Essays on Applied Time Series Econometrics

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Abstract

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This dissertation empirically examines how an exogenous shock can impact on macroeconomy, with a particular focus on the impact of the climate change on the United States macroeconomy and the impact of the global oil price shock to South Korean macroeconomy using applied time series econometrics models.

In Chapter 1, the changing effects of the climate change on the US macroeconomy has been studied with a Bayesian Time-Varying Parameter with Stochastic Volatility model framework. Using Actuaries Climate Index (ACI) and monthly inflation, industrial production and unemployment from July 1975 to February 2024, it captures how the transmission of climate disturbances shift over time. Importantly this research identifies the timing of the structural break in the ACI data and show the importance of the structural break in estimation of parameters with time variation. This approach reveals that both the volatility and the acceleration of the climate change have been intensified over time, amplifying the macroeconomic consequences.

Chapter 2 extends the research about the impacts of climate change on the US macroeconomy by implementing a Factor Augmented VAR (FAVAR) model to present h ow the climate change shock represented by the ACI data could impact on a large set of 123 monthly US macroeconomic variables from the Federal Reserve Economic Data. The richness of the macroeconomic dataset allows to show the impact of climate change shock on all sectors of entangled US macroeconomic variables. This research shows that there exist significant impacts of the climate change shock on: the working hours in goods-producing and manufacturing sectors in the US labor market, housing starts and permits in national level, real M2 money stock, S&P500 in US stock market, treasury and corporate spreads, and the inflation in medical care sector. These results can be used as an alternative measure for the variable selection method that conveys richer economic stories about which of macroeconomic variables and the sectors are more prone to climate change.

Chapter 3 implements the Time-Varying Parameter model to study the changing impacts of the global oil price change on South Korean macroeconomy. This research complements the existing literature by showing empirical evidence about the demand-driven oil price shock could boost economic growth as the exporting countries in Asia could benefit more from the rise in global real economic activities. This research subsequently finds the shift in the initial response of the Korean industrial output from the global oil price change shock, presenting a change in contemporaneous response of Korean industry from the global oil shocks that is turning negative since 2014 although the following responses in later period is still positive, serving as an alarm call for South Korean industry.

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DEDICATION

To my family

Chapter 1

CLIMATE CHANGE AND THE US MACROECONOMY: TIME-VARYING PARAMETER APPROACH WITH STOCHASTIC VOLATILITY

1.1 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, Matthes, and Phan (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 policy-makers. 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), S. 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), Roth Tran and Wilson (2025)). This is somewhat mixed because there are opposing results suggesting the weather shocks generate persistent damage to industrial production with no recovery documented by S. M. 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 chapter proceeds as follows. **Section 1.2** provides the economic model framework for TVP-SVAR-SV model. **Section 1.3** describe the data, including the Actuaries Climate Index (ACI) and its important threshold, as well as macroeconomic data used. **Section 1.4** presents main empirical findings and discussions. Finally **Section 1.5** concludes with a discussion of potential use for policy implications and future works. This Chapter 1 is also available in SSRN as Won (2025).

1.2 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 for the estimation. Suppose that we have a time-varying structural VAR model that is defined as:

$$A_t y_t = F_0 + F_1 y_{t-1} + \cdots + F_p y_{t-p} + \nu_t \quad \text{where} \;\; \nu_t \sim N(0, \Sigma_t \Sigma_t') \tag{1.1}$$

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 ν_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 (1.1)** as a reduced form equation:

$$y_t = B_0 + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t \tag{1.2}$$

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 β which is a $(k + k^2p) \times 1$ vector. Defining $X_t = I_k \otimes (1, y_{t-1}, \ldots, y_{t-p})$ where $\otimes$ is the Kronecker product, **Equation (1.2)** can be reduced to:

$$y_t = X_t\beta + A_t^{-1}\Sigma_t\varepsilon_t \quad \text{where } \varepsilon_t \sim (N, I_k) \tag{1.3}$$

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 β of **Equation 1.3** gives the Time-Varying Parameter Structural VAR with Stochastic Volatility model:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t \quad t = p+1, \ldots, n \tag{1.4}$$

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

$$\begin{cases} \beta_{t+1} \sim N\left(\beta_t, \Sigma_{\beta_0}\right) \\ a_{t+1} \sim N\left(a_t, \Sigma_{a_0}\right) \\ h_{t+1} \sim N\left(h_t, \Sigma_{h_0}\right) \end{cases} \tag{1.5}$$

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.

1.3 Data

1.3.1 Climate Data: Actuaries Climate Index (ACI)

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 (2026) to indicate the climate extremes of the United States and Canada. The ACI is constituted of six sub-categories summarized in **Table 1.1**:

Table 1.1: 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 1.1** 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.

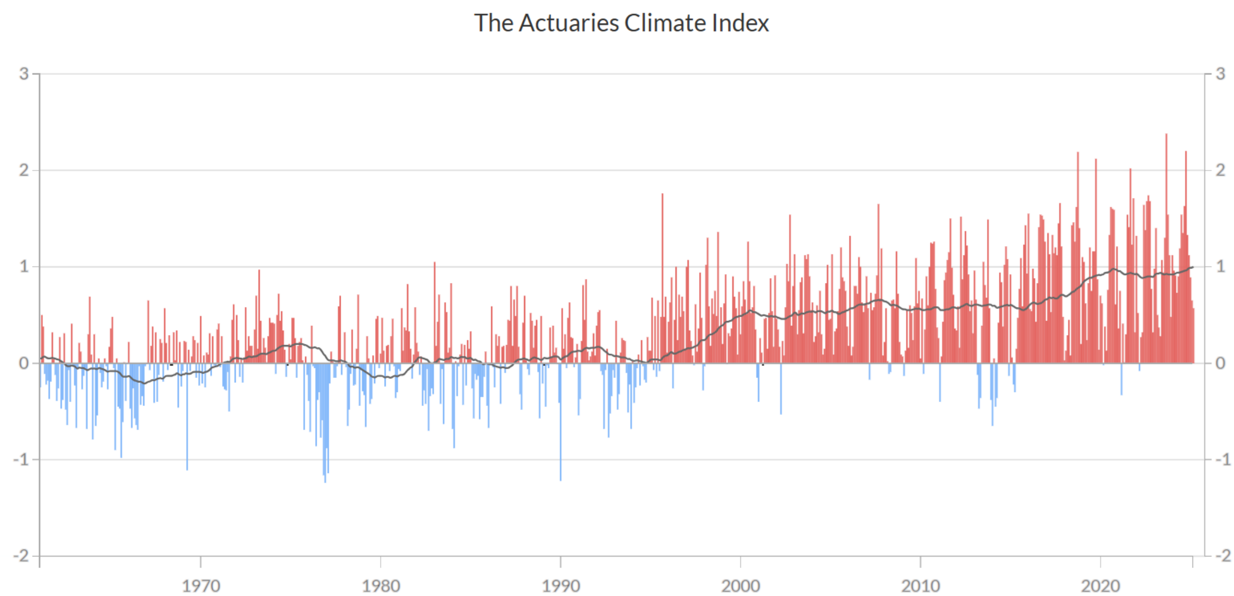


Figure 1.1: Actuaries Climate Index of the continental USA

Figure 1.1 and **Figure 1.2** are retrieved from the official website of Actuaries Climate Index[1] (ACI) by American Academy of Actuaries et al. in the United States and Canada. The ACI is constituted of six components presented in **Table 1.1**, the sub-categorical weather indices are Cool Temperature (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 1.2**. The average values of the ACI in **Figure 1.1** and the components in **Figure 1.2**, 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.

