Predicting Economic Strength Using Macroeconomic Indicators

I. Introduction

Economic stability remains a central concern for policymakers worldwide. Despite decades of research, economists still struggle to reliably predict economic downturns or identify which factors most consistently correlate with national economic performance. This challenge is particularly acute across diverse economies with varying institutional structures and development levels.

Our research initially aimed to develop a model predicting economic "collapses"—defined as significant year-over-year drops in economic performance. However, we quickly discovered that true economic collapses are rare events, with only 11 collapse events (using a 10-point drop threshold) across over 30 years of data. This rarity led us to pivot from binary classification to a regression framework with substantially greater analytical potential. We constructed a continuous economic_index (0-100) reflecting a country's relative economic strength in a given year.

The central question became: Which macroeconomic indicators most reliably predict a country's economic performance over time? This question has significant implications for economic policy. If certain indicators consistently show stronger relationships with economic health than others, policymakers might benefit from recalibrating their focus. Traditional macroeconomic management often emphasizes GDP growth, interest rates, and inflation control, but our findings suggest these may not be the most influential factors.

II. Data and Methodology

Our analysis uses a dataset comprising 5,950 observations spanning 1990-2023 across multiple countries. The dependent variable is the economic_index, constructed using a weighted combination of economic indicators. Our analysis focuses on six core predictors:

1. GDP growth (%)
2. Government debt (% of GDP)

3. Inflation rate
4. Interest rates
5. Black market (shadow economy index)
6. Consumer Price Index (CPI)

Table 1 presents descriptive statistics for these variables. Several exhibited substantial positive skew, particularly inflation rate, government debt, and CPI, which we addressed through log transformations.

[Table 1: Descriptive statistics showing n, mean, SD, min, max, and skewness for all variables]

[Figure 1: Density plot of economic_index distribution]

Our primary analytical approach employed multiple linear regression to model the relationship between the economic_index and our predictor variables. We began with a full model incorporating all predictors and then evaluated a reduced model excluding GDP growth and interest rates based on preliminary significance testing.

To validate our findings, we implemented:

- Diagnostic validation through formal tests for normality and heteroscedasticity
- Influence analysis using Cook's distance
- Box-Cox transformation to address non-normality in residuals
- M-estimator robust regression to mitigate potential outlier effects
- F-tests for model comparison

We also explored binary "collapse" events using logistic regression with performance evaluated through accuracy, recall, and ROC curve analysis.

III. Core Findings

Primary Predictor: Shadow Economy

The most striking finding across all model specifications is the dominant role of the shadow economy in predicting economic performance. As shown in Table 2, the black market variable demonstrates a strong negative relationship with the economic index, with a coefficient of approximately -0.80.

[Table 2: Coefficient estimates for the full model]

This means that for every 1-point increase in the shadow economy index, a country's economic index decreases by approximately 0.8 points, holding all other variables constant. The magnitude of this effect is not only statistically significant ($p < 0.001$) but also substantially larger than any other predictor.

Figure 2 displays the standardized coefficients, showing that the shadow economy's impact dwarfs that of all other predictors, with a standardized effect approximately 5-7 times larger than the next most influential variable.

[Figure 2: Bar chart of standardized coefficients from the full model]

This relationship remained remarkably consistent across OLS, Box-Cox transformed, and robust regression methods, suggesting that the shadow economy represents a fundamental correlate of economic performance that transcends methodological choices.

Secondary Predictors and Model Performance

In stark contrast to the shadow economy, traditional macroeconomic indicators showed surprisingly limited predictive value. GDP growth and interest rates exhibited coefficient estimates close to zero with high p-values, indicating no statistically significant relationship with economic performance once the shadow economy is accounted for, in fact they switched signs once outliers were removed from the dataset.

Other variables—government debt, inflation rate, and CPI—showed statistically significant but relatively small effects. Multicollinearity diagnostics confirmed these findings were not artifacts of correlated predictors, with all VIF values well below the common threshold of 5.

