# Climate Change and the US Macroeconomy: Time-Varying Parameter Approach with Stochastic Volatility

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**Abstract**

This study contributes to the empirical macroeconomics and the climate change literature by employing a Bayesian vector-autoregression model to analyze the evolving effects of climate change shocks on key US macroeconomic variables. Using novel Actuaries Climate Index (ACI) and monthly macroeconomic data from July 1975 to February 2024, the model captures how the transmission of climate disturbances shifts over time by allowing for structural identification of climate shocks with heteroskedasticity, and provides the dynamic effects on inflation, output, and unemployment. This approach reveals that both the volatility and the acceleration of climate change have been intensified, amplifying the macroeconomic consequences, where the estimation is robust to inner-volatility of variables themselves. The result highlights the importance of endogenous structural breakpoint which extends the previous research of Kim, Matthes, and Phan (2025).

Regarding inflation dynamics, the inflation responses dampen more rapidly, yet the initial impact is larger in more recent periods, suggesting that while the persistence of the effects on inflation has declined, the climate shock continues to exert upward pressure on the price level. The output responses also exhibit significant time variation; output growth decreases immediately after a climate shock and such decline exacerbates over time. Unemployment responses also have time-varying patterns: in earlier periods in 1980s a climate shock induced a large initial unemployment, but re-hiring came to place afterwards. Such re-hiring processes vanishes from the early 2000s.

Overall, this study presents the increasingly salient macroeconomic consequences of the climate change and highlights the importance of employing time-variation in analyzing climate-macroeconomic interactions, providing potential policy implications.

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# 1 Introduction

How do episodes of severe weather impact macroeconomic outcomes in the United States, and do these impact evolve over time? This paper aims to answer these questions by employing an empirical Bayesian time-series framework designed to capture the time-varying relationships between the climate extremity shocks and the US macroeconomy, using monthly data from 1975 through 2024. This investigation merges the standard macroeconomic indicators with a novel meteorological data that tracks extreme weather, especially with a discussion about the important threshold that is necessary to be trimmed in the novel climate dataset that is yet commonly used. This research seek to shed light on whether the moments of the severe weather and its corresponding economic effects have changed over time, potentially reflecting both climate change and adaptation across the decades.

Substantial and growing literature addresses the economic consequences of the weather and climate-related disturbances. A common challenge is that the distribution of weather shocks itself appears to shift over time; and simultaneously the economic agents may modify their behavior in ways that mitigate or intensify these shocks. To accommodate the time variation in both the climate severity and their macroeconomic consequences, this study adopts a benchmark Vector Autoregression (VAR) model that has long been a staple in empirical macroeconomics (e.g. Sims, 1980; Cogley and Sargent, 2001, Christiano, Eichenbaum, and Evans, 2005, D'Agostino, Gambetti, and Giannone, 2013). However, unlike a standard linear VAR that assumes constant parameters over the entire sample periods, this study allows for the time variation in parameters to capture changing dynamics in climate change and shifts in macroeconomic responses in the United States. This approach has an advantage over a method simply splitting the samples (e.g. Barreca, Clay, Deschenes, Greenstone, and Shapiro (2016)) because the full time variation could be seen throughout the sample periods. As a methodology, this study implements a Bayesian Time-Varying Parameter Structural VAR with Stochastic Volatility (TVP-SVAR-SV) model following Primiceri (2005) and Nakajima (2011). By allowing the coefficient and variance parameters to be time-varying, the results can capture the shifting effects of the climate change as well as the macroeconomic responses in different decades from 1970s to post-COVID-19 periods.

For empirical implementation, the Actuaries Climate Index (ACI) - a recently introduced time series that combines major climate sources - is used as a climate shock indicator variable for the United States. It is noteworthy to say that this study provides the important threshold date of this index where the climate change starts to appear, alarming not all available ACI data from year 1961 should be used, especially for analysis on inflation. This is something the previous literature using this data (e.g. Liao, Sheng, Gupta, and Karmakar (2024), Sheng, Gupta, and Çepni (2022), Sheng, Gupta, and Cepni (2024), Kim et al. (2025)) did not pay enough attention but the impulse response of the climate shock to inflation can be hugely biased if this threshold is ignored. This importance of the endogenous structural breakpoint of the climate change data is particularly crucial for the inflation dynamics.

The results of this paper reveal compelling evidence of time-varying economic effects of the climate shock and the interactions between macroeconomic variables. Especially toward the end of the sample period, a comparable shock leads to prolonged decline in output, higher inflation and greater initial unemployment shock without rehiring processes. These adverse impacts last for several months to a year and the persistence suggests that even transitory weather disruptions can have lingering macroeconomic effects. These results are robust to the inner-volatility of the variables themselves, for instance the inflation growth was more volatile around the year 2008, the Great Financial Crisis, but such volatility is isolated from the estimated impulse responses by the stochastic volatility terms.

These findings on the climate impact to the inflation is of particular interest to policymakers. Previous research often associates large weather shocks with inflationary pressures primarily in developing country or micro-level setting, yet recent policy discussions highlight growing concern that extreme weather events could compromise the price stability in advanced economies. This study can help the understanding of the time-varying feature of climate shock and the calibration of macroeconomic modeling for climate change.

This work is related to a breadth of empirical studies examining how weather and climate variables shape the economic outcomes (e.g. Dell, Jones, and Olken (2014), Hsiang (2016) and the references within). The earlier literature largely highlights the substantial negative consequences of the weather shocks on growth in comparison to the developing countries (e.g. Dell, Jones, and Olken (2012), Alessandri and Mumtaz (2021)). Much of the compelling evidences for the adverse weather effects in the United States have been centered on especially exposed sectors such as agricultural industry (Roberts and Schlenker (2013), Burke and Emerick (2016)). This research contributes to the macroeconomic literature on developed country like the United States by providing the evidence that the climate shock can impact developed economy, even at national-wise level aggregation, and the impact has been greater as it comes to more recent period.

Turning to the macroeconomic literature on natural disasters, a common presumption has been that disaster shocks impose mostly short-lived disruptions on advanced economies and even stimulating the localized rebuilding activities (Hallegatte (2008), Tran, Wilson et al. (2024)). This is somewhat mixed because there are opposing results suggesting the weather shocks generate persistent damage to industrial production with no recovery documented by Hsiang and Jina (2014) and Kim et al. (2025). The results of this paper encompasses both of two seemingly opposing results; the allowance for the time variation in parameters can capture the different transmission mechanisms in different periods and uncover both of re-building and no-recovery phenomena with one model with different timing in impulse responses.

By presenting the evidence of significant and time-varying macroeconomic responses to severe weather, this paper augments the extant body of research in two main ways. Firstly, it delivers a flexible methodological approach that accommodates evolving distributions of weather shocks alongside shifting macroeconomic dynamics, rather than assuming stability. Secondly, it demonstrates that even a mature, fully-developed economy like that of the United States remains vulnerable to adverse weather events, challenging the notion that highly industrialized nations possess sufficient economic resilience.

The remainder of this paper proceeds as follows. **Section 2** provides the economic model framework for TVP-SVAR-SV model. **Section 3** describe the data, including the Actuaries Climate Index (ACI) and its important threshold, as well as macroeconomic data used. **Section 4** presents main empirical findings and discussions. Finally **Section 5** concludes with a discussion of potential use for policy implications and future works.

# 2 Methodology

This section presents the empirical estimation strategy employed to capture the changing impacts of climate extremities on key macroeconomic variables. Taking account for the structural change over the periods, the time-varying parameter with stochastic volatility model of Nakajima (2011) is used.

Suppose that we have a time-varying structural VAR model that is defined as:

$$A_t y_t = F_0 + F_1 y_{t-1} + \cdots + F_p y_{t-p} + \nu_t \quad \text{where} \;\; \nu_t \sim N(0, \Sigma_t \Sigma_t') \tag{1}$$

where $y_t$ is the $k \times 1$ vector of variables of observation, $F_0$ is $k \times 1$ intercept matrix, $A_t$ is $k \times k$ simultaneous relation matrix and $F_1, \ldots, F_s$ are $k \times k$ coefficient matrices. The standard deviation matrix of the structural error $\nu_t$ is defined as:

$$\Sigma_t = \begin{pmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{k,t} \end{pmatrix}$$

The structural form matrix $A_t$ represents the simultaneous relations of the observed variables to the structural shock. We construct this matrix to be identified by recursive ordering identification, assuming that $A_t$ is lower-triangular square matrix such that:

$$A_t = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{k1,t} & \cdots & \alpha_{k(k-1),t} & 1 \end{pmatrix} \quad s.t. \quad A_t^{-1} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \tilde{a}_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \tilde{a}_{41,t} & \cdots & \tilde{a}_{k(k-1),t} & 1 \end{pmatrix}$$

Every lower-triangular matrix is invertible so we can write the **Equation (1)** as a reduced form equation:

$$y_t = B_0 + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t \tag{2}$$

where $u_t = A_t^{-1}\nu_t$ is a reduced form error and $B_i = A_t^{-1}F_i$ for $i = 1, \ldots, p$ number of lags. Stacking the row elements of the $B_i$'s gives $\beta$ which is a $(k + k^2 p) \times 1$ vector. Defining $X_t = I_k \otimes (1, y_{t-1}, \ldots, y_{t-p})$ where $\otimes$ is the Kronecker product, **Equation (2)** can be reduced to:

$$y_t = X_t\beta + A_t^{-1}\Sigma_t\varepsilon_t \quad \text{where } \varepsilon_t \sim (N, I_k) \tag{3}$$

Notice that the reduced form error $u_t = A_t^{-1}\nu_t = A_t^{-1}\Sigma_t\varepsilon_t$ because $\nu_t \sim N(0, \Sigma_t\Sigma_t')$ and $\varepsilon_t \sim N(0, I_k)$. By incorporating the time-varying factor to the $\beta$ of **Equation 3** gives the Time-Varying Parameter Structural VAR with Stochastic Volatility model:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t \quad t = p+1, \ldots, n \tag{4}$$

Note that here the coefficients $\beta_t$, simultaneous parameters $A_t$ and $\Sigma_t$ are all time-varying. Following Primiceri (2005) and Nakajima (2011) the parameters are assumed to follow the random walk process:

$$\begin{cases} \beta_{t+1} \sim N\left(\beta_t, \Sigma_{\beta_0}\right) \\ a_{t+1} \sim N\left(a_t, \Sigma_{a_0}\right) \\ h_{t+1} \sim N\left(h_t, \Sigma_{h_0}\right) \end{cases} \tag{5}$$

with stochastic volatility terms $h_t = (h_{1t}, h_{2t}, \ldots, h_{kt})'$, where $h_{jt} = \log \sigma_{jt}^2,\ j = 1, \ldots, k$ and $t = p+1, \ldots, n$. The block diagonal variance-covariance matrix represents the structure of the parameter correlations:

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right)$$

Following Nakajima (2011), the prior distributions are assumed for the $i$-th diagonals of the covariance matrices: $(\Sigma_\beta)_i^2 \sim IG(20, 0.0001)$, $(\Sigma_\alpha)_i^2 \sim IG(4, 0.0001)$, $(\Sigma_h)_i^2 \sim IG(4, 0.0001)$. The initial states are set to $\mu_{\beta_0} = \mu_{\alpha_0} = \mu_{h_0} = 0$ and $\Sigma_{\beta_0} = \Sigma_{\alpha_0} = \Sigma_{h_0} = 10 \times I$. The estimation via Markov Chain Monte Carlo (MCMC) discards first 5000 burn-ins and then draws 20000 samples after burn-ins, totaling 25000 sample draws.

# 3 Data

## 3.1 Climate Data: Actuaries Climate Index (ACI)

The Actuaries Climate Index (ACI) is an aggregate measure reported by American Academy of Actuaries, Canadian Institute of Actuaries, Causalty Actuarial Society, and Society of Actuaries (2024) to indicate the climate extremes of the United States and Canada. The ACI is constituted of six sub-categories summarized in **Table 1**:

**Table 1:** Actuaries Climate Index (ACI) and its six components

| | | |
|---|---|---|
| $T90$ | High Temperature | Frequency of temperatures exceeding the 90th percentile |
| $T10$ | Low Temperature | Frequency of temperatures less than the 10th percentile |
| $P$ | Precipitation | Maximum rainfall across five consecutive days |
| $D$ | Dry Days | Annual Maximum consecutive dry days |
| $W$ | Wind Speed | Frequency of wind speed exceeding 90th percentile |
| $S$ | Sea Level | Sea level changes |
| $ACI$ | Actuaries Climate Index | $mean(T90_t^{std} - T10_t^{std} + P_t^{std} + D_t^{std} + W_t^{std} + S_t^{std})$ |

The top five components of ACI in **Table 1** except for Sea Level are based on 2.5 degrees latitude by and 2.5 degrees longitude grid data, where Sea Level data is based on tide gauges observed in 100 permanent coastal stations. Each of these components are compared with the reference periods of 1961-1990, for instance, the anomaly in temperature in January in a certain year is compared with January data in 1961-1990.

