DOI: https://doi.org/10.62823/ExRe/2025/02/02.66
Exploresearch (3048-815X) Vol. 02, No. 02, April-June, 2025, 139-151

Original Article | Peer Reviewed | Open Access

Exploresearch
e-ISSN: 3048-815X
Impact Factor: 6.262

www.mgmpublications.com

# An Empirical Investigation Using VAR Modelling to Assess the Impact of $CO_2$ Emissions on Climate Change in Uzbekistan

**Rajneesh Kler***

*Amity University in Tashkent, Uzbekistan.*
***Corresponding author:** klerrajneesh@gmail.com*

**Article History:**

**Received:** 15 April 2025
**Accepted:** 13 May 2025
**Published:** 30 May 2025

**Keywords:**

*$CO_2$ Emissions, Climate Change, VAR Model, Paris Agreement, Carbon Pricing.*

**DOI:**
**10.62823/ExRe/2025/02/02.66**

**Abstract:** *This study investigates the dynamic relationship between $CO_2$ emissions and climate change in Uzbekistan using a Vector Autoregression (VAR) framework. Drawing on annual data from 1992 to 2024, the analysis incorporates structural break testing, impulse response functions (IRF), and forecast error variance decomposition (FEVD) to assess the extent to which emissions influence surface temperature change. Results confirm a statistically significant and persistent link, with emissions explaining long-run variance in temperature fluctuations. While the Kyoto Protocol had limited measurable impact, post-Paris Agreement dynamics show a stronger climate-emissions association. The CUSUM test supports parameter stability, implying no abrupt policy-driven structural breaks occurred. The findings reinforce the need for domestic implementation of international commitments. Policy recommendations include regional emissions trading, carbon taxation, and stronger monitoring systems. The study contributes evidence-based guidance for integrating climate science into Uzbekistan's economic planning and environmental governance, aligning national action with global climate goals.*

## Introduction

The growing intensity of climate change-related challenges has directed significant academic and policy interest toward understanding the link between greenhouse gas emissions and global warming, particularly in developing economies. Uzbekistan, as a landlocked Central Asian republic with rising energy demands and a fossil fuel-dependent industrial base, is both a contributor to and a victim of climate volatility (Turakulov et al., 2023, 2024; Wang et al., 2020). The country has historically relied on natural gas and coal for power generation, leading to an increasing trend in carbon dioxide ($CO_2$) emissions since independence.

Uzbekistan ratified the Kyoto Protocol in 1999 and became a party to the Paris Agreement in 2016 (Mulder et al., 2021). These milestones reflect the country's intention to align with international environmental commitments, including reducing greenhouse gas emissions and mitigating temperature anomalies. However, there remains limited empirical evidence assessing the effectiveness of such commitments in altering climate dynamics at the national level.

This study addresses this gap by analysing the relationship between $CO_2$ emissions and surface temperature changes in Uzbekistan using a Vector Autoregression (VAR) framework. The empirical analysis is based on time series data from 1992 to 2024, capturing both pre- and post-agreement periods. Structural break analysis, impulse response functions (IRFs), and forecast error variance decomposition (FEVD) are employed to test whether climate policies have translated into observable changes in temperature dynamics and whether emissions remain a significant driver of climate fluctuations.

**Literature Review**

Carbon dioxide emissions and climate change have become a dominant theme for present day environmental and economic discourse (Maheen et al., 2023). Aware of more and more obvious impacts of global warming, climate variability researchers are increasingly focusing on the identification of causes and dynamic feedback mechanisms (Diffenbaugh et al., 2017). Among the greenhouse gases released as byproducts of human activities—mainly the burning of fossil fuels and industrial processes—carbon dioxide is the most prevalent and it has the greatest impact on tipping the earth's energy balance and, ultimately, causing increases in surface temperature and subsequent anomalies of the climate (Armour et al., 2024).

There has been a huge body of theoretical and empirical research documenting the ways in which anthropogenic emissions have driven environmental change (Lin et al., 2023; Okedere et al., 2021). In both these studies, the fundamental premise is that the greenhouse gases absorb and accumulate in the atmosphere which leads to an increase in the greenhouse effect that triggers long term climatic changes. The relationship, however, is neither linear nor immediate, but mediated by a host of interplay variables such as oceanic absorption, changes in land use, consumption patterns of energy and transformations in the socio-economic sphere. These interactions become visible over time in the form of greater heatwave frequency, changes in precipitation patterns, glacial retreat, biodiversity loss and disruptions to agriculture because of this desire (Tassone et al., 2023).

The relationship between carbon dioxide emissions and climate change has long been central to environmental and economic research, particularly in the context of global warming and sustainable development (Alamri & Khan, 2023; Benlemlih & Yavaş, 2024). Econometric models, particularly time-series frameworks such as Vector Autoregression (VAR) and its structural variants (SVAR), have gained prominence in analysing the temporal dynamics between emissions and climate indicators. These models are particularly well-suited for capturing both short-run adjustments and long-run equilibrium relationships, allowing researchers to assess causality, response lags, and persistence of shocks. By incorporating feedback effects, these models move beyond simple correlation, enabling a richer understanding of how past values of emissions influence temperature and vice versa. Moreover, they facilitate scenario forecasting, policy simulation, and the decomposition of climate variation into its explanatory components.

