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# Exploring the Causal Relationship between Total and Renewable Energy Consumption, Agricultural Growth, and $CO_2$ Emissions: A VAR-Based Analysis of Kazakhstan's Path toward Sustainable Development

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**ABSTRACT**

This study investigates the dynamic interplay among agricultural growth, total energy consumption, renewable energy penetration, and $CO_2$ emissions in Kazakhstan, using annual data for 2001-2024. Augmented Dickey-Fuller diagnostics classify all series as I(1), and information criteria favor a parsimonious VAR(1). Variance decompositions indicate that agricultural growth is primarily driven by own shocks, with a growing medium-horizon contribution from $CO_2$. Total energy use remains largely self-propelled, accompanied by modest spillovers from agriculture and a gradual feedback from emissions. The renewable share increasingly reflects movements in total energy demand at longer horizons, while agriculture contributes a smaller but persistent portion; the direct role of $CO_2$ in renewable dynamics is negligible under orthogonalized innovations. Emissions variability is governed chiefly by shocks to aggregate energy demand and by own persistence. Pairwise Granger tests uncover a single predictive channel - total energy use Granger-causing the renewable share - whereas other pairs do not exhibit short-run directionality at conventional thresholds. Taken together, the evidence portrays a demand-led nexus in which aggregate energy conditions steer near-term adjustments, agricultural performance reflects internal dynamics and environmental pressure, and emissions co-move with energy demand. The findings underscore policy relevance for demand management, grid integration with bankable procurement of renewables, and climate-smart upgrades in irrigation and inputs.

**Keywords:** Kazakhstan, Agricultural Growth, $CO_2$ Emissions, Energy Consumption, Renewable Energy, VAR Model
**JEL Classifications:** C32, Q42, Q43, Q54

## 1. INTRODUCTION

Kazakhstan's development path combines high overall energy demand, a still-modest but gradually expanding base of renewables, and a climate-sensitive agricultural sector that remains central to rural livelihoods. In this context, clarifying how total energy use, the renewable share, and $CO_2$ emissions relate to agricultural performance is not just an academic exercise; it is foundational for reconciling productivity, resilience, and decarbonization objectives. Recent country studies point to asymmetric real-sector responses to energy-linked shocks and other external drivers, suggesting that commodity-market conditions can filter into domestic production structures and sectoral output (Baisholanova et al., 2025; Beisenova et al., 2025). Sector-level evidence for Kazakhstan further indicates non-linear emissions income relationships across energy, agriculture, and industry, consistent with EKC-type dynamics and heterogeneous turning points (Issayeva et al., 2024).

International research provides a structured lens for interpreting these interactions. Foundational work on energy, growth, and the environment shows that environmental outcomes co-evolve with income via scale, composition, and technique effects, with turning points that depend on structural features and technology (Stern, 2011; Pao and Tsai, 2011). A broad empirical literature also finds that aggregate energy demand and fossil intensity are first-order determinants of carbon outcomes, while sectoral composition and openness condition the magnitude and timing of responses (Apergis and Payne, 2010; Omri, 2013). These insights motivate a practical distinction between the "demand/intensity" margin - total energy consumption - and the "composition/transition" margin - renewable penetration - when tracing how energy conditions map into emissions and real activity.

A complementary strand suggests that total energy shocks tend to dominate the short run, whereas the benefits of renewables accumulate more slowly. Multi-country studies frequently report that movements in total energy use anchor near-term emissions dynamics, while mitigation through renewables unfolds with lags tied to grid integration, finance, and policy credibility (Shafiei and Salim, 2014; Zoundi, 2017). Recent evidence links the depth and mix of renewable technologies to national carbon intensity, with stronger gains as systems add flexibility, storage, and cross-border interconnection (Sarkodie and Strezov, 2019; Destek and Aslan, 2020). For agriculture, these system characteristics matter: input costs, irrigation and processing energy needs, and exposure to climate risk shape yields, technology adoption, and investment behavior.