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

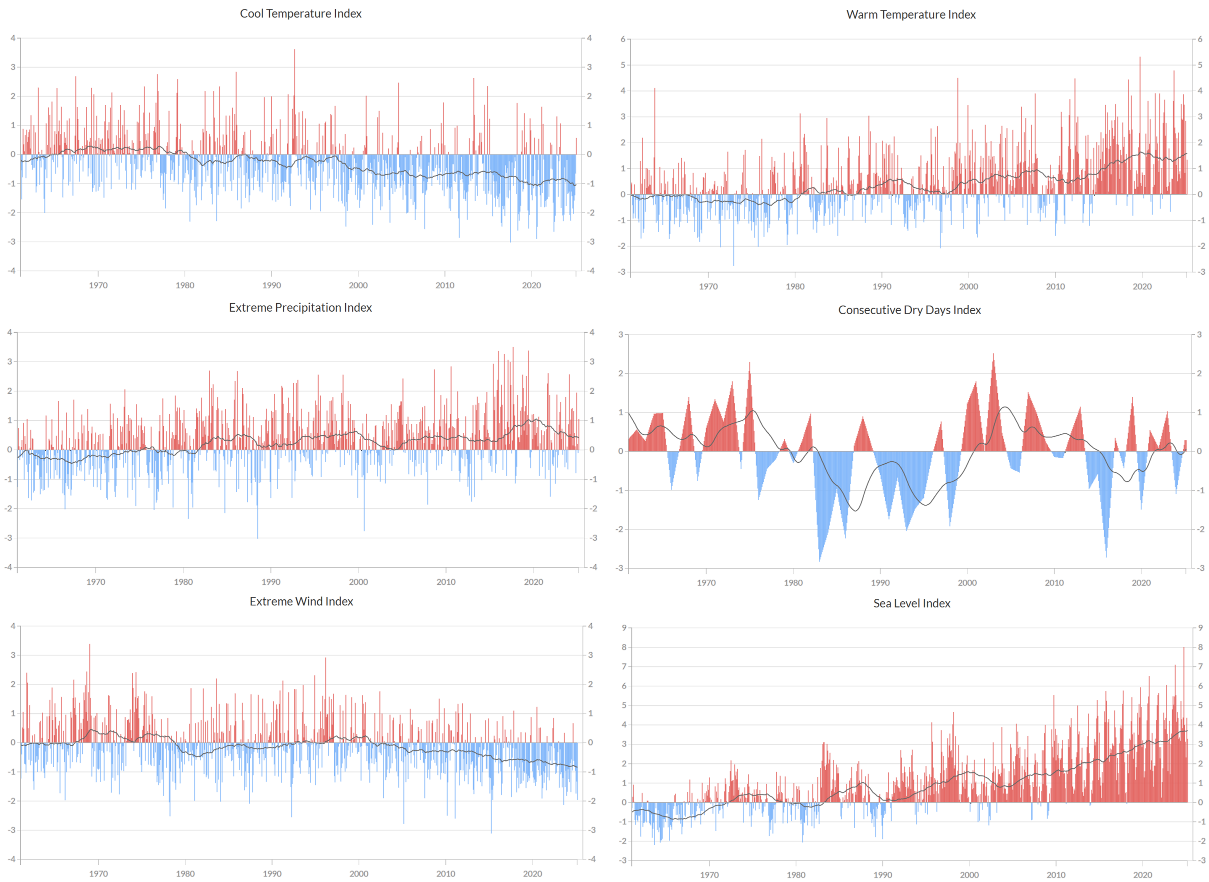


Figure 1.2: Six components of the Actuarial Climate Index (ACI)

1.3.2 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 1.2 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 1.2**, the variable 'du' is statistically

Table 1.2: 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			

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

Table 1.3: 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

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 1.3** 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.

Table 1.4: 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 1.4** 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 coefficient of ‘y.dl4’ that gives full one year interval.

Compared to the Zivot-Andrews test with the monthly frequency ACI data shown in **Table 1.2**, the half of the lagged differences are statistically insignificant even at 10% level. But with a monthly frequency data in **Table 1.2** such statistical insignificance problem of the lagged difference coefficients ‘y.dl’ mostly disappear at 1% significance level. Both Test statistic and F-statistic 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 1.2** has the same ‘du’ coefficient is also statistically 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 1.3**. All breakpoints indicate the year 1975 as a threshold, but the specific month and quarter vary. 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.

For the robustness sake, Bai and Perron (2003) test is also conducted to find structural break with a different mechanism. **Figure 1.3** shows the different structural breaks found from Bai and Perron (2003) test, where BIC value of 949.9 in **Table 1.5** 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).

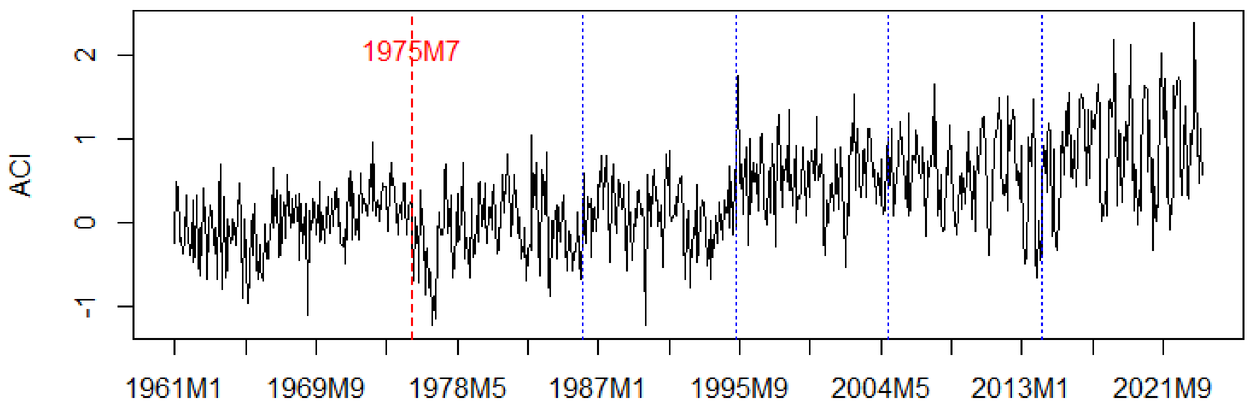


Figure 1.3: Bai-Perron Breakpoint Test on ACI data

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

Table 1.5: 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

because as can be seen from **Table 1.2**, stationarity of the series could be questionable around the structural breakpoint of 1975 and also the estimates can be biased.

1.3.3 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 1.4** 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

[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.