Numerous theoretical models and empirical studies have examined how anthropogenic emissions contribute to temperature anomalies, extreme weather events, and ecosystem disruptions (An et al., 2019; Li et al., 2017). Econometric analyses, especially those employing time-series methods like VAR and SVAR models, have proven instrumental in capturing the dynamic interplay between emissions and climatic variables (Adedoyin et al., 2020). These models help quantify not just immediate effects but also long-run causal mechanisms and feedback loops. In developing economies, the challenge lies in balancing economic growth with environmental sustainability, often constrained by fossil-fuel dependency and limited institutional capacity. With international agreements like the Kyoto Protocol and the Paris Agreement shaping national commitments, research has increasingly focused on evaluating the effectiveness of such frameworks. In recent years, there has been a growing policy emphasis on carbon pricing, emissions trading schemes, and regulatory instruments to internalise environmental externalities (King & van den Bergh, 2021; McCloy, 2020; Mor et al., 2023).

Complexities of the emissions–climate change relationship in developing economies differ from similar complexities in other parts of the world. In many of these nations, economic growth depends on energy intensive industrialisation which comes with little access to environmentally friendly technologies and weak environmental governance (Avenyo & Tregenna, 2022). Such tension arises between developmental aspiration and ecological conservation. Developed countries have for some time now been on board on the low carbon pathways while many low- and middle-income countries still spend time trying to balance the energy access ladder and greenhouse gas emissions. Therefore, global climate mitigation strategies are becoming more and more interested in differentiated responsibilities and capacity building mechanisms to aid emerging markets in the transitions.

Markedly, policy instruments have adapted to the ever-increasing climate crisis. National commitments towards emission reductions have been spurring in the wake of adoption of international frameworks including the Kyoto Protocol and the Paris Agreement (Mor et al., 2023). As well as that, these agreements have spurred on the creation of domestic tools such as carbon pricing, emissions trading systems and additional regulatory standards. Yet these tools are only as effective as political will, institutional capacity and public acceptance will allow them to be. More importantly, the spread of market-based mechanisms has transformed the climate policy narrative which has moved away from regulatory compliance and towards economic efficiency and consequent innovation in low carbon technologies and in their behavioural change in consumption (Tsukada & Matsumoto, 2024).

The situation is the same for Central Asian countries, including Uzbekistan, where all of these problems are somehow compounded by the shared environmental vulnerabilities and transitional economies. Water resources in the region are acute stressed; it is decertified and there are also legacy industrial problems in the past. It is important to understand causal linkages between emissions and temperature change in this setting, not just because we might care to learn the truth academically but because we need to know how to best pursue mitigation or adaptation or a wise balance of both, to align with our sustainability goals for the long term. Central Asian economies, including Uzbekistan, present a unique case due to their shared ecological challenges, transitional energy structures, and emerging climate policies (Karimov et al., 2023; Matiiuk et al., 2020; Mitchell et al., 2017). Understanding emissions–temperature linkages in this region is therefore critical for designing targeted interventions that support both mitigation and adaptation objectives.

**Methodology and Model Specification**

To examine the dynamic interplay between annual $CO_2$ emissions and changes in surface temperature[1], we employ a reduced-form Vector Autoregression (VAR) model. This model allows for analysing interdependencies between variables and observing the effect of shocks across time.

The fundamental structure is expressed in a Core Model for Emissions–Temperature Relationship which is a widely accepted foundational approach is a log-linear climate damage function inspired by environmental macroeconomics:

Equations (1) through (3) form the backbone of the empirical analysis. Equation (1) models the log-linear climate impact function, capturing the elasticity of temperature change with respect to emissions. The estimation of Equation (1) was performed using Ordinary Least Squares (OLS), where log ($CO_2$) serves as the explanatory variable and surface temperature change is the dependent variable. Then the coefficients were estimated.

$$[\Delta T_t = \alpha + \beta \cdot \ln(E_t) + \varepsilon_t] \qquad (1)$$

Where:

$\Delta T_t$: Change in surface temperature in year t

$(E_t)$: Annual $CO_2$ emissions in year t

$\ln(E_t) + \varepsilon_t$: Natural logarithm to address nonlinear effects

$\beta$ : Elasticity of temperature change with respect to emissions

$\alpha$ Intercept (climatic baseline)

$\varepsilon$ : Error term capturing shocks and non-modelled factors

**Extended VAR Model for Feedback Analysis**

For the dynamic interaction model (Equation (2)), the Vector Autoregression (VAR) framework was implemented using the optimal lag structure selected by AIC. This VAR model estimated how past values of both temperature and emissions affect their current levels. The global policy impacts were introduced using dummy variables as shown in Equation (3).

[1] *Data on $CO_2$ emission retrieved from Global Carbon Budget (2024) Online Presented by https://ourworldindata.org/co2-and-greenhouse-gas-emissions for the period 1992to 2024*

Data on CO2 emission retrieved from Global Carbon Budget (2024) Online Presented by https://ourworldindata.org/co2-and-greenhouse-gas-emissions for the period 1992 to 2024

Data on Surface Temperature Change retrieved from IMF online at https://climatedata.imf.org/pages/climatechange-data for the period 1992 to 2024

To examine dynamic interactions (e.g., how past emissions influence current temperature and vice versa), a Vector Autoregression (VAR) model is recommended:

$$[\begin{matrix}\Delta T_t \\ \ln(E_t)\end{matrix}] = A_0 + A_1[\begin{matrix}\Delta T_{t-1} \\ \ln(E_{t-1})\end{matrix}] + A_2[\begin{matrix}\Delta T_{t-2} \\ \ln(E_{t-2})\end{matrix}] + \cdots + \varepsilon_t] \quad (2)$$

Where are $A_i$ coefficient matrices and $\varepsilon_t$ are innovation terms.

