

Research Article

Integrating Political Risk into Portfolio Optimization: A Risk-Adjusted DEA–Malmquist Framework for the Iranian Capital Market

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ABSTRACT

PURPOSE: Political uncertainty strongly affects corporate performance and portfolio returns in emerging capital markets, yet validated political risk indicators have rarely been integrated into efficiency-based portfolio optimization. This study proposes a risk-adjusted data envelopment analysis (DEA)–Malmquist framework for portfolio selection in the Iranian capital market.

DESIGN/METHODOLOGY/APPROACH: Political risk indicators were identified through a systematic literature review and validated by an eleven-member expert panel using the content validity ratio and content validity index. The validated indicators were then entered as additional inputs into an input-oriented super-efficiency DEA model, and dynamic performance was assessed with the Malmquist productivity index. The framework was applied to panel data for 106 firms listed on the Tehran Stock Exchange and Iran Fara Bourse over 2009–2023, and the resulting efficiency and productivity measures were used to construct a twenty-stock portfolio.

FINDINGS: Risk-adjusted super-efficiency scores differ substantially across firms and industries, and productivity change varies widely, driven by both technical efficiency change and technological change. The selected twenty-stock portfolio is weighted toward pharmaceutical and automotive-parts firms that combine relatively high efficiency and productivity growth with lower exposure to political shocks.

RESEARCH IMPLICATIONS: Treating political risk as an explicit component of efficiency measurement, rather than as an external factor, offers investors, portfolio managers, and policymakers a structured decision-support tool for building more resilient portfolios in politically uncertain environments.

ORIGINALITY/VALUE: The study combines expert-validated political risk indicators, super-efficiency DEA, and the Malmquist productivity index within a single portfolio-selection framework for an emerging market exposed to sanctions and policy uncertainty.

RESEARCH HIGHLIGHTS

- Expert-validated political risk indicators enter DEA as additional inputs.
- Super-efficiency DEA and Malmquist indices jointly guide portfolio selection.
- The framework is applied to 106 Iranian listed firms over 2009–2023.

1. Introduction

Financial markets have undergone profound structural transformations over recent decades, becoming increasingly interconnected, information-driven, and sensitive to multiple sources of uncertainty. Whereas traditional financial theory emphasizes firm-specific characteristics and macroeconomic fundamentals as the principal determinants of investment decisions, political uncertainty has become one of the most influential factors shaping market behavior. Political events—including elections, policy changes, geopolitical conflicts, economic sanctions, regulatory reforms, and institutional instability—can rapidly alter investors' expectations, increase market volatility, affect corporate profitability, and reshape asset allocation. Consequently, political risk has evolved from an exogenous environmental factor into a central component of investment analysis and financial risk management (Jakobsen, 2010; Pástor & Veronesi, 2013). Because global markets are closely integrated, political shocks in one country also spill over into international capital flows, exchange rates, commodity prices, and risk perceptions (Caldara & Iacoviello, 2022).

Political risk is particularly important in emerging capital markets, which are characterized by greater information asymmetry, lower market efficiency, weaker institutions, greater dependence on government policy, and higher exposure to macroeconomic fluctuations. In such settings, political events can have immediate and significant effects on stock prices, liquidity, investor confidence, and operating performance, so that investment decisions based solely on financial statements and historical market data may understate the uncertainty that investors face. The Iranian capital market is a particularly suitable setting for studying this issue: over the past two decades, the Tehran Stock Exchange (TSE) and Iran Fara Bourse (IFB) have experienced repeated episodes of uncertainty arising from international sanctions, changes in foreign policy, exchange-rate volatility, inflationary pressure, regulatory reforms, and regional geopolitical developments.

Modern portfolio theory, introduced by Markowitz (1952), established the foundation of portfolio optimization through efficient diversification based on the trade-off between expected return and risk. Numerous extensions have since been developed, including alternative risk measures, robust and stochastic optimization, linear-programming formulations, and multi-objective models (Fabozzi *et al.*, 2010; Kolm *et al.*, 2014; Mansini *et al.*, 2014). Most of these models, however, implicitly assume relatively stable economic and institutional conditions and either ignore political uncertainty or treat it as an uncontrollable external factor. In emerging markets, where political developments frequently dominate economic fundamentals, this omission may bias estimates of expected returns, understate systematic risk, and lead to inefficient asset allocation.

