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System Shift Risk, Chokepoint Severity, and Macroeconomic Resilience: Quarter-Level Exploratory Evidence from A Configuration-Based Framework

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Abstract

This study develops and evaluates the System Shift Economics framework as a configuration-based approach for diagnosing macroeconomic vulnerability and adaptive resilience. The framework proposes that forward-looking macroeconomic outcomes are shaped not only by current status categories, but by the interaction between structural pressure and adaptive capacity. Using 203 quarter-level macroeconomic observations — with forward-looking outcomes available for 199 observations — the study constructs a System Shift Risk Score from seven coded variables: System Condition, Domain Lock, Actor Complexity, Chokepoint Severity, Position Quality, Strategy Quality, and Feedback Maturity. The primary outcomes assessed are four-quarter-ahead GDP loss, crisis status, progression toward adaptive recovery, and overall success. The results provide exploratory support for the framework. Chokepoint Severity significantly predicts both four-quarter-ahead GDP loss and crisis probability. Strategy Quality and Feedback Maturity significantly predict Success and Progression in logistic models. The System Shift Risk Score outperforms the baseline status classification across all outcomes, improving explanatory power for GDP loss and discriminatory performance for crisis, success, and progression. Random Forest feature importance analysis identifies the composite risk score and Feedback Maturity as consistently relevant predictors. Cluster analysis further reveals three theoretically coherent regimes: Adaptive/low-risk, Transitional/medium-risk, and Stagnant/high-risk. The findings suggest that macroeconomic resilience is better understood as a system configuration rather than a static status condition. As the framework is newly operationalised, the evidence should be interpreted as exploratory rather than confirmatory; future validation will require independent samples, robustness checks, and external forecasting benchmarks.

INTRODUCTION

Macroeconomic stress rarely emerges as a single-variable event. It typically manifests when several structural pressures accumulate simultaneously, when chokepoints restrict adjustment, and when feedback mechanisms fail to redirect the system before losses become visible in aggregate output. Standard macroeconomic monitoring often classifies the economy through baseline status labels — including expansion, slowdown, recession, and recovery (Pontes et al., 2024; Sinković et al., 2022; Spelta et al., 2026; Wayne, 2015). Such labels are useful, but they can become too coarse

when the object of analysis is transition risk: the probability that an apparently stable system will move toward crisis, stagnation, or adaptive recovery over the next seve ral quarters.

This paper introduces and empirically examines the System Shift Economics framework, a configuration-based diagnostic approach designed to map macroeconomic vulnerability and resilience. The framework rests on a simple claim: the forward movement of a macroeconomic system depends on the balance between structural pressure and adaptive capacity (Brinkman, 2022; Martin & Sunley, 2020). Pressure-side dimensions include System Condition (SC), Domain Lock (DL), Actor Complexity (AC), and Chokepoint Severity (CP), reflecting the structural and systemic constraints that shape economic fragility and systemic risk (Battiston et al., 2016). Adaptive-side dimensions include Position Quality (POS), Strategy Quality (STR), and Feedback Maturity (FB), representing institutional adaptability, strategic flexibility, and learning capacity within dynamic systems (Walker et al., 2015). These variables are combined into a composite index—the System Shift Risk Score—computed as $SC + DL + AC + CP - POS - STR - FB$, enabling a quantitative assessment of macroeconomic exposure and resilience under shifting global conditions (International Monetary Fund, 2023).

The research gap this study addresses is the relative absence of compact, configuration-based frameworks applicable at the quarter level for diagnosing systemic risk and adaptive capacity (Kuziv et al., 2025). While the macro-financial literature has extensively examined crisis persistence, financial amplification, and state-dependent policy effects, comparatively little attention has been paid to operationalising a diagnostic framework that integrates both pressure-side and adaptive-side dimensions into a single, testable structure. The urgency of this research is underscored by the increasing frequency of economic shocks and the demonstrated limitations of static status classifications in predicting transitions toward crisis or recovery (Araujo et al., 2026; Gautama et al., 2026; Piepers, 2025; Vasin, 2023).