Against this backdrop, Kazakhstan presents a distinctive configuration: a fossil-reliant legacy, a gradual renewable rollout, and a large agricultural base. In such a setting, movements in total energy demand can anchor near-term emissions, while the renewable channel strengthens as integration and capacity expand. Agriculture may both respond to the energy - emissions environment and feed back into energy pathways through technology choices and shifts along the value chain. Framing agricultural growth alongside total energy use, the renewable share, and $CO_2$ emissions therefore addresses a policy-relevant gap for a resource-dependent economy: it clarifies whether the dominant transmission margin lies in demand, composition, or environmental pressure - and how the timing and strength of these channels map into sectoral performance and sustainable development (Baisholanova et al., 2025; Issayeva et al., 2024).

## 2. LITERATURE REVIEW

Evidence from the energy-environment-growth literature suggests that agriculture responds to both fossil energy demand and the speed of the renewable transition. In this review, we focus on studies that inform a Kazakhstan-specific VAR in which agricultural growth is the outcome and total energy use, renewable energy, and $CO_2$ serve as the driving variables.

Zhang et al. (2019) assess farm-sector carbon performance across China's major grain regions using a sector-focused panel design that distinguishes agricultural mechanisms from aggregate dynamics. The analysis identifies agricultural energy intensity as the central driver of $CO_2$ in the rural economy, and shows that output growth interacts with emissions in a non-linear way consistent with an EKC profile. Robustness checks across alternative specifications underscore the roles of structural upgrading and energy-efficiency improvements in lowering the carbon footprint without sacrificing yields. Spatial heterogeneity is also noted: provinces with more modern input mixes tend to decouple earlier. By mapping agriculture-specific channels rather than relying on economy-wide proxies, the study offers parameters and identification cues that carry directly into VAR settings where agricultural output is the dependent variable and energy measures act as drivers. Such sectoral granularity is especially useful for tracing short-run transmission and allocating shock contributions to forecast variance in agriculture-focused models.

Chidiebere-Mark et al. (2022) explore interactions among agricultural output, renewable uptake, FDI, and $CO_2$ across African economies using ARDL-style time-series and panel methods. Greater penetration of renewables is associated with lower emissions, whereas capital inflows and intensive input use can raise carbon intensity where technologies are weak or power systems remain carbon-heavy. Elasticities differ by country group and horizon, pointing to multiple propagation routes. This heterogeneity supports a multivariate specification capable of separating whether changes in renewable shares anticipate shifts in agriculture-related emissions or, alternatively, whether agricultural expansions feed back into the composition of the energy mix.

Tleppayev and Zeinolla (2023) document a durable positive link between Kazakhstan's economic activity and $CO_2$ emissions, highlighting how decarbonization is difficult without a reconfiguration of the energy structure. National institutions and pricing are emphasized as additional constraints shaping the trajectory. These patterns argue for treating emissions as endogenous to macro-energy conditions in country-specific VAR systems, where agriculture can be modeled as the outcome of shocks to total energy use and the carbon pathway.

Sadorsky (2009) analyzes G7 data with panel cointegration and error-correction techniques to connect renewable consumption, emissions, and oil price dynamics. Long-run relations indicate that income and carbon pressures stimulate renewable uptake, while higher renewable use aligns with reduced emissions over time. Oil prices act as external signals that influence the energy mix and the speed of transition. For VAR applications, this implies modeling renewable and total energy jointly, letting energy-price shocks enter the system and allocating variance across fossil and renewable channels.

Halicioglu (2009) applies bounds testing and cointegration to uncover a long-run equilibrium in which energy consumption and income dominate Turkey's emissions trajectory, with trade openness also shaping outcomes. Short-run adjustments reveal meaningful error-correction toward the long-run path. Structurally, this places total energy use at the heart of causal ordering - an approach that matches VAR designs testing whether energy shocks forecast near-term movements in real-sector indicators and the carbon path, particularly when agriculture is specified as the response variable.

Chebbi and Boujelbene (2008) analyze Tunisia's growth-energy-emissions links using country-level time-series tools and report persistent connections between energy use and $CO_2$. Periods of expansion coincide with inefficient energy intensity, limiting progress on decarbonization. The evidence points toward multivariate frameworks that can capture feedback between output and energy demand and trace the transmission of shocks to emissions and sectoral activity.