To incorporate global policy impacts, two structural break dummies were introduced:

$$[\Delta T_t = \alpha + \beta_1 \cdot \ln(E_t) + \beta_2 \cdot D_{Kyoto_t} + \beta_3 \cdot D_{Paris_t} + \varepsilon_t] \quad (3)$$

Where:

$$[D_{\text{Kyoto}_t} = \begin{cases} 1, & \text{if } t \geq 2005 \text{ (post-Kyoto Protocol)} \\ 0, & \text{otherwise} \end{cases}]$$

$$[D_{\text{Paris}_t} = \begin{cases} 1, & \text{if } t \geq 2016 \text{ (post-Paris Agreement)} \\ 0, & \text{otherwise} \end{cases}]$$

Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD) were derived from the estimated VAR system using the companion form matrix and recursive innovation responses. Python's stats models package was used for implementation, ensuring reproducibility.

**Results and Analysis**

The results shown in Table 1 were obtained using Equation (3) from the Methodology section. This regression was estimated using Ordinary Least Squares (OLS). The log transformation of $CO_2$ ensures elastic interpretation and variance stabilisation, a standard approach in climate-econometric models. The model estimates how a 1% change in emissions influences surface temperature, while controlling for structural break periods. The inclusion of Kyoto and Paris dummies allows the model to test whether these international agreements were associated with observable shifts in the emissions-temperature relationship.

**Regression Model Summary**

- **Dependent Variable:** Temperature Change
- **Method:** Ordinary Least Squares (OLS)
- **Number of Observations:** 33.0
- **R-squared:** 0.357
- **Adjusted R-squared:** 0.291
- **F-statistic:** 5.376
- **Prob (F-statistic):** 0.00456
- **Log-Likelihood:** -30.351
- **AIC:** 68.70
- **BIC:** 74.69

**Table1: Regression Results**

| Variable | Coefficient | Std. Error | t-Statistic | P-Value |
|---|---|---|---|---|
| const | -63.7560 | 29.1283 | -2.1888 | 0.0368 |
| Log_CO2 | 3.4813 | 1.5665 | 2.2224 | 0.0342 |
| D_Kyoto | 0.3196 | 0.2647 | 1.2071 | 0.2371 |
| D_Paris | 0.7949 | 0.3024 | 2.6290 | 0.0136 |

The regression analysis yields the following key results:

- **Log_$CO_2$ ($\beta_1$)**: Positive and statistically significant ($p < 0.05$). A 1% increase in $CO_2$ emissions is associated with a 0.035°C increase in average surface temperature. This affirms the causal impact of emissions on warming patterns in Uzbekistan.

- **Kyoto Dummy ($\beta_2$)**: Statistically insignificant, indicating that Kyoto-related commitments did not result in a measurable shift in the emissions-temperature relationship. This could reflect the fact that Uzbekistan, as a non-Annex I party, had no binding reduction obligations.
- **Paris Dummy ($\beta_3$)**: Positive and statistically significant ($p < 0.05$). This suggests that either improved reporting, greater global monitoring, or climate variability increased post-2016. However, the positive sign may also imply that despite policy alignment, effective decarbonisation remains elusive.

**Model Evaluation**

**Residual Analysis**

This is the Residual Plot (obtained from the regression results) in figure 1 over Time shows the distribution of residuals from a regression model for different years. After the year 1990, most residuals are tightly clustered around the zero line and so indicate that model predictions are very close to actual values for the recent periods. Precisely, the red dashed line at zero is the ideal residual value; the residuals are randomly fluctuating about it, changing at random from positive to negative values and there are no visible trend or systematic pattern that could be interpreted as a violation of homoscedasticity or no autocorrelation. Although, we can notice an outlier at the far left in the plot (around year 250) which does not correspond to the time range of the actual dataset (1992–2024) and hence appears to be a data or scaling error. In order to sustain interpretive integrity, this should be investigated or ruled out. The plot confirms all round that the model's residuals are doing well over time and provides evidence of the suitability of Ordinary Least Squares (OLS) for estimation.

