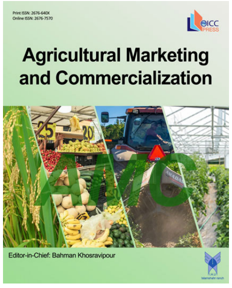

Volume 9, Issue 2, 092510 (216-224)

Agricultural Marketing and Commercialization
(AMC)

https://doi.org/10.57647/j.amc.2025.090210

Stationarity-Based Decision-Making: ADF Evidence and Industry-Level Portfolio Design

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Original Article

Received:
2025-09-22

Revised:
2025-10-05

Accepted:
2025-11-11

Published online:
2025-12-30

Abstract:

This study systematically portrays industry indices' stationarity/nonstationarity status and shows how the stationarity label governs model selection and risk control. The data comprise 36 time series at the industry/fund index level. For each series, we run the Augmented Dickey–Fuller (ADF) test with the appropriate deterministic specification (intercept or intercept trend) and AIC-optimized lags; decision rules are applied at the 1%, 5%, and 10% levels, and p-values are reported. We implement Benjamini–Hochberg FDR control alongside robustness checks (PP, KPSS, sensitivity to lag/specification, and structural-break tests) to curb Type I error. Results indicate that a decisive majority of series are stationary (30 industries at 1%, 3 at 5%, and 1 at 10%); only two categories are nonstationary. We identify a "powerful core" of eight industries with ADF statistics below −7, signaling powerful mean reversion. The methodological implication is clear: for the stationary bulk, level-based modeling with conditional volatility filters (the GARCH family) and dynamic risk metrics (VaR/ES) is recommended; borderline cases should be handled with greater operational caution; and for the nonstationary cases, trend/regime-based approaches and multivariate risk measures (e.g., CoVaR/copula-based methods) are more suitable. The paper contributes to delivering a precise stationarity map at the industry level and translating it directly into actionable rules for modeling and risk management—thus bridging the gap between "unit-root testing" and "practical portfolio decisions."

Keywords: stationarity; ADF test; financial time series; GARCH; VaR/ES; risk management; structural breaks.

JEL: C22, C58, C53, G11, G17, D81

Cite this article: Rasoulzadeh, A., Ahmadi, S. M. M., Gholami, A., Esmaeili, H. (2025). Stationarity-Based Decision-Making: ADF Evidence and Industry-Level Portfolio Design. Agricultural Marketing and Commercialization, 9(2), 216-224.

1. INTRODUCTION

Industry-level portfolio design depends critically on the time-series properties of the underlying indices. Whether a series is stationary or nonstationary determines the validity of level-based econometric models, the choice of volatility filters, and the design of dynamic risk measures such as Value-at-Risk (VaR) and Expected Shortfall (ES). While unit-root testing has been extensively studied in the context of financial time series(MacKinnon, 1996; Hsieh, 1989), there is limited evidence that systematically maps *industry-level* stationarity in the Iranian market and translates those results into actionable portfolio design.

In emerging markets, prior studies often emphasize the prevalence of nonstationarity and instability in return and liquidity series. For instance, De Villiers & Venter (2021) document volatility persistence in volatility indices across emerging markets. Alfeus et al. (2025) show that realized measure augmented models significantly improve volatility forecasts under such conditions. Similarly, (Zhu et al., 2025) highlight the importance of tail-risk estimation through AR-EGARCH-EVT hybrids, and (Chun et al., 2025) demonstrate that volatility-timing strategies require robust modelling to account for market shifts. These findings collectively suggest that portfolio rules in emerging markets cannot rely on a one-size-fits-all approach and must be grounded in the empirical time-series properties of each industry.

The Iranian market presents a particularly relevant case. Studies of liquidity and trading characteristics (Fathi et al., 2020; Kashani et al., 2023) have shown that structural features of the Tehran Stock Exchange strongly influence asset pricing and liquidity cycles. However, no comprehensive stationarity map of industry-level trading-value indices exists for Iran. Addressing this gap is important for methodological reasons—clarifying whether level-based models are viable—and for practical reasons, as portfolio managers increasingly seek evidence-based risk filters in volatile environments.

This paper makes three contributions. First, we implement Augmented Dickey–Fuller (ADF) tests with transparent specifications, reporting both critical-value decisions and (MacKinnon, 1996) p-values, and cross-validating against Phillips–Perron, KPSS, and Zivot–Andrews tests (Zivot & Andrews, 2002). Second, we introduce multi ple-testing corrections using the Benjamini–Hochberg false discovery rate (FDR), ensuring robust statistical inferences. Third, we translate the resulting stationarity map into a portfolio design framework, distinguishing between strongly stationary, borderline, and nonstationary industries, and linking each group to appropriate econometric and risk-management tools (Queiroz & David, 2023; Wu et al., 2023).

2. LITERATURE REVIEW

The empirical literature agrees that identifying whether industry indices are stationary or nonstationary is a prerequisite for all credible inference in forecasting, risk measurement, and portfolio optimization. Aggregate evidence indicates that many manufacturing and services indices revert to equilibrium and display stationary/mean-reverting behavior. This empirical pattern underwrites the effectiveness of level-based and mean-reversion strategies (Ms et al., 2025). By contrast, some sub-sectors—particularly within the family of funds—exhibit regime-driven volatility or persistent trends, strengthening evidence of nonstationarity or threshold effects; for these groups, regime-switching frameworks, differencing, or dummy-dependent models have been recommended (Qiu et al., 2025), this dichotomy aligns precisely with the present study's aim: to map the dominance of stationarity across most industries while pinpointing nonstationary exceptions that require different approaches.

