRD	-1.2459	-6.0837***	-0.7606	-8.0768***

*Note: *** shows significance at 1%.*

Before determining the ARDL short- and long-term coefficients, the F test was performed to determine whether there was a long-term relationship between the variables. The anticipated results of the F-bound test and the lag selection model are compiled in Table 5. The F-bound and t-bound tests for the ARDL model produced an F-statistic and t-statistic are 11.2336 and -6.4848, which is higher than the critical values under different order circumstances. As a result, the factors' association was confirmed.

Table 5: ARDL Bounds Test Results

Test Statistic	Value	Significance	I(0)	I(1)
F-statistic	11.2336	10%	2.45	3.52
k	4	5%	2.86	4.01
		2.5%	3.25	4.49
		1%	3.74	5.06
t-statistic	-6.4848	10%	-2.57	-3.66
		5%	-2.86	-3.99
		2.5%	-3.13	-4.26
		1%	-3.43	-4.60

Table 6 shows the ARDL model estimation results. According to these results, in the long run, only financial development is effective in improving income distribution. Furthermore, economic growth, trade openness, and renewable energy use have a distorting effect on income distribution. In the short run, renewable energy use, trade openness, and financial development have negative impact on income distribution. Based on these results, more effective use of financial transmission mechanisms is necessary to improve income distribution. In addition, it can be concluded that increases in economic growth alone are not sufficient in the long run. Therefore, tax and incentive mechanisms need to be activated. The ECM value's negative sign indicates that the variables employed in this investigation will eventually converge. The pace of convergence will be less than a year given its value between -1 and -2 (Handayani vd., 2022).

Table 6: ARDL Cointegration Results

Long-run			
	Coefficient	t-stat	p-value
ARDL (1,3,1,1,0)			
lnGINI			
lnFD	-0.1925***	-4.10	0.0010
lnREC	0.2050***	6.11	0.0000
lnGDP	0.0644*	1.88	0.0760
lnTRD	0.2044***	4.04	0.0010
C	2.6118***	4.43	0.0000
ECT(-1)	-1.0537***	-6.48	0.0000
R2	0.7860		
Adj. R2	0.6671		
ECM=lnGINI-(-0.1925*lnFD +0.2050*lnREC+0.0644*lnGDP+0.2044*lnTRD)			
Short-run			
	Coefficient	t-stat	p-value
lnFD	-0.0538	-1.49	0.1550
LD.	0.2015***	4.35	0.0000
L2D.	0.0824**	2.21	0.0400
lnREC	0.0950*	1.89	0.0750
lnGDP	-0.1060	-1.11	0.2840
lnTRD	0.2154***	4.42	0.0000

*Note: ***, **, and * show that significance at 1%, 5%, and 10% respectively.*

The ARDL prediction and diagnostic test results are shown in Table 7. According to Islam and Azad (2024), the long-term ARDL model must have certain characteristics, including stable residuals with a normal distribution, no autocorrelation, and no heteroscedasticity. The lower portion

of this table reports the results of diagnostic tests. The CUSUM and CUSUM of squares graphs are stable, and all diagnostic tests are significant (see Figure 2). As a result, the variables have long-term relationships.

Table 7: Diagnostic Test Results

Diagnostic Tests	Coefficien t	p- value	Conclusion
Jarque-Bera analysis	1.2436	0.5370	The residuals have a normal distribution
Breusch-Godfrey LM analysis	0.5041	0.6852	No serial correlation exists
Breusch-Pagan-Godfrey analysis	1.6049	0.1837	No heteroscedasticity exists.
Ramsey RESET analysis	0.0826	0.9352	The model is properly specified

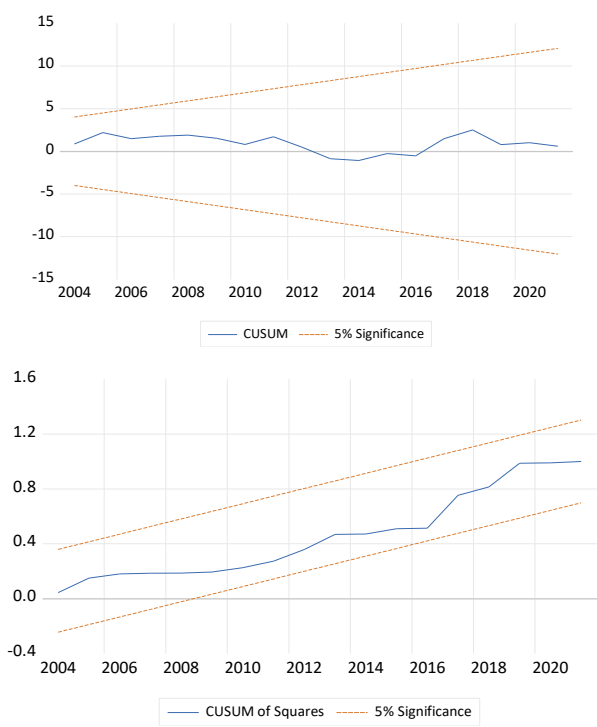


Figure 2: CUSUM and CUSUMQ Plots

Table 8 contains the results of the FMOLS, DOLS, and CCR analyses. Accordingly, all three analyses confirm that financial development has a positive effect on income distribution in the long-term. The negative impact of renewable energy consumption on income distribution is also supported by all three methods. Economic growth and trade openness also have a negative

impact on income distribution. Therefore, these findings support the ARDL test results.

Table 8: Robustness Checks

	FMOLS	DOLS	CCR
lnFD	-0.0982*** [0.0254] (0.0000)	-0.1552** [0.0756] (0.0400)	-0.0977*** [0.0288] (0.0010)
lnREC	0.1684*** [0.0239] (0.0000)	0.1842*** [0.0574] (0.0010)	0.1713*** [0.0266] (0.0000)
lnGDP	0.0006 [0.0179] (0.9970)	0.1078*** [0.0375] (0.0040)	0.0010 [0.0186] (0.9550)
lnTRD	0.1064*** [0.0271] (0.0000)	0.0441 [0.4484] (0.4980)	0.1100*** [0.0350] (0.0020)
_cons	3.2073*** [0.1967] (0.0000)	2.6480*** [0.4484] (0.0000)	3.1748*** [0.2177] (0.0000)
R2	0.6810	0.8962	0.7369
Adj. R2	0.6320	0.7577	0.6965

*Notes: i) ***, **, and * show that significance at 1%, 5%, and 10% respectively. ii) [] shows standard errors and () shows p-values.*

4. CONCLUSION AND POLICY IMPLICATIONS

Income distribution, or the way in which the entire revenue produced in an economy is divided among people, households, or factors of production, reflects both individual productivity and the equity of the social system. Income distribution is affected by a broad range of economic, social, demographic, and political forces. Social wellbeing is shaped by these elements that impact income distribution through both long-term structural changes and short-term economic volatility. Growing income disparities cause long-term economic growth to slow down, social unrest to rise, and consumption demand to decline. While periods of economic expansion are associated with relative drops in the Gini coefficient, high inflation, volatility in exchange values, and spikes in unemployment rates lead the coefficient to increase further. Overall, income distribution remains to be one of the most significant macroeconomic indicators that will be extensively studied in the literature.

This study demonstrates that the fundamental macroeconomic variables affecting income distribution in Türkiye interact in a multi-channel

and context-sensitive manner. Although the decrease in Türkiye's Gini coefficient from approximately 0.44 in the 2000s to 0.39 is closely linked to growth rates and their composition, sustainable recovery is sensitive to cyclical fluctuations. In the case of Türkiye, the findings that financial development reduces inequality for the 1990–2015 period indicate financial deepening, which has a positive impact on income distribution (Destek et al., 2020). The results showing that increased financial depth strengthened income equity between 1988 and 2017 are largely consistent with periods when the banking system expanded credit allocation relatively more (Ertaş, 2019). The findings that financial development reduces poverty and inequality in large country panels are parallel to the findings for Türkiye (Bayar, 2023).

Türkiye has suffered from structural income inequality for decades, and despite growth initiatives, no long-term progress has been made. While previous research on the factors that contribute to income disparity in Türkiye is rich and varied, most previous studies did not a wide range of variables. In this context, the present study argued for the need of taking into account the effects of financial, environmental, and economic factors on income distribution. According to Bayar (2023) increasing financial inclusion enhances income distribution. Koçak and Uzay (2019) and Destek et al. (2020) also supported the notion that financial development lessens income disparity. In addition, the results of this study suggest that the high cost of access to renewable energy sources in Turkey has prevented their income-improving impacts from being evident. The findings also indicate that economic growth and openness alone are not sufficient to improve income distribution. Financial development, institutional regulations, and the provision of social and political participation, along with tax and incentive mechanisms, are also effective components in improving income distribution.

Policies encompassing all segments of society and increasing the use of financial development tools such as credit and funds should be adopted. While increasing energy use may lead to a widening of income distribution in the long run, energy consumption compatible with sustainable energy sources should be preferred. Long-term, low-interest borrowing can protect real income by reducing the likelihood of future tax rate increases. In addition, Türkiye should adopt long-term policies to overcome its unique structural problems, such as import dependency, low human capital, lack of trust in institutions, and high economic and political risk and uncertainty. Future studies can improve this by examining these comprehensive variables across different countries or groups of countries. Furthermore, this issue can be further explored through spatial analysis aimed at examining sectoral effects on income distribution.

