Macroeconomic Forecasting in Oil-Dependent Transit Economies of the East-West Transport Corridor: A Comparative Econometric and Machine Learning Approach

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Abstract. Forecasting macroeconomic indicators in oil-exporting economies is complicated by frequent swings in global energy prices. Azerbaijan and Kazakhstan are representative cases where oil revenues drive fiscal and external balances. Standard linear models struggle to capture the nonlinear dynamics that emerge across different price regimes. This study compares traditional econometric models with machine learning methods, namely Random Forest and Gradient Boosting, and introduces a hybrid regime-switching approach. When Brent falls below the threshold, SARIMA outperforms machine learning alternatives, while during stable periods Random Forest delivers higher accuracy. The hybrid model achieves the lowest RMSE overall. Diebold–Mariano tests confirm hybrid superiority over SARIMA. The results further show that oil prices affect the two economies through different channels: Kazakhstan responds more directly to price movements, while Azerbaijan adjusts primarily through current account dynamics. Regime-based forecasting models therefore provide more reliable signals than static alternatives.

Keywords: GDP forecasting; machine learning; hybrid regime-switching model; Azerbaijan; Kazakhstan; Middle Corridor; SARIMA; Random Forest.

1 Introduction

The Trans-Caspian International Transport Route plays the role of an important logistics bridge connecting East Asia and European export markets. After 2022, the importance of this route increased considerably. Operational problems and restrictions on traditional transport corridors made cargo transportation difficult, and freight operators needed more reliable alternative routes.

Azerbaijan and Kazakhstan, as transit countries, have played an important role in these circumstances and have actively converted their geographical positions into logistics potential. However, the economies of both countries are largely dependent on oil. Changes in oil prices have a direct impact on state revenues, investment flows and overall economic growth. A decrease in oil prices puts pressure on the national currency, leads to a reduction in government spending and weakens the development of non-oil sectors.

The example of Kazakhstan shows that persistent oil price shocks can have not only short-term, but also deeper and longer-term macroeconomic effects [8]. Traditional linear models are not adequate for such a volatile and structurally unstable environment. For example, vector autoregression (VAR) models assume that parameters are constant over time. This assumption is violated when structural relationships change in the context of cyclical commodity price volatility [11, 12].

Machine learning methods offer an alternative approach. These methods can detect complex and nonlinear interactions between variables without requiring prior specification of the functional form [11]. Empirical studies confirm that they provide lower forecast errors at cyclical turning points, especially in periods of high volatility [15]. However, data instability and frequent changes in indicators further complicate the decision-making process.

This study proposes a regime-based hybrid model. The model uses different specifications depending on the level of oil prices: SARIMA is used in volatile low-price periods, and the Random Forest model in more stable periods. A Brent threshold of $55 per barrel is taken as the basis for separating the regimes. The empirical results show that Azerbaijan and Kazakhstan react differently to oil price shocks. The proposed hybrid model provides higher forecast accuracy for both countries, with full-period RMSE values of 2.990 and 2.031 respectively. These results are of particular practical importance, since investment decisions and freight planning along transport corridors depend on such forecasts.

2 Problem Statement

Azerbaijan and Kazakhstan are countries that occupy a special position in the global economy. They act as both resource exporters and transit intermediaries in intercontinental cargo transportation. This dual role creates additional economic risks. A decrease in oil prices reduces state revenues, and when the volume of transit transportation also decreases, employment and investment levels weaken. These processes influence each other, making it harder to maintain economic stability.

Dependence on resource exports is especially pronounced in the Kazakh economy. Budget planning largely depends on correct oil price forecasting, and forecast errors can lead to serious financial problems, particularly when permanent price shifts are mistaken for temporary fluctuations [14]. A similar vulnerability is observed in Azerbaijan, but these effects manifest through different structural channels. Shocks in oil prices affect the dynamics of national income through the current account and currency channels, and these changes cause rapid reactions at the level of investment and production [9, 10].

Another important problem is the phenomenon of Dutch disease [7]. When oil prices increase, the national currency strengthens, which reduces the competitiveness of the non-oil sector. Although this effect is not immediately visible in the short term, it has a negative impact on the economic structure in the long term. In addition, oil price

increases and decreases do not have a symmetrical effect: the impact of an increase is more long-term and gradual, while in the case of a decrease the recovery process is slower [10].