Data envelopment analysis (DEA) offers a complementary approach. Introduced by Charnes *et al.* (1978) and extended by Banker *et al.* (1984), DEA is a non-parametric method for measuring the relative efficiency of decision-making units (DMUs) using multiple inputs and outputs without assuming a functional form for the production technology; it has been applied widely in banking, insurance, health care, manufacturing, energy, and financial markets (Emrouznejad & Yang, 2018; Zhou *et al.*, 2008). In investment analysis, DEA allows firms to be evaluated on several financial dimensions simultaneously—profitability, liquidity, leverage, growth, and market valuation—rather than on a single ratio. Because conventional DEA is static, the Malmquist productivity index is used to measure productivity change over time and to decompose it into technical efficiency change and technological change (Färe *et al.*, 1992).

At the same time, a large literature has examined how political and policy uncertainty affects stock market volatility, investment, risk premia, and market performance (Baker *et al.*, 2016; Jakobsen, 2010; Lehkonen & Heimonen, 2015; Pástor & Veronesi, 2013). This evidence indicates that rising political uncertainty reduces investor confidence, increases risk premia, and weakens corporate investment, and that political uncertainty is a component of systematic risk that cannot be diversified away. Nevertheless, the political risk and DEA-based investment literatures have evolved largely independently: political risk studies focus on identifying uncertainty indicators or estimating their market effects, whereas DEA studies concentrate on operating or financial efficiency. Moreover, where environmental conditions are considered in efficiency analysis, they are usually treated as external explanatory variables—for example, in second-stage regressions—rather than as components of the efficiency measure itself (Daraio & Simar, 2007; Simar & Wilson, 2007).

To address this gap, this study develops a risk-adjusted DEA–Malmquist framework that integrates validated political risk indicators into efficiency evaluation and portfolio selection in the Iranian capital market. The empirical analysis

uses panel data for 106 firms listed on the TSE and IFB over 2009–2023, a period that includes several episodes of severe political and economic uncertainty. Financial and macroeconomic variables enter the DEA model together with political risk indicators that were identified through a systematic literature review and validated by expert judgment.

This study contributes to the literature in three ways. First, it establishes an explicit link between political risk assessment, efficiency analysis, and portfolio optimization, which have previously been studied separately. Second, it treats political uncertainty as a component of efficiency measurement rather than as an external explanatory variable, and it combines static super-efficiency scores with dynamic productivity measures. Third, it offers investors, portfolio managers, and policymakers a decision-support framework for constructing portfolios in politically uncertain environments. The remainder of the paper is organized as follows. Section 2 reviews the theoretical background and related literature and states the research propositions. Section 3 describes the research design, data, variables, and models. Section 4 reports the empirical results, Section 5 discusses them, and Section 6 concludes and outlines the study's limitations and directions for future research.

2. Theoretical Background and Literature Review

2.1. Conceptual and theoretical foundations

2.1.1. Political risk and capital market performance

Political risk originates from government actions, institutional changes, geopolitical developments, regulatory reforms, elections, sanctions, diplomatic conflicts, and social instability, all of which can substantially alter investors' expectations and market behavior. Unlike firm-specific risk, it affects many firms simultaneously and, in integrated markets, can be transmitted across borders through capital flows, exchange rates, and sovereign risk (Jakobsen, 2010; Pástor & Veronesi, 2013). The literature shows that political uncertainty increases information asymmetry and market volatility, weakens investor confidence, and raises the rate of return required by investors; it may also delay investment projects, restrict access to external finance, raise financing costs, and reduce profitability. These effects are particularly severe in emerging markets with weaker institutions.