REFERENCES

- Acheampong, A. O., Boateng, E., ve Annor, C. B. (2023). Do Corruption, Income Inequality And Redistribution Hasten Transition Towards (Non)Renewable Energy Economy? *Structural Change And Economic Dynamics*, 68(1), 329-351.
- Adam, N. A., ve Alzuman, A. (2024). Effect Of Per Capita Income, GDP Growth, FDI, Sectoral Composition, And Domestic Credit On Employment Patterns In GCC Countries: GMM And OLS Approaches. *Economies*, 12(11), 315-340.
- Ağirkaya, M. B. (2022). Türkiye Ekonomik Büyümesinde Yenilenebilir Enerji: Mevcut Durum, Gelecek Beklentileri, İstihdam ve Yatırım Fırsatları. *ODÜSOBİAD*, 12(3), 2327-2350.
- Akar, G. (2010). *Dolaysız Yabancı Sermaye Yatırımlarının Sektörel Kompozisyonunun Ekonomik Büyümeye Etkisi* (Yayımlanmamış Yüksek Lisans Tezi), Karamanoğlu Mehmetbey Üniversitesi.
- Akı, A. (2021). *Türkiye’de Enerji İthalatı ve Bağımlılığının Cari Açık Üzerine Etkileri* (Yayımlanmamış Yüksek Lisans Tezi), Sakarya Üniversitesi.
- Alev, N., Torusdağ, M., ve Yildirimçakar, İ. (2025). Türkiye’de Dış Ticaretin Gelir Dağılımı Üzerindeki Etkileri: 2013-2023 Dönemi Ampirik Analizi. *Uluslararası Ekonomi Ve Yenilik Dergisi*, 11(1), 201-222.
- Altunbaş, Y., ve Thornton, J. (2019). Finance And Income Inequality Revisited. *Finance Research Letters*, 37(2), 1-13.
- Aydin, M. K., Ak, M. Z., ve Altıntaş, N. (2014). Finansal Gelişmenin Büyümeye Etkisi: Türkiye Özelinde Nedensellik Analizi. *Maliye Dergisi*, 167(2), 149-160.
- Ayhan, B., ve İnancı, S. (2022). Türkiye’de Enerji Tüketimi, İktisadi Büyüme ve Cari Açık Arasındaki İlişki. *İnsan ve Toplum Bilimleri Araştırmaları Dergisi*, 11(4), 3456-3472.
- Barbaros, M., Par, A., ve Kalaycı, S. (2018). Türkiye’de Ekonomik Büyüme ve Enerji Tüketiminin Cari Açık Üzerindeki Etkisi. *Avrasya Sosyal Ve Ekonomi Araştırmaları Dergisi*, 5(10), 94-113.
- Baş, S., ve Sertkaya, B. (2021). Türkiye Ekonomisinde İç ve Dış Denge Sorununun Çözümüne Yönelik Kapsamlı Bir Analiz. *Turkish Business Journal*, 2(3), 45-66.
- Bayar, A. (2023). The Impact Of Financial Development On Income Inequality And Poverty. *Plos ONE*, 18(10), 1-23.
- Bezen, S. (2022). *Türkiye’de Doğrudan Yabancı Yatırımların Yenilenebilir Enerji Üretimi Üzerindeki Etkisinin Ekonometrik Analizi* (Yayımlanmamış Yüksek Lisans Tezi), Afyon Kocatepe Üniversitesi.
- Bittencourt, M., Chang, S., Gupta, R., ve Miller, S. M. (2019). Does Financial Development Affect Income Inequality In The U.S. States? *Journal Of Policy Modeling*, 41(6), 10431065.
- Blomme, O., ve Héricourt, J. (2025). Inequality, Current Account Imbalances, And Middle Incomes. *Journal Of International Money And Finance*, 152(4), 103-127.
- Bostan, A., ve Ravanoğlu, G. A. (2019). Türkiye’de Enerji Tüketimi Ve Cari Açığın Büyüme Üzerindeki Etkisinin İncelenmesi. *Manas Sosyal Araştırmalar Dergisi*, 8(2), 1713-1726.
- Cevizli, İ. (2013). *Demokrasi Ve Ekonomik Gelişme İlişkisi* (Yayımlanmamış Yüksek Lisans Tezi) Adnan Menderes Üniversitesi.
- Coşkun, S., Özgenç, N., ve Güneş, S. (2015). Sosyal Performansın Ölçümünde Yeni Yöntem: Sosyal Gelişme Endeksi Ve Türkiye’nin Görünümü. *Sosyal Politika Çalışmaları Dergisi*, 15(34), 121-153.

- Çiftçi, E. (2022). *Türkiye Ekonomisinde Cari İşlemler Açığı Sorunu: 1980-2020 Yılları İçin Karşılaştırmalı Bir Analiz* (Yayımlanmamış Yüksek Lisans Tezi) Selçuk Üniversitesi.
- Çiftçi, F., ve Yıldız, R. (2015). Doğrudan Yabancı Yatırımların Ekonomik Belirleyicileri: Türkiye Ekonomisi Üzerine Bir Zaman Serisi Analizi. *Business And Economics Research Journal*, 6(4), 71-95.
- Destek, M. A., Sinha, A., ve Sarkodie, S. A. (2020). The Relationship Between Financial Development And Income Inequality In Türkiye. *Economic Structures*, 9(11), 1-17.
- Dollar, D., ve Kraay, A. (2004). Trade, Growth, And Poverty. *The Economic Journal*, 114(493), F22-F49.
- Durgun, F. (2024). Türkiye’de Finansal Gelişme İle Ekonomik Büyüme Bağlantısının Analizi: Genişletilmiş NARDL Yaklaşımı. *İktisadi İdari Ve Siyasal Araştırmalar Dergisi*, 8(Özel Sayı), 1-20.
- Eker, T. (2021). *Gelir Dağılımı Ve Yoksulluk Analizi: Türkiye Örneği* (Yayımlanmamış Yüksek Lisans Tezi) Aydın Adnan Menderes Üniversitesi.
- Emin, D. (2021). Geniş Kapsamlı Finansal Gelişmişlik Endeksi İle Türkiye’nin Finansal Gelişmişliğinin Tespiti Ve Gelişmekte Olan Ülkeler İle Karşılaştırılması. *İşletme Araştırmaları Dergisi*, 11(3), 2205-2215.
- Ertaş, C. (2019). *The Impact Of Financial Development On Income Inequality: The Case For Türkiye* (Yayımlanmamış Yüksek Lisans Tezi) Dokuz Eylül Üniversitesi.
- Goldberg, P. K., ve Pavcnik, N. (2007). Distributional Effects Of Globalization in Developing Countries. *Journal Of Economic Literature*, 45(1), 39-82.
- Hacıımamoğlu, T., Sungur, O., Yildirim, K., ve Yapar, M. (2025). Rethinking The Climate Change–Inequality Nexus: The Role Of Wealth Inequality, Economic Growth, and Renewable Energy in CO2 Emissions. *Sustainability*, 17(8), 3335-3352.
- Handayani, B. D., Yanto, H., Pujiati, A., Ridzuan, A. R., Keshminder, J. S., ve Shaari, M. S. (2022). The Implication Of Energy Consumption, Corruption, And Foreign Investment For Sustainability Of Income Distribution In Indonesia. *Sustainability*, 14(1), 159-175.
- Hordofa, D. F. (2023). The Moderating Effect Of Income Inequality On The Relationship Between Economic Growth And Political Economy, Human Capital, Innovation, And Saving Channels In Ethiopia. *Discover Global Society*, 1(1), 1-33.
- IMF. (2025). International Monetary Fund
- İslam, M. S., ve Azad, A. K. (2024). The Impact Of Personal Remittance And Rmg Export Income On Income Inequality In Bangladesh: Evidence From An ARDL Approach. *Review Of Economics And Political Science*, 9(2), 134-150.
- Karabulut, T. (2006). Türkiye’de Kişisel Gelir Dağılımı Araştırmalarının Analizi. *Selçuk Üniversitesi Sosyal Bilimler Meslek Yüksekokulu Dergisi*, 9(1-2), 21-36.
- Karış, Ç., ve Ayla, D. (2018). Türkiye’de Doğrudan Yabancı Yatırımlar Ve Ticari Dış Açıklık İlişkisinin Ekonometrik Analizi. *Bingöl Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 9(16), 1-11.
- Kavya, T. B., ve And Shijin, S. (2020). Economic Development, Financial Development, And Income Inequality Nexus. *Borsa İstanbul Review*, 20(1), 80-93.