ACI documentation provides the justification for the negative sign in $T10_t^{std}$. Since cold temperatures have been decreasing by roughly the same extent as warm temperatures have been rising, combining those two would have largely canceled out the influence of temperature on the index, which is undesirable. The separate reduction in $T10$ and the rise in $T90$ reflect an overall rightward shift in the entire temperature distribution. The decline in cold temperature also brings significant negative consequences, such as reduced insect dieback and increased permafrost thaw. More explanation about this novel dataset is provided in **Appendix B**

## 3.2 Structural Breakpoint of Climate Change

Actuaries Climate Index (ACI) is a fairly novel time series dataset and very few studies are conducted with this data (Kim et al. (2025), Liao et al. (2024), Sheng et al. (2024)). It is important to emphasize that although the ACI is designed to represent the climate anomaly, not all periods in ACI dataset starting 1961 January is in fact the climate change data.

**Table 2:** Zivot-Andrews Test for Monthly frequency ACI

| Variable | Estimate | Std. Error | t value | Pr(>$\|t\|$) |
|---|---|---|---|---|
| (Intercept) | -0.1436 | 0.0761 | -1.8880 | 0.0595 |
| y.l1 | 0.5676 | 0.0815 | 6.9600 | 0.0000 |
| trend | 0.0017 | 0.0008 | 2.2950 | 0.0220 |
| y.dl1 | -0.2813 | 0.0824 | -3.4140 | 0.0007 |
| y.dl2 | -0.2174 | 0.0803 | -2.7080 | 0.0069 |
| y.dl3 | -0.1763 | 0.0769 | -2.2920 | 0.0222 |
| y.dl4 | -0.1364 | 0.0733 | -1.8590 | 0.0634 |
| y.dl5 | -0.2498 | 0.0690 | -3.6220 | 0.0003 |
| y.dl6 | -0.3396 | 0.0646 | -5.2560 | 0.0000 |
| y.dl7 | -0.3072 | 0.0600 | -5.1220 | 0.0000 |
| y.dl8 | -0.3038 | 0.0560 | -5.4210 | 0.0000 |
| y.dl9 | -0.2634 | 0.0534 | -4.9270 | 0.0000 |
| y.dl10 | -0.2631 | 0.0498 | -5.2870 | 0.0000 |
| y.dl11 | -0.1796 | 0.0449 | -4.0000 | 0.0001 |
| y.dl12 | -0.0567 | 0.0371 | -1.5290 | 0.1267 |
| du | -0.2430 | 0.0801 | -3.0340 | 0.0025 |
| dt | -0.0008 | 0.0007 | -1.1400 | 0.2545 |
| Test Statistic | -5.3032 | | [5%, 1%] | [-5.08, -5.57] |
| F-statistic | 48.69 | | | |

**Table 2** shows the Zivot and Andrews (1992) Test to find one endogenous structural break with 12 lags. This test identifies the presence of the unit root in the time series data as well as the possible structural breakpoint. In **Table 2**. The variable 'du' is statistically

**Table 3:** Zivot-Andrews Test Breakpoints for ACI

| Frequency | Statistic | 5% Critical Value | Break Point |
|---|---|---|---|
| Monthly (p=10) | -6.6147 | -5.08 | 1975M7 |
| Monthly (p=11) | -5.6781 | -5.08 | 1975M2 |
| Monthly (p=12) | -5.3032 | -5.08 | 1975M2 |
| Quarterly (p=3) | -5.7026 | -5.08 | 1975Q1 |
| Quarterly (p=4) | -5.8492 | -5.08 | 1975Q1 |
| Quarterly (p=5) | -6.2091 | -5.08 | 1975Q3 |

significant while 'dt' is insignificant, representing there exists a structural change in level but not in trend. The variable 'trend' is statistically significant with t-value of 2.2950 so there is a clear positive trend in the climate index data. Combined with previously mentioned 'dt' variable, there is a trend and the level of the trend has shifted but not the gradient of the trend. The lagged level variable 'y.l1' is 0.5676 which is far different to the value of 1 with 0.0000 p-value, indicating the series does not have the unit root. Throughout 'y.dl1' to 'y.dl12', the lagged level variables are mostly statistically significant except 'y.dl12'. The insignificance of 'y.dl12' is expected as this is a variable exactly a year ago so the lagged change should not be very large as this is a weather data.

The test Statistic is -5.3032, which is greater than 5% significance level critical value of -5.08 but less than that 1% value of -5.57, suggesting that there could be a unit root non-stationarity around the breakpoint. **Table 3** shows the breakpoints tested with different lags and frequencies. Throughout the tests, the breakpoints consistently indicate the threshold year is 1975, although specific months slightly vary.

For the robustness sake, Bai and Perron (2003) test is also conducted to find structural break with a different mechanism. **Figure 1** shows the different structural breaks found from Bai and Perron (2003) test, where BIC value of 949.9 in **Table 4** with a single breakpoint is the smallest, indicating the best fit model specification is with one structural breakpoint. Using results from both Zivot and Andrews (1992) test and Bai and Perron (2003) test, the conservative and prominent threshold point is July 1975 (1975M7).

This finding of year 1975 as a threshold year of climate data is also consistent with

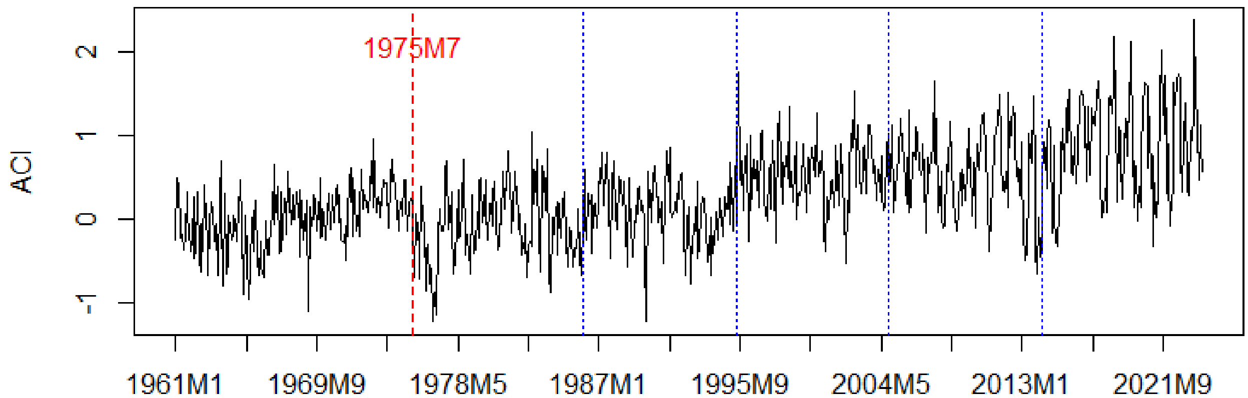



**Figure 1:** Bai-Perron Breakpoint Test on ACI data

**Table 4:** Bai-Perron Test Statistics and Breakpoints

| | Breakpoints ($m$) | | | | | | |
|---|---|---|---|---|---|---|---|
| $m$ | 1 | 2 | 3 | 4 | 5 | RSS | BIC |
| 0 | – | – | – | – | – | 157.9 | 981.9 |
| 1 | (1975M8) | – | – | – | – | 147.4 | 949.6 |
| 2 | (1975M7) | – | (1995M4) | – | – | 144.4 | 954.1 |
| 3 | (1975M7) | – | (1995M6) | – | (2014M4) | 141.6 | 958.8 |
| 4 | (1975M7) | (1986M1) | (1995M6) | – | (2014M4) | 140.1 | 971.0 |
| 5 | (1975M7) | (1986M1) | (1995M6) | (2004M11) | (2014M4) | 139.7 | 988.5 |

natural science literature stating the climate change exhibits a great shift starting mid-1970s: evidences include sea surface temperature and global temperature (Meehl, Hu, and Santer, 2009), reduction in glacier volume (Dyurgerov and Meier, 2000), and air pollution and greenhouse gases (Ramanathan and Feng, 2009). For the main economic analysis, the USA Actuaries Climate Index (ACI) is trimmed so that the series contains data from 1975 July to 2024 February is used for climate data. This is particularly important in VAR model because as can be seen from **Table 2**, stationarity of the series could be questionable around the structural breakpoint of 1975 and also the estimates can be biased. Further details are explained in **Appendix A**

### 3.3 Macroeconomic Data

In addition to the Actuaries Climate Index (ACI), three macroeconomic measures for the United States are used for the analysis: output growth measured by the percentage change of industrial production, inflation growth measured by the percentage change of the consumer price index (CPI), and the change in unemployment.[2] These macroeconomic variables are seasonally adjusted and available in monthly frequency data from the St. Louis Federal Reserve Economic Data (FRED). **Figure 2** shows the time series of the ACI and macroeconomic variables for the empirical analysis; these macroeconomic data from 1975 July to 2024 February are used for economic analysis.

Because the real GDP are released only at quarterly intervals, industrial production serves as a higher frequency proxy for real economic activities; this monthly data is better as it can capture more short-term effects of weather disruptions. Industrial production does not include agricultural output, the key sector where climate change can change the outcomes (Nordhaus, 1991). This feature, however, is not necessarily a bad consequence of choosing industrial production as an output variable because the estimated impact on industrial production would tell a conservative measure of output change facing climate change.

Likewise, choice of Consumer Price Index for All Urban Consumers as the observed inflation variable is justified because the estimated effects on inflation would provide a lower bound of the overall inflationary effects from the climate change. Unemployment rate is used for the labor market variable instead of employment rate because without the loss of generality the unemployment rate change is behaving better than the employment for the analysis during COVID-19 periods.

[2]Federal Reserve Economic Data code for inflation is CPIAUCSL, the code for industrial production is INDPRO and the code for unemployment rate is UNRATE. These data are in change in year-on-year (YoY) form due to seasonality of climate analysis.