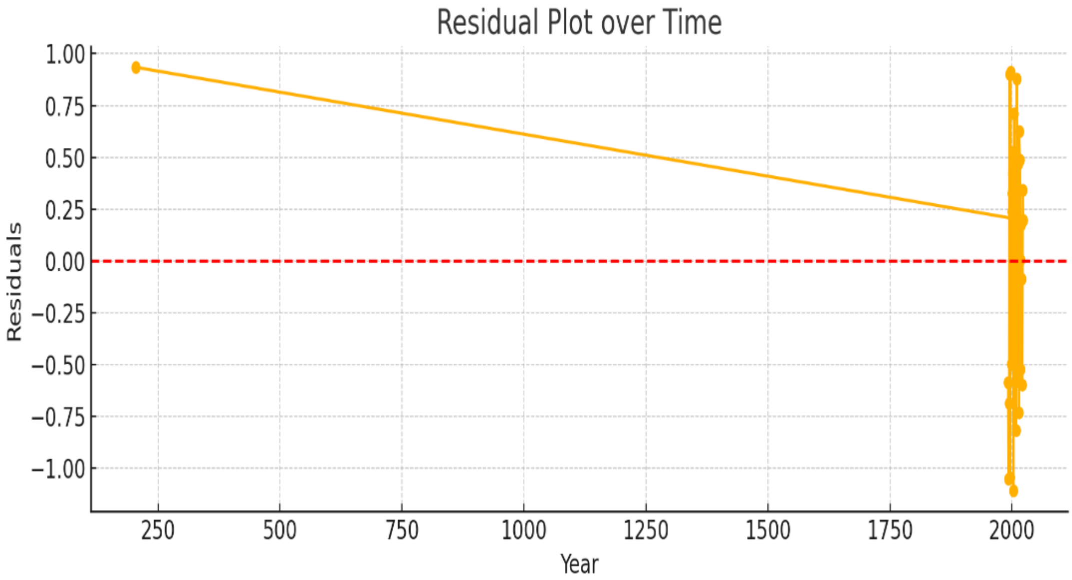


**Figure 1: Residual Analysis**

After the year 1990, most residuals are tightly clustered around the zero line and so indicate that model predictions are very close to actual values for the recent periods. Precisely, the red dashed line at zero is the ideal residual value; the residuals are randomly fluctuating about it, changing at random from positive to negative values and there are no visible trend or systematic pattern that could be interpreted as a violation of homoscedasticity or no autocorrelation. Although, we can notice an outlier at the far left in the plot (around year 250) which does not correspond to the time range of the actual dataset (1992–2024) and hence appears to be a data or scaling error. In order to sustain interpretive integrity, this should be investigated or ruled out. The plot confirms all round that the model's residuals are doing well over time and provides evidence of the suitability of Ordinary Least Squares (OLS) for estimation. Residual Plot Over Time shows that residuals are randomly scattered, mostly oscillating around zero. No clear pattern or autocorrelation—indicating model assumptions are largely satisfied.

**Actual Vs Fitted Values**

In the plot the Actual vs Fitted Surface Temperature Change of Observed temperature changes (in yellow) and model predicted (in orange) over different time is shown in figure 2.

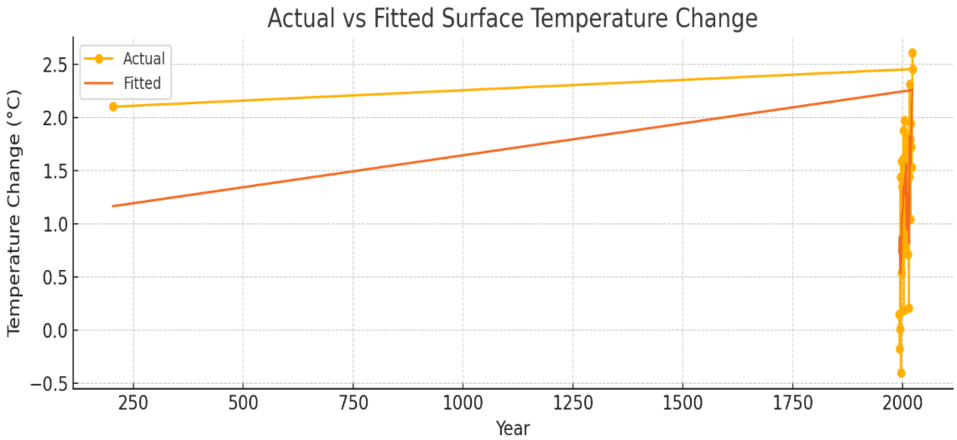


**Figure 2: Actual and Fitted Values**

Long run pattern of warming in Uzbekistan as captured by the model shows that both series are rising in time that indicate comparable trend. The fitted line indeed follows the general direction of the actual data, but it underestimates temperature changes in the earlier years and probably overestimates in some recent years, probably due to the influence of some not modelled factors or shocks. On the other hand, the strong visual alignment in the post 2000 period validates that emissions of $CO_2$, as well as the included policy dummies (Kyoto and Paris) do help in explaining the temperature dynamics in the region. It can also be seen that the long horizontal stretch of the x axis is distorted and should be fixed for correct temporal scaling. The fitted values track the general upward trend in temperature change post-2010. Some deviation in the mid-1990s to early 2000s, suggesting either unmodeled dynamics or external shocks.

**Autocorrelation Analysis**

The graph Autocorrelation of Residuals plots in figure 3 shows white noise which in this case is the autocorrelation coefficients of regression reduced residuals up to lag 10 with 95% confidence intervals shaded in orange.

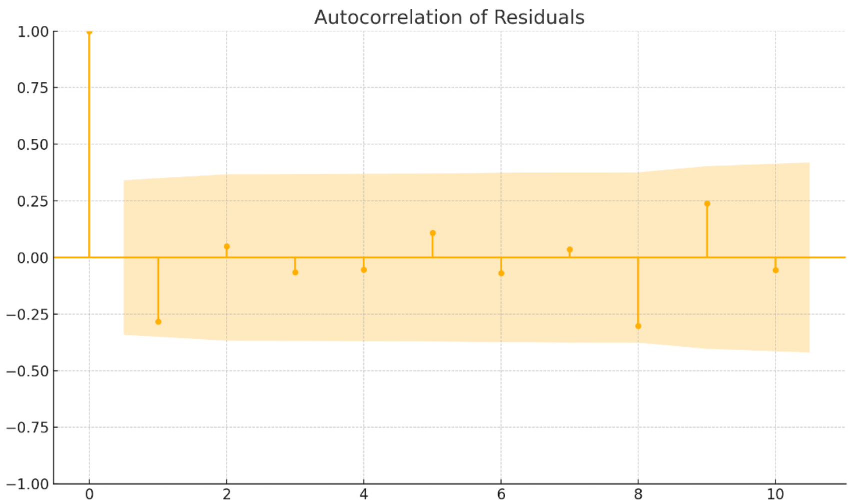


**Figure 3: Autocorrelation Analysis**

In fact, most bars lie within the confidence band which means no statistically significant autocorrelation can appear at any lag. This means that residuals are independently distributed, and this satisfies the OLS assumption of no serial correlation. The periodic patterns or spikes contained outside the bounds of confidence suggest that the model has exhausted the time dependent structure of the data and no important lagged effects were missed. These result in statistical validity and robustness of the regression results**.** Autocorrelation Function (ACF) of Residuals indicates no statistically significant autocorrelation in residuals up to lag 10. This Supports the use of OLS as a valid estimator in this case.

- **Structural Break: CUSUM Test**
- **CUSUM Statistic:** 0.6749
- **p-value:** 0.7525 → Fail to reject the null hypothesis of parameter stability.