The novelty of this research lies in three aspects: first, the operationalisation of a configuration-based diagnostic framework that distinguishes between structural pressure and adaptive capacity; second, the empirical validation of this framework using quarter-level data and multiple analytical techniques, including linear regression, logistic regression, Random Forest, and cluster analysis; and third, the demonstration that the composite risk score provides incremental predictive value over conventional baseline status categories.

The paper tests whether this composite structure offers incremental predictive value relative to a conventional baseline status variable. The empirical setting consists of 203 quarter-level macroeconomic observations. Forward-looking outcomes are available for 199 observations, as the final four quarters do not have a complete four-quarter-ahead horizon. The dependent variables are GDP_Loss_Next4Q_pct, Crisis_Dummy, Progression, and Success. The first captures output loss over the next four quarters; the second identifies crisis or macroeconomic stress; the third captures whether the system moves adaptively over the following year; and the fourth captures conditions of stronger recovery (Aubin et al., 2016; Barnes et al., 2020; Ellis et al., 2017; Hipsey et al., 2015; Tsao & Ni, 2016).

The empirical results support the framework at an exploratory level. CP significantly predicts both GDP loss and crisis status. STR and FB significantly predict Success and Progression (Haritha et al., 2023). The System Shift Risk Score outperforms Status_Baseline across all primary outcomes. Random Forest results identify the composite risk score as the most important feature across

outcomes, and cluster analysis reveals three interpretable regimes: Adaptive/low-risk, Transitional/medium-risk, and Stagnant/high-risk. These findings indicate that macroeconomic resilience can be studied as a systemic configuration rather than merely as an observed state.

RESEARCH METHODS

Data structure

The unit of analysis is the quarter-level macroeconomic observation. The dataset contains 203 observations. Forward-looking outcomes are available for 199 observations because the last four quarters lack a full four-quarter-ahead horizon. This structure is appropriate for testing whether a configuration observed at time t is associated with macroeconomic outcomes over the subsequent four quarters.

The empirical analysis uses the variables reported in the supplied validation document: SC, DL, AC, CP, POS, STR, FB, System_Shift_Risk_Score, GDP_Loss_Next4Q_pct, Crisis_Dummy, Progression, Success, and Status_Baseline.

Variable definitions

GDP_Loss_Next4Q_pct measures GDP loss during the next four quarters. Crisis_Dummy equals 1 when an observation enters macroeconomic crisis or stress. Progression equals 1 when the system moves adaptively over the subsequent four quarters. Success equals 1 when recovery is strong, unemployment improves, and no GDP loss is observed. The composite System Shift Risk Score is computed by adding pressure-side variables and subtracting adaptive-side variables.

Status_Baseline is used as the conventional benchmark category. The comparison between Status_Baseline and System_Shift_Risk_Score provides a test of incremental predictive validity.

Analytical strategy

The analysis proceeds in five stages. First, descriptive statistics profile the distribution of System Shift components and outcomes. Second, Pearson correlations test the directional alignment between pressure variables, adaptive variables, and outcomes. Third, ordinary least squares models estimate the association between CP and GDP_Loss_Next4Q_pct and between System_Shift_Risk_Score and GDP_Loss_Next4Q_pct. Fourth, logistic regressions evaluate binary outcomes: CP predicting Crisis_Dummy, STR and FB predicting Success and Progression, and the composite risk score predicting Crisis_Dummy, Success, and Progression. Fifth, model comparison, Random Forest feature importance, and KMeans clustering evaluate incremental validity and regime structure.

Because the framework is exploratory, the analysis emphasizes theoretical coherence, effect direction, and predictive comparison rather than causal identification. The results should therefore be read as empirical validation of a diagnostic framework, not as proof of structural causality.

RESULTS AND DISCUSSION

Descriptive statistics

The descriptive profile indicates substantial variation in systemic risk components. The mean System_Shift_Risk_Score is -4.064, suggesting that many observations are relatively adaptive, but the maximum value of 13 indicates a pronounced high-risk tail. GDP_Loss_Next4Q_pct is strongly right-skewed: the mean is 0.160, the median is 0, and the maximum is 3.830. This pattern is consistent with macroeconomic data in which normal periods dominate the sample while stress episodes account for much of the realized loss.