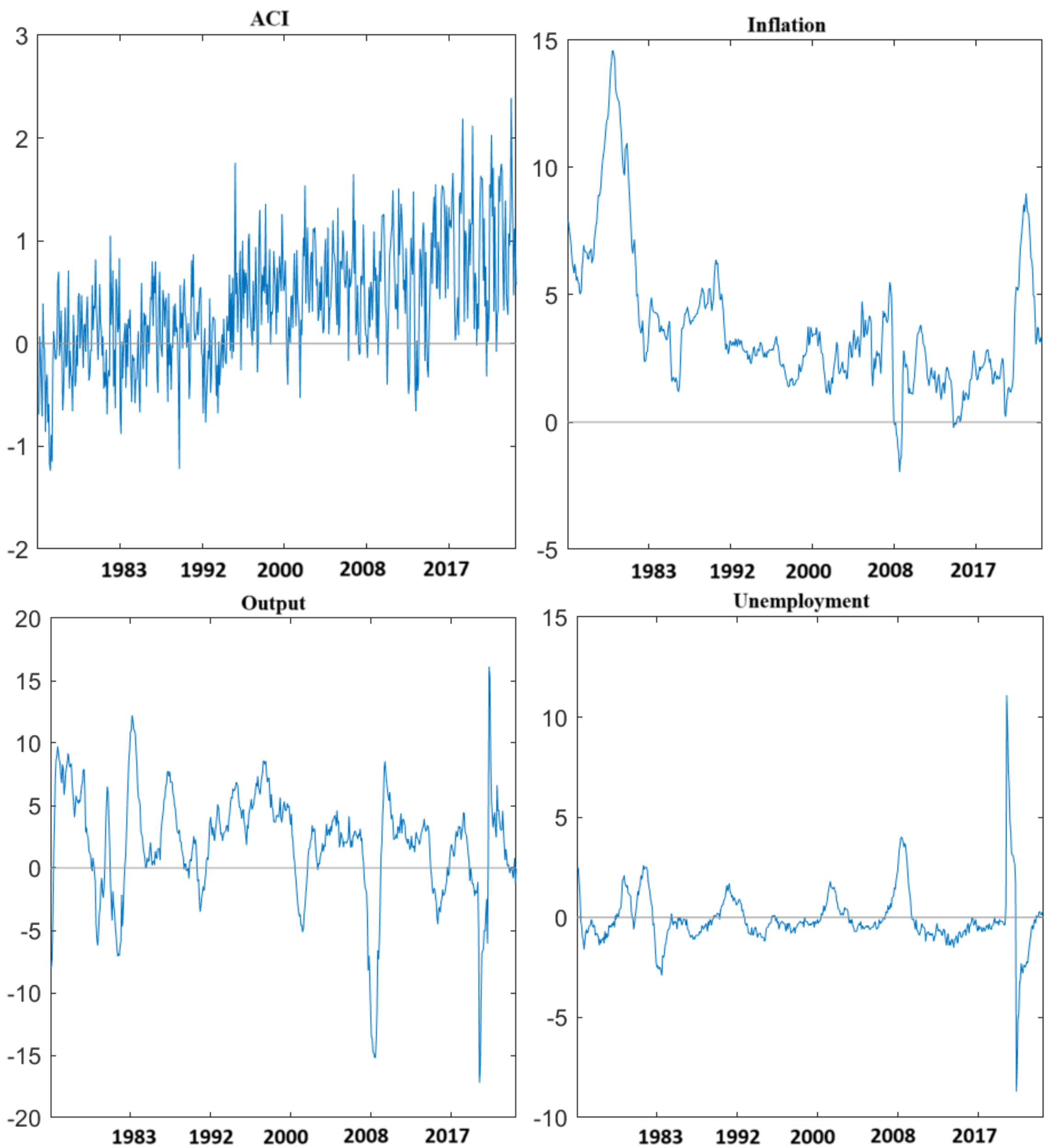


Figure 1.4: ACI, Industrial Production change, Inflation and Unemployment change

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.

1.4 Empirical Results and Discussions

The estimation of this Bayesian Structural VAR model has been conducted using the autoregressive lag length of 2, determined by the smallest criterion number from the Bayesian Information Criterion shown in **Table 1.6**. The criteria with lesser number, i.e. more negative number, indicates better model fit.

Table 1.6: Number of Lags and the 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 1.7 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

Table 1.7: 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

$(\Sigma_\beta)_2$ 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 climate change and the inflation, which are significant so the there is a time-variation in the heteroskedasticity of the variables.

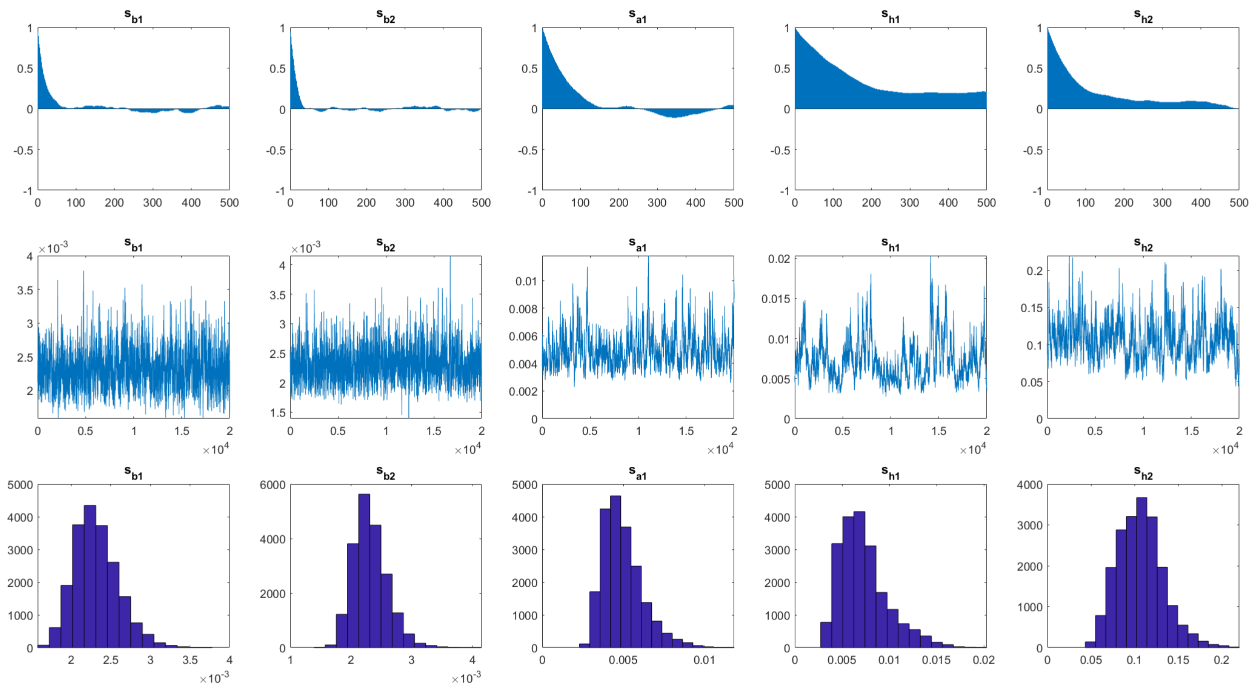


Figure 1.5: Sample Autocorrelation, Sample Path and Posterior Densities

Figure 1.5 shows the sample autocorrelation (top), sample path (middle) and posterior densities for the selected parameters presented in **Table 1.7**. Given that this Bayesian TVP-SVAR-SV model assumes the random walk processes of the parameters presented in **Equation (1.5)**, 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 1.6 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.

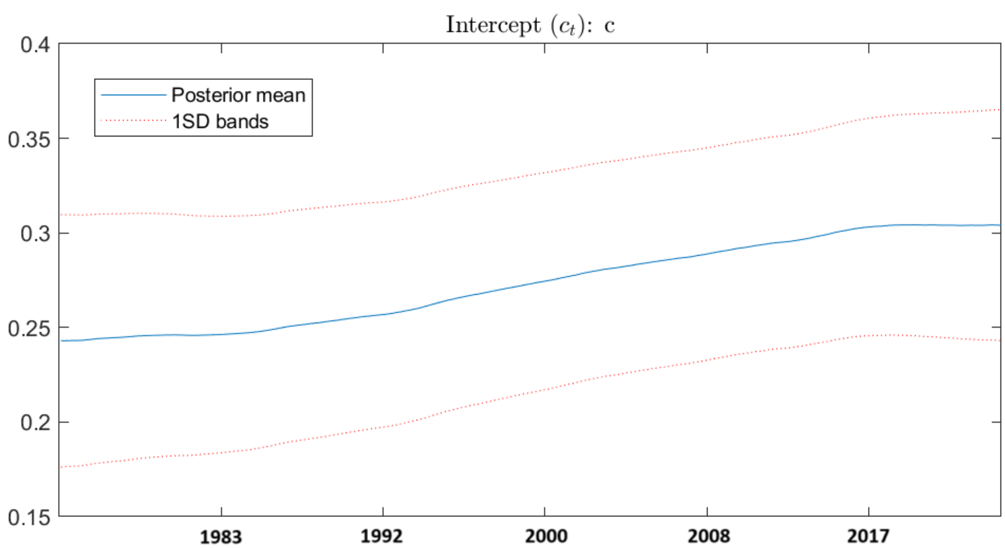


Figure 1.6: Time-varying Intercept of the climate index

Figure 1.7 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 1.7** 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 macroeconomic variables - inflation (p), industrial production (x) and unemployment (u) in **Figure 1.7**. 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 modeling stochastic volatility terms, and thereby provides more robust impulse response analysis from the climate shock.