Ridzuan et al. (2020) evaluate multi-country panel data within an EKC framework and find that renewable consumption is associated with lower $CO_2$, while agriculture and income exhibit non-linear effects. Results remain robust across alternative estimators and control sets, suggesting that both scale and composition effects are operative. The interplay motivates VAR-based designs that test whether renewable expansion can offset agriculture-related emissions and whether agriculture-specific shocks propagate differently from energy shocks; distinguishing these channels is essential for forecasting and for assigning variance contributions across horizons.

Zhai et al. (2024) analyze Kazakhstan's energy-growth nexus using national time-series evidence and report bidirectional associations between energy use and output. Feedback effects help sustain energy intensity when structural change is limited, with implications for both emissions and sectoral performance. A joint system in which energy and output co-evolve provides a natural basis for extending shocks to downstream outcomes such as agricultural growth.

Triantafyllidou and Polychronidou (2025) present EU-wide evidence linking fossil and renewable energy consumption to emissions and growth in an empirical panel framework with dynamic specifications. Fossil energy exerts a strong positive effect on $CO_2$, while renewables provide a statistically significant-though smaller-mitigating influence. Dynamic responses and variance-style metrics assign a larger share of emissions uncertainty to fossil-energy shocks. For VAR practice, the implication is direct: include both total and renewable energy as distinct drivers and allow their innovations to transmit to real-sector outcomes, including agriculture, through short-run channels that can be identified and quantified.

## 3. METHOD

Joint dynamics are examined with a Vector Autoregression, VAR($p$), in which all series are endogenous and respond to both own lags and the lags of the remaining series (Sims, 1980). Let $y_t \in \mathbb{R}^k$ be the $k$-vector of variables at time $t$. The general form of VAR is:

$$y_t = \mu + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t \tag{1}$$

Where μ collects intercepts, $A_i$ are coefficient matrices, and $u_t$ are reduced-form innovations with covariance $\Sigma_u$. Each equation is estimated by OLS; because the regressor set is identical across equations, this yields consistent and asymptotically efficient reduced-form estimates (Lütkepohl, 2013).

Prior to estimation, series are scaled consistently and assessed for stochastic trends using the Augmented Dickey-Fuller unit-root test (Dickey and Fuller, 1979; Said and Dickey, 1984). The ADF results determine whether variables enter the system in levels or after standard transformations. To keep the analysis coherent, the chosen representation is then applied unchanged across all VAR outputs - lag selection, coefficient estimation, variance decomposition, and causality testing - so that results are directly comparable (Lütkepohl, 2013).

Lag order $p$ is selected using the standard VAR lag-length criteria: the Akaike Information Criterion (AIC), the Schwarz/Bayesian Information Criterion (SC/BIC), and the Hannan-Quinn (HQ) measure, complemented by the Final Prediction Error (FPE) and sequential likelihood-ratio (LR) tests. These criteria balance in-sample fit against parsimony, helping to avoid over-parameterization in small samples (Akaike, 2003; Schwarz, 1978; Hannan and Quinn, 1979; Akaike, 1969). The selected $p$ is then held fixed for all subsequent procedures, ensuring a single dynamic structure underlies the reported tables (Sims, 1980).

With $p$ fixed, Vector Autoregression estimates are reported by equation, with attention to the sign and statistical significance of lagged effects to characterize short-run transmission across variables. For variance decomposition, forecast-error variance for each variable is attributed to orthogonalized reduced-form innovations obtained from a lower-triangular factorization of $\Sigma_u$. The economically motivated ordering is stated explicitly, and variance shares are reported at conventional horizons to quantify the relative importance of shocks within the same reduced-form and lag structure as the regression estimates (Lütkepohl, 2013).