Existing forecasting models may not be sufficiently effective in such complex and volatile conditions. Simple linear models do not adequately reflect the sharp structural changes occurring in the economy [11]. Although machine learning models offer a more flexible approach, they also depend on a stable information environment to train effectively [11, 15]. The oil market is characterized by high volatility, and such stability is often not observed.

The data used in the study start from 2000. The 1990s were a period of post-Soviet institutional collapse, hyperinflation, and high instability for both countries. The economic indicators available during that period do not reflect the current economic structure. In the period after 2000, the relative increase in economic stability forms a more reliable basis for analysis. It is not appropriate to conduct model selection in a static manner in these types of economies, since instability and shocks are inherent features of these economic systems. Forecasting models must adapt to changing conditions and account for regime transitions.

3 Literature Review

Studies show that there is a strong long-term relationship between the main macroeconomic indicators of Azerbaijan and oil prices [9]. An important feature of this relationship is its asymmetric nature: while an increase in oil prices has a stronger and longer-term impact on economic indicators, a decrease in prices does not have the same intensity [10]. Models based on average historical behavior cannot adequately reflect these differences.

In Kazakhstan, this effect is realized through a different mechanism. An increase in oil prices leads to a strengthening of the national currency, which reduces the competitiveness of the non-oil sector [7]. This phenomenon is known in the economic literature as Dutch disease. As a result, the economy gradually becomes more dependent on the oil sector and the development of other sectors weakens [5]. Eliminating this problem requires a long-term and consistent economic policy. The type of oil price shock is also important for model design. Permanent shocks have a more serious and lasting impact on fiscal conditions than tempo-rary fluctuations [14]. Models that evaluate all price changes in the same way give incorrect signals at precisely the moments when accuracy matters most.

In recent years, machine learning methods have been widely used in economic forecasting. These approaches, especially Random Forest and Gradient Boosting, show higher accuracy in forecasting GDP growth compared to traditional linear models [19]. This advantage is especially evident in periods of instability and high volatility [15]. Global financial indicators also help identify early signals of economic changes in developing countries, which is particularly valuable during crises [3].

In the medium term, the economic stability of Azerbaijan and Kazakhstan directly affects freight flows along the East-West transport corridor. According to current projections, cargo transportation along this route is expected to increase significantly by 2030, but ensuring this growth depends on continuous investment flows [16]. Reliable macroeconomic forecasts are a prerequisite for the investment environment that makes such growth possible [6].

One of the additional problems in Azerbaijan is the weakening influence of monetary policy on inflation over time, which means that static VAR specifications cannot track the shifting relationship between policy instruments and prices [12]. In Kazakhstan, the tenge-oil price relationship tightens asymmetrically during times of crisis [1]. As a result, oil price declines in both countries lead to currency depreciation, which directly affects the trade balance, government revenues, and investment levels [4]. If these processes are not accurately predicted, existing economic problems can deepen.

4 Methodology

Non-stationary time series can cause spurious regression problems. Therefore, stationarity of the data is checked at the initial stage using the Augmented Dickey–Fuller test. Lag length in multivariate specifications is determined by the Akaike Information Criterion. All models are estimated on a recursive expanding window, using only data available at each forecasting point, so that no future observations enter the training process.

The Vector Autoregression model is used as a baseline approach to assess how oil price changes transmit through the macroeconomy [8]. Its main limitation is the assumption of parameter stability over time. In practice, this assumption is often violated because structural relationships shift across commodity cycles [11, 12]. SARIMA provides the univariate counterpart, capturing the internal time-series structure of GDP growth without cross-variable dynamics.

Machine learning methods offer a more flexible alternative and do not require a predefined functional form [11]. The Random Forest model aggregates the results of multiple decision trees through bootstrap aggregation, which tends to produce more stable forecasts [19]. Gradient Boosting reduces prediction error in a stepwise manner and handles complex nonlinear interactions effectively [19]. Empirical comparisons show that both methods produce lower errors than linear benchmarks at cyclical turning points [15].