- Keskin, N. (2022). Türkiye’de Finansal Gelişmenin Gelir Eşitsizliği Üzerindeki Etkisi: Farklı Gelir Grupları İçin Mukayeseli Bir Analiz. *Cumhuriyet Üniversitesi İktisadi Ve İdari Bilimler Dergisi*, 23(4), 915-931.
- Koç, P. (2021). Türkiye’de Kişi Başına Düşen Gelir Ve Hanehalkı Büyüklüğünün Enerji Tüketimi Üzerindeki Etkisinin Analizi: Bölgesel Bir Yaklaşım. *Üçüncü Sektör Sosyal Ekonomi Dergisi*, 56(4), 2498-2515.
- Koçak, E., ve Uzun, N. (2019). The Effect Of Financial Development On Income Inequality In Türkiye: An Estimate Of The Greenwood-Jovanovic Hypothesis. *Review Of Economic Perspectives*, 19(4), 319-344.
- Lang, V. (2016). *The Economics Of The Democratic Deficit: The Effect Of IMF Programs On Inequality* (Discussion Paper No. 617). University Of Heidelberg, Department Of Economics.
- Mahiroğulları, B. H. (2021). *Türkiye’de Enerji Tüketimi Kaynakları Ve İktisadi Büyüme Arasındaki İlişkinin Ekonometrik Analizi* (Yayımlanmamış Doktora Tezi), İstanbul Üniversitesi.
- Makhdum, M. A., Zohor, A., ve K. Ebadi, H. (2022). Finansal Gelişmişlik Düzeyinin Ekonomik Büyüme Üzerine Etkisi: BRICS Ülkeleri İle Türkiye İncelemesi. *Üçüncü Sektör Sosyal Ekonomi Dergisi*, 57(4), 3418-3433.
- Meschi, E., ve Vivarelli, M. (2009). Globalization And Income Inequality in Developing Countries. *World Development*, 37(2), 287-303.
- Mucuk, M., ve Uysal, D. (2009). Türkiye Ekonomisinde Enerji Tüketimi Ve Ekonomik Büyüme. *Maliye Dergisi*, (157), 105-115.
- Nguyen, T. C., Vu, T. N., Vo, D. H., ve Dao, H. (2019). Financial Development And Income Inequality In Emerging Markets: A New Approach. *Journal Of Risk And Financial Management*, 12(4), 173.
- Ofori, P. E., Ofori, I. K., ve Annan, K. (2024). The Role Of Energy Equity And Income Inequality In Environmental Sustainability. *Journal Of Cleaner Production*, 470, 143183.
- Oğuztimur, S. (2023). Nüfus İle Kişi Başına Düşen GSYH İlişkisi: Türkiye’nin 2000’li Yıllarının Değerlendirmesi. *İnsan Ve Toplum Bilimleri Araştırmaları Dergisi*, 12(2), 733-760.
- Park, J.Y. (1992). Canonical Cointegrating Regressions. *Econometrica*, 60(1), 119-143.
- Pesaran, M. H., ve Shin, Y. (1995). *An Autoregressive Distributed Lag Modelling Approach To Cointegration Analysis* (Cambridge Working Papers In Economics No. 9514). University Of Cambridge, Faculty Of Economics.
- Pesaran, M. H., Shin, Y., ve Smith, R. J. (2001). Bounds Testing Approaches To The Analysis Of Level Relationships. *Journal Of Applied Econometrics*, 16(3), 289-326.
- Phillips, P. C. B., ve Hansen, B. E. (1990). Statistical Inference In Instrumental Variables Regression With I (1) Processes. *The Review of Economic Studies*, 57(1), 99-125.
- Siddique, M. A. B., ve Lee, K. K. (2024). Too Much Finance And Top-Income Concentration: A Dynamic Panel Data Analysis. *Global Economic Review*, 53(4), 283-303.
- Solt, F. (2016). The standardized world income inequality database. *Social Science Quarterly*, 97(5), 1267–1281.

- Stock, J. H., ve Watson, M. W. (1993). A Simple Estimator Of Cointegrating Vectors In Higher Order Integrated Systems. *Econometrica*, 61(4), 783-820.
- Stolper, W. F., ve Samuelson, P. A. (1941). Protection And Real Wages. *The Review Of Economic Studies*, 9(1), 58-73.
- Thornton, J., ve Tommaso, C. D. (2019). The Long-Run Relationship Between Finance And Income Inequality: Evidence From Panel Data. *Finance Research Letters*, 32, 101180.
- TÜİK. (2025). Türkiye İstatistik Kurumu.
- WORLD BANK. (2025). World Development Indicators.

A Three-Layered Enriching Artificial Learning Architecture for BIST 100 Forecasting via Traditional and AI-Based Methods – TRINET-FIN¹

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ABSTRACT

This study aims to improve the accuracy of complex financial time series forecasting by developing a multi-layer hybrid learning framework named TriNet-Fin. The framework's predictive performance is comparatively evaluated against traditional and artificial intelligence (AI) methods. TriNet-Fin integrates conventional approaches (VAR, VECM, SARIMAX, Kalman Filter) with AI-based models (LSTM, MLP, 2D-CNN, GRU, RNN). Empirical analysis uses daily data (2002–2024), employing the BIST 100 index as the dependent variable. Independent variables include interest rates (TLREF), exchange rates (USD/TRY), CDS, gold, Brent oil, VIX, NASDAQ, and S&P 500 indices. Performance is measured using MSE, Adjusted R^2 , and Accuracy metrics on the test dataset. Findings reveal that standalone models suffer from generalization failure, exhibiting high prediction errors. Conversely, TriNet-Fin-supported hybrid models deliver robust forecasts, achieving high explanatory power ($\text{Adj } R^2 > 0.70$), low MSE, and accuracy rates exceeding 97%. These results demonstrate that a multi-layer hybrid structure enriched with contextual information is critical for overcoming the limitations of single-method approaches in financial forecasting. The proposed framework contributes methodologically to the literature and offers practitioners a reliable decision-support mechanism for market predictions.

Keywords – TriNet-Fin Framework, Hybrid Learning Models, Financial Time Series Forecasting, Multi-layer Architecture, Predictive Performance Evaluation.

INTRODUCTION

Since their emergence in the mid-twentieth century, digital computers have evolved far beyond their original purpose of performing mathematical calculations, gradually acquiring the capacity to handle multi-layered tasks such as data processing, text analysis, and image recognition. At the core of this transformation lies the von Neumann architecture, which enabled program instructions and data to be stored within the same memory space (von Neumann, 1945), making computers indispensable tools across disciplines ranging from engineering and the natural sciences to medicine and the social sciences.

Nevertheless, digital computers are fundamentally grounded in deductive logic, processing binary information according to fixed, predefined rules. Artificial intelligence systems, by contrast, operate through an inductive approach, deriving decisions from patterns learned in data rather than explicitly defined instructions. Artificial neural networks represent information in a distributed manner across numerous connections and weights, significantly enhancing learning capacity and adaptive behavior (Elmas, 2018). Thus, the fundamental distinction between the two paradigms

lies not merely in computational power, but in their divergent approaches to information and their inherent capacity for learning.

The rapid advancement of artificial intelligence has attracted widespread attention across technical, academic, and public spheres. Large language models developed by OpenAI have demonstrated remarkable performance in critical thinking, reasoning, and multi-step problem-solving (Bubeck et al., 2023; OpenAI, 2023), indicating that artificial intelligence has moved beyond information retrieval toward knowledge restructuring. The success of models such as ChatGPT and DALL·E in creative domains further suggests that AI is increasingly capable of approximating intuitive forms of cognition (Martinengo et al., 2022; Roose, 2022).

However, progress in artificial intelligence has not been uniform across all domains. Motor-skill-dependent applications continue to lag behind advances in cognitive tasks. Autonomous vehicles still face significant safety and control challenges (Jolly, 2023), while warehouse robots struggle to handle objects of varying shapes and materials consistently (OECD, 2021; Young, 2023). Issues related to data diversity, generalization capacity, and adaptation to cultural and regional contexts further constrain the global scalability of AI systems.

Across sectors ranging from education and healthcare to law, economics, and national security, artificial intelligence is not merely enhancing operational efficiency but fundamentally transforming decision-making processes and institutional structures. In this regard, artificial intelligence represents not simply a technological advancement, but a multi-layered paradigm shift encompassing economic, social, ethical, and normative dimensions.

Excluding the introduction and conclusion, this article comprises two main sections. The first provides a comprehensive literature review, while the second constitutes the applied component, detailing the datasets used, the feature engineering processes, and the three-layer financial forecasting framework referred to as TriNet-Fin, followed by a comparative performance analysis against traditional and AI-based approaches

2. Literature Review

Financial time series forecasting has evolved around the insight that markets are governed by nonlinear and heterogeneous dynamics, shifting from classical statistics toward AI-based hybrid strategies. Early traditional models, such as ARIMA and GARCH, effectively captured linear dependencies; however, as demonstrated by Abdulrahman et al. (2020) and Hajizadeh et al. (2012), they exhibit limited capacity when faced with regime-dependent behavior and turbulence.

A more dominant strand of literature emphasizes Artificial Neural Networks (ANN). Studies by Akcan and Kartal (2011), Demir (2024), and Moein Aldin et al. (2012) provide strong evidence that ANN-based architectures outperform classical models in short-term tasks by learning nonlinear patterns. Furthermore, deep learning architectures—specifically LSTM and GRU—have emerged as superior tools for modeling sequential dependencies. Empirical evidence from Ali et al. (2023) and Pardeshi et al. (2024) consistently shows that these recurrent architectures outperform shallow networks, while hybrid CNN–LSTM frameworks further yield superior performance through automated feature extraction (Yousuf et al., 2024).

The most robust conclusion in the literature concerns the absolute superiority of hybrid models. Comparative studies overwhelmingly indicate that combining multiple paradigms leads to significantly lower forecasting errors than standalone approaches (Tsaih et al., 1998; Yinka-Banjo et al., 2023). Hybridization typically involves decomposing tasks into linear and nonlinear components (Banik et al., 2025; Pai & Lin, 2005) or employing signal decomposition techniques like EMD and wavelet transforms (Abdollahi, 2020; Metwally et al., 2025). Integration of meta-heuristic algorithms like GA and PSO further enhances adaptability in noisy environments (Asadi et al., 2012; Rulving, 2024).

Despite these advances, existing hybrid models remain fragmented and lack a unified architecture capable of simultaneously modeling sequential dynamics and global structural relationships. Addressing this gap, the TriNet-Fin architecture proposed in this study disentangles heterogeneous information sources through specialized learning modules and integrates them via a dynamic ensemble strategy, offering a holistic solution to the conceptual limitations of current literature.