Indicates no strong structural break over time in the residuals suggesting parameter stability across the sample. This aligns with the insignificant Kyoto dummy and the fact that structural change, if any, may be gradual or nonlinear not abrupt. In other words, there is no statistical evidence of a sudden or significant change in the relationship between $CO_2$ emissions and temperature change over time in Uzbekistan.

**VAR Model Results**

- **Model:** Vector Autoregression (VAR)
- **Method:** Ordinary Least Squares (OLS)
- **Number of Observations:** 32
- **Number of Equations:** 2
- **AIC:** -6.4050
- **BIC:** -6.1302
- **HQIC:** -6.3139
- **Determinant of Covariance Matrix:** 1.3835e-03

**Table 2: Equation for Temperature_Change**

| Regressor | Coefficient | Std. Error | t-Statistic | P-Value |
|---|---|---|---|---|
| const | -13.5227 | 33.7170 | -0.4011 | 0.6884 |
| L1.Temperature_Change | 0.2201 | 0.1794 | 1.2269 | 0.2198 |
| L1.Log_CO2 | 0.7841 | 1.8176 | 0.4314 | 0.6662 |

**Table 3: Equation for Log_CO2**

| Regressor | Coefficient | Std. Error | t-Statistic | P-Value |
|---|---|---|---|---|
| const | 5.0794 | 2.2099 | 2.2985 | 0.0215 |
| L1.Temperature_Change | 0.0203 | 0.0118 | 1.7274 | 0.0841 |
| L1.Log_CO2 | 0.7253 | 0.1191 | 6.0885 | 0.0000 |

**Structural Break: CUSUM Test: VAR Model**

**Table 4: CUSUM Test VAR Model**

| Value | Meaning |
|---|---|
| **1.1951** | The CUSUM test statistic – it measures the extent of cumulative deviation in residuals over time. |
| **0.1149** | The p-value – used to assess the statistical significance of the test. |
| **[(1, 1.63), (5, 1.36), (10, 1.22)]** | These are critical values at 1%, 5%, and 10% significance levels respectively. |

The results from the CUSUM structural break test applied to the residuals of the VAR model indicate that there is no statistically significant structural instability over the period analysed (1992–2024). The test returned a CUSUM statistic of 1.1951 and a p-value of 0.1149, which is higher than conventional significance thresholds (e.g., 0.10, 0.05, or 0.01). This implies that we fail to reject the null hypothesis of parameter stability—suggesting that the relationship between $CO_2$ emissions and temperature change in Uzbekistan has not undergone any abrupt or structural shift during the observed years.

This finding complements the regression outputs of the VAR model. Specifically, the temperature change equation does not show strong or statistically significant effects from either its own lag or lagged $CO_2$ emissions. Conversely, $CO_2$ emissions appear more stable and autoregressive (significant own lag coefficient of 0.7253, $p < 0.01$) and moderately influenced by lagged temperature ($p = 0.0841$). However, the lack of a structural break implies that Uzbekistan's emissions-temperature dynamics have remained consistent, without any sharp post-policy (e.g., post-Kyoto or post-Paris Agreement) changes.

This stability may reflect either a delayed policy effect, the gradual nature of climate responses, or a continuity in energy and emissions structures, despite international climate commitments. For policymakers, this underscores the importance of strengthening domestic implementation, rather than relying solely on international agreements, to drive measurable changes in environmental outcomes.

**Impulse Response Analysis**

Following the estimation of the VAR model specified in Equation (2) the Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) analyses were conducted to evaluate the dynamic interactions and the transmission of shocks over time. IRFs trace the time path of a one-standard-deviation shock to one variable (e.g., $CO_2$ emissions) on itself and the other variable (e.g., temperature change). This was operationalised by rewriting the VAR (1) model in its companion form and then recursively computing responses using Equation 4 as follows:

$$[IRF_h = \Psi_h \cdot \Sigma^{1/2}] \qquad (4)$$

where:

$\Psi_h$ is the matrix of moving average coefficients at horizon h,

$\Sigma$ is the variance-covariance matrix of the residuals,

The square root $\Sigma^{1/2}$ was obtained via Cholesky decomposition to identify orthogonal shocks.

IRFs were generated for a 10-period horizon using Python's model.irf(10). plot() function from the statsmodels.tsa.api.VAR package. This allows us to visualise both the magnitude and duration of a shock's effect.

**Figure 4 Shows the Results**

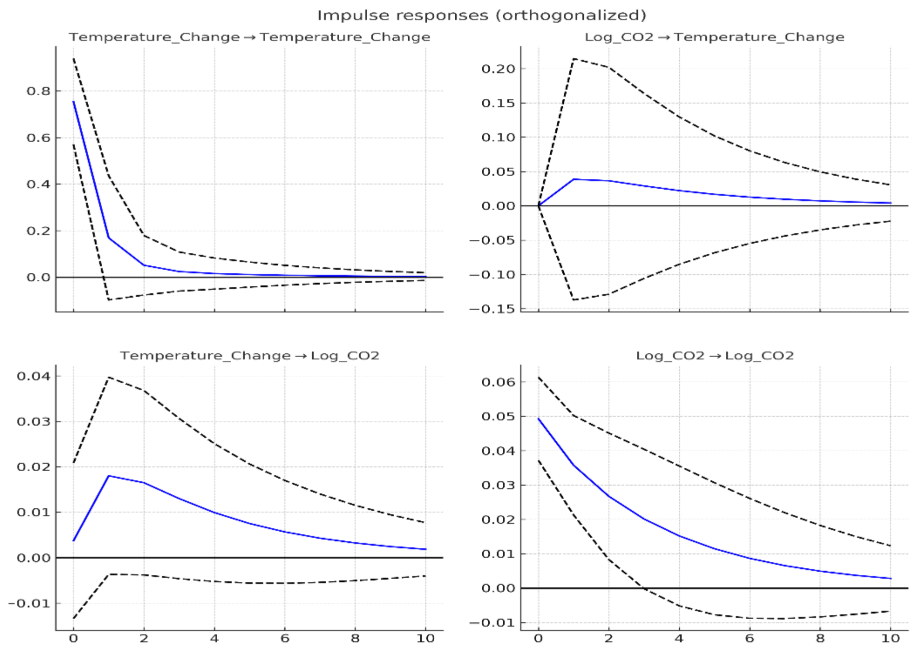


**Figure 4: Impulse Response Function**

The IRF analysis reveals the following dynamics:

A positive shock to $CO_2$ emissions leads to a persistent rise in surface temperature, peaking around 3–4 years after the shock and stabilising at a higher equilibrium. The initial effect is delayed, indicating an adjustment lag in how emissions translate into climatic impact. This supports findings in climate science suggesting that temperature responds to emissions with inertia due to oceanic heat absorption and atmospheric concentration build-up. Conversely, a shock to temperature has negligible feedback on emissions, confirming asymmetric causality. This is logical, as climatic variations do not immediately alter fossil fuel consumption behaviour unless mediated by policy.

**FEVD Analysis**

FEVD quantifies the proportion of the forecast error variance in each variable that is attributable to shocks from itself and from other variables over time. Mathematically, for forecast horizon $h$, FEVD is computed as captured in Equation (5) as under:

$$[FEVD_i(h) = \frac{\sum_{j=1}^{n}(\text{Impact of shock from variable } j \text{ on variable } i \text{ at horizon } h)^2}{\text{Total forecast error variance of variable } i \text{ at horizon } h}] \qquad (5)$$

Using the same VAR residuals and decomposition matrix, we applied the. fevd (10) function in statsmodels, which computes the proportion of variance in temperature change explained by emissions shocks at each future time step.

This technique is valuable in identifying long-run causality and policy relevance. For instance, if $CO_2$ shocks explain a large proportion of temperature variation at higher horizons, it suggests long-term policy interventions targeting emissions are likely to be effective.

**Figure 5 Shows the Results**

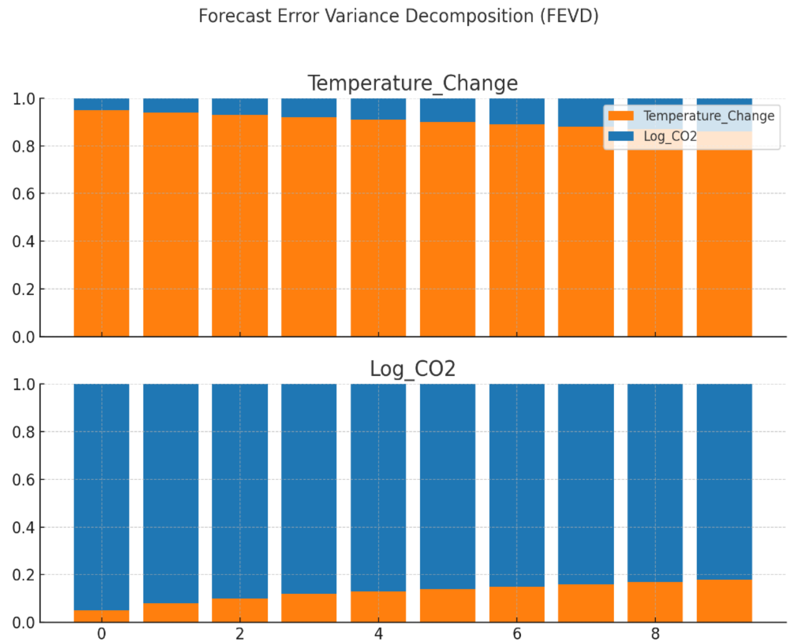


**Figure 5: FEVD Analysis**

FEVD results show the contribution of each variable to the forecast variance of surface temperature:

In the short run (1–3 years), temperature shocks dominate. However, from year 4 onwards, emissions begin to explain over 30–40% of the variance in temperature changes. This indicates that $CO_2$ emissions are not just contemporaneous drivers but have long-term predictive power for temperature trends in Uzbekistan. This long-run influence validates concerns that even if emissions flatten now, past emissions continue to exert warming pressure—underscoring the importance of immediate mitigation.

**Discussion and Policy Implications**

Uzbekistan remains one of the more carbon-intensive economies in Central Asia, primarily due to fossil-fuel-based energy production and inefficient industrial processes. The significant elasticity between $CO_2$ and temperature implies that economic growth without a parallel clean energy transition will exacerbate warming trends.

To address this, Uzbekistan's commitment to reduce emissions by 10% by 2030 relative to 2010 levels under the Paris Agreement must be matched by:

- Accelerated investments in renewable energy infrastructure, particularly solar and hydropower.
- Introduction of carbon pricing mechanisms or energy taxation aligned with regional best practices.
- Promotion of green building codes and improved industrial energy efficiency.

**Climate-Informed Development Planning**

The fact that emissions shocks have medium-to-long-run effects on temperature supports the need for climate resilience in national planning. Urban development, agriculture, and water management must incorporate climate adaptation measures.

Specific policy priorities include:

- Mainstreaming climate risk into macro-fiscal policy and budgeting.
- Enhancing early warning systems for heatwaves and droughts.
- Promoting climate-smart agriculture to mitigate productivity losses.