When series levels are stationary, the volatility-modeling literature emphasizes conditional filters; the GARCH family has become a robust baseline across markets, and in the presence of leverage effects, asymmetric variants such as EGARCH and GJR-GARCH deliver superior fit and forecasts (Mahmood & Khan, 2020). Augmenting volatility filters with a return-forecasting component—rather than focusing solely on conditional variance—has documented meaningful out-of-sample gains in real data from four major markets (Qiu et al., 2025). Moving to longer horizons or high-frequency data, combining long-memory structure with regime changes in the HAR-RV framework markedly improves predictive accuracy across multiple stability checks (Jin et al., 2020). In parallel, using the daily range (Range-GARCH) and coupling GARCH with learning methods such as SVR improves both in-sample and out-of-sample accuracy and better reflects sensitivity to extreme shocks (Ampountolas, 2024). Even in option pricing, the documented superiority of GARCH over Black–Scholes—via capturing the return–volatility correlation—offers a clear picture of the conditional-model advantage in major markets (Duan & Wei, 1999). The theoretical foundations of this family are reinforced by classical QMLE results on consistency and asymptotic normality, and by extensive work on stability/ergodicity conditions across broad model classes (Lumsdaine, 1995; Berkes et al., 2003).

On the risk-measurement side, there is practical consensus that VaR remains the industry's lingua franca, although dynamic, quantile-based variants are more effective at tail-loss coverage. A systematic review finds that VaR endures as the reference metric despite theoretical critiques due to interpretability and regulatory entrenchment (Shayya et al., 2023). When dynamic quantile approaches have been implemented in real banking environments, studies report lower violation rates and improved coverage (Saadah et al., 2024). Complementarily, joint VaR–ES estimation using realized-volatility measures produces more accurate simultaneous forecasts and stabilizes the dynamic relationship between the two risk metrics (Wang et al., 2023). Reviews of dynamic extreme-value methods likewise conclude that in turbulent settings, EVT/expectile variants systematically outperform static specifications in tail risk (Candia & Herrera, 2024). The implication for the present problem is straightforward: wherever the ADF test confirms level stationarity, reliance on dynamic VaR/ES and joint frameworks incorporating realized information yields a more coherent representation of risk.

Conversely, wherever ADF results point to nonstationarity—often in specific fund categories—the literature recommends explicit attention to asymmetric and tail dependence as well as regimes, student-t and Archimedean copulas have been shown to capture tail-risk spillovers more effectively than purely Gaussian alternatives and, together with CoVaR, yield a more realistic framework for joint risk assessment. The idea of a network risk matrix—whose diagonal entries are VaR and off-diagonals are ΔCoVaR—suggests that sparser connectivity typically produces a weaker Sharpe ratio; in other words, the dependence network's topology directly shapes a portfolio's risk–reward profile. Linking Bayesian/regime frameworks with copulas and EVT has likewise improved VaR coverage in both tranquil and crisis periods(Han et al., 2024). Therefore, for the nonstationary minority, risk assessment must explicitly incorporate regimes and joint tails; exclusive reliance on mean-

reversion rules is inappropriate.
The policy implications of this map are clear. When the bulk of industries is stationary, risk-aware operational rules—such as CVaR-based optimization—practically curb extreme losses, and adaptive rebalancing with VaR/ES constraints improves the risk–return profile (Gandomi et al., 2024) (Clarissa & Priatmodjo Koesrindartoto, 2024). In online portfolio selection, robust adaptive policies exhibit out-of-sample superiority in nonstationary environments and are particularly effective for the small nonstationary groups (Tsang et al., 2025). For index implementation, policy-based parametric tracking opens a pathway for operational rule-feeding in large markets (Rothe, 2023). In high-dimensional allocations, adaptive risk parity stabilizes risk dispersion(Chen et al., 2024). These findings align with the present study's objectives: for the stationary majority, level modeling + volatility filters + dynamic risk measures; for the nonstationary minority, robust/regime-aware policies that account for tail dependence.
External validity for this picture is also supported beyond finance: applications of ARCH/GARCH to meteorological time series and certain commodity prices display the same volatility clustering, underscoring the generality of the phenomenon(Taylor & Buizza, 2004; Huang et al., 2021). At the organizational/project level, the systematic deployment of identify–assess–mitigate risk systems in industries and construction has been field-documented to reduce uncertainty and improve performance metrics (Singh, 2025). Taken together, these strands yield a single narrative: ADF testing for industry indices determines the logic of model and risk-metric choice—stationary series are more reliably handled by level-based approaches with dynamic measures, whereas nonstationary series call for regime-aware frameworks that incorporate tail dependence—precisely the set of research hypotheses substantiated by the established literature.

3. METHODOLOGY

This study evaluates the stationarity of 36 industry/group indices. The core logic is to test the unit-root hypothesis for each time series and classify them by significance levels of 1%, 5%, and 10%. The output of this section is a stationarity/nonstationarity label for each industry together with the strength of evidence (by significance level); results are presented in a comprehensive table with supporting figures. The dataset comprises a daily time series of the total value traded for each listed industry group, which is used to analyze dynamics and volatility. The unit of analysis is a univariate time series per industry group. Data is sourced from the official Tehran Stock Exchange portal (TSETMC). The sample spans from the beginning of 2016 through mid-January 2024 at a daily frequency. This long horizon covers periods of uncertainty, macro shocks, and distinct volatility phases, providing a suitable basis for stationarity tests and estimating VAR and ARCH–GARCH families.