Since oil-dependent economies respond asymmetrically to positive and negative shocks [20], a regime-based hybrid model is appropriate. In the proposed approach, SARIMA is applied when the Brent oil price falls below $55 per barrel, and Random Forest is applied above this threshold. The threshold was not chosen arbitrarily. Three converging lines of evidence support it. First, it aligns with fiscal break-even oil price estimates for Azerbaijan and Kazakhstan during 2014–2016, which independent assessments placed in the $50–$60 range for both countries [14]. Below this level, fiscal

balances move into deficit and currency pressures intensify. Second, the historical record confirms this boundary: in 2015 and 2016, when Brent averaged $52 and $44 per barrel, Azerbaijan devalued the manat twice and Kazakhstan devalued the tenge by approximately 50 percent, with both economies recording near-zero or negative growth. Third, the threshold was validated through leave-one-out cross-validation on the 2000–2016 training period only. A grid search over $35–$75 per barrel showed that average CV-RMSE across both countries reached its minimum in the $50–$60 range. No test-period data were used at any stage of this process.

Forecast accuracy is evaluated using root mean square error (RMSE), mean absolute error (MAE), and the Theil U statistic. RMSE is the primary criterion because it penalizes large errors more heavily, which matters when shock episodes define the policy-relevant observations. The Theil U statistic compares each model against a naive random walk: values below 1.0 confirm that the model outperforms simple persistence. The Diebold–Mariano test assesses whether observed accuracy differences are statistically distinguishable from sampling variation.

One limitation of this study is that the data are at annual frequency and the number of test-period observations is limited. Only two years, 2017 and 2020, fall below the $55 threshold in the 2017–2024 test window, so regime-specific results should be read as directional evidence rather than statistically precise estimates. Full-period comparisons, which draw on eight test observations per country, carry the weight of the analysis.

5 Data

The data used in this study were obtained from the World Development Indicators database provided by the World Bank [18]. GDP growth was selected as the main variable and data covering 2000–2024 were used for Azerbaijan and Kazakhstan. Brent crude oil price data are drawn from the World Bank Commodity Markets Pink Sheet [17]. Two important economic shocks were observed during this period: a sharp decline in oil prices in 2015–2016 and the global economic contraction in 2020. These events are important for assessing model behavior across different macroeconomic conditions.

The main reason for choosing 2000 as the starting year is that the 1990s were a period of transition and high instability for both countries. The economic indicators available for that period do not adequately reflect the current economic structure, as those years were characterized by hyperinflation and institutional transformation. The period after 2000 provides a more stable and appropriate basis for comparison.

The main variables used in the model are GDP growth, inflation rate, current account balance, and Brent crude oil price. Oil price acts as the primary external variable since the economies of both countries are highly dependent on energy exports. Changes in oil prices have direct and indirect effects on the macroeconomic indicators of these countries [8, 9]. The main variables used in the model are GDP growth, inflation rate, current account balance (measured as a percentage of GDP), and Brent crude oil price. All variables are expressed in annual percentage terms.

Table 1 shows the ADF unit root test results. Real GDP growth and Brent prices are non-stationary for both countries, while inflation and the current account balance are stationary. Price levels and trade balances mean-revert; growth rates and energy prices do not. This distinction shapes how the models are specified and which variables require differencing before estimation.

Table 1. Augmented Dickey–Fuller unit root test results for Azerbaijan and Kazakhstan

Country	Variable	ADF Statistic	p-value
Azerbaijan	GDP growth	−1.7131	0.4244
Azerbaijan	Inflation	−3.5412	0.0070***
Azerbaijan	Current account	−6.2823	0.0000***
Azerbaijan	Brent price	−1.6022	0.4825
Kazakhstan	GDP growth	−2.3504	0.1562
Kazakhstan	Inflation	−3.6844	0.0043***
Kazakhstan	Current account	−3.4351	0.0098***
Kazakhstan	Brent price	−1.6022	0.4825

Source: Results of calculations performed using Python based on data from World Bank [17, 18].

*Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ADF test includes intercept; lag length selected by AIC. Null hypothesis: series contains a unit root.*

Granger causality tests reveal a structural divide between the two economies. For Kazakhstan, Brent price Granger-causes GDP growth at lag 1 with $F = 4.7912$ ($p = 0.0400$), consistent with the direct fiscal exposure that natural resource export concentration creates [8]. For Azerbaijan, current account dynamics Granger-cause GDP growth at lag 1 ($F = 9.9449$, $p = 0.0048$) and lag 2 ($F = 5.4139$, $p = 0.0144$), pointing to trade balances and foreign currency inflows as the primary transmission channel [9]. Oil price shocks still affect Azerbaijani industrial activity [10], but they do so indirectly rather than through the direct fiscal channel that dominates in Kazakhstan. This structural difference is what motivates a regime-switching approach. A single static model cannot simultaneously accommodate two economies with different shock transmission architectures.

Table 2a. Granger causality results: predictors of GDP growth, Azerbaijan

Country	Cause	Lag	F-Statistic	p-value
Azerbaijan	Brent price	1	1.8407	0.1893
Azerbaijan	Brent price	2	1.3995	0.2723

Azerbaijan	Brent price	3	1.2894	0.3142
Azerbaijan	Inflation	1	0.0699	0.7941
Azerbaijan	Inflation	2	0.0738	0.9291
Azerbaijan	Inflation	3	1.4880	0.2581
Azerbaijan	Current account	1	9.9449	0.0048***
Azerbaijan	Current account	2	5.4139	0.0144**
Azerbaijan	Current account	3	3.6740	0.0364**

Source: Results of calculations performed using Python based on data from World Bank [17, 18].
*Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ADF test includes intercept; lag length selected by AIC. Null hypothesis: series contains a unit root.*

Table 2b. Granger causality results: predictors of GDP growth, Kazakhstan

Country	Cause	Lag	F-Statistic	p-value
Kazakhstan	Brent price	1	4.7912	0.0400**
Kazakhstan	Brent price	2	1.5017	0.2494
Kazakhstan	Brent price	3	0.8798	0.4736
Kazakhstan	Inflation	1	0.0760	0.7854
Kazakhstan	Inflation	2	0.5377	0.5932
Kazakhstan	Inflation	3	0.4211	0.7406
Kazakhstan	Current account	1	0.4148	0.5265
Kazakhstan	Current account	2	0.0946	0.9102
Kazakhstan	Current account	3	0.6780	0.5789

Source: Results of calculations performed using Python based on data from World Bank [17, 18].
*Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ADF test includes intercept; lag length selected by AIC. Null hypothesis: series contains a unit root.*

6 Results and Discussion

The results are presented in three parts: full-period performance, shock-period performance, and normal-period performance. This structure makes it possible to see not only which model wins overall, but why it wins and under what conditions it falls short.

Over the full test period of 2017–2024, the Hybrid records an RMSE of 2.990 and a Theil U of 0.642 for Azerbaijan, below every benchmark: SARIMA at 8.004 (Theil U = 1.718), VAR at 10.406 (Theil U = 2.234), Random Forest at 3.103, and Gradient Boosting at 3.703. A Theil U above 1.0 means the model performs worse than simply repeating last year's growth rate as a forecast. Both SARIMA and VAR exceed this threshold for Azerbaijan, confirming that they add no predictive value beyond naive persistence. For Kazakhstan, the Hybrid records RMSE = 2.031 and Theil U = 0.550, outperforming SARIMA (2.594), VAR (3.672), Random Forest (2.318), and Gradient Boosting (2.743). A Theil U of 0.550 means the Hybrid generates roughly half the error of a naive forecast.

Table 3a. Forecast accuracy: full test period (2017–2024)

Country	Model	MAE	RMSE	Theil U
Azerbaijan	SARIMA	7.531	8.004	1.718
Azerbaijan	VAR	9.765	10.406	2.234
Azerbaijan	Random Forest	2.352	3.103	0.666
Azerbaijan	Gradient Boosting	2.850	3.703	0.795
Azerbaijan	Hybrid (SARIMA+RF)	2.187	2.990	0.642
Kazakhstan	SARIMA	2.356	2.594	0.702
Kazakhstan	VAR	3.599	3.672	0.994
Kazakhstan	Random Forest	1.448	2.318	0.627
Kazakhstan	Gradient Boosting	2.029	2.743	0.742
Kazakhstan	Hybrid (SARIMA+RF)	1.453	2.031	0.550

Source: Results of calculations performed using Python based on data from World Bank [17, 18].
Notes: Theil U < 1.0 indicates the model outperforms naive persistence.