Finally, predictive linkages within the estimated VAR($p$) are assessed using pairwise Granger causality tests. These are implemented as Wald/F tests of joint zero restrictions on the lagged coefficients of a candidate predictor in a target equation; rejection indicates that the predictor's lags add incremental forecasting content in the VAR setting (Granger, 1969). The pipeline - ADF pre-tests, information-criterion-based lag selection, OLS reduced-form estimation, variance decompositions under a stated orthogonalization, and Granger tests with the same $p$ - provides a compact, reproducible VAR methodology suitable for applied macro-energy research (Lütkepohl, 2013; Sims, 1980).

## 4. FINDINGS

This research examines how agricultural growth, total energy consumption, renewable energy adoption, and $CO_2$ emissions co-evolve in Kazakhstan. Agricultural growth - represented by the Agricultural Production Index - serves as the outcome variable, reflecting sectoral performance that is central to sustainable development. Total energy consumption, expressed in kilograms of oil equivalent per capita, captures the scale and intensity of energy demand. The share of renewable energy in total final consumption is used to track the pace of the energy transition. $CO_2$ emissions, measured in metric tons of $CO_2$-equivalent, outline the environmental burden that conditions production and broader sectoral dynamics.

Variable definitions and data provenance for Kazakhstan's agriculture-energy-emissions system are summarized in Table 1. The empirical sample spans 2001-2024. The research data were retrieved from https://data.worldbank.org and https://w3.unece.org (Date of Access: September 09, 2025).

The sample exhibits stable descriptive and distributional features, as reported in Table 2. Across 2000-2024, AGRI averages 4.48 with a standard deviation of 0.27; ENRC averages 8.15 (0.19); RENE averages 1.86 (0.44); and CO2E register 5.36 (0.21). Jarque-Bera probabilities of 0.40, 0.23, 0.82, and 0.09, respectively, indicate no rejection of normality at the 5% level, validating these series for subsequent VAR-based inference.

The time path of agricultural output, total energy consumption, renewable share, and $CO_2$ emissions is reported in Graph 1. AGRI follows a clear upward trajectory from 2000, with brief dips around 2009 and 2015, and then advances to record levels after 2018. ENRC climbs steadily through 2011-2012, contracts in 2014-2016, and settles on a lower plateau from 2017 onward, signaling a break from the prior growth trend. RENE remains small (≈1-3%), falls through the late-2000s and early-2010s, and then edges higher after 2015, indicating a slow but ongoing re-entry of renewables into the mix. CO2E largely mirror total energy use: a sustained rise to an early-2010s peak, a pronounced drop in 2015-2017, and a partial rebound to a near-flat level thereafter. Co-movement between ENRC and CO2E is pronounced, whereas AGRI rises mostly independent of short-run energy fluctuations, and the small RENE implies only limited aggregate mitigation.

**Table 1: Variable definitions and sources**

| Variable | Short description | Source |
|---|---|---|
| AGRI | Agricultural production index | https://w3.unece.org |
| ENRC | Energy consumption (kg of oil equivalent per capita) | https://data.worldbank.org |
| RENE | Renewable energy consumption (% of total final energy consumption) | https://data.worldbank.org |
| CO2E | Total carbon dioxide ($CO_2$) emissions (Mt $CO_2$e) | https://data.worldbank.org |

**Table 2: Descriptive statistics findings of variables**

| Statistics | AGRI | ENRC | RENE | $CO_2E$ |
|---|---|---|---|---|
| Mean | 4.476629 | 8.154698 | 1.860000 | 5.363428 |
| Median | 4.535820 | 8.191115 | 1.900000 | 5.427958 |
| Maximum | 4.862522 | 8.443715 | 2.800000 | 5.656689 |
| Minimum | 3.925926 | 7.704171 | 1.100000 | 4.871154 |
| Standard deviation | 0.268393 | 0.192332 | 0.436845 | 0.213716 |
| Skewness | −0.264404 | −0.839137 | −0.008570 | −1.073223 |
| Kurtosis | 1.784387 | 3.196775 | 2.392069 | 3.256100 |
| Jarque-Bera | 1.830577 | 2.974292 | 0.385285 | 4.867518 |
| Probability | 0.400401 | 0.226017 | 0.824777 | 0.087707 |