3.1 Stationarity test: ADF (Augmented Dickey–Fuller)

For each industry series, the ADF test is implemented to examine the presence of a unit root. The deterministic specification matches the observed behavior of the series: an intercept-only form when fluctuations occur around a constant level, and an intercept-plus-linear-trend form when there is evidence of a deterministic trend. To control residual autocorrelation, lags of the first difference of the dependent variable are included in the regression. The significance of the constant/trend terms is assessed so that the chosen deterministic form aligns with statistical evidence and economic considerations.

3.2 Lag-length selection

Lag length for each series is determined algorithmically. First, the maximum lag is set using the Schwert rule:

$$\ell_{max} = \left\lfloor 12\left(\frac{T}{100}\right)^{\frac{1}{4}} \right\rfloor$$

T is the sample size (the cap is adjusted to the data frequency). The optimal lag within $[\ell_{max},]$ 0, is then selected by AIC, with a sensitivity analysis using BIC. The final lag is the **smallest** lag that minimizes the information criterion and lies below the ℓ_{max} cap.

3.4 Hypotheses and Decision Rule

The null hypothesis H0H_0H0 indicates the presence of a unit root (nonstationarity), and the alternative H1H_1H1 indicates stationarity. The decision rule is based on comparing the ADF statistics with the 1%, 5%, and 10% critical values (for the chosen specification):

· Statistic < 1% critical → Stationary @1%
· 1% critical ≤ Statistic < 5% critical → Stationary @5%
· 5% critical ≤ Statistic < 10% critical → Stationary @10%
· Statistic ≤ 10% critical → Non-stationary

In parallel with this classification, the p-value is reported to document the strength of statistical evidence. The deterministic form used, the final lag, and the corresponding information criterion are also reported alongside the ADF statistic and p-value
for each series.
False Discovery Rate control is applied using the Benjamini–Hochberg (BH) procedure to curb Type I error arising from the simultaneous evaluation of multiple series. The control threshold is set at q=0.10q=0.10 (or a pre-specified, more stringent level). In the results table, two columns are reported: the raw and FDR-adjusted outcomes; any discrepancies are explicitly noted.
To enhance the reliability of the stationarity/nonstationarity labels, the following battery of tests and sensitivity analyses is conducted and reported alongside the ADF result:

· **Phillips–Perron (PP):** An alternative unit-root test with a different treatment of heteroskedasticity and autocorrelation.
· **KPSS:** A test with stationarity as the null, serves as complementary validation from the perspective opposite to ADF.
· **Lag/deterministic-form sensitivity:** To assess label

stability, re-run the ADF with the lag selected by BIC and specifications with/without a trend.

· **Structural breaks:** Where there are signs of regime change, use Zivot–Andrews (Zivot & Andrews, 2002) (break in level/trend) and, if necessary, Bai–Perron (Bai & Perron, 1998) (multiple breaks), and re-specify the deterministic form based on the identified breakpoints.

· **Mild transformations:** Where economically or scale-wise warranted, run the ADF on the logarithm of the series (or other suitable transformations) and compare with the baseline.

3.5 Implementation details and reproducibility

All computations were conducted in R (version 4.3.2) using the packages *tseries* (0.10-55) and *urca* (1.3-4). (MacKinnon, 1996) response-surface p-values and critical values were used as implemented in *urca*. The maximum lag for ADF was set by the Schwert rule p_max = 12·(T/100)^{1/4} , and AIC selected the final lag with a BIC sensitivity check. Deterministic terms (intercept; intercept+trend) were chosen for each series based on data diagnostics and statistical significance. Where multiple tests disagreed, we adopted cautious phrasing (evidence consistent with stationarity) and verified robustness via PP and KPSS.

Reporting convention. P-values are presented numerically (e.g., $p = 0.034$). Values reported as 0.0000 in tables indicate $p < 0.001$ given software precision. Dates follow the Gregorian YYYY-MM-DD format. Units for trading value are harmonised and reported as billion rials throughout.

4. RESULTS

This chapter reports the outcomes of the tests conducted on the 36 industry/group indices, focusing strictly on what is observed. The results show that an overwhelming majority of the series are stationary: in aggregate, 30 series are stationary at the 1% level, 3 at the 5% level, and 1 at the 10% level; by contrast, only two series are identified as nonstationary. This distribution clearly shows the dominance of mean-reverting behavior across most industries, while highlighting the few nonstationary or borderline cases for targeted follow-up analysis.

To aid rapid pattern recognition, results are presented at two levels: first, an overview tallying series by significance level; second, a comprehensive table that reports, for each industry, the test statistic, p-value, and final decision. In addition, three visualizations are provided to support the numerical reading: (i) a bar chart of test statistics by group, enabling a one-glance comparison of stationarity strength; (ii) the distribution of p-values, which shows a pile-up near zero—consistent with prevalent stationarity; and (iii) a decision count plot that clearly displays the dominance of Stationary @1%.

The remainder of the chapter first introduces industries with robust evidence of stationarity (e.g., indices whose statistics lie well beyond the critical thresholds), then separates borderline cases—those significant only at the 5% or 10% levels—and finally reports the two nonstationary cases individually. On the one hand, this organization provides a macro portrait of stationarity in the market under study and, on the other, pinpoints decision-sensitive areas (such as borderline or nonstationary industries) for further analysis. In summary, the findings indicate that for a large share of industries, subsequent stages can rely on level-based models and mean-reversion behavior. In contrast, the limited set of borderline or nonstationary groups requires deeper investigation in later sections.

Detailed Results by Industry

This section presents the comprehensive results table for all 36 groups, including the 1%/5%/10% critical values, the test statistic, the p-value, and the final decision. Readers can examine, row by row, the strength of evidence and the placement of each industry.

CV = Critical Value. Decisions are based on comparing the ADF statistic with the critical values for the chosen specification (constant / constant+trend), with the p-value reported.