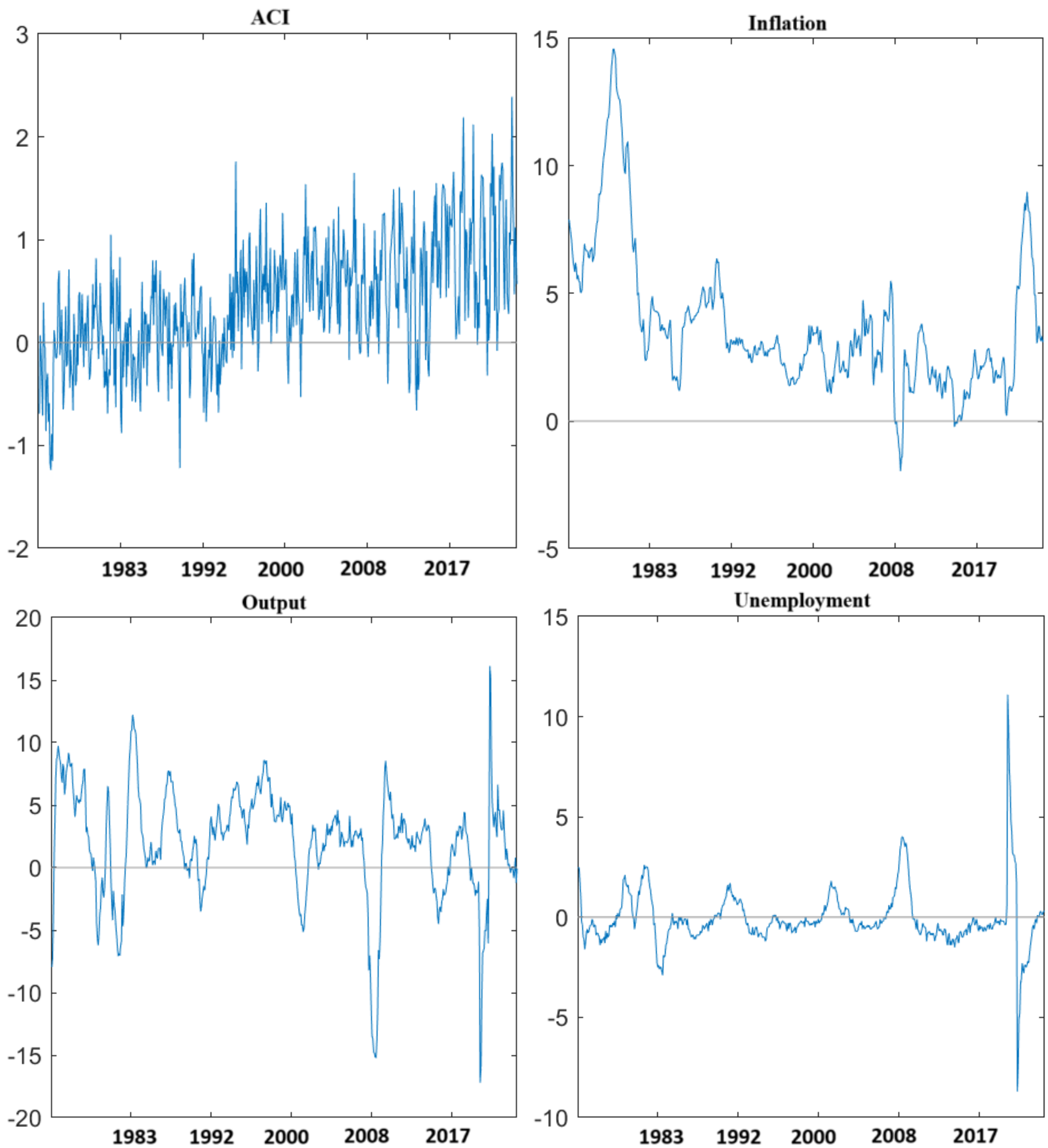



**Figure 2:** ACI, Industrial Production growth, Inflation growth and Unemployment change

# 4 Empirical Results and Discussions

The estimation of this Bayesian Structural VAR model has been conducted using the auto-regressive lag length of 2, determined by the smallest criterion number from the Bayesian Information Criterion shown in **Table 5**. The criteria with lesser number, i.e. more negative number, indicates better model fit.

**Table 5:** Number of Lags and Information Criteria

| | $p = 1$ | $p = 2$ | $p = 3$ |
|---|---|---|---|
| BIC | -38.49 | -283.72 | -258.68 |

Here $p$ refers to the number of lags in the model and BIC refers to Bayesian Information Criterion.

**Table 6** shows the selected parameters in the model. These posterior estimates of the variances of coefficients are significant within the 95% coverage interval, i.e. the null hypothesis of the variances of coefficients are zeros is rejected, and therefore the model specification should truly be a time-varying parameter model; because constant parameters should have the value of the variances of coefficients to be zero. The variables $(\Sigma_\beta)_1$ and $(\Sigma_\beta)_2$ indicate the variance of the VAR coefficients, the intercept and the first own-lag, to the climate variable; the statistical significance of them indicate that the coefficients are not constant, i.e. time-varying. The variable $(\Sigma_a)_1$ shows the structural VAR coefficient presenting the impact of the climate shock to the inflation, which is also significant. The stochastic volatility terms $(\Sigma_h)_1$ and $(\Sigma_h)_2$ are the selected stochastic volatility terms of the

**Table 6:** Estimation of selected parameters in the TVP-SVAR-SV model

| **Parameter** | **Mean** | **Stdev** | **95%U** | **95%L** |
|---|---|---|---|---|
| $(\Sigma_\beta)_1$ | 0.0023 | 0.0003 | 0.0018 | 0.0029 |
| $(\Sigma_\beta)_2$ | 0.0023 | 0.0003 | 0.0019 | 0.0029 |
| $(\Sigma_a)_1$ | 0.0050 | 0.0012 | 0.0032 | 0.0080 |
| $(\Sigma_h)_1$ | 0.0073 | 0.0026 | 0.0037 | 0.0136 |
| $(\Sigma_h)_2$ | 0.1066 | 0.0259 | 0.0629 | 0.1645 |

*Note:* Mean denotes posterior means; Stdev denotes standard deviations climate change and the inflation, which are significant so the there is a time-variation in the heteroskedasticity of the variables.

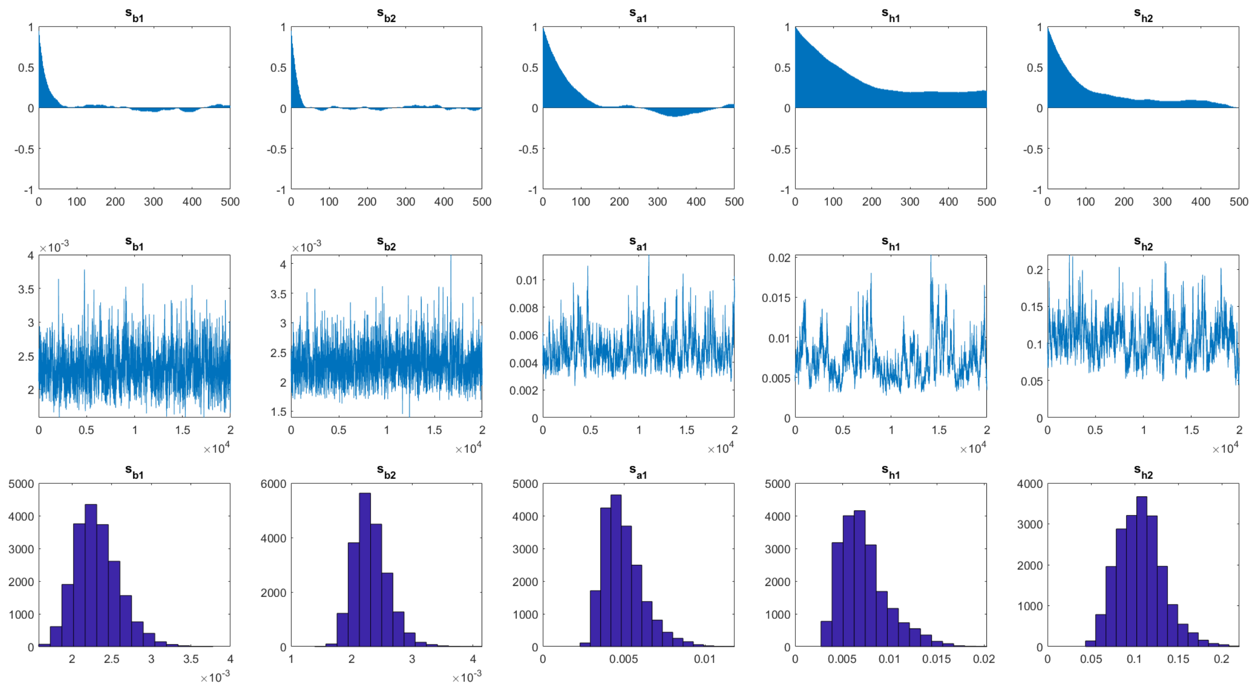



**Figure 3:** Sample Autocorrelation, Sample Path and Posterior Densities

**Figure 3** shows the sample autocorrelation (top), sample path (middle) and posterior densities for the selected parameters presented in **Table 6**. Given that this Bayesian TVP-SVAR-SV model assumes the random walk processes of the parameters presented in **Equation (5)**, the sample autocorrelation stably drops and the sample path exhibits reasonably stable movements after 5000 burn-in draws. The sample autocorrelation drops nicely so that the previous draws have little impact to the next draws. The sample path presents wiggly-random walking behavior as modeled and the posterior densities present nicely modal draws.

## Role of Stochastic Volatility

**Figure 4** shows the intercept term of the $ACI_t$ equation in the model. The intercept is statistically significant where in the beginning period of year 1975 the value is 0.27. The value of this intercept parameter continues to increase over periods, ending with a value of

0.36 in the year 2024. This intercept represents the baseline climate severity in ACI data; suggesting that the level of severity in climate extremes represented by the Actuaries Climate Index (ACI) has been rising throughout decades.

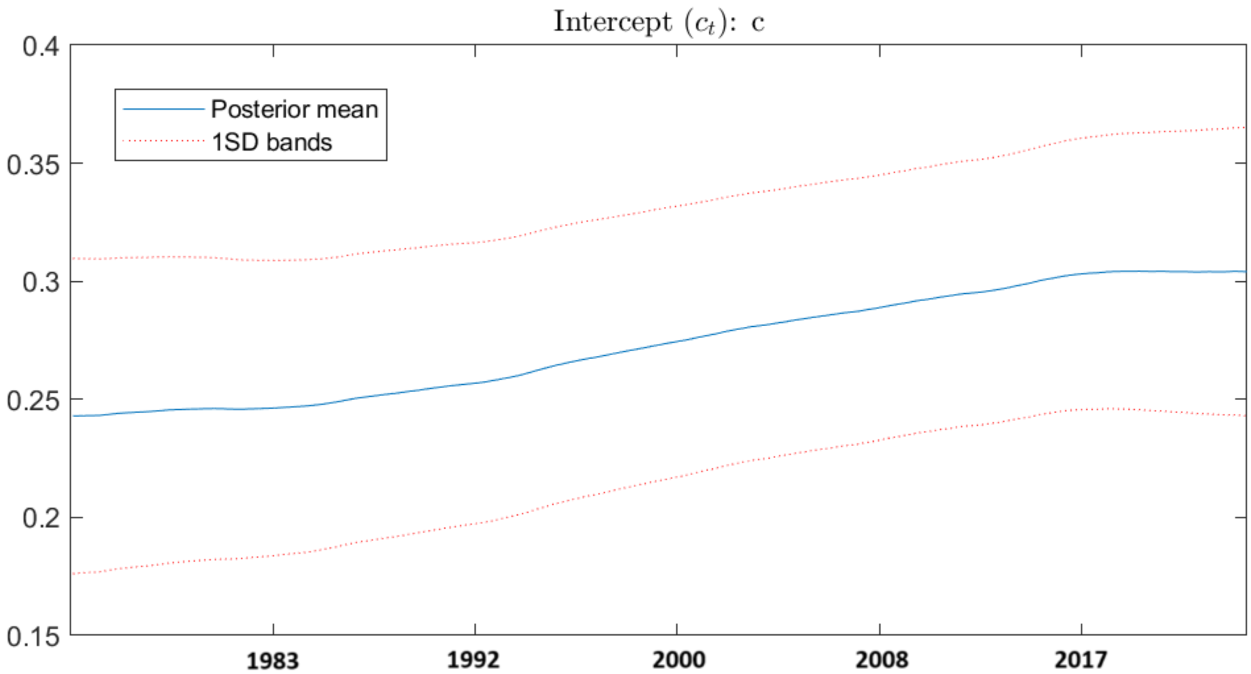



**Figure 4:** Time-varying Intercept of the climate index

**Figure 5** altogether shows the stochastic volatility terms of all four variables - climate index, inflation, industrial production as output and unemployment rate. Top-left graph of **Figure 5** is the stochastic volatility term of the $ACI_t$. This is one of the biggest merits of TVP-SVAR-SV model, because not only the time variation of coefficient parameters but also the time variation of the variance of the structural error term is depicted through model specification. This graph represents the time-varying feature of the volatility of the climate severity in ACI data. Starting from the value of about 0.16 in the beginning year of 1975, the stochastic volatility continues to rise throughout decades whilst keeping its statistical significance. As the Actuaries Climate Index itself denotes the deviation anomaly of climate composites compared to the normal reference, this rise in time-varying variance can be explained as an acceleration. The climate anomalies are increasing not only in their level, but also in their volatilities, which have been accelerating throughout.