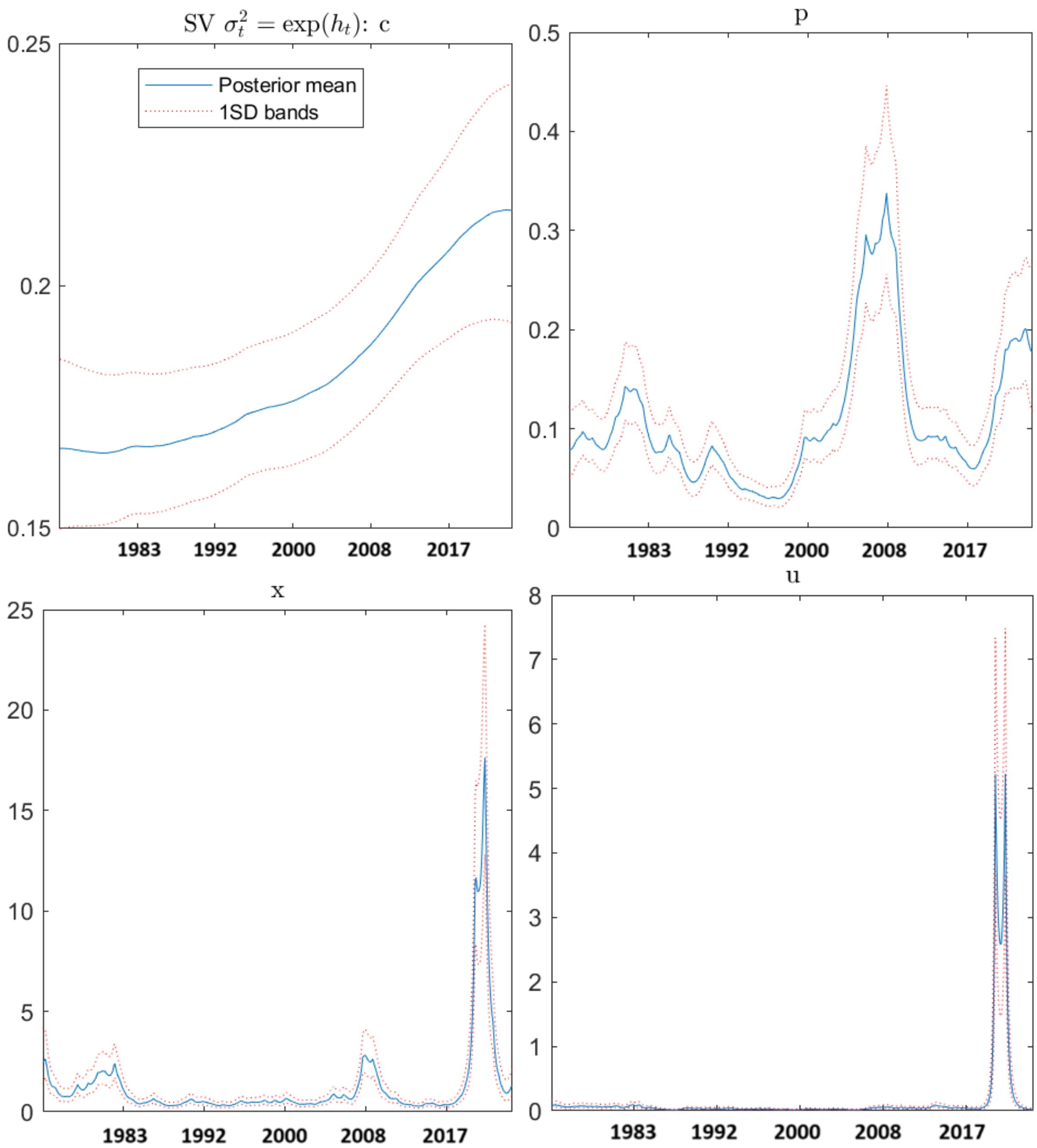


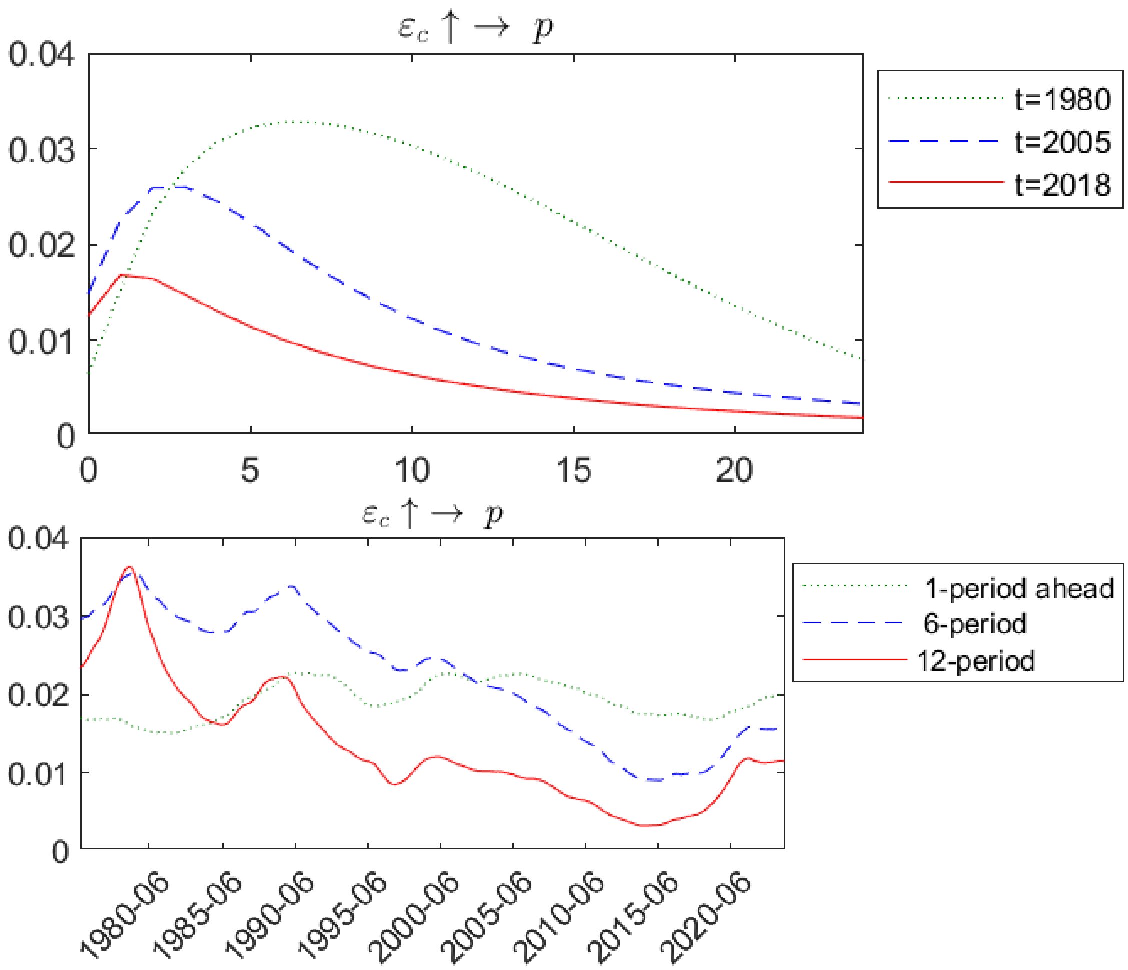
Figure 1.7: Stochastic Volatility terms of four variables

Impulse Response analysis

Figure 1.8, **Figure 1.9** and **Figure 1.10** present 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 (β_t) throughout all periods. Though these 3D impulse response functions are available in **Appendix A.2**, 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 1.8 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 1.8**, the green dot line presents year 1985 impulse response; 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 factors 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



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 1.8: Impulse Response of climate shock to inflation

percentage point increase but then it exhibits even faster return toward the baseline.