During the two shock years, 2017 and 2020, when Brent fell below $55 per barrel, the rankings shift. For Azerbaijan, SARIMA posts RMSE = 4.973 while Random Forest reaches 5.243 and Gradient Boosting 4.984. The gap between models is narrow, and the reason for this is structural. In 2017, Brent averaged $54.39 per barrel and Azerbaijan's GDP growth was 0.15 percent, driven by post-devaluation adjustment rather than a direct oil-fiscal shock. In 2020, the 4.20 percent contraction combined a COVID demand shock with the oil price collapse. Because Azerbaijani output responds to oil prices through trade balances and foreign currency inflows rather than direct budget revenue [9], SARIMA's time-series structure retains predictive content even during low-price episodes. This is why machine learning and SARIMA converge in accuracy for Azerbaijan during shock years.

Kazakhstan shows a sharper contrast. SARIMA records RMSE = 3.635 against Random Forest at 4.266 and Gradient Boosting at 4.713. Here the direct oil-fiscal channel dominates [8]. When oil prices fall, Kazakhstani output contracts in a relatively linear and predictable pattern, which is exactly what SARIMA is designed to track. Machine learning models, which depend on stable nonlinear patterns in the training data, struggle to adapt when those patterns break down under commodity stress [11, 15]. The Hybrid inherits SARIMA's shock-period performance by switching to it entirely below the $55 threshold.

Table 3b. Forecast accuracy: shock periods (2017 and 2020, Brent < $55/bbl)

Country	Model	MAE	RMSE
Azerbaijan	SARIMA	4.147	4.973
Azerbaijan	VAR	11.205	12.846
Azerbaijan	Random Forest	4.807	5.243
Azerbaijan	Gradient Boosting	4.556	4.984
Azerbaijan	Hybrid (SARIMA+RF)	4.147	4.973
Kazakhstan	SARIMA	3.301	3.635
Kazakhstan	VAR	3.336	3.398
Kazakhstan	Random Forest	3.280	4.266
Kazakhstan	Gradient Boosting	3.661	4.713
Kazakhstan	Hybrid (SARIMA+RF)	3.301	3.635

Source: Results of calculations performed using Python based on data from World Bank [17, 18].

Normal periods reverse the rankings entirely. In the six years when Brent exceeded $55 per barrel, Random Forest and the Hybrid share identical RMSEs of 1.916 for Azerbaijan and 1.048 for Kazakhstan, since the switching mechanism assigns all normal-period observations to Random Forest. SARIMA falls to 8.784 for Azerbaijan and 2.138 for Kazakhstan. The Azerbaijan gap is particularly large. SARIMA was estimated on a training period that included the 2015–2016 shock with dummy variable corrections. Once those corrections no longer apply in the test period, SARIMA's forecasts drift into negative territory while actual growth was positive. Machine learning models, learning from lagged GDP values and oil price levels directly, track the recovery far better [19]. This is why no single model structure covers the full range of conditions these economies face.

Table 3c. Forecast accuracy: normal periods (2018, 2019, 2021, 2022, 2023, 2024)

Country	Model	MAE	RMSE
Azerbaijan	SARIMA	8.659	8.784

Azerbaijan	VAR	9.285	9.454
Azerbaijan	Random Forest	1.534	1.916
Azerbaijan	Gradient Boosting	2.281	3.163
Azerbaijan	Hybrid (SARIMA+RF)	1.534	1.916
Kazakhstan	SARIMA	2.041	2.138
Kazakhstan	VAR	3.686	3.759
Kazakhstan	Random Forest	0.837	1.048
Kazakhstan	Gradient Boosting	1.485	1.621
Kazakhstan	Hybrid (SARIMA+RF)	0.837	1.048

Source: Results of calculations performed using Python based on data from World Bank [17, 18].