Table 1: Summary of Literature Review

Author(s) / Year	Dataset / Sample	Methodology / Model	Variables Used / Data Transformations	Main Findings
Abdulrahman et al. (2020)	Ghana Stock Exchange data	Hybrid ARIMA– LSTM model (decomposition via Fourier-based low-pass filtering)	Discrete Fourier Transform, data filtering, RMSE comparison	The hybrid ARIMA– LSTM model outperforms standalone ARIMA and LSTM models by producing lower RMSE values.
Akcan & Kartal (2011)	ISE Insurance Index – stock prices of 7 insurance companies	Artificial Neural Network (ANN) models	Stock price time series	High accuracy is achieved in short- term forecasts (up to one month); ANN models serve as effective tools for investment decision- making.
Çam (2024)	Stocks listed in the BIST 100 index	Hybrid VAR (linear) + ANN (nonlinear) model	Closing prices and volatility structure; integration of VAR and ANN outputs	The VAR–ANN hybrid model generally produces the lowest forecast errors, outperforming other models for most stocks except AKBNK, ALBRK, BUCIM, DOHOL, GSDHO, TSKB, SKBNK, and SNGYO.
Demir (2024)	11 NASDAQ- listed stocks (daily data, 2018–2023)	Artificial Neural Network (5 layers; cross- validation and hyperparameter optimization)	Technical indicators: SMA, Bollinger Bands, RSI, MACD, Stochastic Oscillator, CCI; Buy/Sell signals	An accuracy rate of 82.63% is achieved on the test set, indicating strong directional prediction performance of ANN models.
Gajewski & Gresse (2007)	London Stock Exchange hybrid system / Euronext Paris central order book	Transaction cost comparison analysis	Trade size segmentation; presence of market makers; execution cost components (adverse selection, inventory costs)	The central electronic order book offers lower transaction costs than hybrid systems; market makers increase large trade frequency but raise costs for small trades.
Gao et al. (2024)	Daily data from 10 sector indices of the Shanghai	AI-driven Industry Asset Allocation Hybrid (IAAH) system; enhanced	Simulation of subjective return views; parameter optimization via Dynamic Conditional	The IAAH system demonstrates strong investment performance, robustness to subjective view

	Stock Exchange	Black–Litterman model	Correlation (DCC); downside-risk-oriented objective functions	changes, and mitigates limitations of the traditional Black–Litterman framework.
Hadavandi et al. (2010)	TEPIX (Tehran Stock Exchange Index) data	Hybrid evolutionary model (Genetic Algorithm + ANN)	Network weight optimization via GA; data preprocessing techniques	The proposed model effectively handles market volatility and delivers higher accuracy than BPNN and comparable methods.
Hajizadeh et al. (2012)	S&P 500 index returns	Two hybrid EGARCH–ANN models	EGARCH forecasts, historical explanatory variables, simulated data series	Hybrid models provide more accurate volatility forecasts than EGARCH, particularly in volatile markets; the second hybrid model achieves the best performance.
Kaur, Dhar & Guha (2015)	BSE30, Hang Seng, Nikkei, Taiwan Weighted Index	ANFIS with subtractive clustering; hybrid learning (Least Squares + Backpropagation)	Optimization-based fuzzy membership functions; index time series	ANFIS performs successfully across all indices, offering an effective and contemporary forecasting approach for stock market indices.
Mehmood & Ali (2023)	Closing prices of two banking stocks listed on the Pakistan Stock Exchange	News sentiment + LSTM + attention-based BiLSTM hybrid model	Historical prices, news sentiment scores; 30-day-ahead forecasts	Incorporating news sentiment reduces prediction errors and improves forecast accuracy; high performance is achieved for 30-day forecasts.

3. Econometric Analysis

3.1. Development Environment and Tools Used

This study utilizes Python for data analysis and machine learning, with the process conducted through the Anaconda platform to facilitate library management and integration. Analyses are performed using the Spyder IDE, while Python’s interpreted nature and dynamic typing enable rapid and flexible development. This integrated framework ensures the reliable and sustainable execution of machine learning applications.

3.2. Datasets and Variable Definitions

The dataset consists of 5,388 daily observations from December 2002 to August 2024, including both domestic macroeconomic indicators and global financial risk factors, allowing the model to capture local dynamics alongside international uncertainties. The data were obtained from the Bloomberg Terminal, ensuring reliability and consistency.

Prior to analysis, the data were preprocessed through missing value treatment and detrending, and all variables were synchronized at a daily frequency in a time-series format. These steps improve the reliability of model estimates and ensure suitability for hybrid machine learning applications.

- **BIST_100:** The benchmark index representing the performance of the 100 most liquid and highest-volume companies listed on Borsa İstanbul.
- **TLREF:** The reference interest rate published by the Central Bank of the Republic of Türkiye, considered an indicator of liquidity costs. It is particularly utilized to model the effects of short-term interest rate shocks.
- **KUR:** The daily USD buying exchange rate published by the Central Bank of the Republic of Türkiye, reflecting volatility in the foreign exchange market.
- **CDS (Credit Default Swap):** The risk premium investors are willing to pay against the probability of default on Türkiye's external debt. This indicator reflects the level of confidence of both domestic and foreign investors in the national economy.
- **S&P 500:** The index representing the performance of the 500 largest companies in the United States.
- **NASDAQ:** A major indicator capturing innovation-driven market sentiment, particularly dominated by technology-oriented firms.
- **VIX:** The volatility index calculated by the Chicago Board Options Exchange (CBOE), commonly referred to as the "Fear Index," reflecting market expectations of volatility.
- **GOLD:** The international market price of gold measured in ounces.
- **BRENT:** The price of Brent crude oil, a key indicator in determining energy costs and, consequently, production costs.

Table 2. Variables, Definitions, and Data Sources

Abbreviation	Variable Type	Description	Source
BIST100	Dependent Variable	Borsa İstanbul 100 Index	Bloomberg Terminal
TLREF	Independent Variable	Turkish Lira Overnight Reference Interest Rate	Bloomberg Terminal
CDS	Independent Variable	Türkiye 5-Year Credit Default Swap (CDS) Premium	Bloomberg Terminal
KUR	Independent Variable	USD Buying Exchange Rate Published by the Central Bank of the Republic of Türkiye	Bloomberg Terminal
GOLD	Independent Variable	Gold Price per Ounce	Bloomberg Terminal
BRENT	Independent Variable	Brent Crude Oil Price	Bloomberg Terminal
VIX	Independent Variable	Volatility Index (Fear Index)	Bloomberg Terminal
NASDAQ	Independent Variable	NASDAQ Technology Index	Bloomberg Terminal
S&P500	Independent Variable	Standard & Poor's 500 Index	Bloomberg Terminal

3.3. Correlation Matrix

The correlation matrix is constructed to quantitatively assess the degree of linear association among the variables. The heatmap visualization is employed to highlight variable pairs exhibiting high correlation coefficients, thereby facilitating the early detection of potential multicollinearity issues. The correlation structure among the variables is presented below.

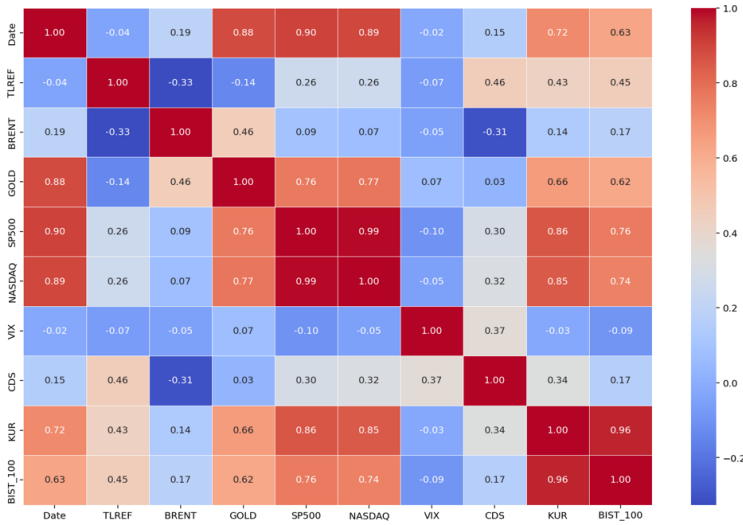


Figure 1. Correlation Matrix Heatmap

The correlation matrix reveals significant relationships between the BIST 100 index, domestic macroeconomic indicators, and global financial conditions. The most prominent finding is the exceptionally strong positive correlation with the exchange rate (USD/TRY) (~ 0.96), suggesting that the index serves as a critical inflation hedge during periods of currency depreciation. Similarly, the moderate positive correlation with TLREF (~ 0.45) indicates that under high inflationary pressure, stocks function as a preferred store of value rather than being suppressed by rate hikes.

From a global perspective, BIST 100 exhibits strong positive correlations with the S&P 500 (~ 0.76) and NASDAQ (~ 0.74), reflecting synchronization with global risk appetite. The near-perfect correlation between S&P 500 and NASDAQ (~ 0.99) signals a potential multicollinearity risk, justifying the use of PCA in the modeling phase. The positive relationship with Gold (~ 0.62) further underscores simultaneous appreciation during expansionary monetary policies and domestic uncertainty.