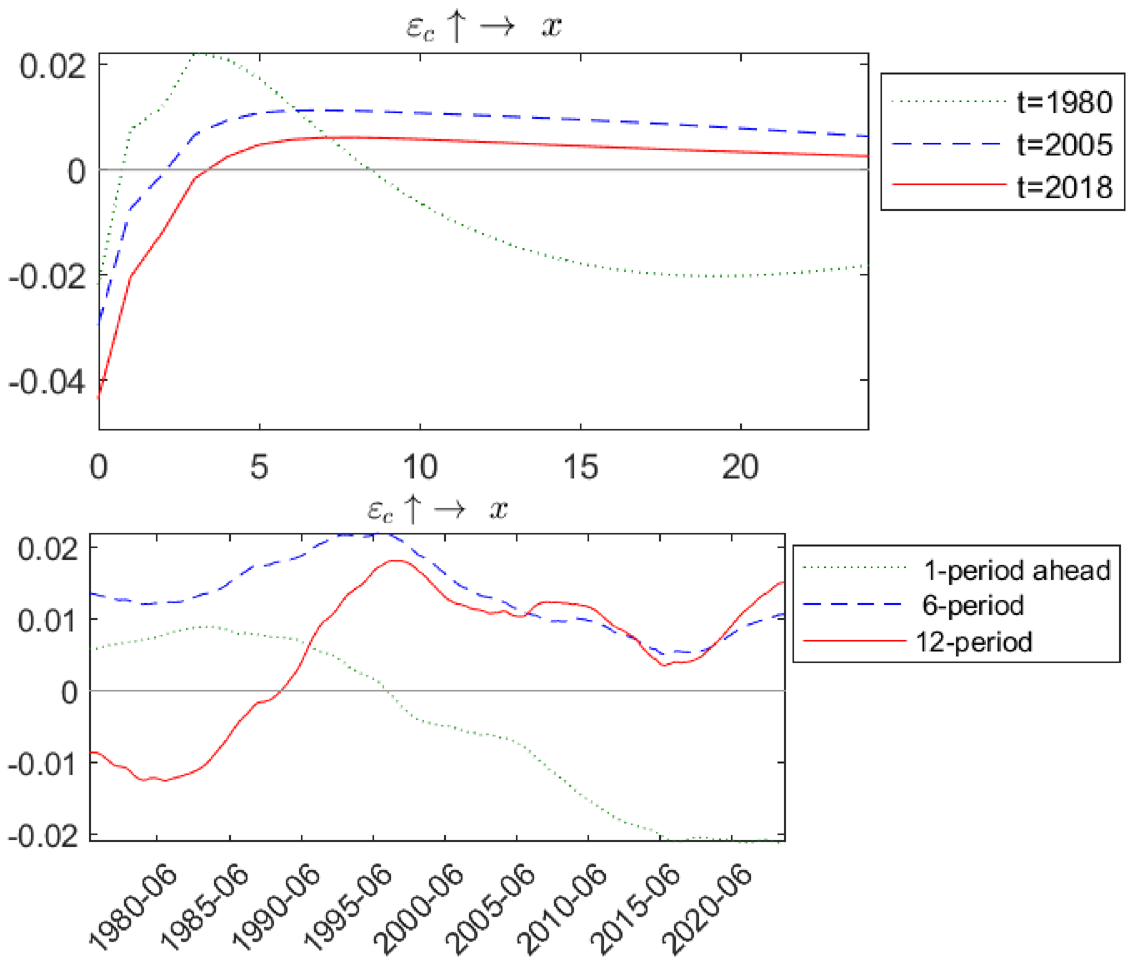
On the bottom panel of **Figure 1.8**, the horizontal axis represents the chronological time from year 1975 to 2024. The green dot line depicts the immediate shock at impulse horizon of $h = 1$ right after the initial shock. Across all years in the sample, the one-period-ahead response to a climate shock (green dot at bottom) is positive. Importantly, the trimming of

ACI data aforementioned in **Section 1.3.2** 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 1.8**. Due to aforementioned reason in **Section 1.3.2**, 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 1.9 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



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

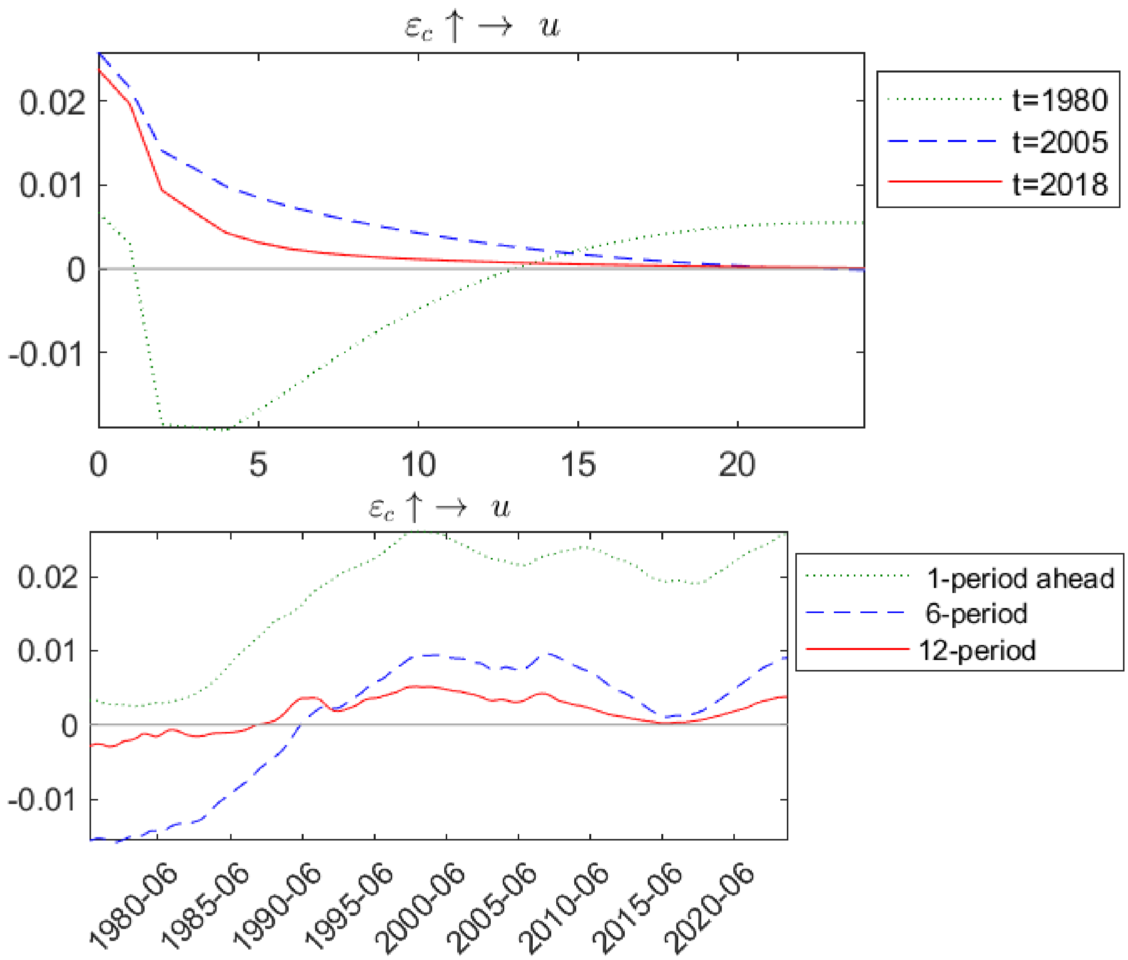
Figure 1.9: Impulse Response of climate shock to output

"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 fueled 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 resilience 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 1.9** 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.

Figure 1.10 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



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 1.10: Impulse Response of climate shock to unemployment

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 1.10** 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 1.11** 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 to 2024 February which the start date is chosen by the structural breakpoint tests explained in the **Subsection 1.3.2**. 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.