Table 1. Descriptive Statistics of System Shift Variables and Macroeconomic Outcomes

Variable	N	Mean	SD	Min	Median	Max
SC	203	1.768	0.985	1	1	5
DL	203	1.941	0.830	1	2	5
AC	203	2.975	0.876	2	3	5
CP	203	1.645	0.971	1	1	5
POS	203	4.148	0.958	1	4	5
STR	203	3.621	0.850	1	4	5
FB	203	4.626	0.603	3	5	5
System_Shift_Risk_Score	203	-4.064	4.471	-10	-5	13
GDP_Loss_Next4Q_pct	199	0.160	0.578	0	0	3.830
Crisis_Dummy	199	0.201	0.402	0	0	1
Progression	199	0.754	0.432	0	1	1
Success	199	0.633	0.483	0	1	1

Correlation analysis

Pressure-side variables are positively associated with negative outcomes and the composite risk score. SC, DL, AC, and CP all correlate positively with GDP_Loss_Next4Q_pct, Crisis_Dummy, and System_Shift_Risk_Score. The relationships with macro outcomes are moderate, which is expected given the multi-causal nature of GDP loss and crisis episodes. Adaptive-side variables show the reverse pattern: POS, STR, and FB correlate negatively with GDP loss and positively with Progression and Success. FB exhibits the strongest adaptive association, with correlations of 0.347 with Progression and 0.323 with Success.

Table 2. Correlations Between Pressure-Side Variables and Macroeconomic Outcomes

Predictor	GDP_Loss_Next4Q_pct	Crisis_Dummy	System_Shift_Risk_Score
SC	0.278	0.461	0.869
DL	0.157	0.205	0.778
AC	0.266	0.352	0.696
CP	0.151	0.385	0.848

Table 3. Correlations Between Adaptive-Capacity Variables and Macroeconomic Outcomes

Predictor	GDP_Loss_Next4Q_pct	Progression	Success
POS	-0.232	0.276	0.160
STR	-0.129	0.209	0.136
FB	-0.138	0.347	0.323

Linear regression

The linear models indicate that both CP and the composite risk score significantly predict GDP_Loss_Next4Q_pct. CP has a coefficient of 0.0931, with $R2 = 0.0228$ and $p = 0.0335$. The effect is statistically significant but modest as a single predictor. The System_Shift_Risk_Score has a coefficient of 0.0352, with $R2 = 0.0723$ and $p = 0.0001$. Thus, the composite score explains more variance in future GDP loss than CP alone, supporting the proposition that cumulative system configuration is more informative than a single bottleneck variable.

Table 4. Linear Regression Results for GDP Loss Prediction

Model	Coefficient	R2	p-value	Interpretation
GDP_Loss_Next4Q_pct ~ CP	0.0931	0.0228	0.0335	CP is significant but limited as a single predictor.
GDP_Loss_Next4Q_pct ~ System_Shift_Risk_Score	0.0352	0.0723	0.0001	Composite risk explains greater variance.

Logistic regression

Logistic models provide stronger support for the framework in binary outcomes. CP significantly predicts Crisis_Dummy, with a coefficient of 0.9051, odds ratio of 2.4721, accuracy of 0.8442, and AUC of 0.6734. This means that each one-point increase in CP is associated with approximately 147% higher odds of crisis status. STR and FB significantly predict both Success and Progression. FB is the stronger adaptive predictor: its odds ratio is 3.4570 for Success and 4.0744 for Progression. The composite risk score also behaves as expected: it increases crisis probability and decreases the probability of Success and Progression.

Table 5. Logistic Regression Results for Crisis, Success, and Progression Outcomes

Outcome / model	Predictor	Coef.	Odds ratio	Accuracy	AUC	p-value
Crisis_Dummy ~ CP	CP	0.9051	2.4721	0.8442	0.6734	<0.001
Success ~ STR + FB	STR	0.4089	1.5051	0.7136	0.7097	0.0323
Success ~ STR + FB	FB	1.2404	3.4570	0.7136	0.7097	<0.001
Progression ~ STR + FB	STR	0.7382	2.0921	0.7688	0.7752	0.0016
Progression ~ STR + FB	FB	1.4047	4.0744	0.7688	0.7752	<0.001
Crisis_Dummy ~ Risk Score	Risk Score	0.2587	1.2952	0.8442	0.7905	<0.001
Success ~ Risk Score	Risk Score	-0.1148	0.8915	0.6281	0.6554	0.0010
Progression ~ Risk Score	Risk Score	-0.1727	0.8414	0.7688	0.7372	<0.001