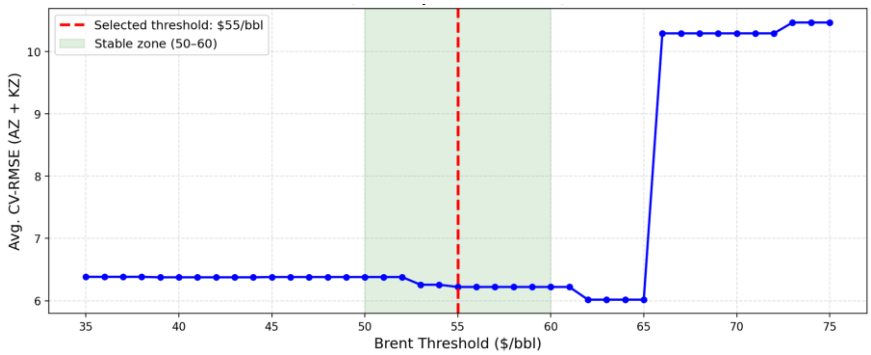
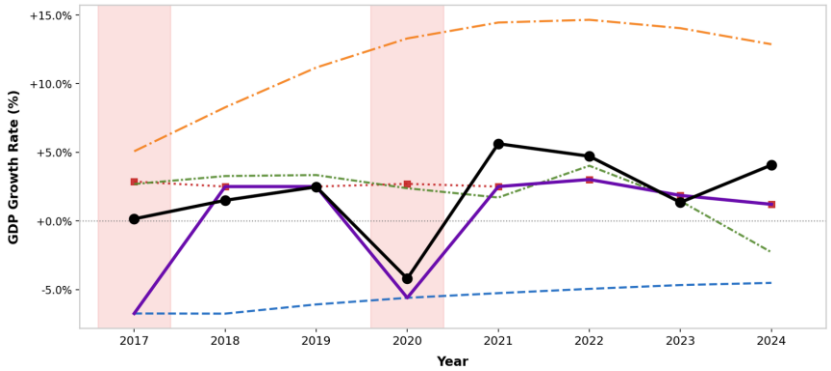


Fig. 1. Threshold selection via leave-one-out cross-validation on training data (2000–2016).



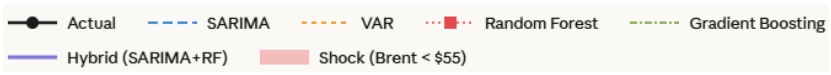


Fig. 2. GDP growth rate and model forecasts for Azerbaijan (2017–2024). Shaded bars indicate shock years (Brent < $55/bbl).

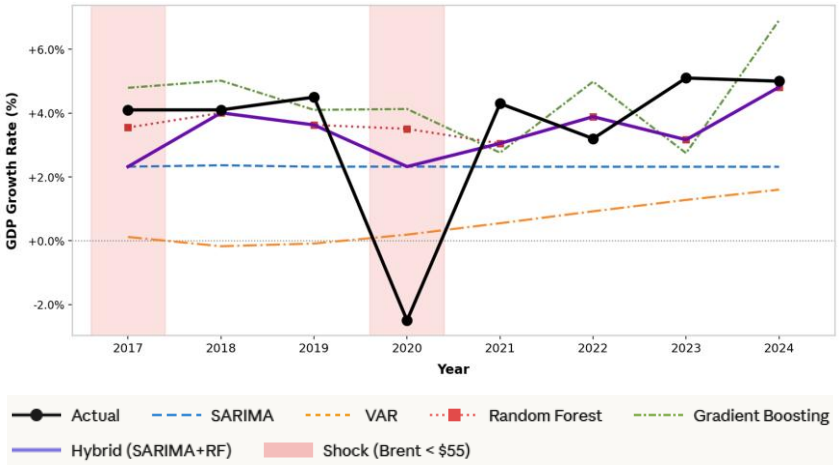


Fig. 3. GDP growth rate and model forecasts for Kazakhstan (2017–2024). Shaded bars indicate shock years (Brent < $55/bbl).

Table 4 reports the Diebold–Mariano test results. The Hybrid serves as the baseline in all comparisons. A positive DM statistic means the benchmark generates larger squared errors than the Hybrid. For Azerbaijan, the DM statistic against SARIMA is 6.2345 ($p < 0.001$) and against VAR is 3.1529 ($p < 0.01$). For Kazakhstan, the figures are 2.9349 ($p < 0.01$) against SARIMA and 3.5244 ($p < 0.001$) against VAR. These results confirm that the Hybrid's advantage over linear benchmarks is not a product of sampling variation. Comparisons against Random Forest and Gradient Boosting are not statistically significant in either country. During normal periods the Hybrid is functionally identical to Random Forest, so their errors differ only in the two shock years. Two observations are not enough for the DM test to reach conventional significance. The RMSE figures still show the Hybrid ahead overall, but these comparisons should be treated as directional rather than conclusive.