Augmented Dickey-Fuller diagnostics indicate that none of the series rejects the unit-root null in levels, while each rejects it after first differencing in Table 3. Accordingly, agricultural growth (AGRI), energy consumption (ENRC), renewable energy share (RENE), and $CO_2$ emissions (CO2E) are treated as integrated of order one, I(1), over 2000-2024. This pattern is typical of macro-energy indicators that evolve with persistent trends and occasional structural shifts. Modeling choices therefore rely on stationary transformations to ensure that estimated short-run dynamics capture genuine co-movements rather than shared drifts. Taken together, the ADF evidence provides a consistent statistical basis for the subsequent VAR specification, interpretation of transmission mechanisms, and comparison of results across procedures.

Lag selection is assessed with the sequential LR test, the Final Prediction Error, and the AIC/SC/HQ information criteria, as reported in Table 4. All three information criteria reach their lowest values at one lag, and FPE is also minimized at $P = 1$. The LR statistic clearly rejects a zero-lag specification in favor of one lag at the 5% level, while the additional move to $P = 2$ offers no meaningful improvement. Although the log-likelihood increases when more lags are added, the associated penalties in AIC/SC/HQ outweigh these small gains at $P = 2$, signaling diminishing returns and potential over-parameterization for an annual sample of this size. With roughly two dozen usable observations after adjustments, a parsimonious structure helps control estimation uncertainty and preserves degrees of freedom for downstream analysis. Taken together, the criteria align on a baseline VAR(1), which balances fit and tractability and is well suited for tracing short-run transmission, variance decomposition, and Granger causality.

On impact, AGRI is explained entirely by its own innovations; external shocks begin to matter only as the forecast horizon extends in Table 5. The own contribution declines from 100% to roughly three-fifths by period 10, while the share attributed to CO2E rises steadily to about two-fifths, pointing to a substantive environmental transmission channel. In contrast, contributions from ENRC and RENE remain consistently small across horizons - each staying below roughly 2% even at longer leads. Taken together, CO2E shocks are the dominant external force behind AGRI fluctuations, whereas ENRC and RENE provide only limited incremental explanatory power.

ENRC is predominantly driven by its own innovations across horizons: the own share falls from about 93% on impact to

**Table 3: Results of the ADF unit root test**

| Variable | Level | | 1st difference | |
|---|---|---|---|---|
| | t- Statistics | P value | t- Statistics | P value |
| AGRI | −1.153613 | 0.6760 | −14.09324 | 0.0000 |
| ENRC | −2.374618 | 0.1589 | −4.482451 | 0.0019 |
| RENE | −1.880682 | 0.3351 | −4.320027 | 0.0028 |
| CO2E | −2.404640 | 0.1510 | −4.278562 | 0.0030 |
| Test critical values | | | | |
| 1% level | −3.752946 | | −3.752946 | |
| 5% level | −2.998064 | | −2.998064 | |
| 10% level | −2.638752 | | −2.638752 | |