It is noteworthy to mention the importance of the stochastic volatility terms of other

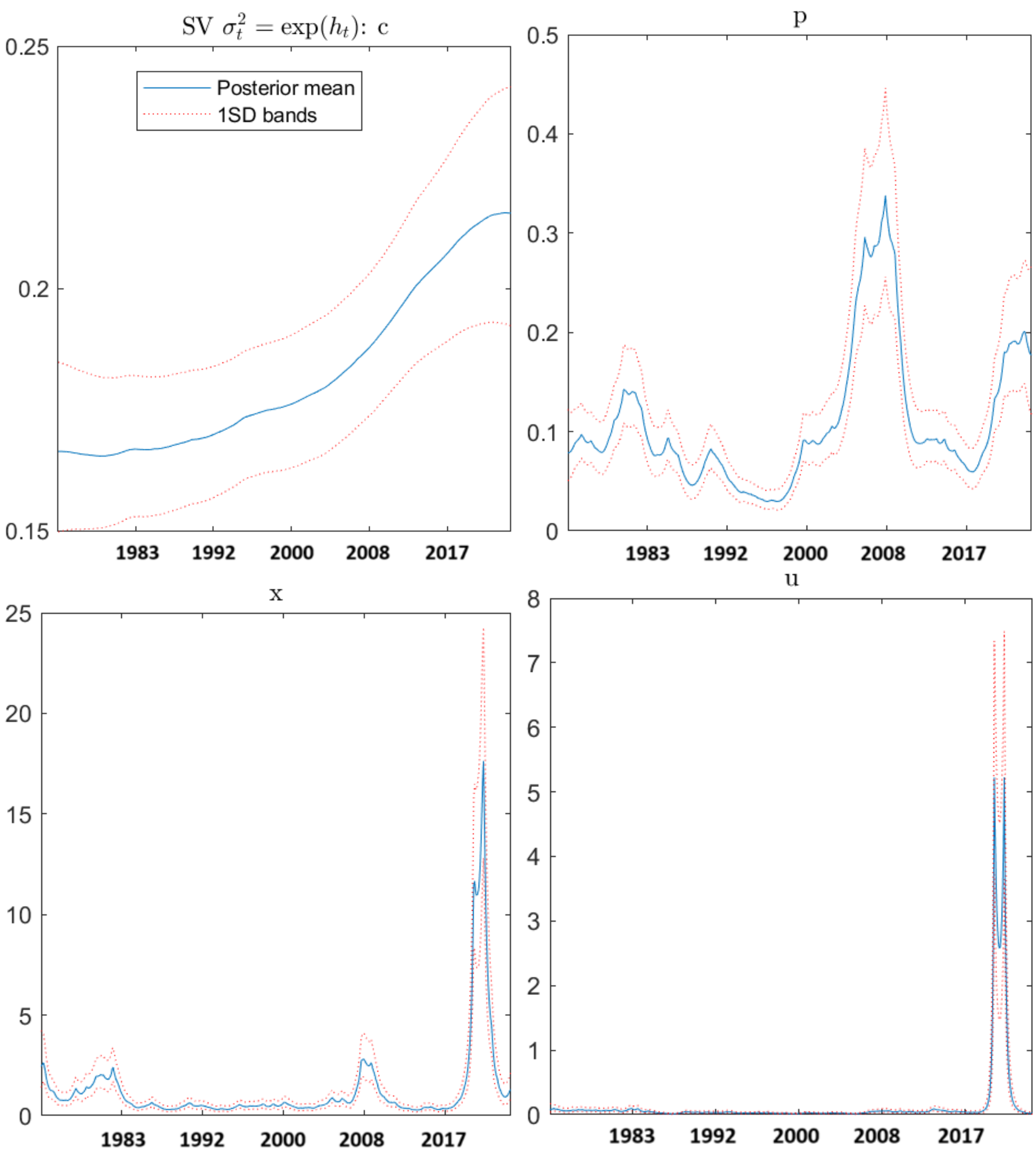



**Figure 5:** Stochastic Volatility terms of four variables

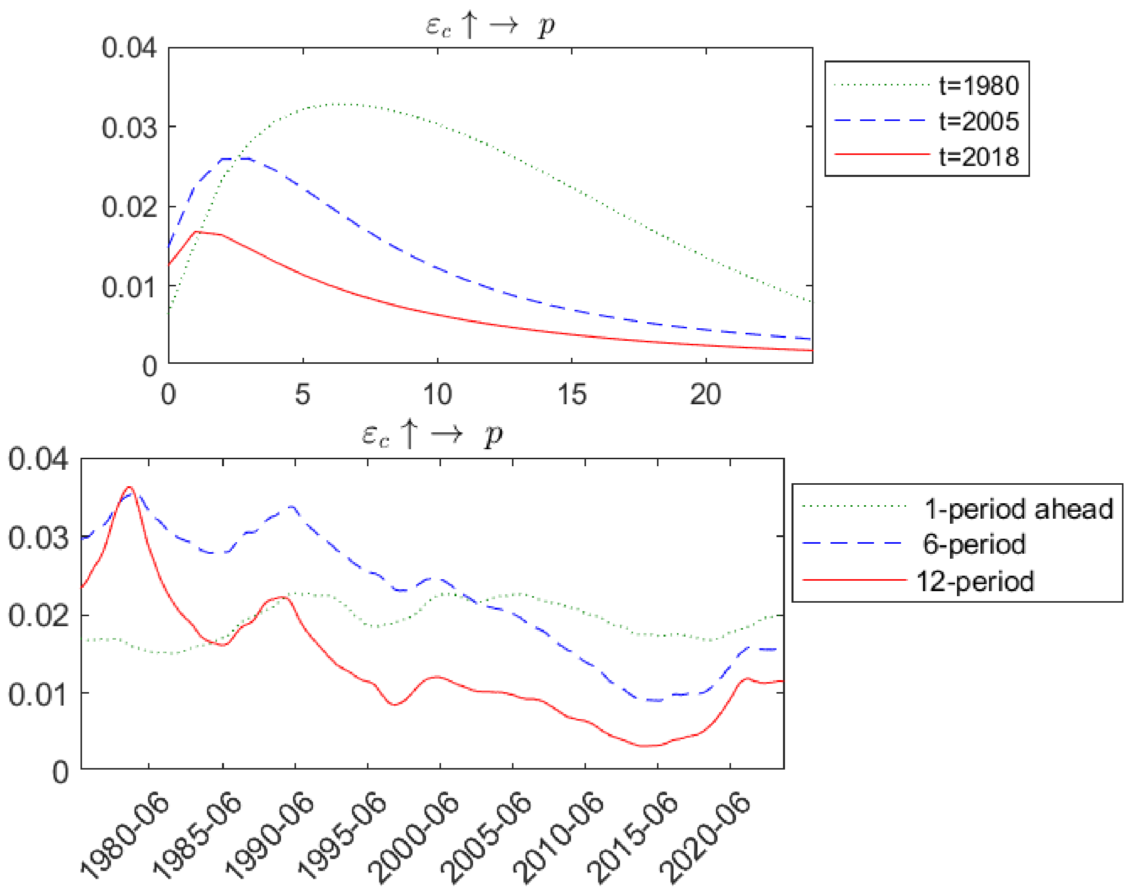
macroeconomic variables - inflation ($p$), industrial production ($x$) and unemployment ($u$) in **Figure 5**. There are periods of time where the macroeconomic variables are more volatile; for instance the growth in inflation was more volatile around the year 2008, the Great Financial Crisis (GFC). Output measured by industrial production experienced more volatile periods during GFC and COVID-19 era, and the change in the unemployment rate has peaked its volatility during COVID-19 periods. These inner-volatilities are important because one could argue that the change in the time-variation of the impulse response analysis could be from the change in macroeconomic variables by themselves, i.e. the there is a time variation in impulse response because of the heteroskedasticity of the variables themselves. This study, however, separates out the heteroskedasticity of the variables through modelling stochastic volatilty terms, and thereby provides more robust impulse response analysis from the climate shock.

## Impulse Response analysis

**Figure 6-8** shows the main result of VAR model, the impulse response of ACI shock to observed macroeconomic variables. Note that TVP-SVAR-SV model actually cast the impulse response function in 3D because there exist different coefficient parameters ($\beta_t$) throughout all periods. Though these 3D impulse response functions are available in **Appendix D**, in the main analysis the impulse response functions are sliced into two parts for comprehensiveness. To provide a reference point for the impulse response analysis, the commonly referenced Bayesian DSGE framework of Smets and Wouters (2007) finds that the monetary policy shock and the productivity shock account for about 5-6 percentage points of the fluctuation of inflation according to its point estimate and impulse response functions.

**Figure 6** shows two panels illustrating the effect of a ACI climate shock on inflation across different time periods and horizons. In broad terms, these impulse responses depict how an exogenous disturbance, here attributed to climate severity factor, transmissions into movements in inflation in both the short run and over more extended horizons.

On the top panel of **Figure 6**, the green dot line presents year 1985 impulse response;




Top: Green dot line: year 1985, Blue dot line: year 2005, Red solid line: year 2018
Bottom: Green dot: 1-month, Blue dot: 6-months, Red solid line: 12-months ahead horizon

**Figure 6:** Impulse Response of climate shock to inflation

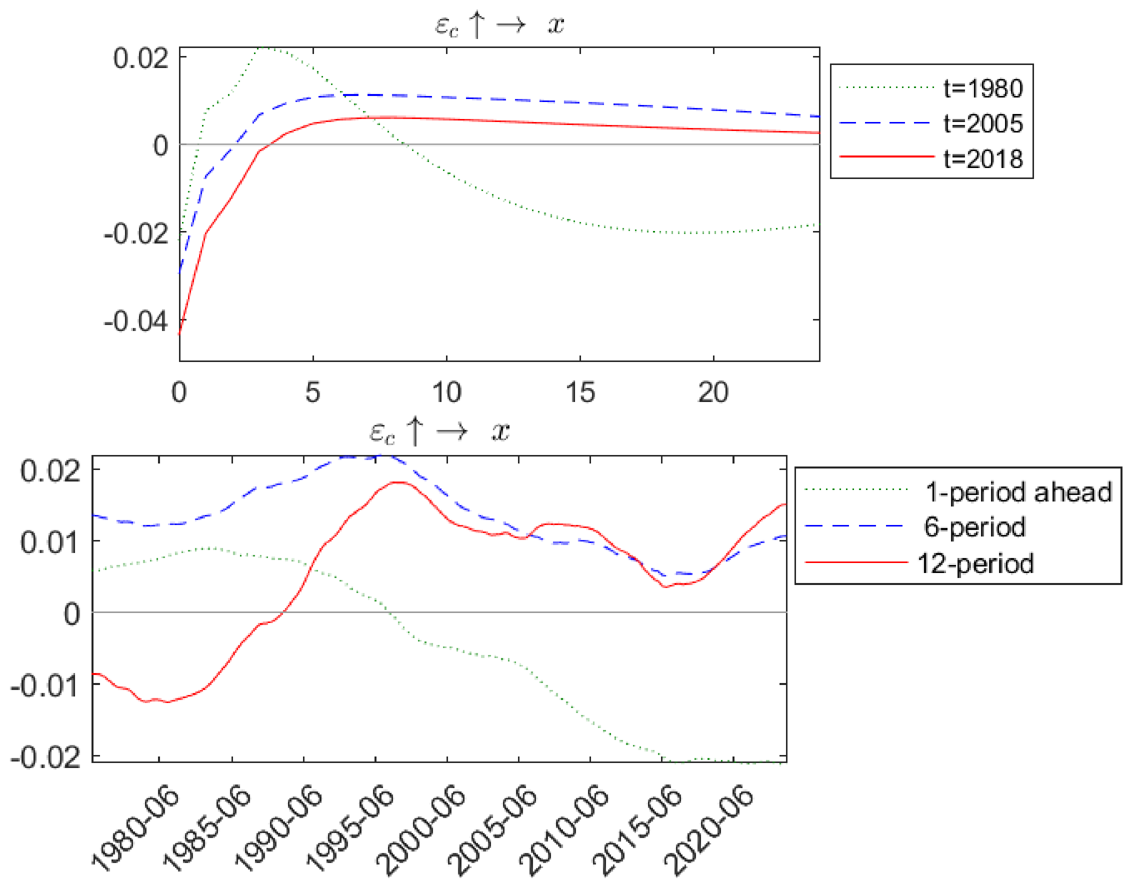
this 1985 impulse response shows the initial shock brings less than about 1 percentage point increase in inflation but it remains sizable over several subsequent periods, reflecting the inflationary effects linger. Blue dot line represents the impulse of the year 2005, the initial shock to inflation is 1.5 percentage point increase to inflation which is larger than 1980s and it peaks to 2.5 percentage point afterwards. But the magnitude of this response starts to dampen more quickly compared to the past; it could be due to several factos such as improved policy frameworks and better adaptation. The red line shows the impulse of the year 2018. Inflation rises in the immediate aftermath of the shock to slightly lower than 1.5 percentage point increase but then it exhibits even faster return toward the baseline.

On the bottom panel of **Figure 6**, the horizontal axis represents the chronological time from year 1975 to 2024. The green dot line depicts the immediate shock at impulse horizon of $h = 1$ right after the initial shock. Across all years in the sample, the one-period-ahead response to a climate shock (green dot at bottom) is positive. Importantly, the trimming of ACI data aforementioned in **Section 3.2** plays huge role for attaining reasonable, positive shock responses to the inflation across all time periods.