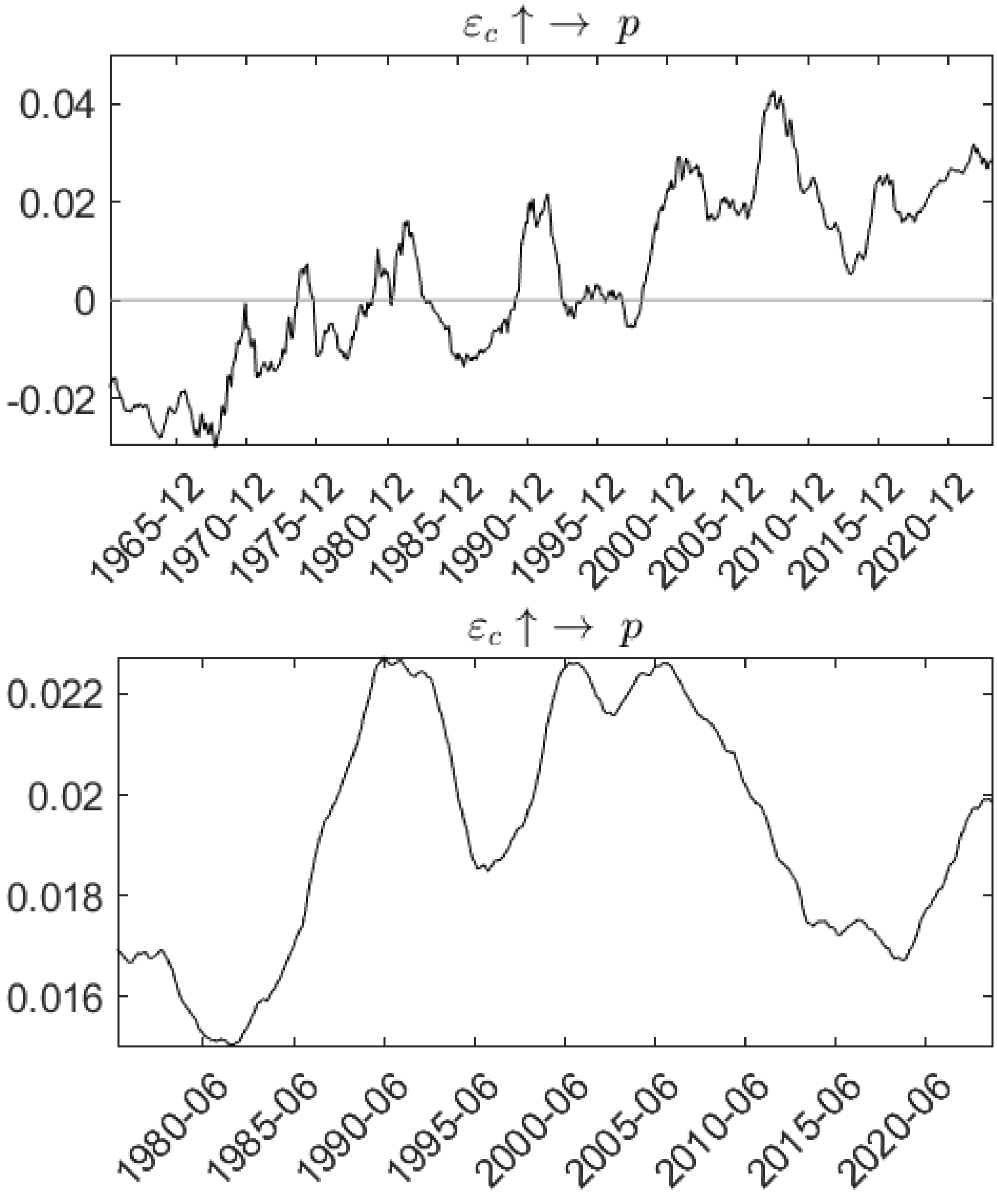


Figure 1.11: 1-month impulse responses of inflation with data from 1961M1 vs. from 1975M7

(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 1.3.2**, 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

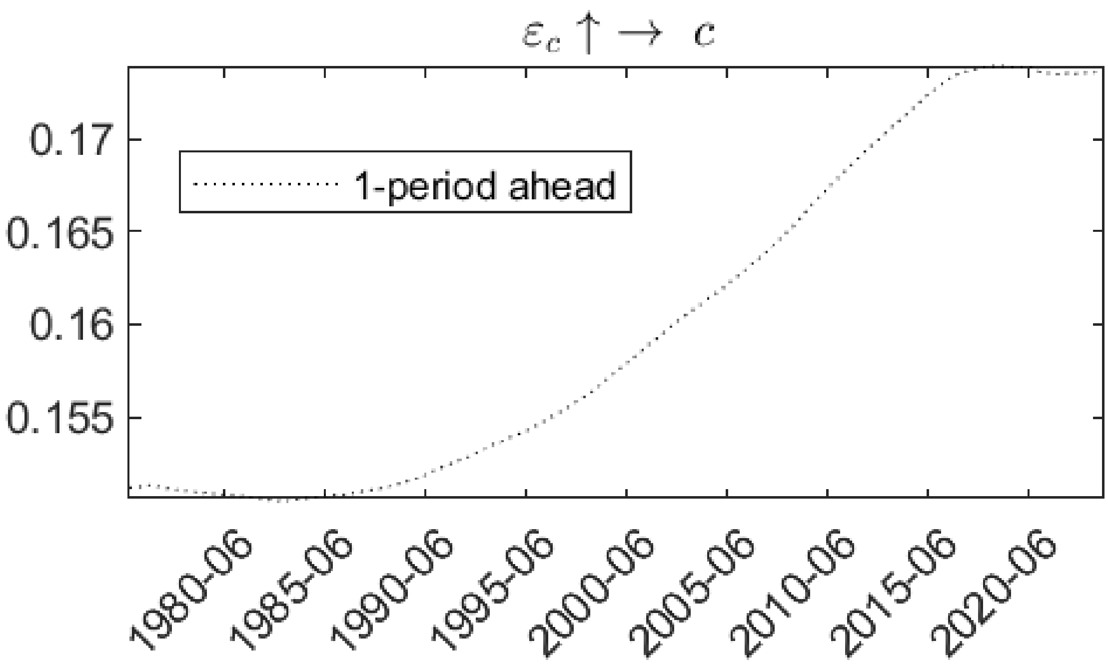


Figure 1.12: Initial zero period and 1-month ahead Impulse Response of climate index

Figure 1.12 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 1.6** and the top-left figure of **Figure 1.7**, 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.