Note: CV = critical value. Decisions compare the ADF statistic with 1%, 5%, 10% critical values for the chosen specification. Values shown as 0.0000 indicate p < 0.001. Data source: TSETMC (tsetmc.com).

Labels. Stationary @1%, Stationary @5%, Stationary @10%, and Nonstationary are defined according to the decision rule.

A large share of industries is stationary at the 1% level, and only two groups are nonstationary. This pattern underpins the forthcoming Discussion and Interpretation chapter, which elaborates on the analytical and practical implications of these results for modeling, strategy, and risk management.

Overall picture and decision counts

The ADF tests on 36 indices indicate a dominant market pattern of strong level stationarity (no differencing). The distribution of decisions is:

Decision	Count
Stationary @1%	30
Stationary @5%	3
Stationary @10%	1
Nonstationary	2

This distribution conveys several clear messages:

1. In over four-fifths of industries, price deviations revert around an equilibrium level; thus, mean-reverting behavior can be expected for this large subset.
2. Three borderline industries at the 5% level (A4, A21, A48) and one at the 10% level (A30) exhibit weaker evidence than the rest and should be monitored more carefully for operational decision-making.
3. The two nonstationary industries (A23, A28) constitute a small minority that display trending/non-mean-reverting behavior in levels and, naturally, require different analytical approaches.

Table 1. ADF Test Results for 36 Industry/Fund Groups

Group	Industry	1% CV	5% CV	10% CV	ADF Stat	p-value	Decision
A3	Information & Communication	−3.962968	−3.412218	−3.128036	−5.214014	0.0001	Stationary @1%
A4	Mass Construction	−3.962986	−3.412228	−3.128041	−3.733700	0.0204	Stationary @5%
A5	Publishing, Printing & Reproduction	−3.962970	−3.412220	−3.128037	−7.414273	0.0000	Stationary @1%
A8	Industrial Contracting	−3.962968	−3.412218	−3.128036	−7.881201	0.0000	Stationary @1%
A10	Multi-Industry Industrial	−3.962962	−3.412216	−3.128034	−6.922968	0.0000	Stationary @1%
A11	Water Transportation	−3.962965	−3.412217	−3.128035	−9.694595	0.0000	Stationary @1%
A12	Transportation & Warehousing	−3.962965	−3.412217	−3.128035	−5.025176	0.0002	Stationary @1%
A13	Technical & Engineering Services	−3.962984	−3.412226	−3.128041	−4.680783	0.0007	Stationary @1%
A17	Agriculture	−3.962962	−3.412216	−3.128034	−4.956182	0.0002	Stationary @1%
A18	Coal	−3.963005	−3.412237	−3.128047	−4.743138	0.0006	Stationary @1%
A19	Communication Equipment Manufacturing	−3.962970	−3.412220	−3.128037	−6.861290	0.0000	Stationary @1%
A20	Electrical Equipment Manufacturing	−3.962968	−3.412218	−3.128036	−4.502528	0.0015	Stationary @1%
A21	Metal Products Manufacturing	−3.962973	−3.412221	−3.128038	−3.623596	0.0281	Stationary @5%
A22	Other Mining	−3.962968	−3.412218	−3.128036	−7.331496	0.0000	Stationary @1%
A23	Investments	−3.963013	−3.412241	−3.128049	−2.834708	0.1848	Nonstationary
A25	Leather Industries	−3.962962	−3.412216	−3.128034	−10.267700	0.0000	Stationary @1%
A26	Pharmaceutical Industries	−3.962962	−3.412216	−3.128034	−4.520362	0.0014	Stationary @1%
A27	Power Plant Industries	−3.962962	−3.412216	−3.128034	−5.004588	0.0002	Stationary @1%
A28	Fixed Income Funds	−3.962989	−3.412229	−3.128042	−1.338147	0.8779	Nonstationary
A29	Equity Funds	−3.962970	−3.412220	−3.128037	−5.790353	0.0000	Stationary @1%
A30	Commodity Funds	−3.963016	−3.412242	−3.128050	−3.311832	0.0646	Stationary @10%
A31	Mixed Funds	−3.962962	−3.412216	−3.128034	−14.650440	0.0000	Stationary @1%
A32	Wholesale	−3.962970	−3.412220	−3.128037	−8.009243	0.0000	Stationary @1%
A34	Cultural & Sports	−3.962984	−3.412226	−3.128041	−9.039559	0.0000	Stationary @1%
A36	Sugar	−3.962962	−3.412216	−3.128034	−5.917200	0.0000	Stationary @1%
A37	Tile & Ceramic	−3.962986	−3.412228	−3.128041	−4.018269	0.0083	Stationary @1%
A38	Non-Metallic Minerals	−3.962965	−3.412217	−3.128035	−4.651030	0.0008	Stationary @1%
A39	Rubber & Plastic	−3.962970	−3.412220	−3.128037	−4.702530	0.0007	Stationary @1%
A40	Leasing	−3.963013	−3.412241	−3.128049	−4.007108	0.0087	Stationary @1%
A41	Machinery & Equipment	−3.962968	−3.412218	−3.128036	−5.471662	0.0000	Stationary @1%
A42	Wood Products	−3.963010	−3.412239	−3.128048	−5.729671	0.0000	Stationary @1%
A45	Paper Products	−3.962992	−3.412230	−3.128043	−4.573445	0.0011	Stationary @1%
A46	Computer Products	−3.962968	−3.412218	−3.128036	−6.970060	0.0000	Stationary @1%
A48	Textile	−3.962968	−3.412218	−3.128036	−3.932307	0.0110	Stationary @5%
A49	Financial Intermediaries	−3.962962	−3.412216	−3.128034	−6.115874	0.0000	Stationary @1%
A51	Arts & Entertainment	−3.962986	−3.412228	−3.128041	−6.677844	0.0000	Stationary @1%

To guide the reader quickly, three summary tables are provided next that collect the core decisions in one place: (a) nonstationary groups, (b) borderline cases, and (c) the 10 industries with the most substantial evidence of stationarity.