**Graph 1:** Research variables time series graph

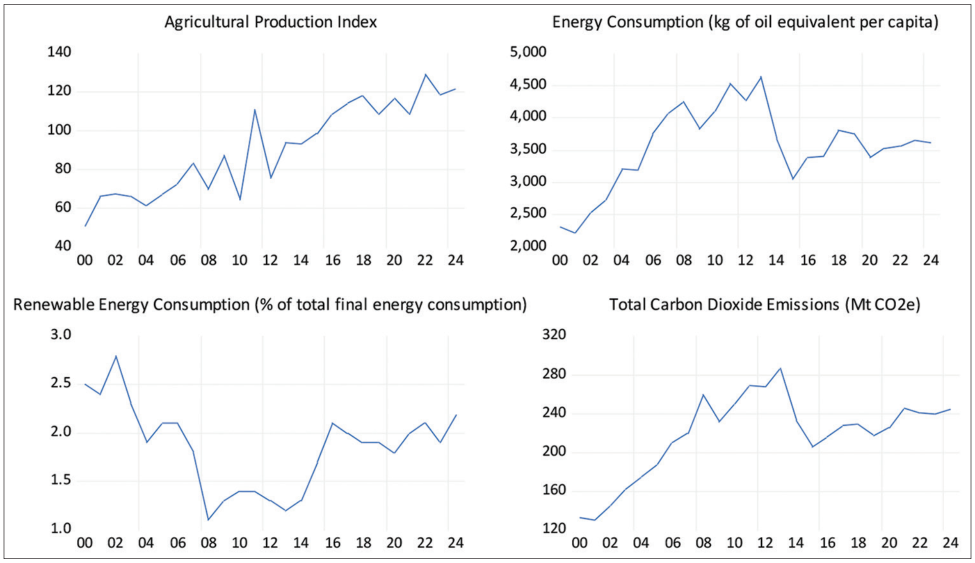


**Table 4: VAR lag length criteria**

| Lag | LogL | LR: Sequential modified LR test statistic (each test at 5% level) | FPE: Final prediction error | AIC: Akaike information criterion | SC: Schwarz information criterion | HQ: Hannan-Quinn information criterion |
|---|---|---|---|---|---|---|
| 0 | 50.88708 | NA | 1.99e-07 | −4.077137 | −3.879660 | −4.027472 |
| 1 | 96.92328 | 72.05666* | 1.50e-08* | −6.688981* | −5.701595* | −6.440656* |
| 2 | 111.7664 | 18.06985 | 1.93e-08 | −6.588380 | −4.811085 | −6.141396 |

**Table 5: Variance decomposition of AGRI**

| Variance period | Decomposition standard error | LOG_AGRI | LOG_ENRC | RENE | LOG_$CO_2$E |
|---|---|---|---|---|---|
| 1 | 0.141088 | 100.0000 | 0.000000 | 0.000000 | 0.000000 |
| 2 | 0.180840 | 69.48031 | 0.023843 | 0.897639 | 29.59820 |
| 3 | 0.200487 | 67.24239 | 0.392125 | 0.865880 | 31.49961 |
| 4 | 0.212160 | 64.62201 | 0.358402 | 0.821128 | 34.19846 |
| 5 | 0.219212 | 63.17785 | 0.376647 | 0.803270 | 35.64223 |
| 6 | 0.223847 | 62.00243 | 0.537118 | 0.777886 | 36.68256 |
| 7 | 0.227037 | 61.09452 | 0.783165 | 0.756998 | 37.36531 |
| 8 | 0.229311 | 60.38550 | 1.048637 | 0.742147 | 37.82372 |
| 9 | 0.230950 | 59.84726 | 1.288616 | 0.732438 | 38.13169 |
| 10 | 0.232137 | 59.44578 | 1.485980 | 0.726258 | 38.34198 |

**Table 6: Variance decomposition of ENRC**

| Variance period | Decomposition standard error | LOG_AGRI | LOG_ENRC | RENE | LOG_$CO_2$E |
|---|---|---|---|---|---|
| 1 | 0.094451 | 6.752830 | 93.24717 | 0.000000 | 0.000000 |
| 2 | 0.133049 | 8.935231 | 86.64530 | 1.847575 | 2.571895 |
| 3 | 0.147736 | 8.306121 | 86.20880 | 2.384193 | 3.100891 |
| 4 | 0.154480 | 7.841034 | 85.71044 | 2.665739 | 3.782786 |
| 5 | 0.157473 | 7.558006 | 85.35257 | 2.766102 | 4.323320 |
| 6 | 0.158952 | 7.424518 | 85.01452 | 2.796181 | 4.764782 |
| 7 | 0.159762 | 7.380118 | 84.72030 | 2.799142 | 5.100440 |
| 8 | 0.160255 | 7.377813 | 84.47758 | 2.794155 | 5.350455 |
| 9 | 0.160579 | 7.391542 | 84.28721 | 2.787919 | 5.533334 |
| 10 | 0.160801 | 7.408687 | 84.14277 | 2.782477 | 5.666070 |

roughly 84% by period 10 in Table 6. AGRI shocks account for a stable secondary portion - around 7-9% initially and near 7.4% at longer leads - indicating limited but persistent spillovers from the real sector. The influence of CO2E rises monotonically from near zero to about 5-6% by period 10, suggesting a gradual environmental feedback into energy demand. RENE shocks contribute the least (≈2-3% at longer horizons), implying that shifts in the renewables ratio have only a weak short-run effect on aggregate ENRC. Overall, ENRC dynamics are self-driven, with modest contributions from agriculture and emissions and minimal renewable-induced variance.