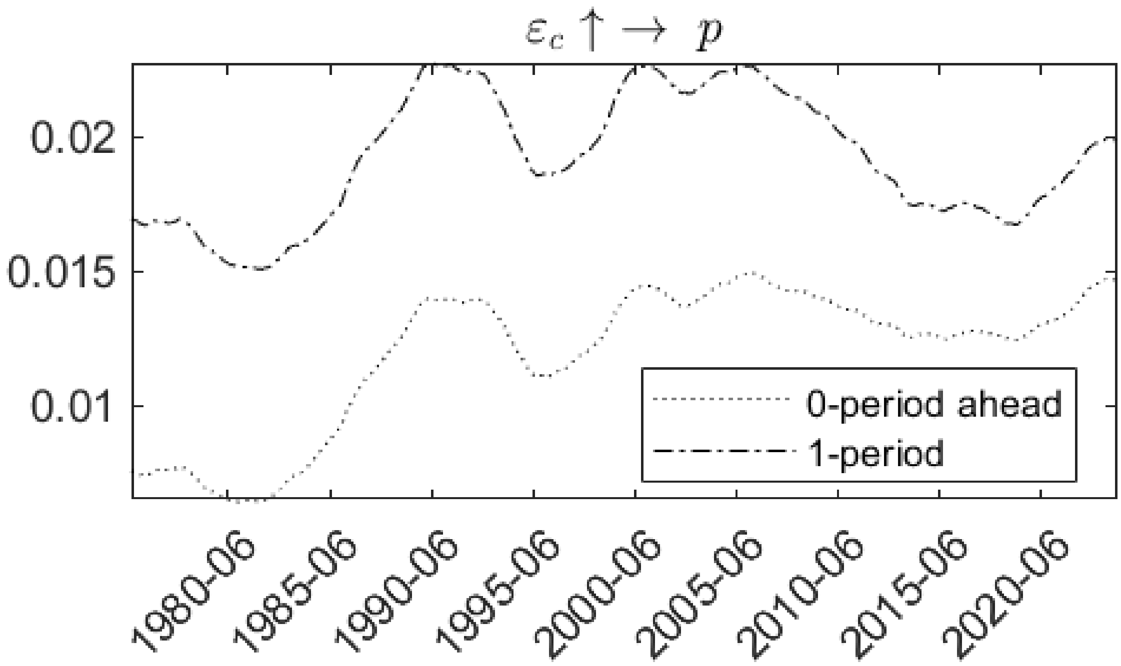


Figure 1.13: Initial zero period and 1-month ahead Impulse Response of Inflation

Figure 1.13 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 initial climate shock increases inflation and such increase is intensified after the initial shock.

Figure 1.14 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

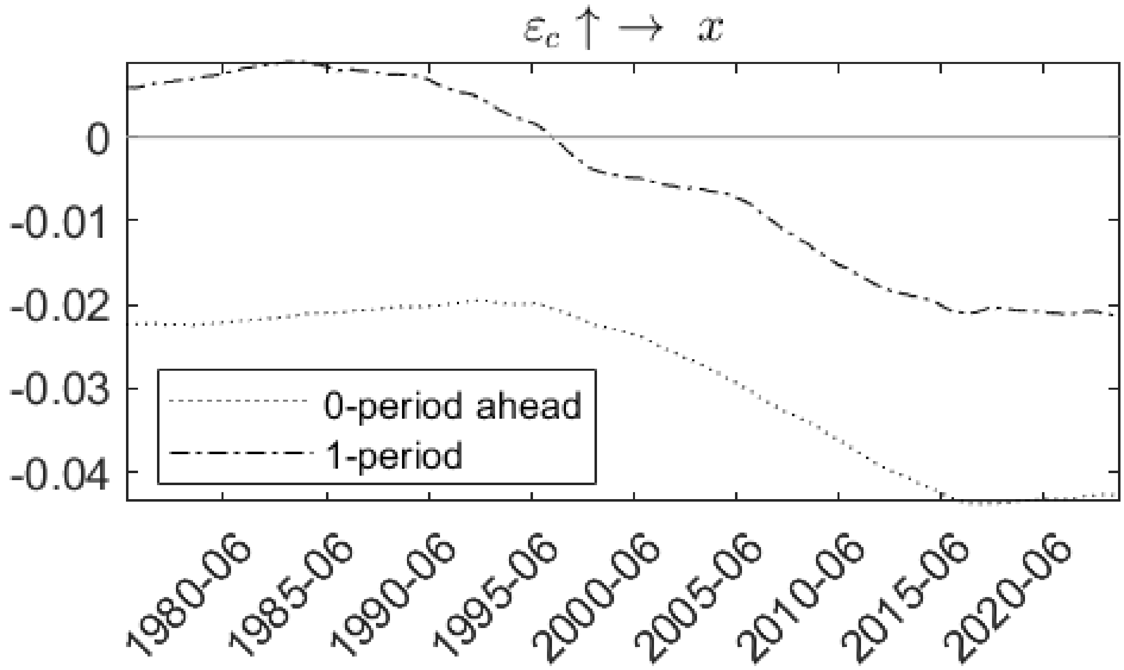


Figure 1.14: Initial zero period and 1-month ahead Impulse Response of Output

month after, the initial negative impact is mitigated; climate shock decreases the output but it catches up in subsequent periods.

Figure 1.15 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.

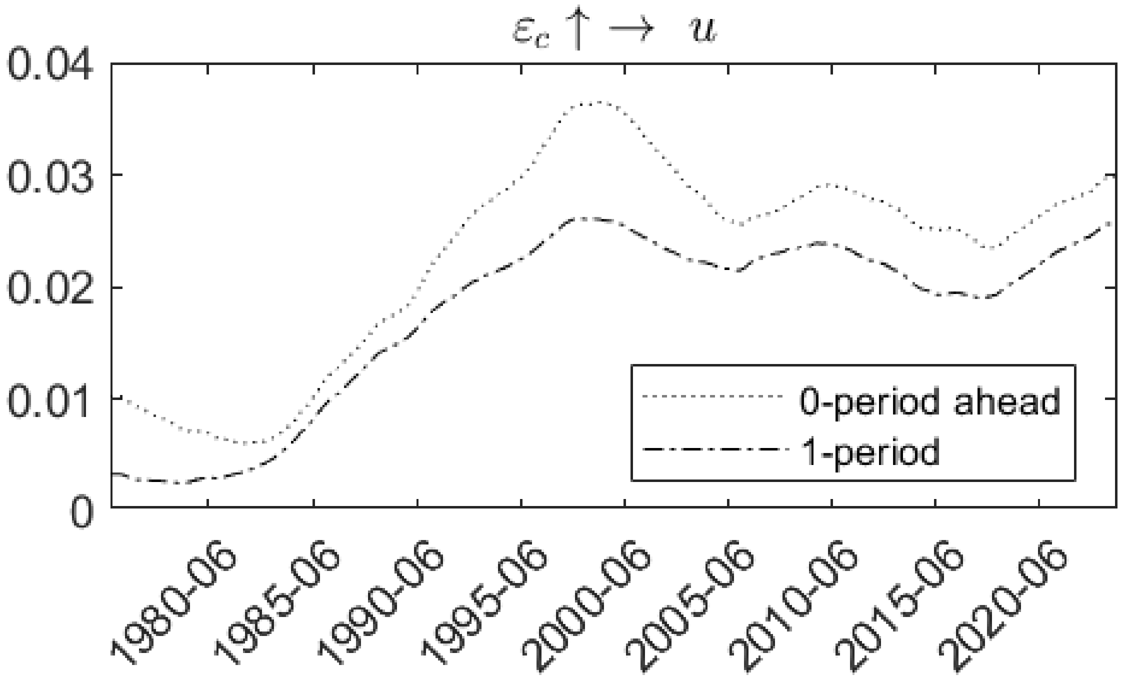


Figure 1.15: Initial zero period and 1-month ahead Impulse Response of Unemployment