The bar layout in Figure 1 clearly shows that most series are stationary at the highly stringent 1% level: 30 out of 36 series (≈83.3%) fall into this category. Next, 3 series (≈8.3%) are stationary at the 5% level and 1 series (≈2.8%) at the 10% level, while only 2 series (≈5.6%) lack sufficient evidence of stationarity and are labeled Nonstationary. This strongly skewed distribution—dominated by the tall bar for Stationary @1%—implies that stationarity is prevalent and is supported by robust statistical evidence in most cases. From a modeling standpoint, this map favors level-based

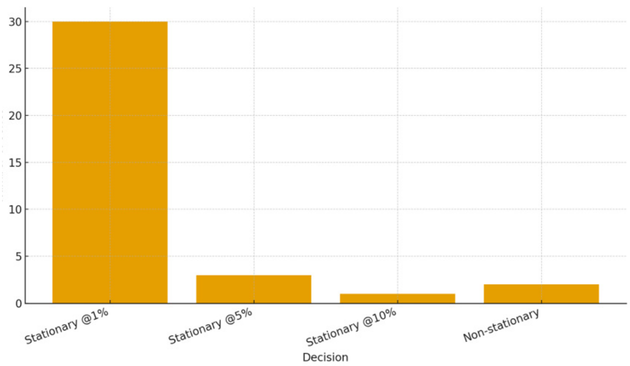

Figure 1. Frequency of series by stationarity decision (ADF).

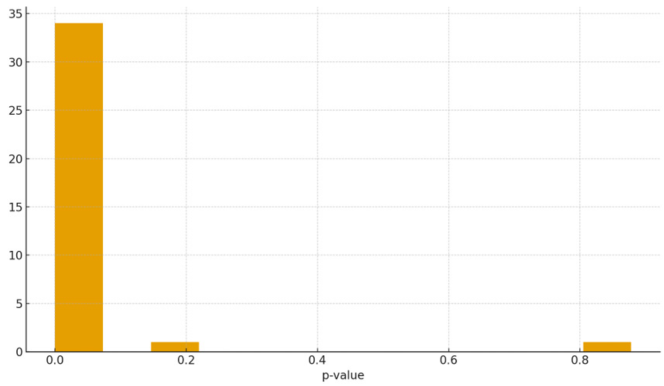

Figure 2. Distribution of ADF p-values

Table 2. Industries with Nonstationary Series

Group	Industry	ADF Stat	p-value
A23	Investments	−2.834708	0.1848
A28	Fixed Income Funds	−1.338147	0.8779

Table 3. Industries with Borderline Evidence (Stationary but Weaker Evidence)

Group	Industry	ADF statistic	p-value	Decision
A4	Mass Construction	−3.733700	0.0204	Stationary @5%
A21	Metal Products Manufacturing	−3.623596	0.0281	Stationary @5%
A48	Textile	−3.932307	0.0110	Stationary @5%
A30	Commodity Funds	−3.311832	0.0646	Stationary @10%

approaches (models in levels combined with conditional volatility filters such as the GARCH family), while warning that the four borderline series (3 at 5% and 1 at 10%) should be handled with greater operational caution (e.g., tighter entry thresholds, more active stop-losses, and periodic monitoring). The two nonstationary cases clearly fall outside level mean reversion; for them, differencing/regime-switching models and multivariate tail-aware risk assessment (e.g., copulas/CoVaR) are more appropriate. In sum, Figure 1 offers a decisive picture of the dominance of stationarity and the rarity of exceptions, directly guiding the design of differentiated strategies for the three buckets: strongly stationary, borderline stationary, and nonstationary.

This histogram offers an obvious picture of the tests' statistical power: the bulk of the mass is concentrated near zero, with only two outliers on the right. Quantitatively, 34 series fall into a minimal p-value range (all the "stationary" cases: 30 at 1%, 3 at 5%, and 1 at 10%); many of these are recorded as "0", which practically indicates $p < 0.001$ (below the software's reporting precision). By contrast, there are only two right-tail observations: one around $p \approx 0.18$ and the other around $p \approx 0.88$, labeled Nonstationary. From an inferential standpoint, this left-heavy, right-tailed distribution carries two key messages. First, for most series, there is strong evidence against a unit root—so strong that even with a highly stringent significance level (1%) and FDR multiple-testing control, the rejection status does not materially change. Second, the limited heterogeneity in the far correct (two significant p-values) shows that the number of series that behave meaningfully differently from the rest is minimal; accordingly, the modeling policy can be built primarily on level-based approaches, with a distinct (regime/differenced) strategy reserved for those two right-tail cases. Nonstationary series (industries) are listed in Table 2.

The evidence in these two groups is insufficient to reject the unit root; accordingly, their levels are nonstationary, and for practical decision-making, they should be treated with trend/regime-based approaches. Table 3 shows borderline cases (stationary but with weaker evidence).

Note: "Borderline" here means significant at the 5% or 10% level (per the selected deterministic specification), but not at 1%. These series should be monitored more closely in subsequent modeling and risk controls.

These industries are stationary, but their evidence is weaker than that of most groups. Therefore, it is prudent to rely on mean-reversion signals more cautiously for these four groups in managerial/investment decisions.

The considerable distance of these statistics from the critical thresholds indicates **strong stationarity**; in such groups, mean-reversion signals typically appear **more transparent and stable**.