RENE is driven by its own shocks at the outset, but this influence fades quickly as the horizon lengthens in Table 7. By the tenth period, movements in ENRC account for the largest share of forecast-error variance - around three-fifths - signaling that aggregate energy demand and system constraints largely steer renewable uptake. AGRI contributes a smaller yet durable portion - roughly one-quarter - consistent with sectoral complementarities and investment co-movements. The role of CO2E remains negligible across horizons, indicating limited direct emissions-led adjustments under the chosen orthogonalization. Overall, RENE dynamics appear chiefly demand-led, with own shocks dissipating relatively quickly.

CO2E variability is driven chiefly by shocks to ENRC: İnnovations in ENRC explain roughly three-quarters of the forecast-error variance across horizons in Table 8. Own-shock persistence is the next most important factor, with the CO2E component rising from about one-fifth to nearly one-quarter by the tenth period, indicating a durable emissions process. Contributions from AGRI and RENE remain small and stable - generally around 1-2% - once system-wide energy shocks are orthogonalized. Taken together, the decomposition portrays emissions as largely demand-led by aggregate ENRC, with modest self-propagation and only limited incremental roles for AGRI and RENE over the forecast horizon.

Using annual observations for 2000-2024 and a one-lag specification, the Granger causality tests reveal limited short-run predictability among agricultural growth (AGRI), total energy consumption (ENRC), the renewable share (RENE), and $CO_2$ emissions (CO2E) are shown in Table 9. One linkage stands out: ENRC → RENE. Innovations in aggregate ENRC possess incremental forecasting power for subsequent movements in the RENE, whereas the reverse direction does not clear conventional significance thresholds. No other pairs display reliable directional effects at this horizon, suggesting that the remaining interactions are predominantly contemporaneous or adjust more slowly than a 1-year lag captures.

In Kazakhstan's setting, the ENRC → RENE result is consistent with a demand-led energy system: changes in overall energy conditions precede adjustments in the RENE, while AGRI and CO2E offer little short-run predictive content for each other or

**Table 7: Variance decomposition of RENE**

| Variance period | Decomposition standard error | LOG_AGRI | LOG_ENRC | RENE | LOG_$CO_2$E |
|---|---|---|---|---|---|
| 1 | 0.186146 | 21.52645 | 1.615342 | 76.85821 | 0.000000 |
| 2 | 0.287551 | 25.08426 | 41.33600 | 32.79216 | 0.787582 |
| 3 | 0.361829 | 24.75076 | 53.32425 | 21.41125 | 0.514045 |
| 4 | 0.397104 | 24.00208 | 57.04357 | 13.52664 | 0.427708 |
| 5 | 0.411919 | 23.57098 | 58.35997 | 17.66652 | 0.402535 |
| 6 | 0.417471 | 23.34510 | 58.85109 | 17.40160 | 0.402209 |
| 7 | 0.419420 | 23.23667 | 59.03273 | 17.31938 | 0.411215 |
| 8 | 0.420080 | 23.18709 | 59.09804 | 17.29299 | 0.421876 |
| 9 | 0.420309 | 23.16515 | 59.11993 | 17.28348 | 0.431442 |
| 10 | 0.420396 | 23.15561 | 59.12601 | 17.27926 | 0.439116 |