In contrast, weak correlations with CDS (~ 0.17), Brent crude (~ 0.17), and VIX (~ -0.09) suggest that BIST 100 maintains resilience against global volatility in the long run, with its dynamics predominantly driven by domestic economic factors and investor behavior.

3.4. Data Preparation and Feature Engineering

Data preparation and feature engineering constitute critical stages that directly determine the predictive performance and generalizability of forecasting models. The primary objective is to transform raw data into a structured, analysis-ready format. In this process, missing observations, outliers, and inconsistencies are systematically addressed, while techniques such as standardization, normalization, and logarithmic transformation are applied to ensure comparability across variables. Additionally, strict measures are implemented to prevent data leakage, thereby enabling an accurate assessment of real-world model performance.

Beyond basic preprocessing, feature engineering involves the derivation of new variables to capture latent information embedded in the data. In time series contexts, incorporating lagged values, moving averages, and differencing techniques allows the model to learn complex dynamics such as stationarity, seasonality, and volatility. These engineered features enhance the model's ability to capture both short-term fluctuations and long-term trends. Overall, a well-structured data preparation and feature engineering process forms the foundational basis for achieving robust and accurate forecasting outcomes.

3.4.1. Data Cleaning and Missing Value Control

Missing observations in the dataset used in this study are identified prior to analysis, and appropriate data cleaning procedures are applied. Since

missing values may adversely affect the learning process of models and reduce forecasting accuracy, mitigating such distortions is of critical importance. In this context, observations containing missing values are directly removed from the dataset using a listwise deletion approach (dropna), ensuring that the model training process relies solely on complete and internally consistent data. This procedure enhances the quality of the learning process while preserving the structural integrity of the training dataset.

3.4.2. Scaling and Data Leakage Control

Feature scaling is a critical preprocessing step to improve model accuracy, accelerate convergence, and enhance generalization in financial time series with heterogeneous variable ranges. This study evaluates two scaling techniques: MinMaxScaler transforms features into a $[0, 1]$ range, preserving the original distribution when extreme outliers are limited. RobustScaler, on the other hand, mitigates outlier influence by using median and interquartile range (IQR)-based transformations, making it more suitable for volatile financial data.

To prevent data leakage, scaling parameters are calculated exclusively on the training set and subsequently applied to the test set, ensuring an objective assessment of the model's true predictive capability.

3.4.3. Exogenous Indicators and Derived Feature Structures

A two-layer feature architecture is implemented to capture the complex dynamics of the BIST 100 index. The first layer incorporates exogenous macro-financial variables (TLREF, Brent oil, Gold, CDS, USD/TRY, VIX), while PCA is applied to merge the highly correlated S&P 500 and NASDAQ (~ 0.99) into a single component (SP_NASDAQ_PCA), mitigating multicollinearity risk.

The second layer enriches the model with temporally derived features (MA7, Lag14, Diff1, Var7) to capture momentum and volatility patterns. Additionally, a regime-identifier variable (regime_id) is introduced to account for structural breaks, distinguishing seven critical historical turning points:

- 15.09.2008: Lehman Brothers bankruptcy (Global financial crisis)
- 01.06.2013: Gezi Park protests (Türkiye)
- 15.07.2016: Coup attempt in Türkiye
- 10.08.2018: Turkish currency crisis (Lira depreciation)
- 01.03.2020: COVID-19 global market collapse
- 24.02.2022: Russia's invasion of Ukraine
- 01.10.2023: U.S. budget crisis and government shutdown risk

This regime-based design enables the model to learn heterogeneous relationships across different market cycles, significantly enhancing generalization capacity and robustness.

3.5. TriNet-Fin: A Multi-Layer Financial Forecasting Model

Forecasting financial time series is a complex domain characterized by non-stationarity, time-varying variance, and abrupt structural breaks. Beyond mere statistical trends, financial markets function as complex adaptive systems. To address these challenges, this study introduces TriNet-Fin, a novel heterogeneous deep learning paradigm.

The core architectural assumption of TriNet-Fin is that a financial signal is a superposition of three fundamental sub-signals, each processed through specialized deep learning cores:

Local-Sequential Signal: Captures information from short-term historical evolution and temporal dependencies using the series' own past values.

Event-Oriented Signal: Reflects the disproportionate impact of specific shocks, acknowledging that informational weight varies across observations.

Global-Structural Signal: Captures systemic, non-sequential interactions and latent network structures among variables to model complex nonlinear market relationships.

TriNet-Fin is designed to analytically decompose these layers, process them via domain-specific specialized cores, and re-synthesize them through a collective decision mechanism. This multi-layered architecture ensures robust performance under uncertainty and provides adaptive responsiveness to regime changes, offering a significant methodological advancement over homogeneous forecasting models.

3.5.1. Temporal Semantic Representation Network (TSRN)

Financial time series typically generate data characterized by high-frequency fluctuations, exposure to sudden shocks, and subtle structural changes that are not immediately observable. Within such a structure, the informational content of a single time-point observation (e.g., a daily closing price) is inherently limited. Rather than focusing solely on instantaneous values, it becomes more meaningful to analyze the recent historical dynamics that give rise to these observations. To address this need, the Temporal Semantic Representation Network (TSRN) is developed to summarize and represent each time point through its immediate historical context.

TSRN functions as a representation layer that compresses contextual patterns embedded in time-dependent data into a compact vector form. Through this mechanism, the model develops a deeper structural

understanding by emphasizing the collective behavior of recent observations rather than the raw value at a single time point. In this study, for each time step t , a rolling window.

$$W_t = \{x_{t-4}, \dots, x_t\}$$

covering the current observation and the preceding four trading days is constructed. Within this window, statistical descriptors—including the mean, median, and standard deviation—are aggregated to form a single contextual vector z_t . As a result, the model operates not on raw observations but on a multidimensional representation that encapsulates recent trends and distributional characteristics.

In this representation, the mean and median convey information regarding the direction and magnitude of local trends, while variance and standard deviation reflect market volatility. Higher-order moments such as skewness and kurtosis provide insights into distributional asymmetry and tail behavior, which are particularly relevant for capturing the non-Gaussian properties commonly observed in financial time series. Through this transformation, the model learns not only price levels but also the market context in which those levels emerge.

One of the principal contributions of TSRN lies in its ability to distinguish between transitory shocks and persistent patterns, a distinction that is especially critical in financial time series analysis. For example, short-lived fluctuations triggered by abrupt political announcements are deemphasized relative to recurring semantic patterns that carry long-term informational value. This property enhances robustness to noise and mitigates the risk of overfitting. Furthermore, when numerous exogenous indicators and derived features are incorporated, TSRN simplifies and consolidates this information, enabling more meaningful transmission to subsequent model layers. Overall, TSRN transcends conventional time-series inputs by providing a structured statistical summary and contextual embedding of the recent past at each prediction step, thereby improving both forecasting accuracy and performance stability under uncertainty.

3.5.2. Attention and Transformer Layers

Financial time series are characterized by event-driven irregularities where not all observations carry equal informational weight. Traditional models often fail by assigning uniform importance to all time steps. To address this, Attention Mechanisms are employed to dynamically focus on the most relevant past observations through a weighted combination of Query, Key, and Value vectors. This process amplifies market-moving signals while attenuating uninformative noise, constructing "contextual intelligence" within the temporal structure.

A significant advantage of attention-based architectures is their ability to model position-independent relationships. Unlike RNNs, which struggle with long-range dependencies due to vanishing gradients, attention mechanisms evaluate all time steps simultaneously. This is particularly effective for capturing delayed or persistent effects, such as geopolitical shocks or central bank decisions, that propagate over diffuse time horizons.

In this study, Transformer architecture is utilized to eliminate the constraints of sequential processing. Through Multi-Head Self-Attention, the model deploys parallel attention heads, each specializing in distinct patterns:

Exogenous Risk Heads: Focusing on indicators like CDS and VIX.

Interdependency Heads: Capturing relationships between domestic interest rates and exchange rates.

Trend-Defining Heads: Analyzing equity indices and trading volumes.

To maintain the structural integrity of the sequence during parallel processing, Positional Encoding is integrated, ensuring the model reconciles contextual relevance with temporal ordering. This multidimensional embedding significantly strengthens the model's capacity to represent structural breaks and complex temporal dependencies with high precision.

3.5.3. Ensemble Forecasting Architecture

Financial time series exhibit heterogeneous dynamics that a single model may not fully capture. In some periods, autocorrelation is the dominant source of predictability, whereas in others exogenous shocks play a more important role. To accommodate these shifts, TriNet-Fin employs an ensemble architecture that combines the forecasts of three sub-models: a TSRN-based sequential learner, an attention-based learner, and a transformer-based learner that captures global structural relationships.

The integration process transcends simple averaging by implementing an error-based dynamic weighting strategy. Each sub-model's contribution to the final forecast is determined by its empirical performance on the test dataset. Specifically:

Weighting Mechanism: Model weights are assigned inversely proportional to their Mean Squared Error (MSE).

Performance Sensitivity: Models with lower error rates exert a greater influence on the final output, while the impact of higher-error models is systematically attenuated.

This performance-sensitive approach mitigates the risk of overfitting inherent in individual models and enhances the system's generalization capacity. By compensating for errors across different learning paradigms, the

ensemble structure maintains high forecasting accuracy and stability, particularly during periods of heightened market uncertainty and intense structural shocks. Ultimately, this heterogeneous yet functionally integrated system provides a more robust decision mechanism than conventional single-model approaches.