Noticeably the immediate shock to inflation is generally stable in magnitude, suggesting the impact of climate change to inflation is prevalent throughout all time. Blue and the red lines present further 6-months ahead and 12-months ahead period impulse response functions respectively. Notably in the 1980s, the impulse remained elevated for longer duration even up to 12 months, whereas in more recent years the response decline quicker. Such observation hints at the adaptation or learning mechanism; in longer horizon the US economy can mitigate the climate-induced inflationary effects.

This result is slightly different to the results of recent and directly related work of Sheng et al. (2024) using the same ACI data, stating the time-varying effects of the climate shock to inflation is smaller in recent periods possibly due to improved adaptation to climate change. Although the adaptation effects could be seen in the bottom figure, the initial shock has become greater as can be seen in the top figure of **Figure 6**. Due to aforementioned reason in **Section 3.2**, their results could have been biased because the trimming of ACI data has not been done. Furthermore considering the tuning of prior of a-la-Primiceri type model is typically done with first 10 years of observation if OLS estimates are used to set prior, the prior may also be wrong because the first 10 years of ACI data: year 1961 to 1971 is not actually the periods representing climate change so called global warming, the posterior estimates should also be biased.

**Figure 7** represents the impulse response of the climate shock to output. On the top panel, the climate shock brings initial negative impact to output. Green dot line represents the output response in 1980s, the initial negative effect is the smallest and it quickly recovers back with overproduction represented by a large overshooting in the graph. This "overproduction" effect is still visible in blue dot line representing year 2005; it resonate with micro-level evidence such as that of Hallegatte (2008). For instance, Hurricane Katrina in 2005 caused a sharp immediate loss in output but subsequent reconstruction effects fu-



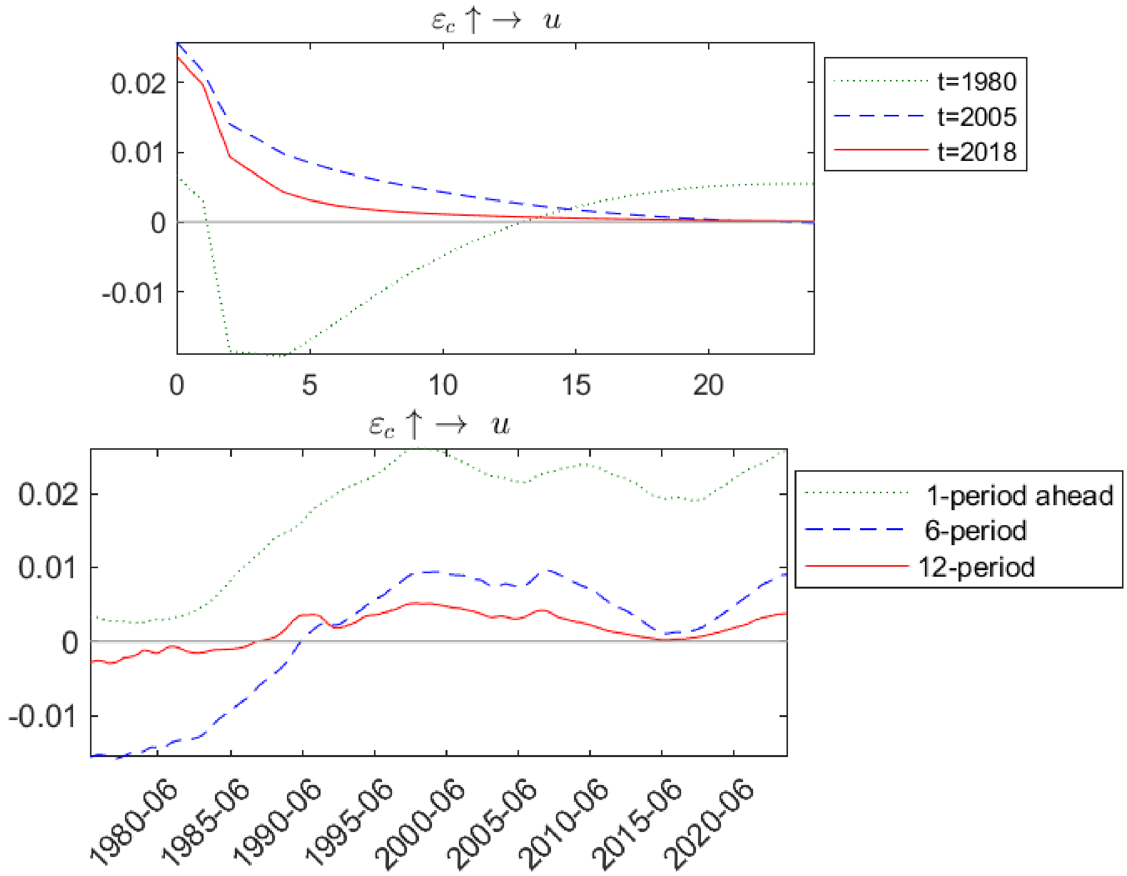

Top: Green dot line: year 1985, Blue dot line: year 2005, Red solid line: year 2018
Bottom: Green dot: 1-month, Blue dot: 6-months, Red solid line: 12-months ahead horizon

**Figure 7:** Impulse Response of climate shock to output

eled a compensatory economic recovery that temporarily pushed output above the baseline. In more recent period in year 2018 represented by red line, the impulse of output is more negative at the initial shock and the rebound of the economy is much weaker.

It is also noteworthy to emphasize that the initial negative impact on output has become greater across decades; in 1980s the reduction to output is only about 2 percentage point but in 2018 the reduction is more than 4 percentage point. The longer-run resilence of the output is mixed, shocks in 1980s generally return to positive growth above the baseline quickly, whereas more recent shock may remain persistently. These results could be because of the changing economic structures that respond differently to disruptions and due to globalized supply chain in more recent periods has made the economy more vulnerable to a shock in terms of output production.

On the bottom panel of **Figure 7** the green dot line represents the response to output at horizon $h = 1$; the output right after the initial shock. It recovers back to positive quickly until year 1995. But after year 1995 the recovery is not as swift as before; it stays negative after the initial shock and the magnitude of negative impact is greater as it comes to more recent era. This suggests that the recovery process of economy in terms of output is getting slower as time goes by. 6-months and 12-months horizon impulse responses represented by blue and red line stay generally positive after 1990, representing the economic recovery with time lag.




Top: Green dot line: year 1985, Blue dot line: year 2005, Red solid line: year 2018
Bottom: Green dot: 1-month, Blue dot: 6-months, Red solid line: 12-months ahead horizon

**Figure 8:** Impulse Response of climate shock to unemployment

**Figure 8** shows the impulse response function of ACI shock to unemployment change. On the top panel of it, the shock to unemployment all has initial positive impact, i.e. an increase in unemployment. However, in the earlier sample period of 1980s the climate shock is followed by a drop in unemployment below its baseline after an initial shock. One interpretation is that the damages from climate events such as natural disasters necessitated significant manpower for clean-up, reconstruction and repairs. In year 1985 (green dot line of top figure) it was predominantly manual and labor-intensive economy so firms needed to rehire workers rapidly in order to restore. However moving to more recent periods in 2000s and 2010s represented by blue and red lines, these re-hiring processes appear less pronounced and the unemployment shocks seem to last longer periods. The initial effect of the climate shock is positive and higher than the past, where the drop below the baseline in subsequent periods disappears. This could suggest the tighter labor market and more capital-intensive production technology have made the recovery processes do not require as much as manpower as before in more recent periods. This is consistent with the findings of Graff Zivin and Neidell (2014) that finds exposure to extreme weather conditions or temperature shock reduce labor hours more persistently.

On the bottom panel of **Figure 8** the green dot line and blue line trace the immediate and intermediate impulse responses of the unemployment at horizon 1-month ahead and 6-months ahead. There is a clear rise in the increase in unemployment over decades, suggesting that the climate shock to unemployment has become stronger and stronger across the periods. In 12-months horizon represented by the red line, the unemployment returns to the baseline almost for all periods, suggesting that the climate shock impact to unemployment usually does not last more than a year.

## The importance of the Structural Breakpoint of ACI data

This sub-section emphasizes the importance of the breakpoint and the needs for the trimming of Actuaries Climate Index (ACI) data portrayed via the impulse response shock of the climate index to inflation variable.

The top figure of **Figure 9** presents the estimated impulse response function of climate shock to inflation using data from all available period starting year 1961 to 2024. The bottom shows the impulse response function of climate shock to inflation using data from 1975 July

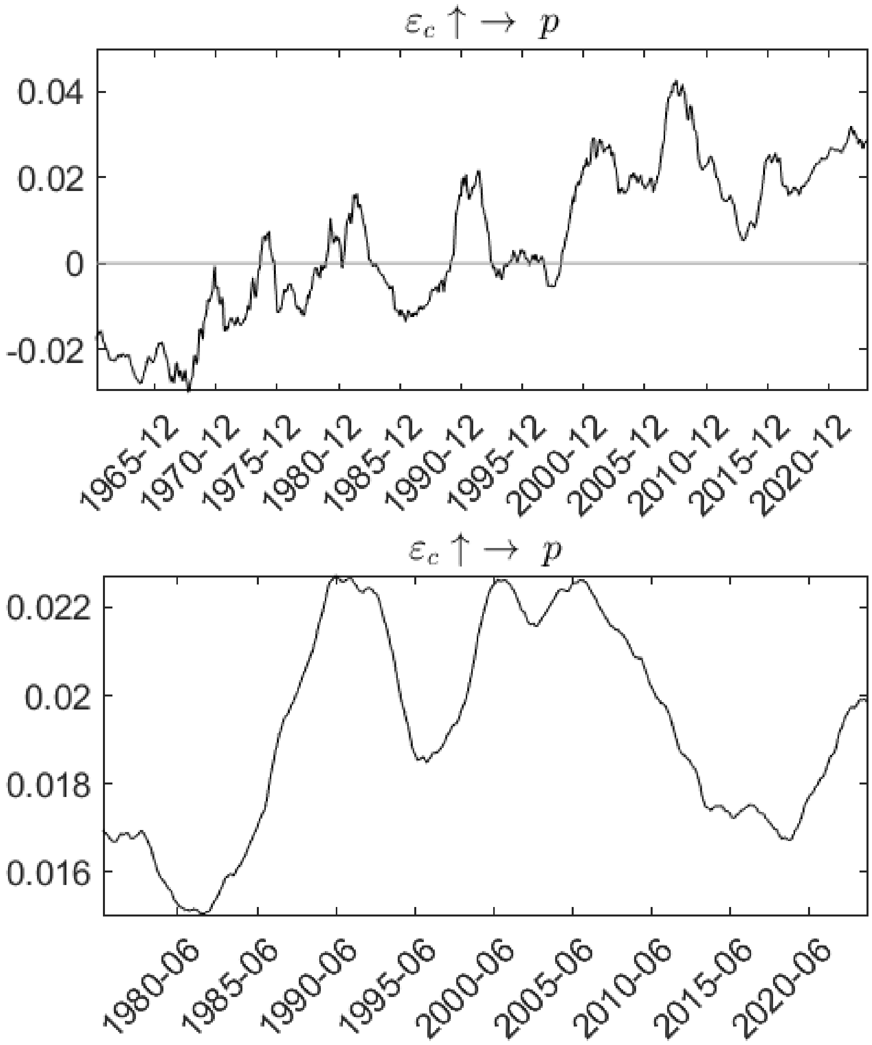



**Figure 9:** 1-month impulse responses of inflation with data from 1961M1 vs. from 1975M7

to 2024 February which the start date is chosen by the structural breakpoint tests explained in the **Subsection 3.2**. Note that the class of time-varying parameter VAR models are robust to the regime shifting and structural break in long term, but it does not capture the precise timing of the change per se. In the bottom graph the climate shock increases inflation but in the top graph such positive impact on inflation is not present until 1980s. This is actually a big problem because existing literature using ACI data (e.g. Liao et al. (2024), Sheng et al. (2024), Kim et al. (2025)) did not pay attention to the structural break of Actuaries Climate Index data whilst dealing with inflation issue.

Furthermore, a-la-Primiceri type model typically tune the prior using the first 10 years of observed data, but as shown in **Subsection 3.2**, the year 1961 to year 1975 may not be climate change periods. Wrongfully tuned prior with the data before climate change periods could hugely bias the estimation, and the consequent analysis about the impacts of the climate change on the macroeconomic variables could go wrong. For mixed effect of temperature shock and inflation across different economies, see Cevik and Jalles (2024).