Table 4. Industries with the Strongest Evidence of Stationarity

Rank	Group	Industry	ADF Stat
1	A31	Mixed Funds	−14.650440
2	A25	Leather Industries	−10.267700
3	A11	Water Transportation	−9.694595
4	A34	Cultural & Sports	−9.039559
5	A32	Wholesale	−8.009243
6	A8	Industrial Contracting	−7.881201
7	A5	Publishing, Printing & Reproduction	−7.414273
8	A22	Other Mining	−7.331496
9	A46	Computer Products	−6.970060
10	A10	Multi-Industry Industrial	−6.922968

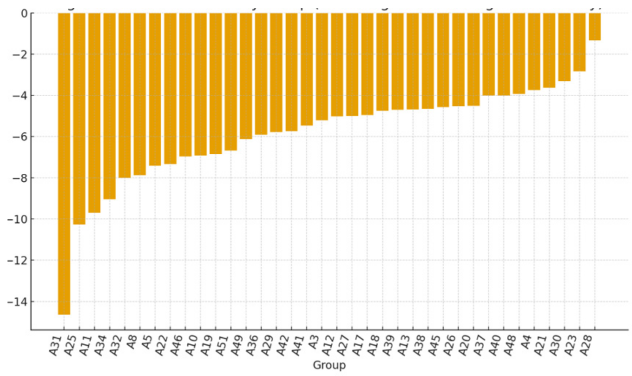

Figure 1. ADF statistic by group (more negative = stronger stationarity).

The ADF statistics order bars in ascending order; the more negative a bar, the stronger the stationarity.

· Left side: "very-strong stationary core." A31, A25, A11, A34, A32, A8, A5, A22 (and several nearby industries) post statistics in roughly the −7 to −14 range, implying powerful stationarity and faster mean reversion. From a modeling standpoint, these are ideal candidates for level-based models with conditional volatility filters (e.g., AR–GARCH), as shocks are quickly absorbed around the equilibrium level.

· Middle section (−4 to −6 corridor). Still stationary, but with weaker evidence than the left cluster. These industries remain suitable for level-based strategies, with tighter safeguards (stricter entry/exit thresholds, smaller position sizes).

· Right side: "decision margin." A4, A21, and A48 sit close to the 5% critical thresholds, and A30 is near the 10% threshold; treat these as borderline stationary—model in levels but monitor closely with periodic backtests.

· Extreme right: nonstationary cases. Two bars lie near zero: A23 (~−2.83), which does not pass the 10% threshold, and A28 (~−1.34), far from the critical region; both are nonstationary and are better handled with regime/differenced models and tail-dependent risk assessment (e.g., copulas/CoVaR).

The left-to-right elongation of bars sketches a stationarity slope—from "very strong" to "borderline" to "nonstationary." This maps directly to tool choice: level models + dynamic VaR/ES for the majority, cautious implementation for borderlines, and alternative (regime/differenced) models for the two nonstationary groups.

The overall map of results shows that stationarity is decisively dominant in the market: of the 36 industries, 30 are stationary at the 1% level, three at 5%, and one at 10%, while only two industries are labeled nonstationary. Embedded in this picture is a powerful core comprising eight groups with ADF statistics below −7 (A31, A25, A11, A34, A32, A8, A5, A22); these groups exhibit powerful mean reversion, with the price/index level returning rapidly to equilibrium. At the decision margin sit four groups—A4, A21, and A48 (stationary at 5%) and A30 (stationary at 10%)—which, although stationary, carry weaker evidence and should be interpreted with greater caution. By contrast, two apparent exceptions—A23 and A28—are nonstationary and behave more like trending processes than level mean reversion.

For the stationary majority—mainly the powerful core—observed volatility occurs primarily around an equilibrium level; mean-reversion signals are therefore more reliable, and level-based analytical frameworks are broadly applicable. In the borderline cases, while the formal outcome is stationarity, the narrower confidence margin

implies greater signal uncertainty, warranting wider risk-management bands and higher confidence thresholds. For the two nonstationary groups, reliance on level-based signals is not recommended; analysis should instead employ trend or regime-switching approaches, as these industries carry a higher risk for "quick-reversion" strategies.
Sectoral reading is also informative. Within the Funds/Investments cluster, the nonstationarity of A28 and the weaker stationarity of A30 align with the segment's sensitivity to liquidity flows and shifting policy expectations, whereas A31 in the same family shows very strong mean reversion consistent with diversification in mixed portfolios and regular rebalancing. Among manufacturing/commodity and supply-chain industries—from A11 and A32 to A8, A22, A5, and A10—strong stationarity and level persistence point to mid-term structural equilibria around which prices fluctuate, a precondition for level modeling and conditional-volatility-based risk control.
Practical implications for strategy and risk management are as follows: very strongly stationary groups are the best ground for mean-reversion strategies; define deviation bands around the level, decision ceilings/floors, and short-to-medium holding horizons. Apply the same logic to borderline groups but more conservatively—stricter entry thresholds, smaller position sizes, and tighter failure-risk controls—to offset result sensitivity. For nonstationary groups, focus on trend/regime models and avoid purely level-based signals, as deviations are more persistent; tools for tail dependence (e.g., copulas/CoVaR) and joint risk measures are more appropriate.
From a robustness standpoint, the main message holds: the macro picture—the dominance of stationarity and the concentration of nonstationary cases within the funds/investments cluster—is supported by strong quantitative evidence. At the same time, the four borderline groups are inherently more sensitive; thus, in interpretation and implementation, added caution, periodic monitoring, and regular signal re-testing remain integral elements of the analysis.