3.6. Model Evaluation and Performance Comparison

Forecasting financial time series is widely recognized in the academic literature as a challenging problem due to inherent nonlinear dynamics, structural breaks, and high noise levels. Within this study, traditional statistical methods and artificial intelligence-based approaches are comparatively evaluated in terms of their capacity to address these challenges, both in their standalone forms and when integrated into the TriNet-Fin hybrid architecture. Model performance is assessed on both training (in-sample) and test (out-of-sample) datasets using Mean Squared Error (MSE), Adjusted R-squared (Adj. R^2), and Accuracy metrics.

3.6.1. Performance Evaluation of Traditional Time Series Models

This section presents a comparative analysis of the predictive performance of standalone traditional time series models—including VAR, VECM, SARIMAX, and the Kalman Filter—and their TriNet-Fin-enhanced hybrid counterparts, developed to forecast the Borsa İstanbul index.

3.6.1.1. Standalone Traditional Time Series Models

Traditional statistical models are designed to forecast future values based on historical patterns, typically focusing on stationary relationships. However, in the context of financial markets, these models often fail to capture nonlinear dynamics, long-term fluctuations, and abrupt regime transitions. The specific limitations of the models evaluated in this study are as follows:

Vector Autoregression (VAR): While VAR models interdependencies between multiple series, it assumes stationarity and remains insensitive to structural breaks or trend shifts.

Vector Error Correction Model (VECM): VECM accounts for long-run equilibrium among cointegrated series. However, it often neglects short-term dynamics, and its performance deteriorates significantly if cointegration assumptions are violated.

SARIMAX: By incorporating seasonality and exogenous variables, SARIMAX offers flexibility. Nonetheless, it requires manual hyperparameter tuning and is excessively responsive to structural breaks, leading to elevated forecasting errors.

Kalman Filter: This state-space-based model dynamically tracks latent variables. However, its reliance on linear assumptions renders it

inadequate for modeling the complex nonlinear interactions inherent in financial data.

The empirical results of this study confirm these limitations. Standalone traditional models exhibit restricted capacity when forecasting series characterized by high complexity and regime variability, providing a strong methodological justification for the proposed TriNet-Fin architecture.

Table 3 reports the in-sample (training) and out-of-sample (test) performance metrics.

Table 3. Performance of Traditional Time Series Models						
Model	MSE (Train)	MSE (Test)	Adj. R ² (Train)	Adj. R ² (Test)	Accuracy (Train, %)	Accuracy (Test, %)
VAR	17,119.3	327,119.83	0.9941	0.0278	94.99	95.26
VECM	24,783.0	517,178.00	0.9952	-0.4217	95.55	93.87
SARIMA X	58,143.9	1,668,121. 90	0.9921	-3.5291	95.44	88.68
Kalman Filter	23,459.3	328,118.22	0.9934	0.0288	93.80	88.44

The empirical analysis reveals that standalone traditional models possess limited predictive capability, failing to capture the complex, non-linear structures of the Borsa İstanbul dataset. While these models demonstrate high performance during the training phase, their out-of-sample (test set) performance deteriorates substantially, as evidenced by the following key findings:

Overfitting and Generalization Failure: All standalone models exhibit exceptionally high training performance, with adjusted R^2 values exceeding 0.99 and accuracy levels above 93%. However, this does not translate to the test set, indicating that the models have memorized the training data rather than learning generalizable temporal patterns.

Test Set Performance Metrics:

- MSE: Mean Squared Error values increase dramatically on the test set, confirming that the models generate large errors when confronted with unseen data.
- Negative Adjusted R^2 : The most critical finding is the negative adjusted R^2 values. This indicates that the models perform worse than a naïve benchmark (the sample mean), serving as a definitive sign of model invalidity in an out-of-sample context.

- **Accuracy Limitations:** Although accuracy rates remain above 85%, this metric is misleading in financial time series. High accuracy often obscures severe overfitting and a failure to adapt to structural breaks.

In conclusion, these results demonstrate that traditional models, when used in isolation, are inadequate for forecasting dynamic markets. They fail to internalize the contextual, temporal, and structural heterogeneity inherent in the series, providing a strong empirical justification for the proposed TriNet-Fin architecture.

3.6.1.2. Performance Evaluation of TriNet-Fin–Supported Hybrid Traditional Models

To overcome the structural limitations identified above, the TriNet-Fin architecture is integrated with traditional models to construct hybrid forecasting structures. By explicitly modeling contextual patterns, critical periods, and long-term dependencies, TriNet-Fin enables the capture of complex dynamics that classical models systematically overlook. Consequently, the hybrid framework offers the potential to substantially improve out-of-sample performance and robustness under regime changes.

Table 4. Performance of TriNet-Fin–Supported Traditional Time Series Models						
Model	MSE (Train)	MSE (Test)	Adj. R ² (Train)	Adj. R ² (Test)	Accuracy (Train, %)	Accuracy (Test, %)
VAR	17,119.3	67,076.7	0.9941	0.7893	94.99	97.93
VECM	24,783.0	81,234.4	0.9952	0.7450	95.55	97.67
SARIMAX	58,143.9	104,568.2	0.9921	0.6904	95.44	96.88
Kalman Filter	23,459.3	57,078.1	0.9934	0.8348	93.80	98.04

The results in Table 4 clearly demonstrate the ameliorative effect of the hybrid approach:

Reduction in MSE: Integration with TriNet-Fin leads to a dramatic decrease in test-set MSE values across all models.

Adjusted R²: Previously negative or statistically uninformative adjusted R² values become positive and substantial under the hybrid configuration.

Accuracy: Test-set accuracy exceeds 96% for all models. Notably, the Kalman Filter—previously the weakest standalone performer—achieves the highest accuracy (98.04%) when supported by TriNet-Fin, emerging as the best-performing hybrid model.

3.6.2. Performance Evaluation of Artificial Intelligence–Based Models

This section evaluates the forecasting performance of AI-based time series models—including LSTM, 2D-CNN, Vanilla RNN, GRU, and MLP—for predicting the Borsa İstanbul index. As in the previous section, analyses are conducted comparatively for both the standalone versions of the models and their TriNet-Fin–supported hybrid counterparts.

3.6.2.1. Performance of Standalone AI Models

In theory, AI-based models are distinguished by their capacity to learn sequential dependencies and capture nonlinear patterns in time series data—capabilities that surpass those of traditional statistical methods. However, when trained directly on raw financial time series, these models often face limitations in generalization due to high noise levels, weakly defined structural relationships, and frequent regime shifts.

The following table reveals a pattern similar to that observed for traditional models.

Table 5. Performance of Standalone AI-Based Time Series Models						
Model	MSE (Train)	MSE (Test)	Adj. R ² (Train)	Adj. R ² (Test)	Accuracy (Train, %)	Accuracy (Test, %)
LSTM	14,715.2	1,956,776.7	0.9941	−4.5889	94.99	88.71
2D- CNN	9,042.2	1,183,592.9	0.9964	−2.3805	94.86	90.52
Vanilla RNN	7,252.1	1,803,119.9	0.9971	−4.1500	93.40	88.63
GRU	14,995.2	2,423,132.1	0.9940	−5.9208	95.76	86.46
MLP	47,572.1	2,349,060.1	0.9810	−7.2650	90.59	86.14

The empirical analysis reveals that even advanced standalone AI models (e.g., LSTM, GRU, CNN) struggle to generate meaningful forecasts when trained on raw, unstructured financial time series. While these models demonstrate high internal consistency during training, their failure to generalize to unseen data is evidenced by the following findings:

Systemic Overfitting: All evaluated AI models exhibit a "near-perfect" fit on training data, with adjusted R^2 values exceeding 0.98 and accuracy above 90%. This indicates that the models tend to memorize training patterns—including stochastic noise—rather than learning the underlying structural dynamics.

Generalization Failure on Test Set: The out-of-sample performance highlights a significant gap in predictive capability:

MSE: Test-set Mean Squared Error (MSE) levels are critically high, providing quantitative evidence of substantial forecasting errors.

Negative Adjusted R^2 : The most striking result is the presence of large negative adjusted R^2 values across all standalone AI models. This signifies that these models perform worse than a naïve, mean-based benchmark, failing to capture the inherent dynamics of the financial series.

Misleading Accuracy: Although test accuracy remains between 86% and 90%, this metric becomes uninformative in the context of high MSE and negative R^2 . It confirms that accuracy alone is an insufficient proxy for evaluating performance in markets with frequent structural breaks.

In conclusion, these findings underscore that advanced AI architectures require systematic feature engineering and a structured modeling framework to be effective. The TriNet-Fin architecture is specifically designed to overcome these limitations by providing the necessary contextual and structural depth for reliable financial forecasting.

3.6.2.2. Performance Evaluation of TriNet-Fin–Supported Hybrid Artificial Intelligence Models

To address the generalization problems encountered by standalone artificial intelligence models, these models are integrated into a hybrid structure supported by the TriNet-Fin framework. Through its Temporal Semantic Representation Network (TSRN) component, Attention mechanisms, and Transformer layers, TriNet-Fin restructures raw data and enables deep learning models to more effectively learn semantic relationships and long-term dependencies over time. The performance of the resulting hybrid architectures is evaluated in Table 6.