Political uncertainty affects financial markets through several channels. First, unexpected political events increase uncertainty about future economic policy and thus affect corporate investment (Baker *et al.*, 2016). Second, political instability changes investors' risk perceptions, leading to portfolio reallocation and higher volatility. Third, regulatory uncertainty influences firms' strategic planning, financing decisions, and operating efficiency. Finally, geopolitical conflicts and international sanctions affect trade, exchange rates, inflation, and macroeconomic stability (Caldara & Iacoviello, 2022). In Iran, sanctions, exchange-rate fluctuations, inflation, policy reforms, and regional tensions have repeatedly generated such uncertainty, so investment models based solely on financial indicators may provide incomplete assessments of corporate performance.

2.1.2. Portfolio optimization theory

Since Markowitz (1952), portfolio selection has focused on the optimal trade-off between expected return and risk through diversification, showing that portfolio performance depends not only on the characteristics of individual assets but also on their covariance structure. Subsequent extensions of the mean–variance framework include robust optimization, stochastic and fuzzy programming, multi-objective programming, conditional value-at-risk optimization, linear-programming models, and heuristic algorithms, which address estimation uncertainty, downside risk, transaction costs, liquidity constraints, and multiple objectives (Fabozzi *et al.*, 2010; Kolm *et al.*, 2014; Mansini *et al.*, 2014). Despite these advances, conventional models still rely mainly on historical returns, covariance matrices, accounting ratios, betas, and volatility, and political uncertainty is ignored or captured only indirectly through market volatility. In emerging markets, two firms with similar financial characteristics may therefore have very different investment prospects because of different exposure to political uncertainty.

2.1.3. Data envelopment analysis in financial decision-making

Building on Farrell's (1957) measurement of productive efficiency, DEA evaluates the relative efficiency of homogeneous DMUs through linear programming, without requiring assumptions about the functional relationship

between inputs and outputs (Banker *et al.*, 1984; Charnes *et al.*, 1978; Coelli *et al.*, 2005). In financial markets, DEA has important advantages over ratio analysis: it considers multiple financial inputs and outputs within a single optimization framework, providing a comprehensive measure of corporate competitiveness, and it identifies efficient frontier firms that serve as benchmarks for less efficient ones (Zhu, 2014). From an investment perspective, frontier firms often exhibit stronger operating performance and better resource allocation, which makes them attractive candidates for portfolio selection.

2.1.4. Malmquist productivity index and dynamic efficiency

Because corporate performance is dynamic and shaped by technological innovation, managerial improvement, economic fluctuations, and institutional change, static efficiency measures may fail to capture productivity change over time. Färe *et al.* (1992) introduced the DEA-based Malmquist productivity index (MPI) to measure changes in total factor productivity (TFP) and to decompose them into technical efficiency change (the catch-up effect) and technological change (the frontier-shift effect) (Coelli *et al.*, 2005). The former reflects a firm's ability to improve its use of resources relative to best-practice firms, whereas the latter captures shifts of the frontier resulting from innovation or structural transformation. For investors, the MPI provides evidence on firms' ability to sustain productivity growth under changing conditions, which is particularly valuable in emerging markets exposed to macroeconomic instability, regulatory reform, exchange-rate volatility, and political uncertainty.

2.2. Empirical evidence and unresolved gap

The literature shows substantial progress in three largely separate areas: political risk assessment, portfolio optimization, and DEA-based efficiency evaluation. Political risk studies investigate the effects of political uncertainty on stock returns, volatility, foreign direct investment, and macroeconomic performance (Baker *et al.*, 2016; Lehkonen & Heimonen, 2015; Pástor & Veronesi, 2013). Portfolio optimization research emphasizes risk–return optimization, stochastic programming, robust optimization, and multi-objective techniques (Kolm *et al.*, 2014; Mansini *et al.*, 2014), but rarely incorporates validated political risk indicators as explicit determinants of investment efficiency. DEA studies, in turn, measure operating or financial efficiency with conventional financial variables, and when environmental conditions are considered, they typically enter as external explanatory variables rather than as part of the efficiency measure (Simar & Wilson, 2007). Studies of Iranian listed firms have also confirmed the usefulness of DEA for evaluating corporate efficiency (Doaei *et al.*, 2016).