Incremental predictive validity

The key validation test compares System_Shift_Risk_Score with Status_Baseline. The composite risk score outperforms the baseline model in all outcomes. For GDP loss, R2 increases from 0.0314 to 0.0723. For Crisis_Dummy, AUC increases from 0.6961 to 0.7905. For Success, AUC increases from 0.5528 to 0.6554. For Progression, AUC increases from 0.5824 to 0.7372. The largest gain appears for Progression, the outcome most directly linked to the theory of adaptive movement.

Table 6. Comparison of Predictive Performance Between Status Baseline and System Shift Risk Score

Outcome	Metric	Status_Baseline	System_Shift_Risk_Score	Increment
GDP_Loss_Next4Q_pct	R2	0.0314	0.0723	+0.0409
Crisis_Dummy	AUC	0.6961	0.7905	+0.0944
Success	AUC	0.5528	0.6554	+0.1026
Progression	AUC	0.5824	0.7372	+0.1548

Random Forest feature importance

Random Forest models provide a nonlinear robustness check. Cross-validated performance is strongest for binary outcomes: CV AUC = 0.8533 for Crisis_Dummy, 0.7725 for Success, and 0.8269 for Progression. For GDP_Loss_Next4Q_pct, CV R2 = 0.0775. Across outcomes, System_Shift_Risk_Score appears as the most important feature, while FB is consistently relevant for adaptive outcomes.

Table 7. Random Forest Performance and Feature Importance Across Outcomes

Outcome	Performance	Top features
GDP_Loss_Next4Q_pct	CV R2 = 0.0775	System_Shift_Risk_Score, AC, SC, FB, DL
Crisis_Dummy	CV AUC = 0.8533	System_Shift_Risk_Score, SC, FB, AC, CP
Success	CV AUC = 0.7725	System_Shift_Risk_Score, FB, AC, DL, STR
Progression	CV AUC = 0.8269	System_Shift_Risk_Score, FB, AC, STR, POS

Cluster analysis

KMeans clustering was conducted using SC, DL, AC, CP, POS, STR, FB, and System_Shift_Risk_Score. Although the highest silhouette score occurs at k = 2 (0.4246), the theory predicts three regimes; the k = 3 solution has a silhouette score of 0.2888 and remains substantively interpretable. The clusters form a clear gradient: Adaptive/low-risk (n = 118), Transitional/medium-risk (n = 58), and Stagnant/high-risk (n = 27).

Table 8 Cluster Characteristics and Outcome Profiles Across System Shift Regimes

Cluster	N	SC	DL	AC	CP	POS	STR	FB	Risk Score	GDP Loss	Crisis	Progression	Success
Adaptive / low-risk	118	1.161	1.475	2.500	1.127	4.797	3.822	4.763	-7.119	0.052	0.085	0.864	0.729
Transitional / medium-risk	58	2.172	2.431	3.414	1.897	3.603	3.569	4.672	-1.931	0.260	0.246	0.649	0.526
Stagnant or high-risk	27	3.556	2.926	4.111	3.370	2.481	2.852	3.926	4.704	0.454	0.667	0.458	0.417

Predictive validity of the System Shift configuration

The results support the central proposition that macroeconomic outcomes are better understood through system configuration than through baseline status alone. The evidence is not merely directional. The System Shift Risk Score improves predictive performance over Status_Baseline across all four outcomes. This pattern is particularly important because the baseline variable already captures conventional macro status. The additional performance of the System Shift score therefore indicates incremental information in the configuration of pressure and adaptive capacity.