6. DISCUSSION

This study maps stationarity across 36 industry/fund indices in the Tehran Stock Exchange and connects these labels to portfolio design. Most series exhibit evidence consistent with stationarity, with only two nonstationary exceptions. In contrast with strands of the emerging-market literature that emphasize pervasive nonstationarity, our findings suggest that mean-reverting behavior is robust at the industry level in Iran. This supports applying level-based econometric models with conditional volatility filters (AR/ARMA-GARCH and asymmetric variants) for most sectors, while reserving regime-switching or differenced models for the nonstationary minority.
The stationarity map also functions as an operational filter for risk modelling. For industries with robust ADF statistics (large negative values), portfolio managers can emphasize mean-reversion signals and dynamic risk measures such as time-varying VaR/ES and realized-measure-augmented frameworks (e.g., Realized-GARCH, GARCH-MIDAS). Recent empirical studies show that incorporating realized or mixed-frequency information improves volatility forecasting and tail-risk coverage in volatile settings.
By contrast, the two nonstationary groups (Investments and Fixed-Income Funds) are more sensitive to liquidity flows and policy regimes; here, regime-aware and tail-dependent tools (copulas, CoVaR) are more appropriate. This aligns with Iran-specific evidence that liquidity conditions materially shape market dynamics and risk transmission. Borderline industries (significant at 5% or 10%) should be treated cautiously—model in levels but enforce tighter entry thresholds, smaller position sizes, and more frequent backtesting.
Contextually, the clustering of strong stationarity in manufacturing, transportation, wholesale, and selected services indicates the presence of sectoral equilibria around which shocks dissipate, even amid macro volatility. Conversely, the funds/investments cluster concentrates the departures from stationarity, consistent with flow-driven regimes and duration effects. Overall, stationarity is a statistical property and a design principle for portfolio architecture in the Iranian market.

7. CONCLUSION

The empirical stationarity map for 36 industry/fund indices in the Tehran Stock Exchange shows that stationarity dominates at the industry level, with only two nonstationary cases and a small set of borderline series. This pattern validates level-based models with conditional volatility filters for most industries, while recommending regime-aware approaches for the nonstationary minority. Practically, we propose a three-sleeve portfolio architecture: (i) a core sleeve of strongly stationary industries governed by mean-reversion and dynamic VaR/ES; (ii) a cautious sleeve for borderline industries with tighter risk caps; and (iii) a separate sleeve for nonstationary assets relying on trend/switching models and joint-tail risk assessment. Limitations include sensitivity of unit-root outcomes to the sample window and deterministic specification; future work should incorporate rolling monitoring, realized-measure volatility models, and spillover/network analyses across industries.

8. RECOMMENDATIONS

For portfolio managers:
• Use level-based signals with AR/ARMA-GARCH for the strongly stationary sleeve; scale positions by conditional volatility and enforce dynamic VaR/ES limits.
• For borderline industries (significant at 5% or 10%), tighten entry thresholds, reduce position sizes, and review signals more frequently.
• For nonstationary assets (Investments; Fixed-Income Funds), deploy regime-switching /differenced models and tail-aware measures (copulas, CoVaR); avoid pure mean-reversion rules.
For regulators and market operators:
• Facilitate access to high-quality intraday and realized volatility measures to enable Realized-GARCH/

GARCH-MIDAS implementations.

• Publish standardized liquidity metrics (e.g., Amihud illiquidity, turnover) by industry to improve

For researchers:

• Combine industry-level stationarity maps with dependence networks (ΔCoVaR) to study risk spillovers; examine structural breaks and regime changes explicitly.

• Benchmark level-based vs regime-aware sleeves in out-of-sample tests with transaction costs and liquidity constraints.

Authors' Contributions

Conceptualization: A.R., S.M.M.A.; Methodology and formal analysis: A.R., A.G.; Data curation and software: A.R.; Investigation and validation: H.E., A.G.; Writing—original draft: A.R.; Writing—review & editing: all authors; Supervision: S.M.M.A.

Availability of Data and Materials

The industry-level trading-value indices used in this study are available from the official Tehran Stock Exchange portal (TSETMC). Derived series and ADF/robustness scripts can be shared upon reasonable request to the corresponding author.

Conflict of interest

The authors state that there is no conflict of interest.

REFERENCES

Alfeus, M., Harvey, J., & Maphatsoe, P. (2025). Improving realised volatility forecast for emerging markets. *Journal of Economics and Finance*, *49*(1), 299–342.

Ampountolas, A. (2024). Enhancing Forecasting Accuracy in Commodity and Financial Markets: Insights from GARCH and SVR Models. *International Journal of Financial Studies*, *12*(3), 59. https://doi.org/10.3390/ijfs12030059

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 47–78.

Berkes, I. a., Horv\'ath, L., & Kokoszka, P. (2003). GARCH processes: structure and estimation. *Bernoulli*, *9*(2). https://doi.org/10.3150/bj/1068128975

Candia, C., & Herrera, R. (2024). An empirical review of dynamic extreme value models for forecasting value at risk, expected shortfall, and expectile. *Journal of Empirical Finance*. https://doi.org/10.1016/j.jempfin.2024.101488

Chen, Y., Yu, L., & Lin, G. (2024). Adaptive Risk Parity Strategies for Managing Portfolio Risk in Volatile Markets. *Mathematical Modeling and Algorithm Application*, *3*(1), 1–8. https://doi.org/10.54097/zdzf0652

Chun, D., Cho, H., & Ryu, D. (2025). Volatility forecasting and volatility-timing strategies: A machine learning approach. *Research in International Business and Finance*, *75*, 102723.