Two limitations follow. First, because political uncertainty is excluded from efficiency measurement, firms with identical financial performance receive similar efficiency scores regardless of their exposure to political risk, even though their long-term investment prospects may differ substantially. Second, many DEA-based portfolio studies use static models that ignore productivity change, so firms with temporary improvements may receive scores similar to those of firms with sustained competitiveness. A significant gap therefore remains for a decision-support framework that simultaneously integrates validated political risk indicators, DEA, and the Malmquist productivity index within portfolio selection. Addressing this gap is the principal motivation of the present study.

2.3. Research propositions

Based on the preceding discussion, the study is guided by two research propositions:

P1. Incorporating validated political risk indicators into super-efficiency DEA changes firms' efficiency rankings relative to conventional DEA and improves the discriminatory power of efficiency evaluation.

P2. Portfolios composed of firms with high risk-adjusted efficiency and sustained productivity growth are more resilient to political uncertainty than portfolios selected on conventional financial criteria alone.

3. Data and Methodology

3.1. Research design and analytical framework

This study adopts an applied, mixed-methods design that integrates qualitative and quantitative procedures. The framework comprises four sequential stages. First, political risk indicators were identified through a systematic review of the literature on political risk, investment decision-making, financial engineering, and capital market

performance. Second, the extracted indicators were evaluated by an expert panel to establish their relevance and content validity. Third, the validated indicators were integrated with financial and macroeconomic variables in a super-efficiency DEA model and the Malmquist productivity index to evaluate static and dynamic efficiency. Finally, efficiency scores, productivity measures, and political risk exposure were jointly used to construct an investment portfolio. Political uncertainty thus enters the framework as a component of efficiency evaluation rather than as an external macroeconomic factor.

3.2. Population, sample, data sources, and study period

The population consists of firms continuously listed on the TSE and IFB from 2009 to 2023. This period includes several episodes of substantial political and economic uncertainty, including international sanctions, exchange-rate shocks, inflationary pressure, regulatory reforms, and geopolitical developments. Firms with incomplete financial statements, irregular trading, changes in fiscal year-end, or insufficient historical data were excluded. Commercial banks and other financial intermediaries were excluded because of their different asset structures and regulatory requirements, whereas selected insurance companies with high transparency and consistent operating data were retained because they are key risk-mitigating entities in the market. The final sample comprises 106 firms from multiple industrial and service sectors. Financial statements, market data, macroeconomic variables, and political risk data were collected from official financial databases, annual reports, and capital market information systems and were checked for completeness, consistency, and accuracy before the efficiency models were estimated.

3.3. Variables, constructs, and measurement

Political risk indicators. An initial list of political risk indicators was compiled from the international literature on political risk, financial markets, portfolio optimization, institutional quality, and geopolitical uncertainty. The list was then evaluated by an expert panel of eleven members, comprising university faculty, financial engineering specialists, portfolio managers, and capital market professionals, who assessed the relevance, clarity, necessity, and applicability of each indicator in the Iranian context. The essentiality of each indicator was assessed with the content validity ratio (CVR) of Lawshe (1975), and indicators below the critical CVR value were excluded. The remaining indicators were evaluated with the content validity index (CVI) for relevance, simplicity, and clarity (Polit *et al.*, 2007), and only indicators satisfying both criteria were retained. The validated indicators cover government stability, regulatory uncertainty, international sanctions, geopolitical tensions, institutional effectiveness, policy consistency, and political decision-making.

Financial and macroeconomic variables. Following the financial engineering and portfolio optimization literature and the qualitative findings of the first phase, the DEA inputs comprise macroeconomic and financial conditions that affect firms' financing costs and operations—gross domestic product (GDP) growth, the inflation rate, the interest rate, the risk-free rate, and the interbank rate—together with the validated political risk indicators. The outputs reflect financial and market performance: earnings per share (EPS), stock return, systematic risk (beta), and return variance. Table 1 summarizes the variables.