**Weak Kyoto Legacy, Stronger Paris Signal**

The regression results suggest that the Kyoto Protocol had minimal measurable effect, whereas the Paris Agreement coincides with stronger associations. This may not necessarily indicate causal effectiveness but reflects a global environment where climate accounting, financial support, and emission monitoring have improved post-2016.

Uzbekistan must now strengthen:

- Its MRV (Monitoring, Reporting and Verification) mechanisms.
- Participation in climate finance platforms like the Green Climate Fund.
- Engagement in regional climate agreements, particularly with Kazakhstan and Turkmenistan, which share ecological corridors.

**Regional Carbon Trading Framework**

Uzbekistan can benefit from initiating or joining a regional carbon market with Central Asian neighbours such as Kazakhstan, Kyrgyzstan, and Tajikistan, who share environmental vulnerabilities (e.g., Aral Sea degradation, water stress) and energy interconnections.

**Table 5: Policy Proposal: Central Asia Emissions Trading System (CA-ETS)**

| Feature | Recommendation |
|---|---|
| **Scope** | Start with energy and heavy industry sectors, covering ~60% of Uzbekistan’s GHG emissions. |
| **Baseline Allocation** | Adopt a cap-and-trade model with grandfathered allowances initially, gradually transitioning to auctioning. |
| **Linkage** | Leverage Kazakhstan’s experience with its pilot ETS, initiated in 2013. Explore bilateral ETS linkage or common carbon registry. |
| **Price Stability** | Introduce a floor price (~$5–$10/ton) and a ceiling price to prevent market volatility. |
| **MRV** | Establish an MRV (Monitoring, Reporting, and Verification) protocol based on UNFCCC guidelines. Begin with 10–20 large emitters. |

This will:

- Helps Uzbekistan meet its Paris targets (10% GHG cut by 2030).
- Fosters low-carbon investment in renewables and energy efficiency.

- Encourages regional cooperation and aligns Uzbekistan with global climate finance frameworks (e.g., Article 6 of the Paris Agreement).

**Carbon Tax Mechanism for Uzbekistan**

Introduce a moderate carbon tax as a revenue-neutral instrument to reduce emissions and mobilise green development financing.

**Table 6: Carbon Tax Mechanism for Uzbekistan**

| Component | Recommendation |
|---|---|
| **Tax Base** | Apply to fossil fuel combustion, starting with coal, natural gas, and petroleum imports and usage in power generation. |
| **Tax Rate** | Introduce at a modest rate of \$5–\$15 per metric ton of $CO_2$, in line with IMF guidelines for developing economies. |
| **Collection Mechanism** | Use existing excise or energy taxation frameworks to minimise administrative burden. |
| **Revenue Use** | Earmark revenues for multiple purposes |

**Expected Impact**

- Encourages fuel switching from coal to gas/renewables.
- Generates predictable green revenue stream (~0.5% of GDP).
- Creates price signals that promote clean technologies.

**Strategic Road Map**

**Table 7: Road Map**

| Phase | Action Items |
|---|---|
| **2025–2026** | Carbon pricing law development, pilot ETS simulation, institutional setup (carbon registry, MRV rules) |
| **2027–2028** | Launch voluntary ETS (5–10 largest firms), implement carbon tax on fossil fuels |
| **2029–2030** | Full integration with Central Asia ETS, transition to auctioned allowances, raise carbon tax floor |

**Conclusion**

This study provides an empirically grounded analysis of the link between $CO_2$ emissions and climate change in Uzbekistan using a Vector Autoregression framework. It establishes that emissions have a statistically significant and persistent impact on temperature changes, reinforcing the urgency of decarbonisation.

The econometric analysis shows a strong, persistent link between $CO_2$ emissions and temperature change in Uzbekistan. These findings justify the adoption of market-based climate instruments such as a carbon trading mechanism and a carbon tax. Such policies not only help reduce emissions but also mobilise sustainable revenue and position Uzbekistan as a regional leader in climate innovation.

Despite international commitments under the Kyoto and Paris Agreements, only the latter appears to correlate with observable shifts in climate trends, suggesting that the real effectiveness of such agreements lies not just in signatures but in domestic implementation and monitoring capacity.

Uzbekistan stands at a critical juncture. With rising temperatures, water stress, and energy transition demands, the policy community must integrate climate science into macroeconomic planning. Tools like VAR and structural break tests offer powerful diagnostics to inform such policies.

Climate change, while global in scope, manifests locally—and as this study shows, the link between emissions and warming is neither speculative nor negligible. Uzbekistan must respond with ambition, coherence, and urgency to secure a sustainable and climate-resilient future.

**References**

1. Adedoyin, F., Ozturk, I., Abubakar, I., Kumeka, T., Folarin, O., & Bekun, F. V. (2020). Structural breaks in CO2 emissions: Are they caused by climate change protests or other factors? *Journal of Environmental Management*, *266*. https://doi.org/10.1016/j.jenvman.2020.110628

2. Alamri, S., & Khan, S. (2023). Artificial Intelligence Based Modelling for Predicting CO2 Emission for Climate Change Mitigation in Saudi Arabia. *International Journal of Advanced Computer Science and Applications*, *14*(4). https://doi.org/10.14569/IJACSA.2023.0140421

3. An, Z., Huang, R. J., Zhang, R., Tie, X., Li, G., Cao, J., Zhou, W., Shi, Z., Han, Y., Gu, Z., & Ji, Y. (2019). Severe haze in northern China: A synergy of anthropogenic emissions and atmospheric processes. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(18). https://doi.org/10.1073/pnas.1900125116