## Change in the initial responses across the time horizon

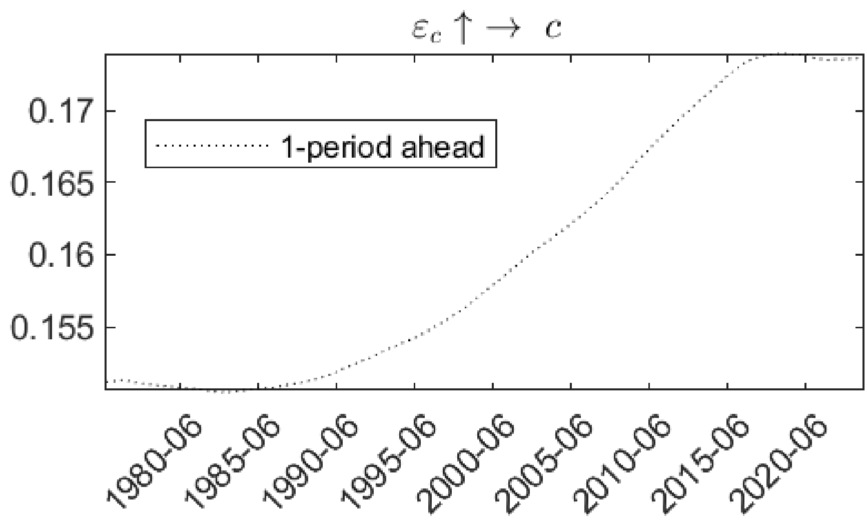



**Figure 10:** Initial zero period and 1-month ahead Impulse Response of climate index

**Figure 10** shows the time variation in the 1-month impulse response function of the climate shock to the climate index. As the shock here itself is an own-variable shock, the zero-period impulse response is just a flat one standard deviation shock. The 1-month impulse response of the ACI data from its own-shock, however, presents a clear increasing trend, from 0.15 in the year 1985 to 0.173 in the year 2015. Together with **Figure 4** and the top-left figure of **Figure 5**, the climate index has an increase in its level, volatility and the impulse response from its own shock across the time periods. From these the amplification of the climate change impact can be seen, as the impact of the climate shock shows a clear upwarding trend.

**Figure 11** shows the time variation in the initial zero-period impulse response and the consequent 1-month impulse response function of the climate shock to the inflation. The

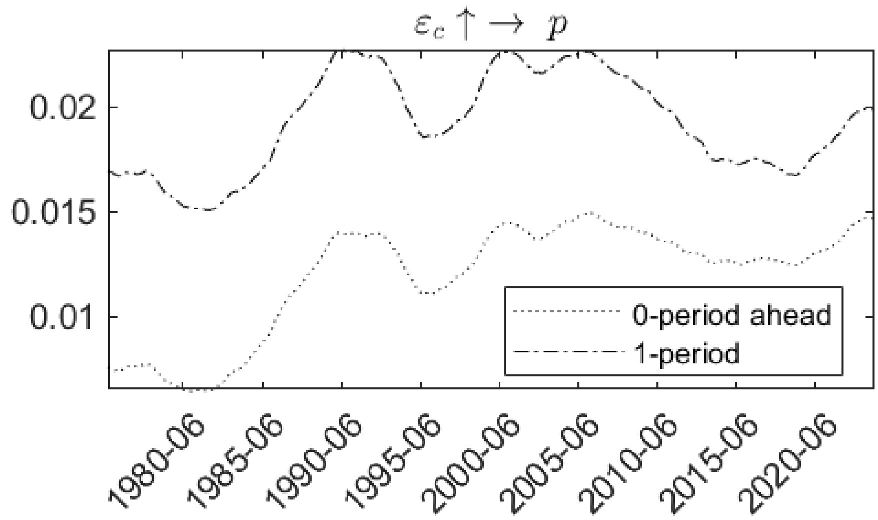



**Figure 11:** Initial zero period and 1-month ahead Impulse Response of Inflation

initial climate shock increases inflation and such increase is intensified after the initial shock.

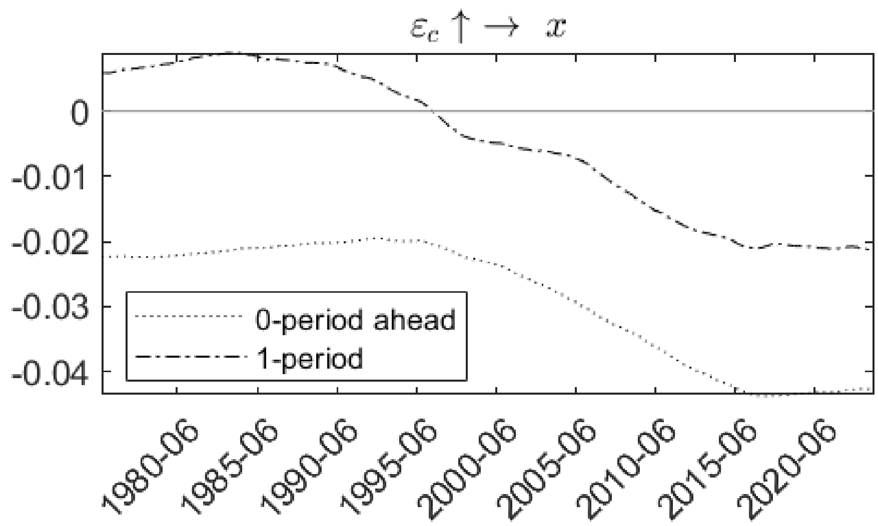



**Figure 12:** Initial zero period and 1-month ahead Impulse Response of Output

**Figure 12** shows the time variation in the initial zero-period impulse response and the consequent 1-month impulse response function of the climate shock to the industrial production as an output measure. The initial climate shock to the output has a negative impact where the magnitude of the initial impact is generally growing across the period. One month after, the initial negative impact is mitigated; climate shock decreases the output but it catches up in subsequent periods.

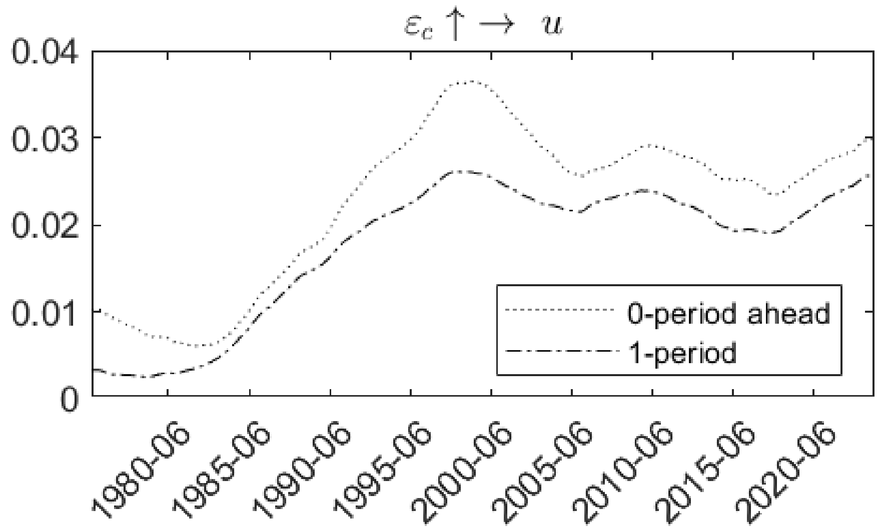



**Figure 13:** Initial zero period and 1-month ahead Impulse Response of Unemployment

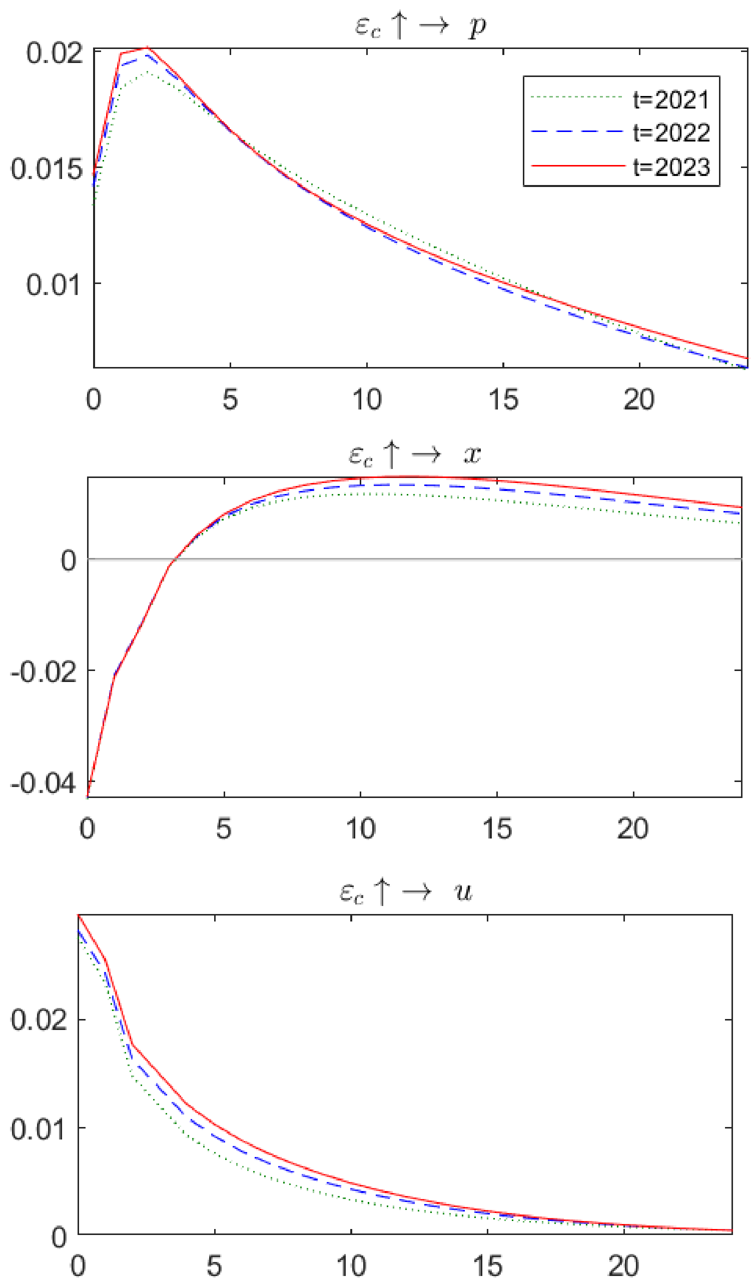
**Figure 13** the time variation in the initial zero-period impulse response and the consequent 1-month impulse response function of the climate shock to the unemployment. Note that the initial impulse responses from the climate shock are always greater than the 1-period impulse responses, suggesting that the climate change increases the unemployment, but such impacts start to decline after.

## After COVID-19

**Figure 14** shows the impulse response function of ACI shock on inflation, output and unemployment after COVID-19. In the top panel, the climate shock generates an increase of approximately 1.5 percentage points in inflation. Noticeably this level is comparable to the largest responses oberved in earlier pre-COVID-19 episodes and it is distinctly higher than the year 2018 right before the COVID-19. This finding signals that the post-pandemic macroeconomic environment may be more vulnerable to cost-push pressures from climate-related supply disruptions.

On the middle panel of **Figure 14**, output drops by about 4 percentage points in response to the climate shock, but it comes with recovery processes within 3 months. Although the impulse response of the output looks similar to each other, the impulse is more peaked and

**Figure 14:** Impulse Response Functions after COVID-19




Green dot: year 2021, Blue dot: year 2022, Red solid line: year 2023 the return to the zero basis is slower in year 2023 compared to year 2022 and 2021. This turn-back could be attributed due to the recovery of environment documented during COVID-19 periods where the great shutdown gave significantly economic damages but positive environmental benefits (Yamaka, Lomwanawong, Magel, and Maneejuk (2022), Ojeda-Castillo, Murillo-Tovar, Hernández-Mena, Saldarriaga-Noreña, Vargas-Amado, Herrera-López, and Díaz (2024)).

The bottom panel of **Figure 14** indicates that the climate shock raises unemployment by about 2.5 percentage points, slightly higher than typical pre-COVID estimates and the initial negative shock seems to become greater in more recent year. This greater effects could stem from ongoing pandemic-related shifts in labor markets; firms may be more cautious about hiring new workers and/or try to rely on technology and automation. Unlike year 2018 impulse response shown in **Figure 8**, the unemployment rate does not go below baseline after one year, suggesting the weaker re-hiring effect is the same as right before pandemic.