**Table 8: Variance decomposition of CO2E**

| Variance period | Decomposition standard error | LOG_AGRI | LOG_ENRC | RENE | LOG_$CO_2$E |
|---|---|---|---|---|---|
| 1 | 0.080038 | 1.795434 | 69.80688 | 0.995372 | 27.40231 |
| 2 | 0.111001 | 1.413810 | 76.17364 | 0.849250 | 21.56330 |
| 3 | 0.129400 | 1.199349 | 76.56096 | 1.342337 | 20.89735 |
| 4 | 0.139091 | 1.038650 | 76.02459 | 1.604364 | 21.33239 |
| 5 | 0.144452 | 1.029490 | 75.15760 | 1.715613 | 22.09730 |
| 6 | 0.147574 | 1.133343 | 74.29525 | 1.747247 | 22.82416 |
| 7 | 0.149523 | 1.284174 | 73.54734 | 1.747752 | 23.42074 |
| 8 | 0.150806 | 1.437443 | 72.94712 | 1.738594 | 23.87684 |
| 9 | 0.151682 | 1.570840 | 72.48637 | 1.728200 | 24.21459 |
| 10 | 0.152293 | 1.677880 | 72.14221 | 1.719234 | 24.46068 |

**Table 9: Results of the Granger causality analysis**

| Null hypothesis | Observations | F-statistic | Probability |
|---|---|---|---|
| LOG_ENRC does not Grander Cause LOG_AGRI | 24 | 0.27461 | 0.6057 |
| LOG_AGRI does not Grander Cause LOG_ENRC | | 0.10314 | 0.7513 |
| RENE does not Grander Cause LOG_AGRI | 24 | 0.26099 | 0.6148 |
| LOG_AGRI does not Grander Cause RENE | | 0.12007 | 0.7324 |
| LOG_CO2E does not Grander Cause LOG_AGRI | 24 | 1.78844 | 0.1954 |
| LOG_AGRI does not Grander Cause LOG_CO2E | | 0.02382 | 0.8788 |
| RENE does not Grander Cause LOG_ENRC | 24 | 0.79300 | 0.3833 |
| LOG_ENRC does not Grander Cause RENE | | 13.3905 | 0.0015 |
| LOG_CO2E does not Grander Cause LOG_ENRC | 24 | 0.03685 | 0.8496 |
| LOG_ENRC does not Grander Cause LOG_CO2E | | 0.41460 | 0.5266 |
| LOG_CO2E does not Grander Cause RENE | 24 | 2.45462 | 0.1321 |
| RENE does not Grander Cause LOG_CO2E | | 0.78271 | 0.3863 |

for energy variables. Taken together, the pattern complements the broader VAR evidence by indicating that near-term RENE uptake is chiefly responsive to movements in ENRC conditions rather than to lagged shifts in AGRI or CO2E.

## 5. CONCLUSION AND RECOMMENDATIONS

The results portray a demand-led nexus in Kazakhstan in which aggregate energy conditions anchor short-run adjustment. Forecast variance shares show AGRI driven mainly by its own shocks, with a tangible medium-horizon contribution from CO2E. ENRC remains largely self-propelled, while RENE is chiefly shaped by movements in ENRC; own shocks to RENE dissipate quickly, AGRI provides a smaller yet persistent share, and CO2E is negligible once shocks are orthogonalized. CO2E variability, in turn, reflects ENRC innovations and its own persistence. Pairwise Granger tests reinforce this pattern, identifying ENRC-RENE as the only robust link and indicating weak short-run directionality elsewhere. In sum, near-term dynamics originate on the energy-demand margin; renewables and emissions adjust accordingly, whereas agriculture is influenced primarily by internal dynamics and an environmental channel.

Policy should act where transmission is strongest. In the near term, moderating total energy demand through industrial and building efficiency standards, time-of-use pricing, and demand-response programs is most likely to register promptly in both renewable uptake and emissions. Converting these demand signals into durable capacity requires grid-side readiness: greater flexibility and interconnection, clearer dispatch and balancing rules, and a stable pipeline of competitively awarded projects under bankable long-term PPAs, complemented by storage and curtailment-reduction measures. Given the medium-run role of $CO_2$ in agricultural variance, climate-smart upgrades in irrigation, inputs, and post-harvest systems can bolster sectoral resilience without blunting output.

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