Table 1. Variable definitions and measurement

Variable	Role in DEA	Definition	Data source
GDP growth	Input	Annual growth rate of gross domestic product	Official macroeconomic data
Inflation rate	Input	Annual consumer price inflation	Official macroeconomic data
Interest rate	Input	Annual interest rate	Official macroeconomic data
Risk-free rate	Input	Annual risk-free rate of return	Official macroeconomic data
Interbank rate	Input	Annual interbank interest rate	Official macroeconomic data
Political risk indicators	Additional input	Expert-validated indicators of government stability, regulatory uncertainty, sanctions, geopolitical tension, institutional effectiveness, policy consistency, and political decision-making	Literature review and expert panel
EPS	Output	Earnings per share	Financial statements
Stock return	Output	Annual stock return	Capital market data
Beta	Output	Systematic risk relative to the market index	Capital market data
Return variance	Output	Variance of stock returns	Capital market data

Notes: DEA = data envelopment analysis; EPS = earnings per share; GDP = gross domestic product. Political risk indicators enter the model as additional inputs (Equation 2). Data sources are as reported in Section 3.2.

3.4. Model specification and estimation procedure

Super-efficiency DEA. Corporate efficiency is evaluated with an input-oriented super-efficiency DEA model (Andersen & Petersen, 1993; see also Tone, 2001, 2002, for slacks-based extensions). Unlike conventional DEA, the super-efficiency approach excludes the evaluated unit from the reference set, so efficient units can obtain scores greater than one, which allows a complete ranking of efficient firms—an important property for portfolio selection. Assume that n DMUs use m inputs to produce s outputs. For the evaluated unit o , the model is:

$$\begin{aligned}
 & \min \theta_o^{\text{super}} \\
 \text{s. t. } & \sum_{j=1, j \neq o}^n \lambda_j x_{ij} \leq \theta_o^{\text{super}} x_{io}, \quad i = 1, \dots, m \\
 & \sum_{j=1, j \neq o}^n \lambda_j y_{rj} \geq y_{ro}, \quad r = 1, \dots, s \\
 & \lambda_j \geq 0, \quad j = 1, \dots, n; j \neq o
 \end{aligned} \tag{1}$$

where x_{ij} and y_{rj} are the i -th input and r -th output of DMU j ; λ_j are intensity weights; and θ_o^{super} is the super-efficiency score of DMU o . Scores greater than one indicate super-efficient firms located beyond the conventional efficient frontier, whereas scores below one indicate inefficient firms.

Risk-adjusted extension. To incorporate political risk, the model is formulated as a risk-adjusted super-efficiency DEA in which political risk indicators are treated as additional inputs, x^{risk} . Because these indicators represent unfavorable environmental pressures, entering them as inputs penalizes the efficiency scores of firms that fail to mitigate external shocks. The input constraints are therefore expanded as follows:

$$\sum_{j=1, j \neq o}^n \lambda_j x_{kj}^{\text{risk}} \leq \theta_o^{\text{super}} x_{ko}^{\text{risk}}, \quad k = 1, \dots, p \tag{2}$$

where x_{kj}^{risk} is the k -th political risk indicator for DMU j and p is the number of validated indicators. A firm that operates in a politically exposed sector or fails to cushion the effects of political instability requires a larger input vector to maintain its outputs and therefore obtains a lower risk-adjusted efficiency score.

Malmquist productivity index. To capture productivity change between consecutive periods t and $t + 1$, the study uses the output-distance-function form of the Malmquist index (Färe *et al.*, 1992):

$$\text{MPI} = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{1/2} = \text{EC} \times \text{TC} \quad (3)$$

$$\text{EC} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}, \quad \text{TC} = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} \right]^{1/2}$$

where $D(\cdot)$ is the distance function relative to the period- t frontier; EC (technical efficiency change) measures catch-up toward the frontier, and TC (technological change) measures the shift of the frontier between the two periods. $\text{MPI} > 1$ indicates productivity improvement, $\text{MPI} = 1$ no change, and $\text{MPI} < 1$ deterioration.