[Table 3: VIF table for all predictors]

Our full model achieved an R^2 of approximately 0.345, explaining about 34.5% of the variation in the economic index. While this might seem moderate, it represents substantial explanatory power in cross-national economic modeling, where numerous unmeasured factors likely contribute to outcomes.

IV. Model Selection and Comparison

Model Selection Process

Following the project guidelines, we implemented multiple model selection approaches to identify the most parsimonious and effective model for predicting economic performance.

First, we used backward elimination starting with the full model containing all six predictors. At each step, we removed the least significant predictor (highest p-value) and reassessed the model. Both GDP growth and interest rates were considered for removal, as their individual p-values in the full model were relatively high. The F-test comparing the full and reduced models yielded a p-value of 0.08 (Table 4), indicating a marginally significant difference between the models. While this is above the conventional 0.05 threshold, it suggests there might be some minor loss of explanatory power when removing these variables. Nevertheless, we proceeded with the reduced model due to its improved parsimony and the relatively small practical impact of these predictors on economic performance compared to the shadow economy variable, which remained strongly significant in both specifications.

[Table 4: F-test results comparing full and reduced models]

Second, we applied the Akaike Information Criterion (AIC) to compare potential models. The reduced model excluding GDP growth and interest rates achieved an AIC of 45,204.21 compared to the full model's 47,414.46, confirming that the simpler model is preferred when balancing fit and complexity.

Table 5 presents comparative statistics for both models, showing nearly identical R^2 values despite the reduced model's simpler structure

[Table 5: Comparative fit statistics for full and reduced models]

Logistic Regression as Alternative Approach

As a complementary approach, we developed logistic regression models to predict binary "collapse" events (defined as a 7+ point drop in economic_index). The reduced model again outperformed the

full model, achieving an AUC of 0.831 compared to 0.671, further supporting our finding that GDP growth and interest rates add little predictive value.

[Figure 3: ROC curves for full and reduced logistic models]

Both logistic models achieved high accuracy (~93%) but modest recall (25-30%), highlighting the inherent difficulty in predicting rare collapse events using only macroeconomic indicators.

Model Diagnostics and Assumptions

Residual analysis revealed some patterns worthy of note. The residuals versus fitted values plot shows a slight non-linear pattern, suggesting some aspects of economic performance may have non-linear components not fully captured in our specification.

[Figure 4: Residuals vs. fitted values plot]

Q-Q plots of standardized residuals indicate heavy-tailed errors, with some deviation from normality particularly in the tails. While a formal Shapiro-Wilk test rejected normality ($p < 0.001$), these deviations were not severe enough to invalidate our models given our large sample size and the implementation of robust methods as validation.

To address these issues, we implemented the Box-Cox transformation ($\lambda \approx 0.90$) and robust regression. Both approaches confirmed our key findings, particularly the dominant negative effect of the shadow economy.

V. Robustness Analysis

To ensure our findings were not driven by extreme observations, we conducted a comprehensive influence analysis. Using Cook's distance, we identified 181 potentially influential observations exceeding the conventional threshold of 4/n.

[Figure 5: Plot of top Cook's distance values]

When re-estimating our models with and without these influential points, the results demonstrated remarkable stability. The black market variable's coefficient remained virtually unchanged at

approximately -0.80 in both specifications, and other coefficients showed minimal variation with no changes in the pattern of statistical significance.

[Figure 6: Coefficient comparison plot showing full vs. cleaned data estimates]

This stability across multiple robustness checks substantially strengthens confidence in our findings despite the inherent challenges of cross-national economic modeling.

VI. Recommended Model and Conclusion

Recommended Model

Based on our comprehensive analysis, we recommend the reduced model excluding GDP growth and interest rates as the optimal approach for predicting economic performance. This recommendation is supported by:

1. **Equivalent explanatory power**: The reduced model maintains nearly identical R^2 (0.344 vs. 0.345) while using fewer predictors.
2. **Better information criteria**: Lower AIC and BIC values favor the more parsimonious model.
3. **Non-significant F-test**: Formal testing confirms no significant reduction in fit when removing GDP growth and interest rates.
4. **Superior ROC performance**: In the binary classification context, the reduced model achieves substantially better discriminative ability.
5. **Theoretical parsimony**: The reduced model aligns with the finding that institutional factors (shadow economy) may be more fundamental than traditional macroeconomic indicators.