Putting altogether, Policymakers should be mindful that post-pandemic labor markets appear less flexible, potentially slowing re-hiring processes. Meanwhile, inflationary pressures from climate shocks could stay elevated longer than pre-COVID periods, underscoring the importance of well-coordinated monetary and fiscal measures. For DSGE calibrations or other macroeconomic simulations, incorporating these post-COVID impulse responses could better capture the current economic environment and recovery patterns. This feature is also relevant to the calculation of the cost of carbon emission, the calibration of the climate disturbances and the response of financial commodities in asset pricing model (Nordhaus (1993), Golosov, Hassler, Krusell, and Tsyvinski (2014), Hassler and Krusell (2018), Dietz, Gollier, and Kessler (2018)). It could be dangerous to solely use the parameter values calibrated using the data right before the COVID-19 because due to pandemic regime swift the economy might resemble more of earlier sample periods.

# 5 Conclusion

This study employs a novel Actuaries Climate Index (ACI) data for climate extremities in the United States with a time-varying parameter VAR model with stochastic volatility. The climate effects are indeed time-varying across different decades, not only in levels but also in volatility terms. The initial climate shock to inflation is higher in more recent periods, the output reduction and the increase in unemployment rate due to climate shock is also higher in more recent periods. Noticeably the overproduction recovery of the output and re-hiring processes in labor market was visible in distant past but those seem to dampen and starts to disappear in more recent sample periods. The inclusion of the stochastic volatility provides more robust analysis that separates out the heteroskedasticity of the variables themselves.

The estimation also covers post-COVID-19 periods and it alarms that the pandemic has introduced a regime shift, making the post-pandemic economy more akin to earlier sample years in some dimensions like overshooting recovery of the output where it is characterized by more persistent unemployment and heightened inflationary sensitivities. Due to time-varying feature of the model used for this project, the results of this study can be used for many different climate-related applications in the United States across different sample periods: macroeconomic DSGE, calculation of the social cost of air pollution, climate-related asset pricing and so on.

This paper provides the importance of the endogenous structural breakpoint of the climate change and its consequences to the economic analysis but the underlying mechanism of the climate shock is still not fully unveiled by this research project. The potential mechanism could be the oil price transmission mechanism into inflation (Kilian (2009)). Also due to strict assumption required by the ordering identification, the choice and the order of the variable is limited so that the model does not have the full monetary and policy counterparts to the real macroeconomic variables discussed. This limitation could be complemented by a following study with the climate shock translated into financial intermediation and monetary policy.

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# A Robustness check for the Structural Breakpoint test

**Table 7:** Zivot-Andrews Test coefficients for Quarterly frequency ACI

| Variable | Estimate | Std. Error | t value | Pr(>$\|t\|$) |
|---|---|---|---|---|
| (Intercept) | -0.296262 | 0.137069 | -2.161 | 0.03166 |
| y.l1 | 0.346025 | 0.111807 | 3.095 | 0.00220 |
| trend | 0.009246 | 0.003933 | 2.351 | 0.01954 |
| y.dl1 | -0.126980 | 0.108340 | -1.172 | 0.24234 |
| y.dl2 | -0.241200 | 0.095246 | -2.532 | 0.01197 |
| y.dl3 | -0.199132 | 0.079188 | -2.515 | 0.01257 |
| y.dl4 | 0.089169 | 0.064253 | 1.388 | 0.16649 |
| du | -0.380758 | 0.134849 | -2.824 | 0.00515 |
| dt | -0.004324 | 0.003774 | -1.146 | 0.25305 |
| Test Statistic | -5.8492 | | [5%, 1%] | [-5.08, -5.57] |
| F-statistic | 42.2 | | | |

Above **Table 7** represents the Zivot-Andrews test of the quarterly frequency ACI data with the test lag of 4. Here quarterly frequency refers to seasonality: December to February is the winter, March to May is the spring, June to August is Summer and September to November is the fall quarter.

Here the lagged difference 'y.dl1' and 'y.dl4' are statistically insignificant at 10% level. These lagged difference terms represent the short-term dynamics of the series and capture the autocorrelation in the data up to the number of lags chosen for the test. Each lagged difference term indicates the immediate effect of previous time periods' changes on the current period's value. Because these coefficients measure the impact of previous time periods onto the current period, for the quarterly seasonal frequency data, the coefficeint of 'y.dl4' that gives full one year interval.

Compared to the Zivot-Andrews test with the monthly frequency ACI data shown in **Table 2**, the half of the lagged differences are statistically insignificant even at 10% level. But with a monthly freuquency data in **Table 2** such statistical insignificance problem of the lagged difference coefficients 'y.dl' mostly disappear at 1% significance level. Both Test statistic and F-statstic are significant at 1% level, suggesting the test as a whole is statistically significant.

The coefficient 'du' is a dummy variable that captures a potential structural break in the level of the time series data at a specific time point. This is statistically significant even at 1% level in the quarterly seasonal frequency. In the monthly frequency, **Table 2** has the same 'du' coefficient is also statiscially significant. The coefficient 'dt' is a trend dummy, indicating a potential change in the slope. Here, significant 'du' means there is a level change and insignificant 'dt' means the slope change is statistically rejected, both in monthly and quarterly frequencies. Monthly data is more rich in data compared to the quarterly ones so the analysis with the monthly data should be more accurate.

Zivot-Andrews test was conducted with the lags of 10, 11 and 12 with the monthly frequency data and with the lags of 3, 4 and 5 with the quarterly ones; this is shown in **Table 3**. All breakpoints indicate the year 1975 as a threshold, but the specific month and quarter vary. Together with Bai-Perron test in **Table 4** which has a different mechanism to the Zivot-Andrews test, the date 1975 July (1975M7) was chosen for the structural breakpoint of the climate change index data as this value was common in both Zivot-Andrews test and Bai-perron test.

# B Actuarial Climate Index (ACI) data

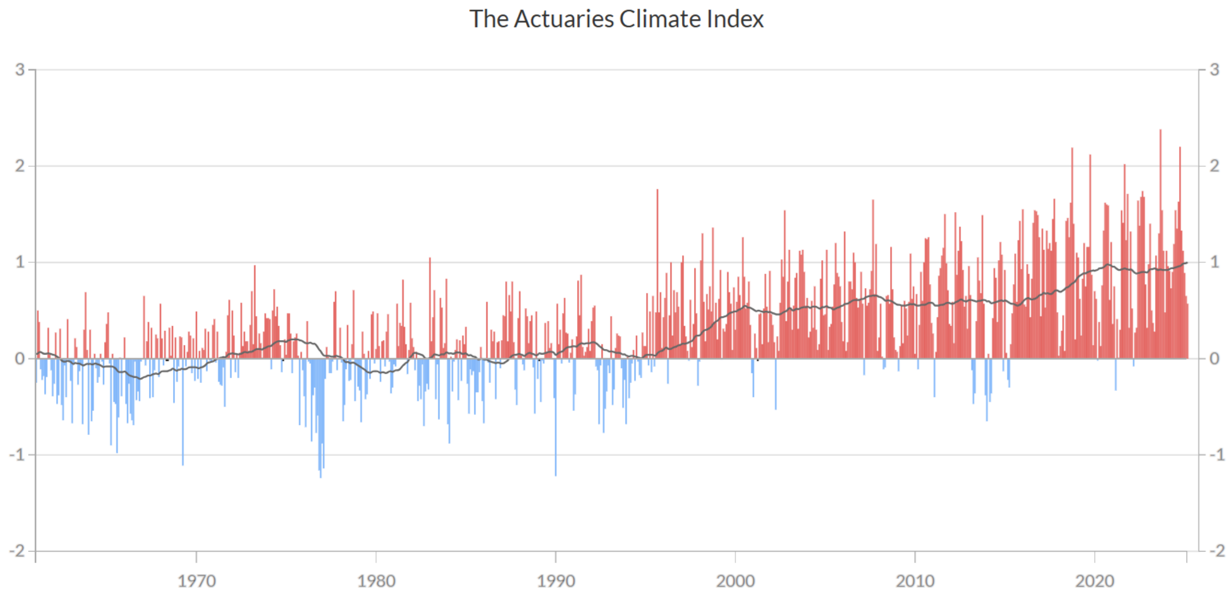


**Figure 15:** Actuaries Climate Index of the continental USA

**Figure 15** and **Figure 16** are retrieved from the official website of Actuaries Climate Index[3] (ACI) by American Academy of Actuaries et al. in the United States and Canada. The ACI is constituted of six components presented in **Table 1**, the sub-categorical weather indices are Cool Tempeature (T10), Warm Temperature (T90), Extreme Precipitation (P), the number of Consecutive Dry Days (D), Wind speed (W) and Sea Level (S). The plot graphs for these sub-category data are presented in **Figure 16**. The average values of the ACI in **Figure 15** and the components in **Figure 16**, except Dry Days (D) and Wind (W) show prominent changes across the time: cold temperature decreases where the warm temperature, precipitation and sea-level increase.