3.5. Validity, robustness, and reproducibility

The content validity of the political risk construct was established with the CVR and CVI procedures described in Section 3.3. The data were pre-processed through consistency checks, removal of missing observations, verification of financial information, and standardization of variables to ensure comparability across firms and periods. Descriptive statistics were computed for all variables before the super-efficiency DEA and Malmquist models were estimated, and the resulting efficiency scores and productivity indices were then combined with political risk exposure to rank firms and construct the portfolio.

4. Results

4.1. Descriptive statistics and preliminary analysis

Table 2 reports descriptive statistics for the research variables. The results indicate considerable variation among firms in financial performance, market returns, and systematic risk, which supports the suitability of the sample for DEA-based efficiency evaluation.

Table 2. Descriptive statistics of the research variables

Variable	Mean	SD	Minimum	Maximum
Beta (β)	0.86	1.12	−3.25	10.66
Return variance	158,019,154.3	1,151,468,043	0	33,127,640,100
Stock return	68.13	151.92	−86.52	2,424.75
EPS	1,478.30	3,718.83	−6,799.67	72,414.66
GDP	448.47	64.39	299.10	584.50
Interest rate	18.26	3.27	12.00	22.00
Risk-free rate	17.46	3.31	12.00	22.00
Interbank rate	18.26	15.40	9.00	52.30

Notes: SD = standard deviation; EPS = earnings per share; GDP = gross domestic product.

The expert evaluation confirmed that all retained indicators satisfied the validity thresholds. Table 3 summarizes the validation procedure.

Table 3. Content validity assessment of the political risk indicators

Validation step	Metric / criterion	Threshold	Outcome
Content validity ratio (CVR)	Lawshe's formula (essentiality)	≥ 0.59 (11 experts)	Accepted / excluded
Content validity index (CVI)	Relevance	> 0.79	Accepted
Content validity index (CVI)	Relevance	0.70–0.79	Revised
Content validity index (CVI)	Relevance	< 0.70	Rejected
Expert consensus	Panel of 11 finance experts	High agreement	Indicators validated

Notes: CVR = content validity ratio (Lawshe, 1975); CVI = content validity index (Polit et al., 2007). The CVR critical value for a panel of eleven experts is 0.59.

4.2. Main findings

4.2.1. Super-efficiency DEA results

The super-efficiency DEA model provides a complete ranking of the sample firms by relative operating and financial efficiency. The results reveal substantial differences in efficiency across firms and industries; the highest scores are obtained by Fanavaran Petrochemical (0.85), Pars Darou (0.78), and Behbahan and Qaen Cement (0.74), whereas several firms exhibit relatively low scores, suggesting managerial inefficiencies and room for improvement. Table 4 reports the twenty highest-ranked firms.

Table 4. Risk-adjusted super-efficiency scores: twenty highest-ranked firms

Rank	Company	Score	Rank	Company	Score
1	Fanavaran Petrochemical	0.85	11	Fars Cement	0.69
2	Pars Darou	0.78	12	Mavad Darou Pakhsh	0.68
3	Behbahan Cement	0.74	13	Zahravi Pharmaceutical	0.68
4	Qaen Cement	0.74	14	Iran China Clay	0.67
5	Kaveh Paper	0.73	15	Informatics Services	0.67
6	Kharg Petrochemical	0.73	16	Sahand Rubber	0.66
7	Pars Tile	0.71	17	Exir Pharmaceutical	0.66
8	Behran Oil	0.70	18	Pars Khazar	0.66
9	Iran Refractories	0.70	19	Iran Radiator	0.65
10	Darou Pakhsh	0.69	20	Iran Yasa	0.65

Notes: Scores are input-oriented super-efficiency scores from Equations (1)–(2).

4.2.2. Malmquist productivity index results

The Malmquist results reveal considerable variation in productivity over time. Some firms experienced continuous improvement owing to technological progress and better managerial efficiency, whereas others showed declining productivity associated with adverse economic conditions, political uncertainty, and operating inefficiency. The decomposition shows that productivity change was driven by both technical efficiency change and technological change, underscoring the value of dynamic rather than purely static evaluation. Table 5 reports the index and its components for selected firms.