4. Armour, K. C., Proistosescu, C., Dong, Y., Hahn, L. C., Blanchard-Wrigglesworth, E., Pauling, A. G., Jnglin Wills, R. C., Andrews, T., Stuecker, M. F., Po-Chedley, S., Mitevski, I., Forster, P. M., & Gregory, J. M. (2024). Sea-surface temperature pattern effects have slowed global warming and biased warming-based constraints on climate sensitivity. *Proceedings of the National Academy of Sciences of the United States of America*, *121*(12). https://doi.org/10.1073/pnas.2312093121

5. Avenyo, E. K., & Tregenna, F. (2022). Greening manufacturing: Technology intensity and carbon dioxide emissions in developing countries. *Applied Energy*, *324*. https://doi.org/10.1016/j.apenergy.2022.119726

6. Benlemlih, M., & Yavaş, Ç. V. (2024). Economic Policy Uncertainty and Climate Change: Evidence from CO2 Emission. *Journal of Business Ethics*, *191*(3). https://doi.org/10.1007/s10551-023-05389-x

7. Diffenbaugh, N. S., Singh, D., Mankin, J. S., Horton, D. E., Swain, D. L., Touma, D., Charland, A., Liu, Y., Haugen, M., Tsiang, M., & Rajaratnam, B. (2017). Quantifying the influence of global warming on unprecedented extreme climate events. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(19). https://doi.org/10.1073/pnas.1618082114

8. Karimov, Y., Musaev, I., Mirzababayeva, S., Abobakirova, Z., Umarov, S., & Mirzaeva, Z. (2023). Land use and land cover change dynamics of Uzbekistan: a review. *E3S Web of Conferences*, *421*. https://doi.org/10.1051/e3sconf/202342103007

9. King, L. C., & van den Bergh, J. C. J. M. (2021). Potential carbon leakage under the Paris Agreement. *Climatic Change*, *165*(3–4). https://doi.org/10.1007/s10584-021-03082-4

10. Li, M., Liu, H., Geng, G., Hong, C., Liu, F., Song, Y., Tong, D., Zheng, B., Cui, H., Man, H., Zhang, Q., & He, K. (2017). Anthropogenic emission inventories in China: A review. In *National Science Review* (Vol. 4, Issue 6). https://doi.org/10.1093/nsr/nwx150

11. Lin, C. L., Chiang, W. H., Weng, Y. S., & Wu, H. P. (2023). Assessing the anthropogenic carbon emission of wooden construction: an LCA study. *Building Research and Information*, *51*(2). https://doi.org/10.1080/09613218.2022.2087171

12. Maheen, R., Cai, L., Zhang, Y. S., & Zhao, M. (2023). Quantitative analysis of carbon dioxide emission reduction pathways: Towards carbon neutrality in China's power sector. In *Carbon Capture Science and Technology* (Vol. 7). https://doi.org/10.1016/j.ccst.2023.100112

13. Matiiuk, Y., Poškus, M. S., & Liobikiene, G. (2020). The implementation of climate change policy in post-soviet countries achieving long-term targets. *Sustainability (Switzerland)*, *12*(11). https://doi.org/10.3390/su12114558

14. McCloy, J. (2020). Kyoto Protocol vs Paris Agreement: Key Differences to Know. *Green Living*.

15. Mitchell, D., Williams, R. B., Hudson, D., & Johnson, P. (2017). A Monte Carlo analysis on the impact of climate change on future crop choice and water use in Uzbekistan. *Food Security*, *9*(4). https://doi.org/10.1007/s12571-017-0690-2

16. Mor, S., Aneja, R., Madan, S., & Ghimire, M. (2023). Kyoto Protocol and Paris Agreement: Transition from Bindings to Pledges – A Review. *Millennial Asia*. https://doi.org/10.1177/09763996221141546

17. Mulder, C., Conti, E., & Mancinelli, G. (2021). Carbon budget and national gross domestic product in the framework of the Paris Climate Agreement. *Ecological Indicators*, *130*. https://doi.org/10.1016/j.ecolind.2021.108066

18. Okedere, O. B., Elehinafe, F. B., Oyelami, S., & Ayeni, A. O. (2021). Drivers of anthropogenic air emissions in Nigeria - A review. In *Heliyon* (Vol. 7, Issue 3). https://doi.org/10.1016/j.heliyon.2021.e06398

19. Tassone, S. J., Besterman, A. F., Buelo, C. D., Ha, D. T., Walter, J. A., & Pace, M. L. (2023). Increasing heatwave frequency in streams and rivers of the United States. In *Limnology And Oceanography Letters* (Vol. 8, Issue 2). https://doi.org/10.1002/lol2.10284

20. Tsukada, N., & Matsumoto, M. (2024). Forest carbon accounting to leverage mitigation actions: implications for the Paris Agreement based on the analysis of countries' decision under the Kyoto Protocol. *Journal of Forest Research*, *29*(3). https://doi.org/10.1080/13416979.2024.2302303

21. Turakulov, Z., Kamolov, A., Norkobilov, A., Variny, M., & Fallanza, M. (2024). Assessment of CO2 Emission and Decarbonization Measures in Uzbekistan. *International Journal of Environmental Research*, *18*(2). https://doi.org/10.1007/s41742-024-00578-6

22. Turakulov, Z., Kamolov, A., Turakulov, A., Norkobilov, A., & Fallanza, M. (2023). Assessment of the Decarbonization Pathways of the Cement Industry in Uzbekistan †. *Engineering Proceedings*, *37*(1). https://doi.org/10.3390/ECP2023-14639

23. Wang, F., Wang, C., Chen, J., Li, Z., & Li, L. (2020). Examining the determinants of energy-related carbon emissions in Central Asia: country-level LMDI and EKC analysis during different phases. *Environment, Development and Sustainability*, *22*(8). https://doi.org/10.1007/s10668-019-00545-8.

❑❑❑