[3]web source: https://actuariesclimateindex.org/explore/regional-graphs/

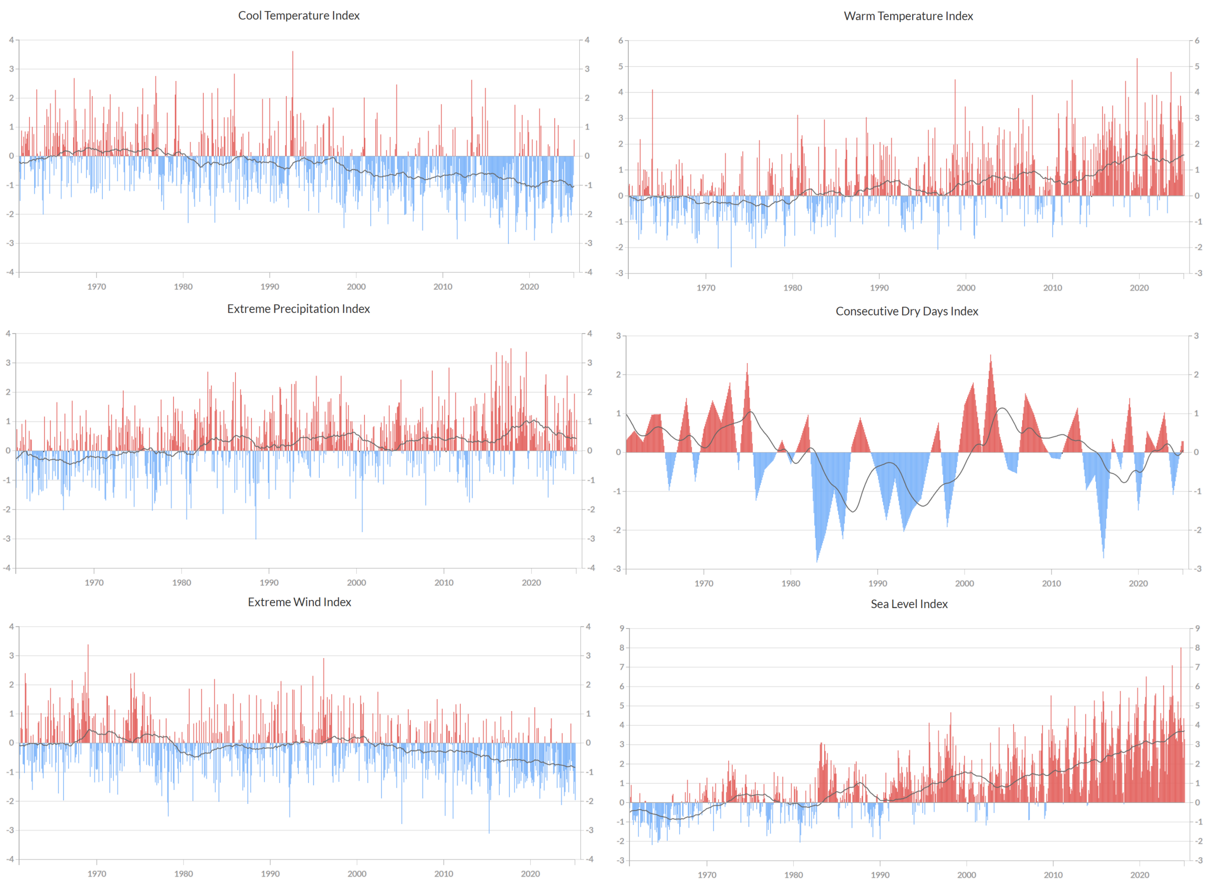


**Figure 16:** Six components of the Actuarial Climate Index (ACI)

# C Simultaneous Relations

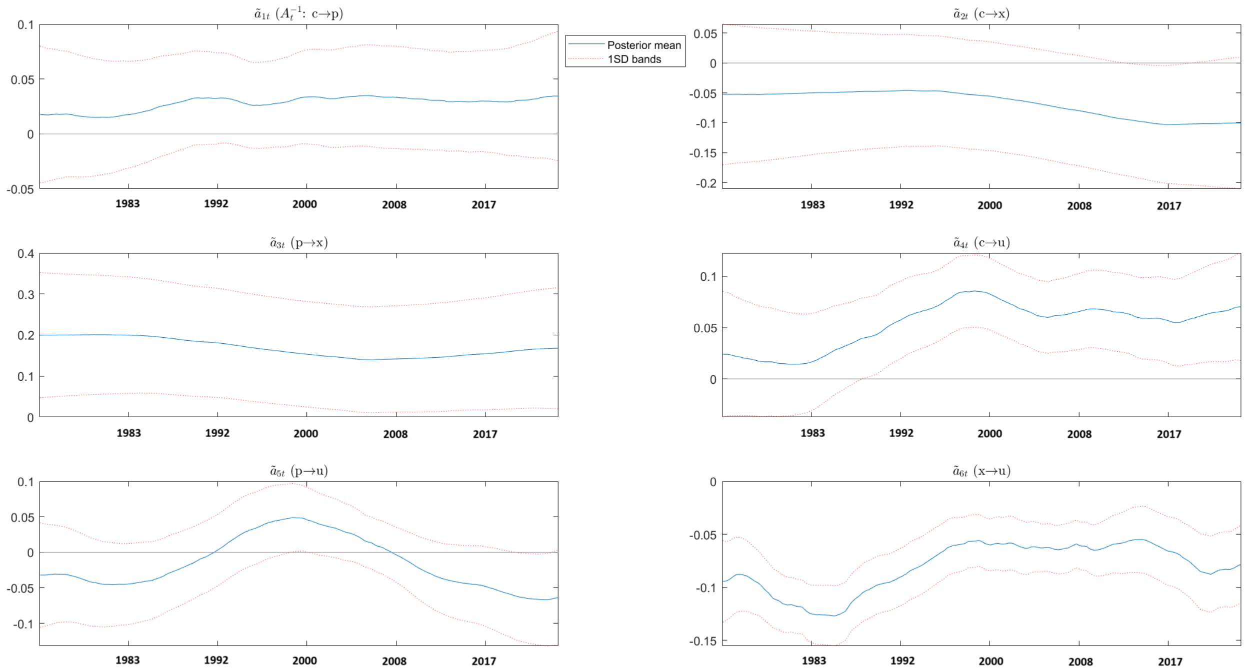


**Figure 17:** Coefficients of Simultaneous Relations

**Figure 17** represents the structural term of the model: the time-varying simultaneous relations in the $A_t^{-1}$ matrix. The simultaneous relation of the ACI to inflation stays positive and steadily increasing over the periods. This simultaenous relation suggests, although it is statistically weak, the climate severity increases the inflation within the same period. By contrast, the simultaneous relations of the climate to the output stays negative and continues to drop over periods, suggesting that the climate severity has negative impact on output within the period and the negative impact is steadily rising. The simultaneous relation of the inflation and output is statistically significant and positive throughout the periods, suggesting that the inflation can influence output within the period and greater inflation could be related to greater output. The ACI and unemployment has a positive simultaneous relations, suggesting that the simultaneous relation of the climate severity and unemployment is positively related.

# D 3D Impulse Response Functions

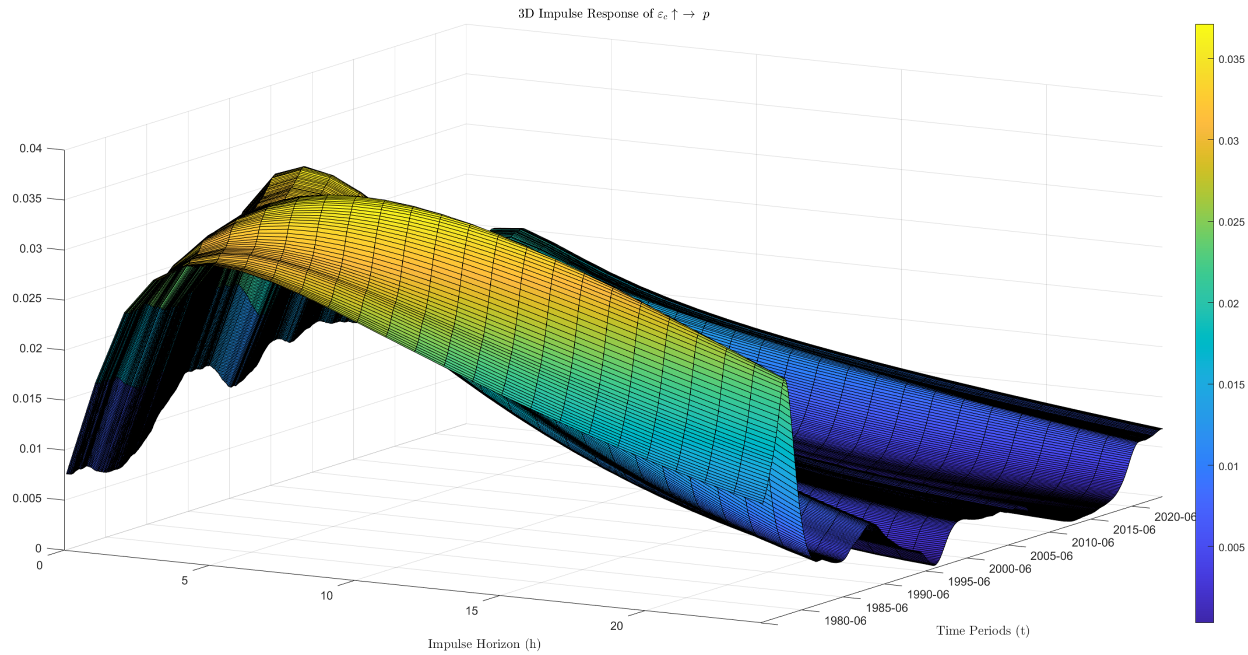


**Figure 18:** 3D impulse response of the climate shock to inflation

**Figure 18** shows the 3D impulse response function of the climate shock to inflation, given that Time-Varying Parameter model has not only the usual impulse response function over time horizon, but also such impulse response function exists for any given time point of the data.

This three-dimensional graph can be cut in two ways: cutting through the horizon gives an impulse response at a chosen time point and cutting through the period gives an impulse responses a periodic impulse response across all time horizon with a specific time ahead, e.g. 1-period ahead. The two different impulse response functions of the climate shock to the inflation variable are presented in **Figure 6**

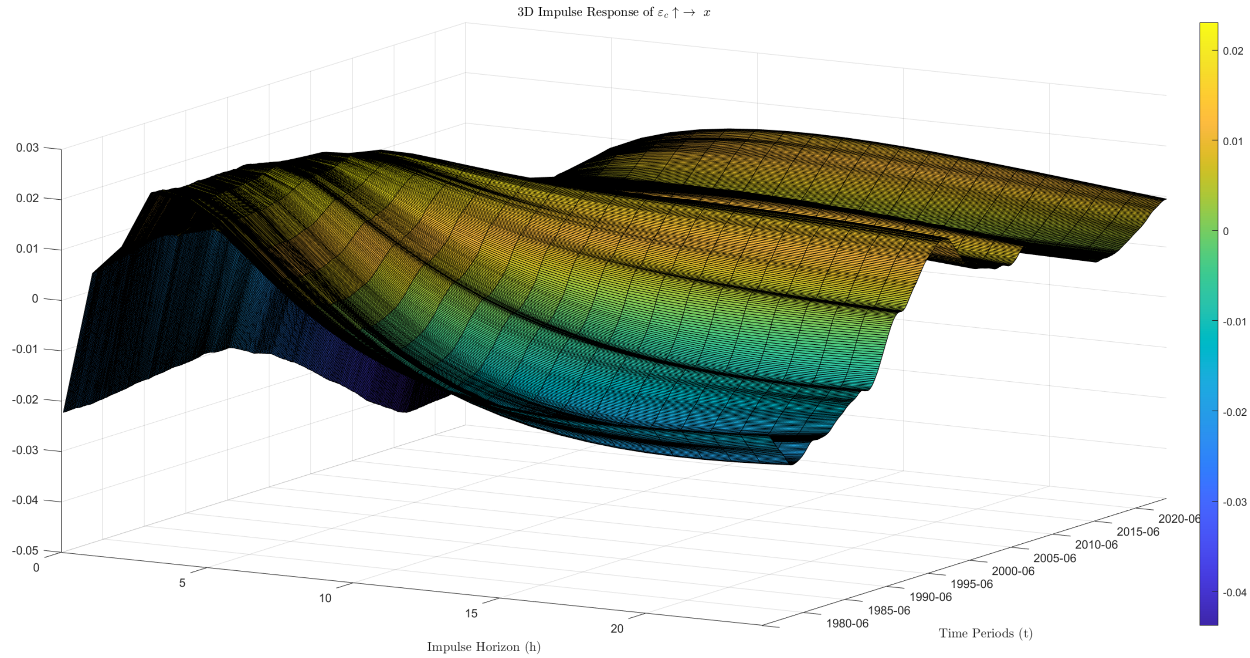


**Figure 19:** 3D impulse response of climate shock to output

**Figure 19** presents the 3D impulse response function of the climate shock to industrial production. Both of horizontal and periodic impulse response functions of the climate shock to the industrial production variable are presented in **Figure 7**

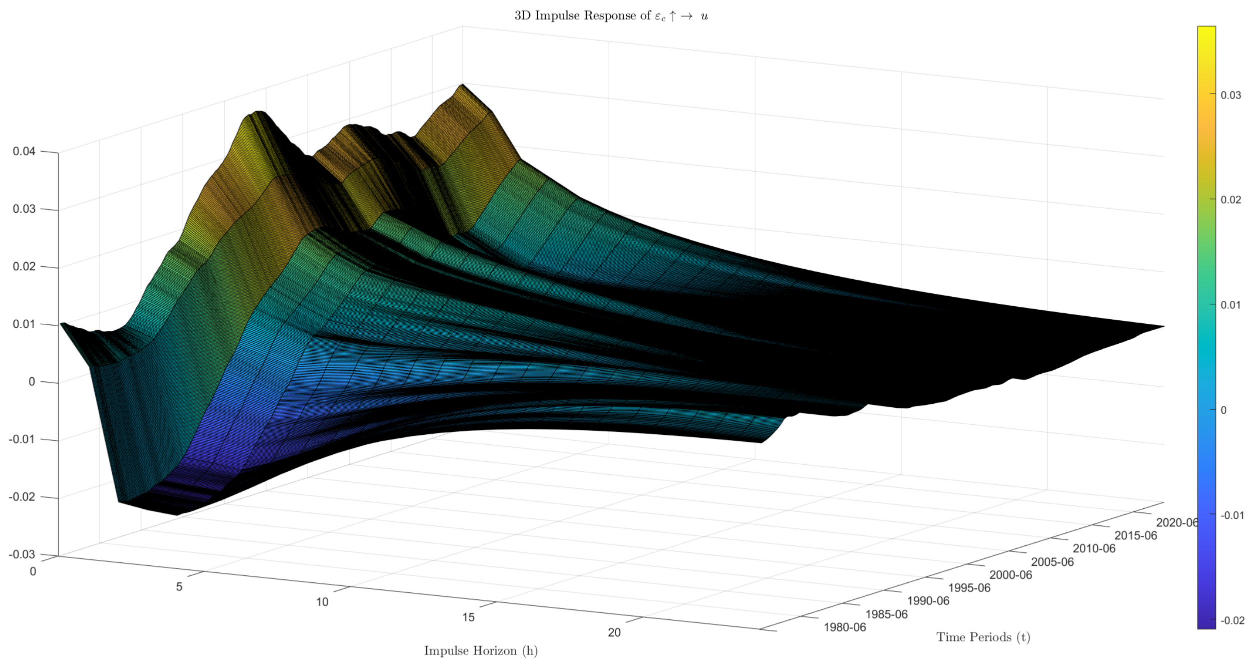


**Figure 20:** 3D impulse response of climate shock to unemployment

**Figure 20** shows the 3D impulse response function of the climate shock to unemployment. Horizontal and periodic impulse response functions of the climate shock to the unemployment rate are presented in **Figure 8**