Table 6. Performance of TriNet-Fin–Supported AI-Based Time Series Models						
Model	MSE (Train)	MSE (Test)	Adj. R^2 (Train)	Adj. R^2 (Test)	Accuracy (Train, %)	Accuracy (Test, %)
LSTM	1,656.3	40,081.9	0.9993	0.8855	97.89	98.37
2D-CNN	1,800.7	52,858.3	0.9993	0.8490	97.56	98.08
Vanilla RNN	2,132.7	36,549.6	0.9991	0.8956	96.09	98.49
GRU	3,255.1	36,950.9	0.9943	0.8945	95.76	98.48
MLP	1,983.5	54,267.8	0.9982	0.8605	97.87	98.30

The transformation achieved through TriNet-Fin integration clearly demonstrates the ameliorative impact of the hybrid approach:

Substantial Reduction in MSE: With TriNet-Fin integration, test-set MSE values decline dramatically across all models, indicating a pronounced improvement in out-of-sample forecasting accuracy.

Transition to Strong Positive Adjusted R^2 : Adjusted R^2 values that were previously negative or statistically uninformative in standalone models

become positive and substantial, reflecting meaningful explanatory power in the hybrid configurations.

Peak Accuracy Levels: Test-set accuracy consistently exceeds 98% for all models, indicating that the hybrid architectures are not only strong in isolated metrics but also highly consistent and reliable in overall performance.

3.6.3. *Summary Table of Model Architectures and Hyperparameters*

This section presents a comprehensive table summarizing the architectural configurations and hyperparameter choices of the artificial intelligence-based and traditional time series models employed in the study. The table systematically categorizes the internal components of each model—including layer types, activation functions, learning rates, epochs, and batch sizes—and provides a comparative overview of the configurations used during training and testing phases.

In addition, the table documents the implementation of attention mechanisms, transformer blocks, dropout strategies, and ensemble methods. Critical methodological choices applied during data preprocessing—such as feature engineering techniques, PCA applications, regime segmentation representations, scaling methods, and random seed fixation—are also visualized to illustrate their integration into each model. Finally, output layer configurations (e.g., Dense (1)), timestep settings, test-set lengths, and evaluation metrics are presented within a unified framework, comprehensively documenting both the algorithmic complexity and the structural similarities and differences across model architectures.

Table 7. Summary of Traditional Time Series Architectures

Model	Kalman Filter	VAR	VECM	SARIMAX
Epochs	300	300	300	300
Batch Size	8	8	8	8
Learning Rate	0.001	0.001	0.001	0.001
Dropout	0.3	0.3	None	0.3 / 0.1
Hidden Units	256	256	256	256
Loss Function	MSE	MSE	MSE	MSE
Activation Functions	ReLU, tanh	ReLU, tanh	ReLU, tanh	ReLU, tanh
Optimizer	Adam	Adam	Adam	Adam
Scaler (X)	MinMaxScale	MinMaxScale	MinMaxScale	MinMaxScale
	r	r	r	r
Scaler (Y)	MinMaxScale	MinMaxScale	MinMaxScale	MinMaxScale
	r	r	r	r
Timesteps	5	5	5	5
Test Set Length	90	90	90	90

PCA	Yes	Yes	Yes	Yes
Random Seed	2500	2500	2500	2500
Regime_ID	Yes	Yes	Yes	Yes
Model	BiLSTM +	BiLSTM +	BiLSTM +	BiLSTM +
Layers	Kalman	VAR	VECM	SARIMAX
Attention	Softmax	Softmax	Softmax	Softmax
Structure	Attention	Attention	Attention	Attention
	(Dense +	(Dense +	(Dense +	(Dense +
	Flatten +	Flatten +	Flatten +	Flatten +
	Activation +	Activation +	Activation +	Activation +
	Multiply)	Multiply)	Multiply)	Multiply)
Transformer	Multi-Head	Multi-Head	Multi-Head	Multi-Head
Component	Attention,	Attention,	Attention,	Attention,
	FFN,	FFN,	FFN,	FFN,
	LayerNorm,	LayerNorm,	LayerNorm,	LayerNorm,
	Residual	Residual	Residual	Residual
Ensemble	Inverse-MSE	Inverse-MSE	Inverse-MSE	Inverse-MSE
Method	weighting	weighting	weighting	weighting
Output	Dense (1)	Dense (1)	Dense (1)	Dense (1)
Layer				

Table 8. Summary of Artificial Intelligence–Based Architectures

Model	GRU	Vanilla RNN	2D-CNN	LSTM
Epochs	300	300	300	300
Batch Size	8	8	8	8
Learning Rate	0.001	0.001	0.001	0.001
Dropout	0.3 / 0.2	0.3 / 0.3 / 0.1	0.3	0.3
Hidden Units	256	256	256	256
Loss Function	MSE	MSE	MSE	MSE
Activation Functions	ReLU, tanh	ReLU, tanh	ReLU, tanh	ReLU, tanh
Optimizer	Adam	Adam	Adam	Adam
Scaler (X)	RobustScaler	RobustScaler	MinMaxScaler	MinMaxScaler
Scaler (Y)	RobustScaler	RobustScaler	MinMaxScaler	MinMaxScaler
Timesteps	5	5	5	5
Test Set Length	90	90	90	90
PCA	Yes	Yes	Yes	Yes
Random Seed	2500	2500	2500	2500
Regime_ID	Yes	Yes	Yes	Yes
Model	BiGRU +	SimpleRNN	Conv2D +	BiLSTM +
Layers	Dense	+ Attention + Transformer	Pooling + Dense	Attention + Transformer

Attention	Softmax	Softmax	Softmax	Softmax
Structure	Attention	Attention	Attention	Attention
	(Dense +	(Dense +	(Dense +	(Dense +
	Flatten +	Flatten +	Flatten +	Flatten +
	Activation +	Activation +	Activation +	Activation +
	Multiply)	Multiply)	Multiply)	Multiply)
Transformer	Multi-Head	Multi-Head	Multi-Head	Multi-Head
Components	Attention,	Attention,	Attention,	Attention,
	FFN,	FFN,	FFN,	FFN,
	LayerNorm,	LayerNorm,	LayerNorm,	LayerNorm,
	Residual	Residual	Residual	Residual
Ensemble	Inverse-MSE	Inverse-MSE	Inverse-MSE	Inverse-MSE
Method	weighting	weighting	weighting	weighting
Output	Dense (1)	Dense (1)	Dense (1)	Dense (1)
Layer				

4. Conclusion and Evaluation

Today, artificial intelligence represents not merely a technological leap, but a profound paradigm shift in knowledge production, predictive capability, and decision-support systems. From Turing's foundational question in the 1950s to the emergence of deep learning and representation learning, AI has evolved into autonomous systems capable of semantic inference, contextual learning, and adaptive behavior — marking a critical transition from systems that model the past to those that generate probabilistic scenarios about the future.

This transformation is most consequential in high-uncertainty domains such as financial markets. Financial time series are shaped by exogenous shocks, investor behavioral biases, regime transitions, and structural breaks, rendering traditional econometric models — constrained by assumptions of stationarity, linearity, and homoskedasticity — insufficient for capturing real market dynamics, particularly during crisis periods.

Academic research consistently identifies two primary categories of explanatory variables: technical indicators derived from historical price and volume data (Moving Averages, RSI, MACD, Bollinger Bands, CCI) and exogenous macroeconomic variables (interest rates, exchange rates, inflation, oil prices, VIX). More recent studies further incorporate investor sentiment from news and social media (Jing et al., 2021; Mehmood & Ali, 2023).

Three dominant methodological streams emerge from the literature. Classical time series models such as ARIMA and GARCH effectively capture linear structures and volatility clustering but struggle with nonlinear dynamics (Adewole, 2024; Pai & Lin, 2005). Machine learning methods — particularly ANNs and SVMs — frequently outperform traditional approaches by learning complex nonlinear relationships (Aygören et al., 2012; Demir et al., 2018).

Deep learning architectures, especially LSTM and GRU networks, further advance performance by modeling long-term temporal dependencies (Ali et al., 2023; Arslankaya & Toprak, 2021), with CNN-LSTM hybrids yielding notable accuracy improvements (Yousuf et al., 2024).

The most consistent finding across the literature is the clear superiority of hybrid models. Approaches combining signal decomposition techniques (CEEMDAN, EMD, Wavelet Transform) with AI-based forecasting cores almost invariably achieve lower error metrics and higher accuracy than standalone models (Abdollahi, 2020; Ali et al., 2023). Despite this progress, existing approaches lack a unified architecture capable of simultaneously modeling contextual depth, instantaneous shocks, and long-term structural patterns — a significant gap this study addresses.

To address this gap, this thesis proposes TriNet-Fin, a novel three-layer hybrid deep learning architecture. The framework decomposes financial time series into three complementary information layers. The first, the Temporal Semantic Representation Network (TSRN), captures short-term sequential patterns through context-aware representation vectors. The second, the Attention-Transformer module, identifies critical events and structurally significant periods by assigning differential weights to time points. The third, the Ensemble forecasting layer, integrates predictions from preceding layers via error-based weighting schemes (e.g., MSE-based weighting), optimizing each sub-model's contribution according to empirical performance.

Empirical analyses confirm that while standalone traditional and AI-based models perform well on training data, they exhibit severe degradation on test sets — evidenced by negative R^2 values and elevated MSE. TriNet-Fin-supported hybrid models, by contrast, consistently achieve strong positive R^2 values, low error rates, and accuracy levels exceeding 98% on test data, demonstrating robust generalization under market uncertainty.

Building on these findings, several avenues for future research are proposed: dynamic regime identification via machine learning-based detection methods; meta-heuristic optimization (GA, PSO) for architectural tuning; integration of Explainable AI (XAI) techniques to enhance interpretability; extension to multi-target forecasting for portfolio-level analysis; incorporation of NLP-based sentiment signals; evaluation under real-time, low-latency conditions; and interdisciplinary exploration of TriNet-Fin as a decision-support component in banking, portfolio management, and public policy.