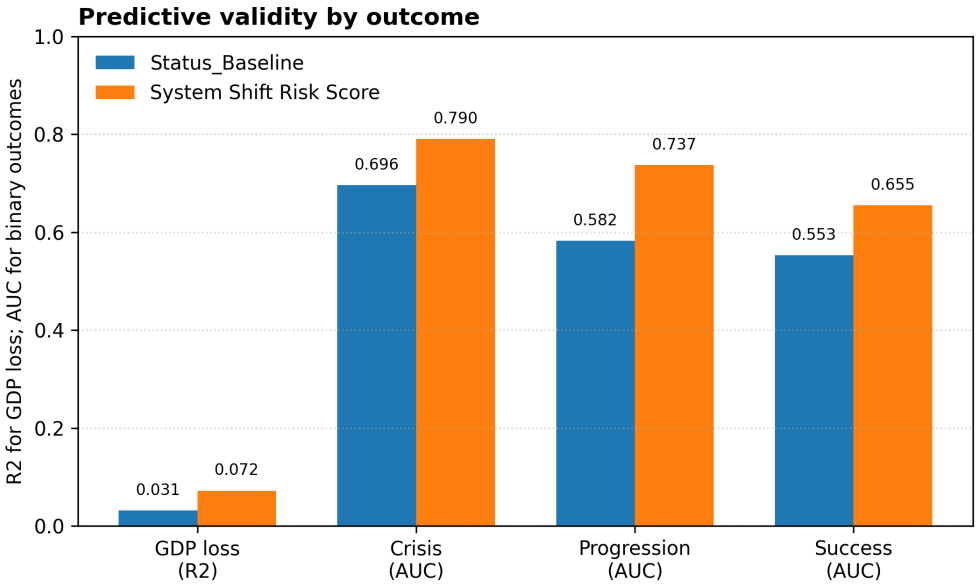


Figure 1. Predictive validity of Status_Baseline versus System Shift Risk Score across outcomes.

Figure 1 shows that the System Shift Risk Score exceeds the baseline model for GDP loss, crisis, progression, and success. The largest improvement occurs for Progression, which is theoretically meaningful. Progression measures whether the system moves adaptively over the following four quarters. A static status category may describe where the system is, but it may not describe whether the system has enough feedback, strategic quality, and positional strength to move. This is precisely the theoretical space in which the System Shift framework adds value.

Regime interpretation and cluster structure

The cluster results strengthen the argument that System Shift is not merely a linear index. The observations form interpretable regimes that correspond to distinct macroeconomic states. The Adaptive/low-risk cluster has low structural pressure, high POS, high FB, low crisis incidence, and high progression and success rates. The Transitional/medium-risk cluster occupies an intermediate position. The Stagnant/high-risk cluster has the highest SC, AC, and CP, the lowest POS and STR, and the highest crisis rate.

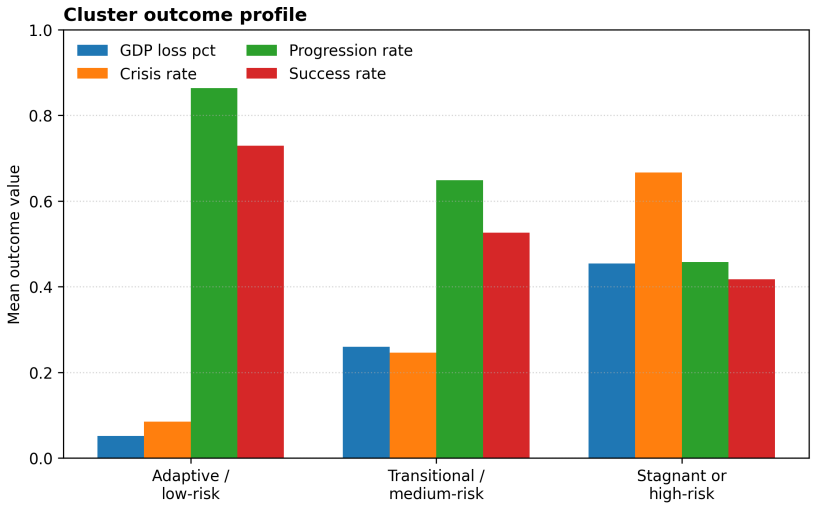


Figure 2. Cluster outcome profile for Adaptive/low-risk, Transitional/medium-risk, and Stagnant/high-risk regimes.