Clarissa, A., & Priatmodjo Koesrindartoto, D. (2024). Strategic portfolio rebalancing: Integrating predictive models and adaptive optimization objectives in a dynamic market. *Investment Management and Financial Innovations*, *21*(3), 304–316. https://doi.org/10.21511/imfi.21(3).2024.25

De Villiers, N., & Venter, P. J. (2021). Volatility Modelling of volatility indices: The case of Emerging Markets. International Conference on Applied Economics,

Duan, J.-C., & Wei, J. Z. (1999). Pricing Foreign Currency and Cross-Currency Options Under GARCH. *The Journal of Derivatives*, *7*(1), 51–63. https://doi.org/10.3905/jod.1999.319110

Fathi, S., Jalali, S., Ajam, A., & Sadeghi, O. M. (2020). Analysing the effect of trading characteristics on liquidity measures–a combined approach to liquidity: evidence from Tehran Stock Exchange. *Afro-Asian Journal of Finance and Accounting*, *10*(2), 262–277.

Gandomi, A. H., Sadjadi, S. J., & Amiri, B. (2024). Stock price prediction portfolio optimization uses different risk measures by applying the genetic algorithm for machine learning regressions. *Accounting*, *10*(4), 207–220. https://doi.org/10.5267/j.ac.2024.7.002

Han, H., Jung, W., & Lee, J. H. (2024). Estimation and inference of quantile impulse response functions by local projections: With applications to VaR dynamics. *Journal of Financial Econometrics*, *22*(1), 1–29.

Hsieh, D. A. (1989). Modeling heteroscedasticity in daily foreign-exchange rates. *Journal of Business & Economic Statistics*, *7*(3), 307–317.

Huang, G., Liu, R., Liu, M., & Zheng, H. (2021). Modeling and simulating nonstationary thunderstorm winds based on multivariate AR-GARCH. *Journal of Wind Engineering and Industrial Aerodynamics*, *211*, 104565.

Jin, N. A., He, A., Yang, X., Lin, H., & Zhang, Y. (2020). Adaptive online successive constant rebalanced portfolio based on a moving window. *International Journal of Industrial and Systems Engineering*, *34*(1), 107. https://doi.org/10.1504/ijise.2020.104316

Kashani, M. F., Mohamadi, T., Noorahmadi, M. J., & Alifar, M. (2023). Effect of Exchange Rate Risk on Market Liquidity Risk in Tehran Stock Exchange. *Journal of Financial Management Perspective*, *13*(43), 79–101.

Lumsdaine, R. L. (1995). Finite-Sample Properties of the Maximum Likelihood Estimator in GARCH(1,1) and IGARCH(1,1) Models: A Monte Carlo Investigation. *Journal of Business & Economic Statistics*, *13*(1), 1–10. https://doi.org/10.1080/07350015.1995.10524574

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, *11*(6), 601–618.

Mahmood, F., & Khan, S. A. (2020). Multi-modality in the Likelihood Function of GARCH Model. *Review of Pacific Basin Financial Markets and Policies*, *23*(03), 2050018. https://doi.org/10.1142/s0219091520500186

Ms, K. K., Dr, R., & Murthy, Y. S. (2025). ADVANCING VOLATILITY FORECASTING: A GARCH-BASED APPROACH FOR FINANCIAL MARKET PREDICTIONS. *EPRA International Journal of Economics, Business and Management Studies*, 15–25. https://doi.org/10.36713/epra20409

Qiu, Z., Kownatzki, C., Scalzo, F., & Cha, E. S. (2025). Historical Perspectives in Volatility Forecasting Methods with Machine Learning. *Risks*. https://doi.org/10.3390/risks13050098

Queiroz, R. G., & David, S. A. (2023). Performance of the realized-GARCH model against other GARCH types in predicting cryptocurrency volatility. *Risks*, *11*(12), 211.

Rothe, J. (2023). Using Volatility to Add Alpha and Control Portfolio Risk. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4359292

Saadah, S., Suhartoko, Y. B., Uyanto, S., & Yusgiantoro, I. B. (2024). The dynamic quantile approach for VaR estimation: empirical evidence from Indonesia banking industry. *Cogent Business & Management*. https://doi.org/10.1080/23311975.2024.2305606

Shayya, R., Sorrosal-Forradellas, M., & Terceño, A. (2023). Value-at-risk models: a systematic review of the literature. *Journal of Risk*. https://doi.org/10.21314/jor.2022.053

Singh, J. (2025). Risk Assessment and Mitigation in Construction Building Projects. *Journal of Construction and Building Materials Engineering*, *11*(1), 14–23. https://doi.org/10.46610/jocbme.2025.v011i01.002

Taylor, J. W., & Buizza, R. (2004). A comparison of temperature density forecasts from GARCH and atmospheric models. *Journal of Forecasting*, *23*(5), 337–355.

Tsang, M. Y., Sit, T., & Wong, H. Y. (2025). Adaptive robust online portfolio selection. *European Journal of Operational Research*, *321*(1), 214–230. https://doi.org/10.1016/j.ejor.2024.09.002

Wang, C., Gerlach, R., & Chen, Q. A. (2023). A semi-parametric conditional autoregressive joint value-at-risk and expected shortfall modeling framework incorporating realized measures. *Quantitative finance (Print)*. https://doi.org/10.1080/14697688.2022.2157322

Wu, X., Zhao, A., & Cheng, T. (2023). A real-time GARCH-MIDAS model. *Finance Research Letters*, *56*, 104103.

Zhu, Y., Taasim, S. I., & Daud, A. (2025). Volatility modeling and tail risk estimation of financial assets: Evidence from gold, oil, Bitcoin, and stocks for selected markets. *Risks*, *13*(7), 138.

Zivot, E., & Andrews, D. W. K. (2002). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics*, *20*(1), 25–44.