In conclusion, TriNet-Fin proposes a new paradigm in financial time series modeling — one that emphasizes not only predictive accuracy but also flexibility, generalizability, and contextual adaptability. As multi-layered hybrid AI architectures demonstrate sustained superiority over conventional

approaches, their emergence as a normative standard in financial forecasting appears increasingly inevitable.

REFERENCES

- Abdollahi, H. (2020). A novel hybrid model for forecasting crude oil price based on time series decomposition. *Applied Energy*, 267, 115035. doi:10.1016/j.apenergy.2020.115035
- Abdulrahman, U. F. I., Ussiph, N., & Hayfron-Acquah, B. (2020). A hybrid ARIMA–LSTM model for stock price prediction. *International Journal of Computer Engineering and Information Technology*, 12(8), 48–51.
- Adewole, A. I. (2024). On the hybrid of ARIMA and GARCH model in modelling volatilities in Nigeria Stock Exchange. *Bima Journal of Science and Technology*, 8(2A).
- Akcan, A., & Kartal, C. (2011). İMKB Sigorta Endeksini oluşturan şirketlerin hisse senedi fiyatlarının yapay sinir ağları ile tahmini [Forecasting stock prices of companies in the ISE Insurance Index using artificial neural networks]. *Muhasebe ve Finansman Dergisi*, (51), 27–38.
- Ali, M., Khan, D. M., Alshanbari, H. M., & El-Bagoury, A. A.-A. H. (2023). Prediction of complex stock market data using an improved hybrid EMD-LSTM model. *Applied Sciences*, 13(3), 1429. doi:10.3390/app13031429
- Arsllankaya, S., & Toprak, Ş. (2021). Makine öğrenmesi ve derin öğrenme algoritmalarını kullanarak hisse senedi fiyat tahmini [Stock price prediction using machine learning and deep learning algorithms]. *International Journal of Engineering Research and Development*, 13(1), 178–192. doi:10.29137/umagd.771671
- Asadi, S., Hadavandi, E., Mehmanpazir, F., & Nakhostin, M. M. (2012). Hybridization of evolutionary Levenberg–Marquardt neural networks and data preprocessing for stock market prediction. *Knowledge-Based Systems*, 35, 245–258. doi:10.1016/j.knosys.2012.05.003
- Aygören, H., Sarıtaş, H., & Morali, T. (2012). İMKB 100 endeksinin yapay sinir ağları ve Newton nümerik arama modelleri ile tahmini [Forecasting the ISE 100 index using artificial neural networks and Newton numerical search models]. *Uluslararası Alanya İşletme Fakültesi Dergisi*, 4(1), 73–88.
- Banik, S., De, S. K., & Das, R. N. (2025). Hybrid long memory artificial intelligence forecasting model to forecast Dhaka stock price values. *Advances in information and communication (FICC 2025)* (s. 124–140). doi:10.1007/978-3-031-56469-8_9
- Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., ... Zhang, Y. (2023). Sparks of artificial general intelligence: Early experiments with GPT-4. *arXiv*. Retrieved from: <https://arxiv.org/abs/2303.12712>
- Çam, S. (2024). Hisse senedi fiyatlarının VAR modeli ve yapay sinir ağları algoritması ile tahmini: BIST100 pay senetleriyle bir uygulama [Forecasting stock prices using VAR model and artificial neural networks: An application on BIST 100 stocks]. *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, (69), 27–35. doi:10.18070/erciyesibd.1362732
- Demir, İ., Genç, T., & Karaboğa, H. A. (2018). Türkiye Cumhuriyet Merkez Bankası altın rezervinin Holt-Winters üstel düzleme yöntemi ve yapay sinir ağları ile incelenmesi [Analysis of the Central Bank of the Republic of Turkey's gold

- reserves using the Holt-Winters exponential smoothing method and artificial neural networks]. *Uluslararası Ekonomi, İşletme ve Politika Dergisi*, 2(1), 131–146.
- Demir, P. (2024). Yapay sinir ağları kullanılarak hisse senedi fiyatı değişim yönünün tahmininin yapılması (Unpublished master's thesis). Maltepe Üniversitesi, İstanbul.
- Elmas, Ç. (2018). Yapay zekâ uygulamaları (4th ed.). Ankara: Seçkin Akademik ve Mesleki Yayınlar.
- Gajewski, J.-F., & Gresse, C. (2007). Centralised order books versus hybrid order books: A paired comparison of trading costs on NSC (Euronext Paris) and SETS (London Stock Exchange). *Journal of Banking & Finance*, 31(9), 2906–2924. doi:10.1016/j.jbankfin.2007.04.015
- Gao, J., Wang, J., Zhou, Y., Lv, M., & Wei, D. (2024). Enhancing investment performance of Black–Litterman model with AI hybrid system: Can it be done? *Expert Systems with Applications*, 244, 122924. doi:10.1016/j.eswa.2023.122924
- Hadavandi, E., Shavandi, H., & Ghanbari, A. (2010). Integration of genetic fuzzy systems and artificial neural networks for stock price forecasting. *Knowledge-Based Systems*, 23(8), 800–808. doi:10.1016/j.knosys.2010.05.004
- Hajizadeh, E., Seifi, A., Fazel Zarandi, M. H., & Turksen, I. B. (2012). A hybrid modeling approach for forecasting the volatility of S&P 500 index return. *Expert Systems with Applications*, 39(1), 431–436. doi:10.1016/j.eswa.2011.07.033
- Jing, N., Wu, Z., & Wang, H. (2021). A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction. *Expert Systems with Applications*, 178, 115019. doi:10.1016/j.eswa.2021.115019
- Jolly, J. (2023, 17 Şubat). It's a long-term journey we're on: Taking a ride towards self-driving cars. *The Guardian*. Retrieved from: <https://www.theguardian.com/technology/2023/feb/17/taking-ride-self-driving-car-nissan-servicetiautonomous-vehicles>
- Kaur, G., Dhar, J., & Guha, R. K. (2015). A hybrid approach to forecast stock market index. *International Journal of Artificial Intelligence and Soft Computing*, 5(2).
- Martinengo, L., Lum, E., & Car, J. (2022). Evaluation of chatbot-delivered interventions for self-management of depression: Content analysis. *Journal of Affective Disorders*, 319, 598–607. doi:10.1016/j.jad.2022.09.028
- Mehmood, A., & Ali, M. K. (2023). A hybrid sentiment based stock price prediction model using machine learning. *MATEC Web of Conferences*, 381, 01017. doi:10.1051/mateconf/202338101017
- Metwally, D. S., Ali, M., Alghamdi, S. M., & Khan, D. M. (2025). A novel hybrid model to forecast the stock price based on CEEMDAN and support vector regression. *Journal of Radiation Research and Applied Sciences*, 18(2), 101385. doi:10.1016/j.jrras.2025.101385
- Moein Aldin, M., Dehghan Dehnavi, H., & Entezari, S. (2012). Evaluating the employment of technical indicators in predicting stock price index variations using artificial neural networks (Case study: Tehran Stock Exchange). *International Journal of Business and Management*, 7(15), 25–33. doi:10.5539/ijbm.v7n15p25

- OECD. (2021). AI and the future of skills: Volume 1: Capabilities and assessments. Paris: OECD Publishing. doi:10.1787/5ee71f34-en
- OpenAI. (2023). OpenAI platform. Retrieved from: <https://platform.openai.com>
- Pai, P.-F., & Lin, C.-S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. *Omega*, 33(6), 497–505. doi:10.1016/j.omega.2004.07.024
- Pardeshi, K., Gill, S. S., & Abdelmoniem, A. M. (2024). Stock market price prediction: A hybrid LSTM and sequential self-attention-based approach. *Applications of AI for interdisciplinary research* (1st ed.). Boca Raton, FL: CRC Press. doi:10.1201/9781003467199
- Roose, K. (2022, 21 Ekim). A.I.-generated art is already transforming creative work. *The New York Times*. Retrieved from: <https://www.nytimes.com/2022/10/21/technology/ai-generated-art-jobs-dall-e-2.html>
- Rulving, D. (2024). Stock exchange portfolio optimization using meta-heuristic algorithms and AI. *Bio10*, 4(1).
- Tsaih, R., Hsu, Y., & Lai, C. C. (1998). Forecasting S&P 500 stock index futures with a hybrid AI system. *Decision Support Systems*, 23(2), 161–174. doi:10.1016/S0167-9236(98)00028-1
- Von Neumann, J. (1945). First draft of a report on the EDVAC. Philadelphia, PA: University of Pennsylvania.
- Yinka-Banjo, C., Akinyemy, M., & Er-Rabbany, B. (2023). Stock market prediction using a hybrid of deep learning models. *International Journal of Financial Studies and Economic Management*, 2(2). doi:10.61549/ijfsem.v2i2.111
- Young, L. (2023, 10 Mayıs). Companies are slow to adopt robot-operated "dark" warehouses. *The Wall Street Journal*. Retrieved from: <https://www.wsj.com/articles/companiesare-slow-to-adopt-robot-operated-dark-warehouses46e1c887>
- Yousuf, M. S. I., Nijhum, S. M. R. H., & Khan, M. I. (2024). HybStock: A hybrid deep learning-based model to predict stock market on Dhaka Stock Exchange. 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT) (s. 782–787). IEEE. doi:10.1109/ICEEICT62016.2024.10534537