Figure 2 makes the regime logic visible. GDP loss and crisis rates rise monotonically from the adaptive cluster to the high-risk cluster, while progression and success decline. This dual movement is central. It shows that System Shift risk is not only about more negative outcomes; it is also about reduced adaptive capacity. The high-risk cluster is therefore not simply a cluster with higher GDP loss. It is a cluster in which the system is less able to transform stress into recovery.

Chokepoints as amplifiers of macroeconomic stress

CP emerges as a significant predictor of both GDP loss and crisis. Its relationship with GDP loss is statistically significant but relatively small in linear magnitude, while its relationship with crisis probability is stronger. This pattern suggests that chokepoints may function primarily as threshold or amplification mechanisms. A bottleneck does not necessarily determine the exact size of GDP loss in isolation, but it raises the likelihood that a system crosses into a stress regime.

Feedback maturity and adaptive recovery

The strongest adaptive pattern appears in FB. Feedback Maturity is positively associated with Success and Progression, and it remains one of the most important features in nonlinear models. This finding is theoretically important because feedback is the mechanism by which systems learn from stress. In a macroeconomic context, feedback includes policy responsiveness, information updating, institutional coordination, and the capacity to revise strategy as conditions change. Without mature feedback, even a system with moderate structural pressure may drift into stagnation.

Relationship to macroeconomic theory

The results are consistent with the macro-financial literature on crisis persistence, financial amplification, and state-dependent policy effects. They also extend that literature by proposing a compact operational framework that can be applied at the quarter level. The System Shift framework does not replace existing models of credit cycles, fiscal multipliers, or crisis propagation. Instead, it functions as a diagnostic overlay that asks whether a macro system has the configuration necessary to avoid, absorb, or recover from stress.

Implications

The framework has three implications for macroeconomic monitoring. First, policymakers should evaluate chokepoint severity as an early-warning variable. CP captures the bottleneck conditions that may convert ordinary stress into crisis. Second, monitoring systems should measure adaptive capacity directly. STR and FB are not merely qualitative descriptors; in this dataset they are statistically linked to success and progression. Third, baseline status categories should be complemented with configuration-based risk scores. The empirical comparison shows that System_Shift_Risk_Score provides incremental predictive value across all outcomes.

For applied macroeconomic research, the framework offers a bridge between interpretable theory and predictive modeling. Its variables are transparent and theoretically grounded, while its empirical evaluation can use both classical and machine-learning tools.

Limitations and Future Research

The study is exploratory. The coding of System Shift variables requires further validation, including inter-rater reliability, external replication, and sensitivity analysis. The current design is

predictive and diagnostic rather than causal. Future work should test whether the framework retains explanatory power after controlling for lagged GDP growth, inflation, unemployment, credit growth, interest rates, external shocks, and policy variables.

A second limitation is that the analysis uses a single dataset structure. Future research should apply the framework to cross-country panels, crisis datasets, and real-time vintages. External validation would allow the framework to be evaluated against established early-warning indicators and benchmark forecasting models. Additional work should also examine whether nonlinear thresholds exist: the impact of CP may become substantially larger once the system passes a critical risk level.

Finally, the framework should be tested as a dynamic model. The present score is evaluated at the quarter level, but the process of system shift is temporal. Future research could model transitions among adaptive, transitional, and high-risk regimes using Markov-switching models, local projections, or dynamic panel methods.

CONCLUSION

This paper provides exploratory empirical support for the System Shift Economics framework. Using quarter-level macroeconomic observations, the study shows that CP predicts forward-looking GDP loss and crisis status, STR and FB predict Success and Progression, and the System Shift Risk Score outperforms a conventional baseline status category across all outcomes. The cluster analysis further reveals three theoretically coherent regimes: Adaptive/low-risk, Transitional/medium-risk, and Stagnant/high-risk.

The central contribution is conceptual and empirical at once. The paper proposes that macroeconomic vulnerability should be understood as a configuration of pressures and adaptive capacities, not merely as a contemporaneous state. In that sense, System Shift Economics offers a disciplined way to study how systems move: not only when they contract, but when they adapt, stagnate, or recover.

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