Table 5. Malmquist productivity index and its components for selected firms

No.	Firm (DMU)	EC	TC	TFPCH
1	Lab Iran	2.800	1.100	1.310
2	Auto Parts	2.780	0.950	2.150
3	Razak Pharma	2.520	0.880	1.250
4	Iran Radiator	1.150	1.800	2.830
5	Exir Pharma	1.050	1.100	1.980
6	Farabi Pharma	0.980	1.040	1.020
7	Manganese Mines	1.210	0.920	1.800
8	Ferrosilice Iran	5.220	0.760	2.560
9	Sobhan Pharma	0.180	0.980	0.850
10	Chemi Darou	1.000	0.840	0.230
11	Farabi Petrochemical	0.850	0.910	0.050
12	Refractory Products	0.170	1.050	0.450

Notes: EC = technical efficiency change; TC = technological change; TFPCH = total factor productivity change. Values greater than one indicate improvement.

4.2.3. Portfolio construction

After efficiency and productivity were estimated, the validated political risk indicators were incorporated into the risk-adjusted DEA–Malmquist framework to construct the portfolio. Integrating political risk excluded firms that were highly vulnerable to political uncertainty despite satisfactory financial performance, so that the selected portfolio consists of firms with relatively high operating efficiency, sustained productivity growth, and greater resilience to political shocks. Table 6 reports the final portfolio.

Table 6. Final portfolio selected by the risk-adjusted DEA–Malmquist framework

Rank	Company (DMU)	Sector	Weight (w_i)	Expected return	Beta (β)
1	Lab Iran	Chemical products	0.085	0.042	0.85
2	Iran Radiator	Auto parts	0.080	0.038	0.92
3	Auto Parts	Auto parts	0.075	0.035	0.88
4	Exir Pharma	Pharmaceuticals	0.070	0.039	0.75
5	Razak Pharma	Pharmaceuticals	0.065	0.031	0.70
6	Ferrosilice Iran	Basic metals	0.060	0.045	1.10
7	Manganese Mines	Mining	0.055	0.033	0.95
8	Farabi Pharma	Pharmaceuticals	0.050	0.028	0.68
9	Sobhan Pharma	Pharmaceuticals	0.050	0.025	0.72
10	Chemi Darou	Pharmaceuticals	0.045	0.022	0.65
11	Informatics Services	Computers and IT	0.045	0.030	0.80
12	Charcheshgar	Auto parts	0.040	0.026	0.82
13	Alborz Darou	Pharmaceuticals	0.040	0.027	0.74
14	Darou Pakhsh	Pharmaceuticals	0.035	0.024	0.71
15	Iran Tire	Rubber and plastics	0.035	0.031	1.05
16	Sina Darou	Pharmaceuticals	0.035	0.023	0.69
17	Osveh Pharma	Pharmaceuticals	0.035	0.021	0.67
18	Zahravi Pharma	Pharmaceuticals	0.035	0.020	0.73
19	Parsian Insurance	Insurance	0.035	0.025	0.78
20	Mellat Insurance	Insurance	0.030	0.022	0.80
	Total		1.000		

Notes: Weights sum to one. Expected return and beta are as estimated over the study period.

The portfolio spans eight sectors but is weighted toward pharmaceuticals (ten firms with a combined weight of 0.460) and automotive parts (three firms with a combined weight of 0.195). The two insurance companies together account for 0.065 of the portfolio. Betas range from 0.65 to 1.10; the portfolio's weighted-average beta is approximately 0.81, and its weighted-average expected return is approximately 0.031.

4.3. Robustness, sensitivity, and additional analyses

Comparing the selected portfolio with conventional DEA-based selection indicates that incorporating political risk removes firms that appear efficient on financial criteria alone but are highly exposed to political uncertainty. A formal comparison of efficiency rankings and out-of-sample portfolio performance between the conventional and risk-adjusted models is identified as a priority for future research (Section 6.1).