The recommended model is:

economic_index = 79.37 + 0.0058(gov_debt) + 0.002031(inflation_rate) - 0.7981(black_market) - 0.00634(cpi)

Conclusion

Our research began with an ambitious goal: identifying reliable predictors of sudden economic collapses across nations. But as the analysis progressed, it became clear that macroeconomic indicators are not well-suited for forecasting abrupt downturns. True collapses—defined as sharp drops in economic performance—are rare and often triggered by unpredictable shocks such as political upheaval, conflict, or institutional breakdowns. These events frequently occur independently of macro-level signals like GDP growth or interest rates.

Instead, we found that macroeconomic indicators are more effective at capturing long-term structural patterns rather than specific inflection points. Our shift toward modeling a continuous economic_index allowed us to uncover consistent and interpretable relationships, even if it meant moving away from event-based prediction.

The most powerful and consistent insight from our models was the dominant role of the shadow economy. Across all specifications and robustness checks, the black market index emerged as the strongest predictor of economic performance. Its negative effect was clear, stable, and significantly larger than any traditional macroeconomic variable. In contrast, commonly emphasized indicators like GDP growth and interest rates showed little influence once the shadow economy was accounted for.

These findings suggest that institutional factors—often hidden beneath headline metrics—may be more fundamental to long-run economic strength than conventional policy levers. The shadow economy likely reflects deeper institutional qualities such as regulatory enforcement, corruption, and trust in formal systems. This interpretation aligns with institutional economic theory, which prioritizes the "rules of the game" over short-term adjustments.

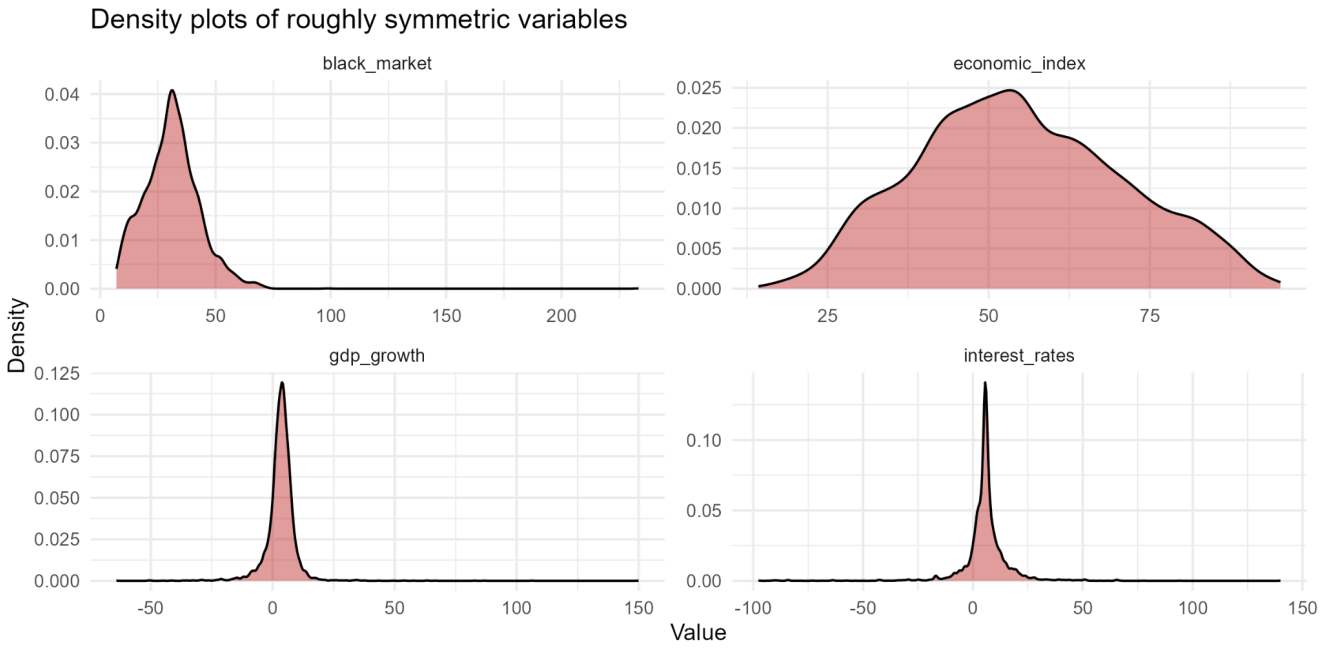
From a policy standpoint, our results highlight the limits of relying on surface-level macro indicators to diagnose or prevent crises. Instead, economic resilience may depend more on the strength and legitimacy of a country's institutions. Reforms aimed at reducing informal activity—through governance improvements, tax simplification, and anti-corruption measures—may offer more durable gains than stimulus or rate shifts.