Table 4. Diebold–Mariano test results: Hybrid (SARIMA+RF) as baseline

Country	Benchmark Model	DM Statistic	p-value
Azerbaijan	SARIMA	6.2345	0.0000***
Azerbaijan	VAR	3.1529	0.0016***
Azerbaijan	Random Forest	0.0856	0.9318

Azerbaijan	Gradient Boosting	0.5580	0.5769
Kazakhstan	SARIMA	2.9349	0.0033***
Kazakhstan	VAR	3.5244	0.0004***
Kazakhstan	Random Forest	0.8331	0.4048
Kazakhstan	Gradient Boosting	1.8093	0.0704*

Source: Results of calculations performed using Python based on data from World Bank [17, 18].



Fig. 4. RMSE heatmap: model performance by regime, Azerbaijan.



Fig. 5. RMSE heatmap: model performance by regime, Kazakhstan.

Figures 4 and 5 show the RMSE heatmaps. The most immediate difference between the two countries is scale: Azerbaijan's errors run consistently higher across all models and regimes. This reflects the indirect transmission channel through the current account, which introduces additional lag between oil price movements and GDP outcomes [9]. VAR stands out as the clear outlier in both heatmaps. Its shock-period RMSEs of 12.846 for Azerbaijan and 3.398 for Kazakhstan confirm that imposing

parameter constancy on transition economies produces severe forecast deterioration under stress [12]. SARIMA holds its position during shock periods, and the Hybrid borrows that stability when Brent falls below the threshold. In normal-period cells, Random Forest and the Hybrid share identical scores, confirming that the switching mechanism operates cleanly above the threshold.

7 Conclusion

The structural weaknesses in the economies of oil-dependent transit countries are not eliminated by economic growth alone. As a result of Dutch disease, the manufacturing sector can weaken even during periods of economic growth, and this effect is often long-term [7]. In Kazakhstan, the economy responds more directly to changes in oil prices [8], while in Azerbaijan this effect is transmitted more through the current account balance and currency channels [9]. Forecasting models therefore need to be calibrated to the specific shock transmission architecture of each country.

Empirical results confirm that traditional linear models are not sufficiently effective in environments with high volatility and structural breaks. VAR cannot account for structural changes and produces large forecast errors, with RMSE figures of 10.406 for Azerbaijan and 3.672 for Kazakhstan [12]. SARIMA performs better as a univariate model, but its advantage is regime-specific: it is useful when Brent prices fall below $55 per barrel, producing shock-period RMSEs of 4.973 and 3.635 for Azerbaijan and Kazakhstan respectively. Random Forest demonstrates higher accuracy in more stable economic periods, with normal-period RMSEs of 1.916 and 1.048 [19].

The proposed hybrid model combines these approaches and activates the appropriate model depending on the oil price level. Full-period RMSEs of 2.990 and 2.031, with Theil U statistics of 0.642 and 0.550, confirm that it outperforms every individual benchmark and beats naive persistence by a meaningful margin. Diebold–Mariano tests confirm that the differences against SARIMA and VAR are statistically significant in both countries. The relatively low forecast errors for Azerbaijan during shock periods are explained by the indirect transmission mechanism in the economic structure: oil price shocks reach output through the current account rather than directly through fiscal revenue [9]. In Kazakhstan, since there is a more direct relationship between oil prices and economic indicators, the impact of shocks is stronger and model differences are more clearly revealed [8].

The development of the Trans-Caspian transport corridor depends directly on the economic stability of both countries [6]. Reliable forecasting models support sound financial and investment decisions. The correct assessment of oil price changes, in particular distinguishing between permanent and temporary shocks [14], allows policymakers to make timely and better-grounded decisions. Permanent shifts require structural policy responses, while temporary fluctuations can be managed through reserve drawdowns. A forecasting framework that cannot tell them apart will consistently give the wrong signal when it matters most.

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