5. Discussion

5.1. Interpretation relative to theory and prior evidence

The findings are consistent with the literature emphasizing the importance of political uncertainty in financial decision-making (Baker *et al.*, 2016; Lehkonen & Heimonen, 2015; Pástor & Veronesi, 2013). Unlike traditional investment models that rely only on accounting and market indicators, the risk-adjusted DEA–Malmquist framework jointly evaluates financial performance, operating efficiency, productivity growth, and political uncertainty, providing a more realistic assessment of firms in emerging markets characterized by institutional instability. The study extends the existing literature by integrating validated political risk indicators directly into the DEA efficiency measure and dynamic productivity analysis rather than treating them as external explanatory variables (Simar & Wilson, 2007).

5.2. Theoretical and methodological contributions

Methodologically, the framework integrates three components—political risk assessment, efficiency evaluation, and dynamic productivity analysis—within a single portfolio-selection model. By treating political risk as part of the efficiency measure, it allows investors to incorporate both internal corporate performance and external political conditions into investment decisions, and by combining super-efficiency scores with the Malmquist index, it distinguishes firms with sustained productivity growth from those whose apparent efficiency is temporary.

5.3. Managerial, regulatory, investment, and policy implications

For institutional investors, portfolio managers, and financial analysts, the framework provides a systematic approach to identifying firms that can maintain operating efficiency under politically uncertain conditions, thereby supporting portfolio resilience. For policymakers, the results highlight the relationship between political stability, institutional quality, and capital market efficiency, which is relevant to the design of policies that strengthen investor confidence and market sustainability.

6. Conclusion

This study developed a risk-adjusted DEA–Malmquist framework to examine the role of political risk in corporate efficiency and portfolio optimization in the Iranian capital market. By integrating expert-validated political risk indicators with super-efficiency DEA and the Malmquist productivity index, the study proposed a decision-support framework that jointly evaluates operating efficiency, productivity dynamics, and political uncertainty. The results indicate that firms that are more resilient to political uncertainty tend to combine higher efficiency with more sustained productivity growth, and they suggest that portfolio models relying solely on traditional financial indicators may understate the effect of political uncertainty on investment decisions in emerging markets.

6.1. Limitations and future research

The analysis is limited to firms listed on the TSE and IFB over 2009–2023, so the findings should be generalized to other markets with caution. In addition, the macroeconomic and political risk inputs are largely common to all firms in a given year, which limits their ability to discriminate between firms within the same period; firm- or industry-specific measures of political exposure would strengthen the framework. The study also does not report a formal comparison of efficiency rankings and portfolio performance between the risk-adjusted and conventional DEA models, nor out-of-sample or risk-adjusted performance measures for the selected portfolio. Future studies may extend the model by incorporating other dimensions of uncertainty, such as geopolitical, environmental, climate-related, and cyber risk, as well as behavioral finance variables, and may compare the framework with portfolio optimization approaches based on machine learning, stochastic or robust optimization, and multi-objective evolutionary algorithms.

Declarations and Transparency Statements

Author contributions (CRediT)

Conceptualization, methodology, data curation, formal analysis, investigation, writing—original draft, and writing—review and editing, M.M. The author approved the final manuscript.

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The author declares no competing interests.

Ethics approval

Not applicable. The study uses publicly available firm-level and macroeconomic data; the expert panel provided professional assessments of indicators and no personal or sensitive data were collected.

Informed consent

Expert panel members participated voluntarily and were informed of the purpose of the study.

Data availability

The financial and market data were obtained from official Iranian capital market information systems. The compiled dataset and the expert evaluation data are available from the author upon reasonable request.

Code availability

The DEA and Malmquist computations can be reproduced from the model specifications in Section 3.4; the code is available from the author upon reasonable request.

Use of generative AI and AI-assisted technologies

During the preparation of this manuscript, an AI-assisted tool was used for language editing, formatting to the journal template, and checking the bibliographic details of the references. The author reviewed and verified all content and takes full responsibility for the accuracy, originality, and integrity of the manuscript.

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