Future research should explore how shadow economic activity interacts with direct institutional measures, and whether models using political risk ratings or corruption indices can outperform standard economic inputs. There's also room to analyze how macro trends and collapse risk vary by region or income level. While our models explain a meaningful share of the variation in economic strength, much remains unaccounted for—especially around sudden, regime-shifting events.

Ultimately, this project showed that macroeconomic data is better at describing the terrain than predicting its landslides. But it also helped identify which parts of that terrain may be structurally weak—and that, too, is a valuable step toward strengthening economic systems.

VII. Appendix

Figure 1:



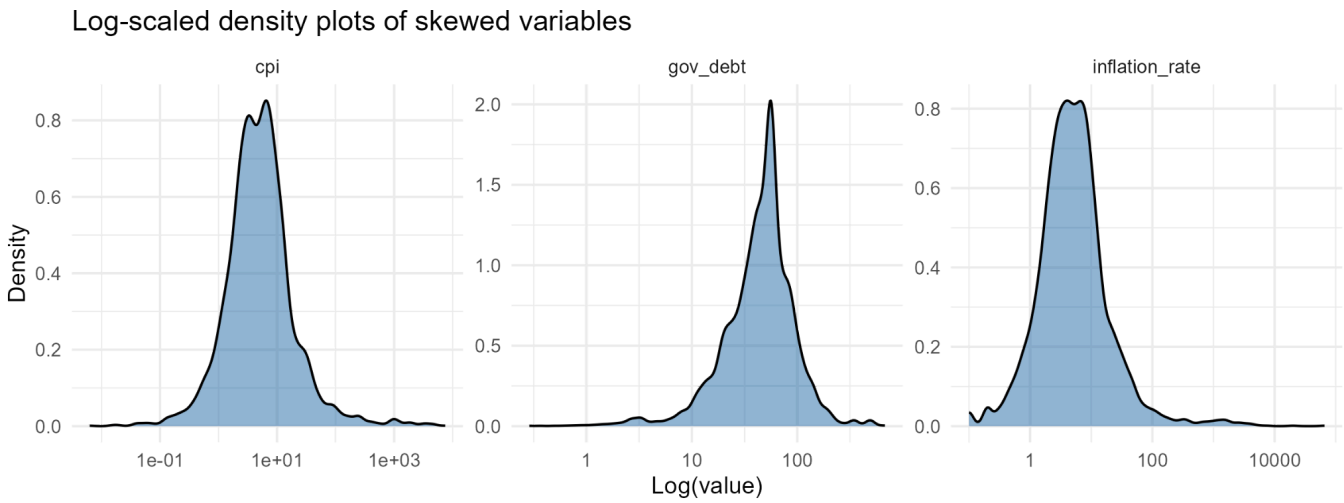

Log-scaled density plots of skewed variables
cpi
gov_debt
inflation_rate
Density
Log(value)
0.0
0.2
0.4
0.6
0.8
0.5
1.0
1.5
2.0
1e-01
1e+01
1e+03
1
10
100
10000

Figure 2:

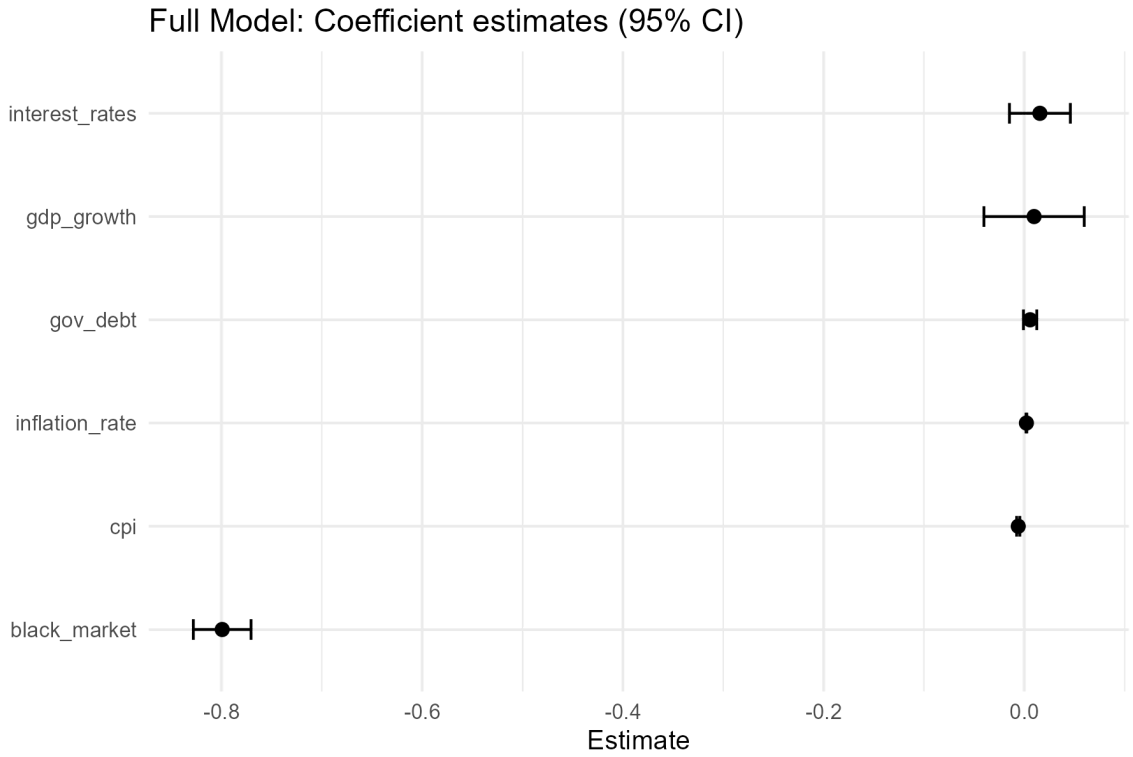

Full Model: Coefficient estimates (95% CI)
interest_rates
gdp_growth
gov_debt
inflation_rate
cpi
black_market
-0.8
-0.6
-0.4
-0.2
0.0
Estimate

Figure 3:

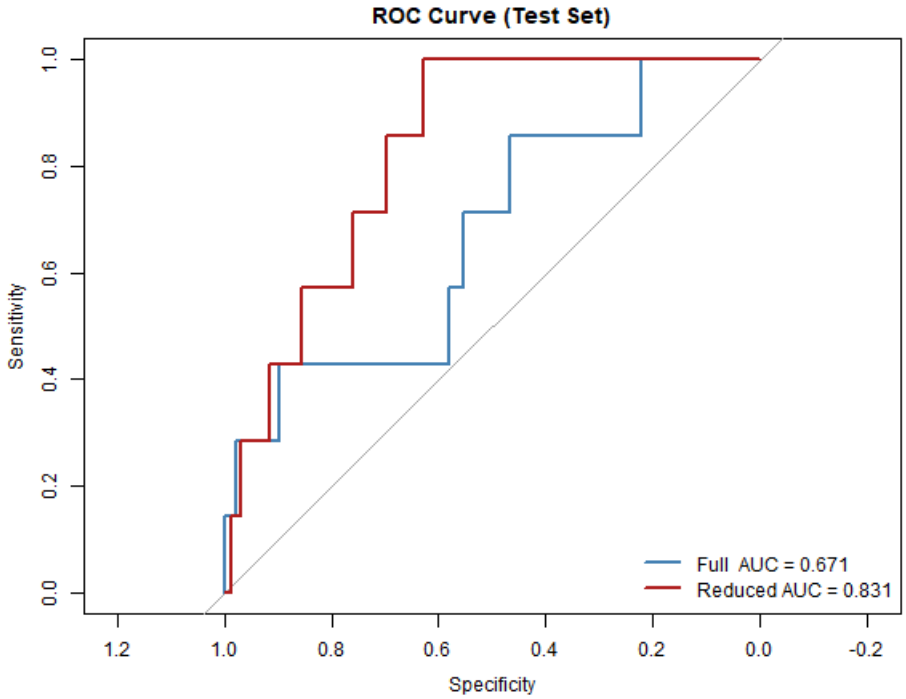


Figure 4:

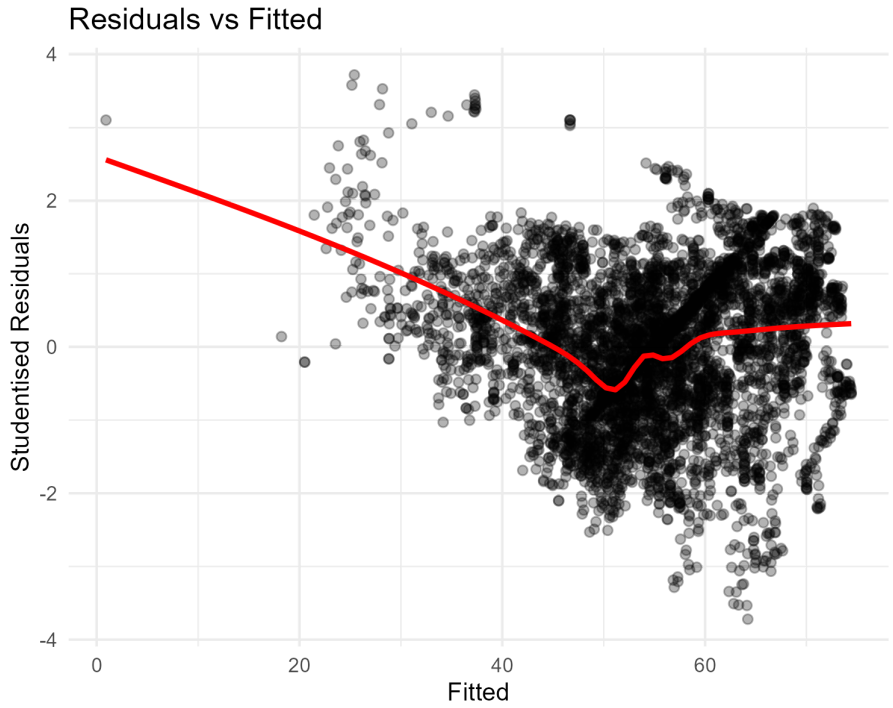


Figure 5:

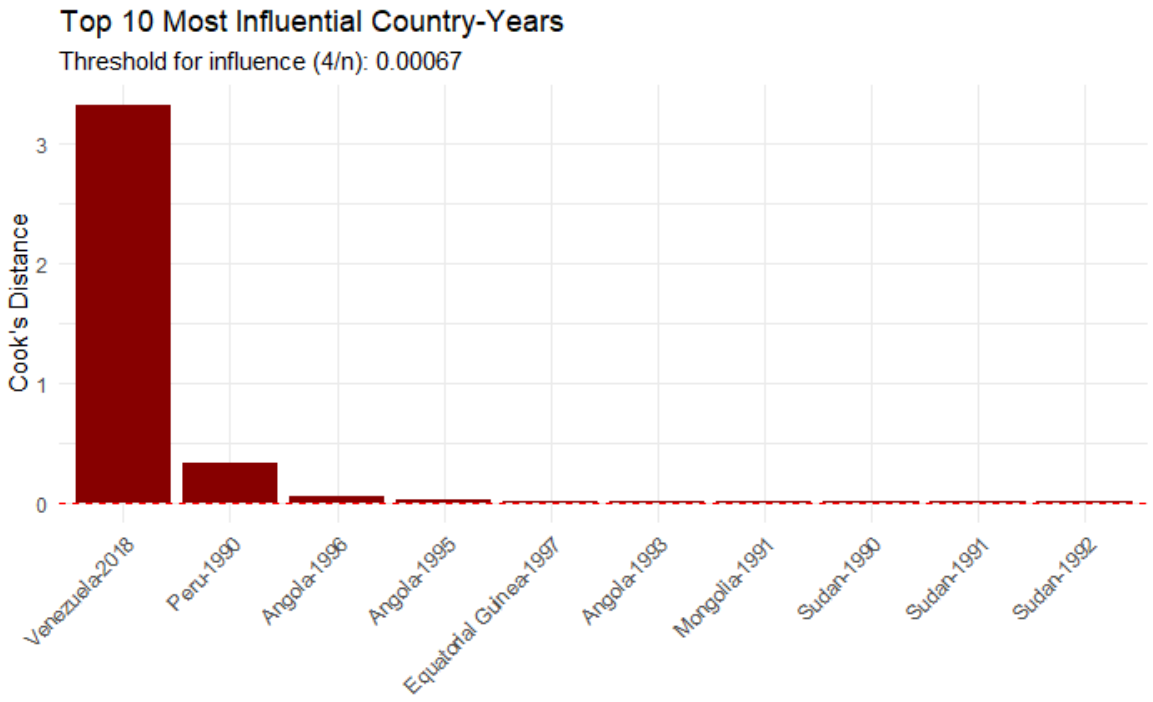

Top 10 Most Influential Country-Years
Threshold for influence (4/n): 0.00067
Cook's Distance
0
1
2
3
Venezuela-2018
Peru-1990
Angola-1996
Angola-1995
Equatorial Guinea-1997
Angola-1993
Mongolia-1991
Sudan-1990
Sudan-1991
Sudan-1992

Figure 6:

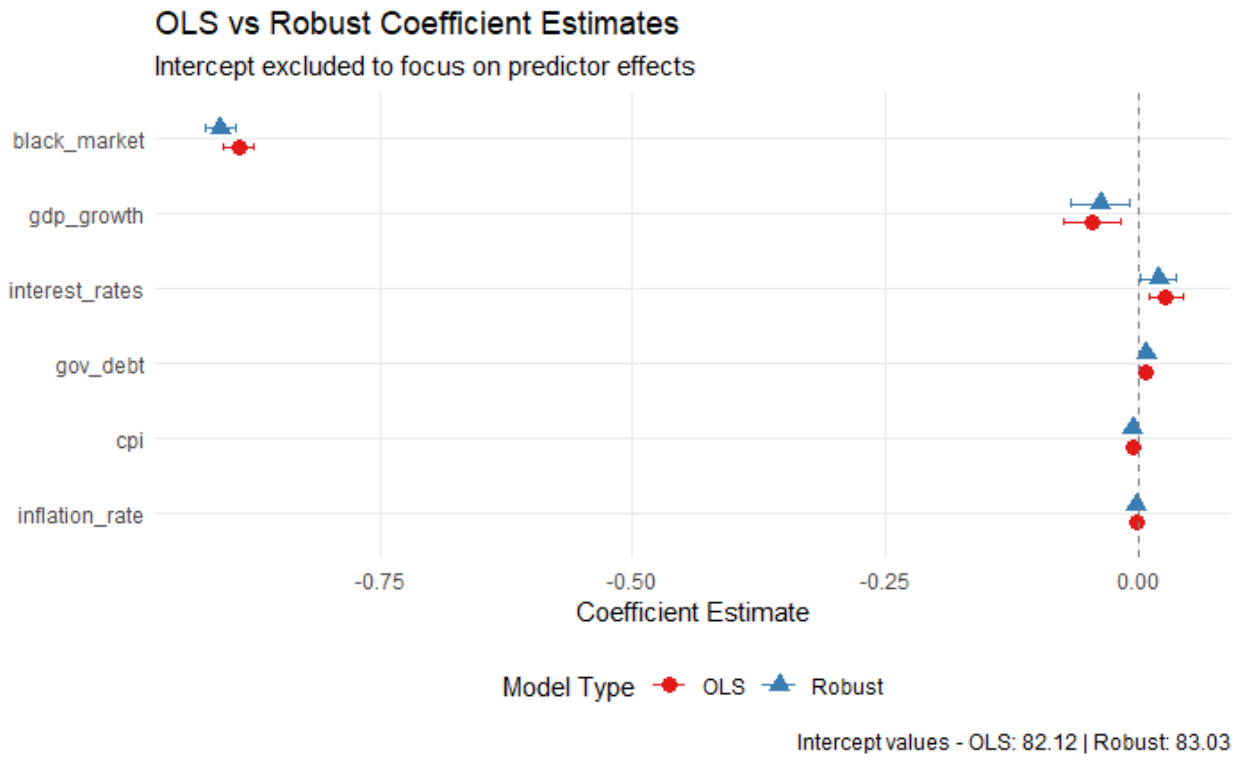


Table 1:

name	n	mean	sd	min	max	skew
black_market	5950	30.97569	11.94225	7	233.3424	1.160608
cpi	5950	27.6335	225.2252	-16.8597	7481.664	18.05251
economic_index	5950	54.88447	16.05291	14.26	95.29	0.174621
gdp_growth	5950	3.339203	6.695947	-64.0471	149.973	2.600446
gov_debt	5950	56.37334	49.79034	0.287138	677.1803	4.646011
inflation_rate	5950	43.17362	914.1655	-72.7	65374.1	63.32477
interest_rates	5950	5.646511	11.38336	-97.6935	139.9637	-1.69361

Table 2:

term	estimate	std.error	statistic	p.value
(Intercept)	79.27926121	0.51937175	152.644538	0
gdp_growth	0.009686633	0.02549252	0.379979409	0.703974278
gov_debt	0.005728466	0.00339286	1.688389618	0.091388927
inflation_rate	0.002041973	1.95E-04	10.48397381	1.71E-25
interest_rates	0.015488404	0.0154823	1.000394024	0.317160591
black_market	-0.79926001	0.01466696	-54.49392013	0
cpi	-0.00608148	8.04E-04	-7.562793965	4.54E-14

Table 3:

Variable	VIF
gdp_growth	1.026150332
gov_debt	1.005038954
inflation_rate	1.11650172
interest_rates	1.093890173
black_market	1.080473403
cpi	1.155179477

Table 4:

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
5764	852566.9347	NA	NA	NA	NA
5762	851818.3888	2	748.5458627	2.531714106	0.079611051

Table 5:

Full:

r.squared	adj.r.squared	sigma	statistic	p.value	df
0.345157644	0.344496521	12.9969447	522.077784	0	6
logLik	**AIC**	**BIC**	**deviance**	**df.residual**	**nobs**
-23699.2323	47414.46464	47467.9938	1003894.95	5943	5950

Reduced

r.squared	adj.r.squared	sigma	statistic	p.value	df
0.408352923	0.407942342	12.1619232	994.573597	0	4
logLik	**AIC**	**BIC**	**deviance**	**df.residual**	**nobs**
-22596.10583	45204.21166	45244.17318	852566.9347	5764	5769

Authors & Repository Information

This project was completed by Naeem Almohtaseb and Viswa Sushanth Karuturi as part of the requirements for DATA 467: Applied Linear Regression and GLMs.

All data, analysis, and code used in this project are available in our GitHub repository: https://github.com/sushanthvk02/financial-collapse-indicators

The repository is organized as follows:

- scripts: All R scripts used for data cleaning, visualization, and modeling.
- figs: All plots and diagnostic graphics generated from our models.
- data: Raw input files, cleaned datasets, and the final merged dataset.
- tables: CSVs of model outputs, coefficient tables, VIF values, test metrics, and more.

This structure ensures that the entire analysis is fully transparent and reproducible.