After COVID-19

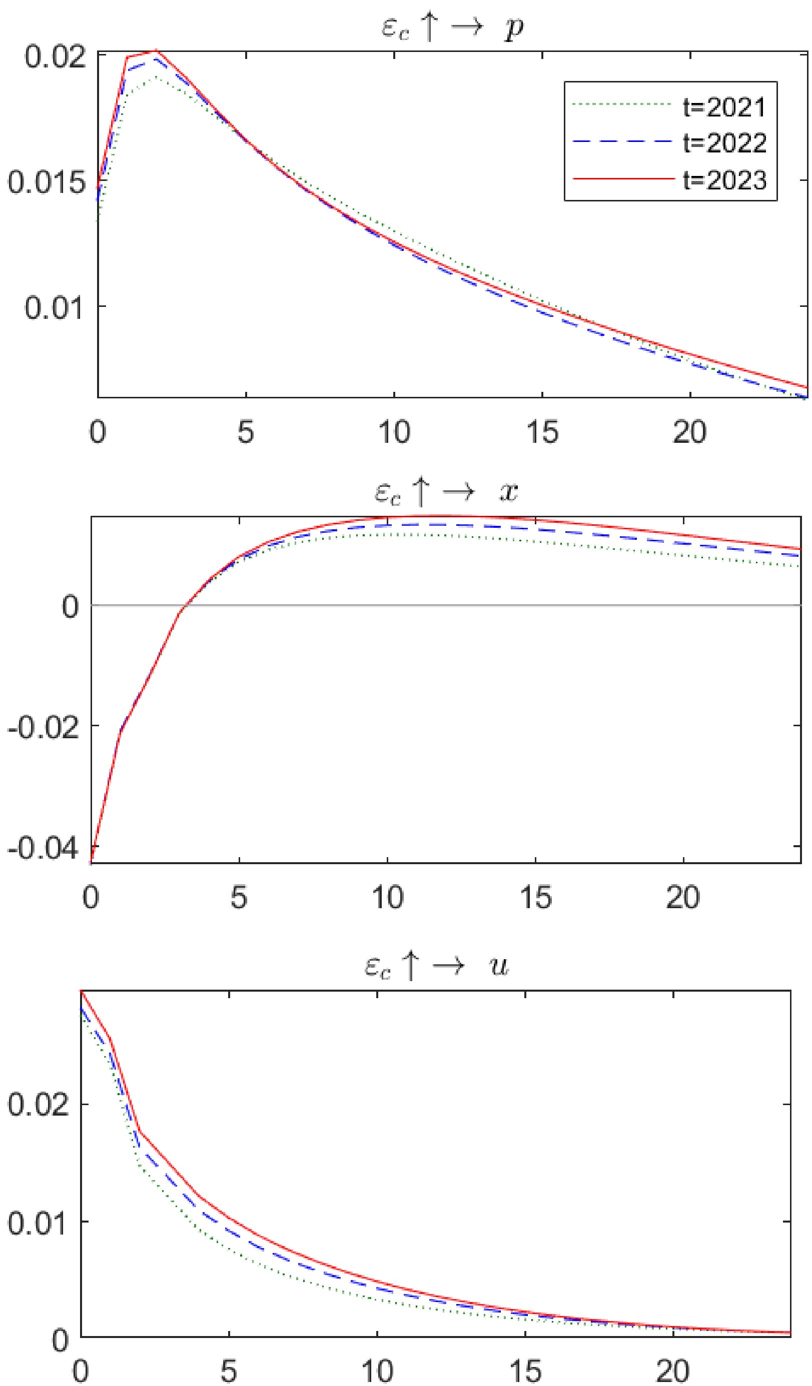
Figure 1.16 shows the impulse response function of ACI shock on inflation, output and unemployment after COVID-19. In the top panel, the climate shock generates an increase of approximately 1.5 percentage points in inflation. Noticeably this level is comparable to the largest responses observed in earlier 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 1.16**, 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 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 et al. (2024)).

The bottom panel of **Figure 1.16** 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 1.10**, 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.

Figure 1.16: Impulse Response Functions after COVID-19



Green dot: year 2021, Blue dot: year 2022, Red solid line: year 2023

1.5 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 finds the importance of the endogenous structural breakpoint of the climate change and its consequences to the economic analysis. However, 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 (2009a)). 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.

Chapter 2

CLIMATE CHANGE AND THE LARGE SET OF US MACROECONOMIC VARIABLES: FAVAR APPROACH

2.1 Introduction

This research complements the research in Chapter 1 by studying the impact of climate change on a comprehensive general macroeconomy of the United States. Using an empirical implementation with the Actuaries Climate Index (ACI) - a recent climate indicator for the North America region, this research provides the analysis about the impact of climate change shock on all sectors of the United States macroeconomy.

This work is related to a series of climate economics literature presenting how weather can influence on the economic outcomes (e.g. Dell et al., 2014; S. Hsiang, 2016). The earlier literature largely emphasizes the negative outcomes of the weather shocks on the economic growth, especially in comparison to the developing countries (Dell et al., 2012; Alessandri and Mumtaz, 2021). Adverse climate shock in the United States have been studied on the exposed sectors in particular, for example agriculture (Roberts and Schlenker, 2013; Burke and Emerick, 2016).

There are growing number of literature using Actuaries Climate Index as a representative measure for the climate change, for instance Sheng et al. (2022), Liao et al. (2024), Sheng et al. (2024), Kim et al. (2025), Won (2025). This paper implements Factor Augmented Vector AutoRegression (FAVAR) model of Bernanke, Boivin, and Eliasz (2005), with the Actuaries

Climate Index (ACI) and 123 macroeconomic variables from Federal Reserve Economic Data, from 1978 March to 2024 February to present comprehensive macroeconomic responses. Note that the start date is chosen in order to account for the endogenous structural break in the ACI data analyzed by Won (2025).

Identification of unobserved factors in the factor models requires the assumption that the unobserved factors are not correlated with the observed ones, or it requires to impose certain timing restrictions in variables. For example, the model introduced by Bernanke et al. (2005), which is the benchmark of the FAVAR type model, assumes a recursive structure of "fast-moving" and "slow-moving" variables. This framework of Bernanke et al. (2005) is widely used, as a stand-alone model or as a model for comparison (Yamamoto, 2019; Dias and Duarte, 2019). Stock and Watson (2005) assumes short-run and long-run restrictions, Bai, Li, and Lu (2016) assumes set of exclusion restrictions with zero contemporaneous correlation between the unobserved factors and the observed ones. Yamamoto and Hara (2022) proposes the identification based on the changes in the variances of the structural shocks instead of timing assumption. List of Factor Augmented VAR models are well summarized in Stock and Watson (2016), and in this research, the fundamental framework of Bernanke et al. (2005) is used for estimation.

The main findings of this research is in twofold. Firstly, this research covers the climate change and its impact to a large and comprehensive dataset of the US macroeconomic variables. This research showcases that there exist significant impacts of the climate change shock on: the working hours in goods-producing and manufacturing sectors in the US labor market, housing starts and permits in national level, real M2 money stock, S&P500 in US stock market, treasury and corporate spreads, and the inflation in medical care sector. Secondly and perhaps more importantly, these results can be used as an alternative measure for the variable selection method that conveys richer economic stories about which of macroeconomic and financial sectors and variables are more prone to the climate change. As the selection of significantly impacted variables are chosen via impulse responses from the one standard deviation climate shock, it offers a different setting to commonly used variable selection methods such as LASSO or Ridge estimator. Such advantage can be easily utilized in policy recommendation, monitoring tool and macroeconomic forecasting.

The remainder of this chapter proceeds as follows. **Section 2.2** provides the econometric model framework for the Factor Augmented VAR (FAVAR) model used for the estimation. **Section 2.3** describes the data used: the monthly-frequency US macroeconomic data and the Actuaries Climate Index (ACI). **Section 2.4** presents main empirical results and discussion. **Section 2.5** concludes. This Chapter 2 is also available in SSRN as Won (2026).

2.2 Model

For the estimation, the Factor Augmented VAR (FAVAR) model introduced by Bernanke et al. (2005) is used. Suppose X_t is the $N \times 1$ vector of N observed variables at time $t \in T$. Let F_t be the $K \times 1$ hidden vector of latent factors and Y_t be the observed variable of interest for the macroeconomic research. The economic system can be represented by the lag polynomial of hidden factors F_t and the observed variable Y_t such that

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \tag{2.1}$$

The observation equation for this Factor Augmented VAR model can be modeled as:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{2.2}$$

where Λ^f is an $N \times K$ factor loadings matrix, Λ^y is an $N \times 1$ loadings vector on the variable of interest and e_t is an $N \times 1$ vector of the idiosyncratic error term.

This system of equations allow to utilize many macroeconomic series of X_t that one can observe in the real world, with an assumption that hidden unobserved economic factors F_t drive the macroeconomy as a whole so the observed X_t are entangled by the common factors. Y_t is the observable variable of interest for the research. Each of macroeconomic variable series moves due to hidden factors, the variables of interest and some idiosyncratic noise terms e_t.

The transition equation of this FAVAR with the latent factor F_t and the observed variable of interest Y_t is denoted as

$$Z_t = \begin{bmatrix} F_t \\ Y_t \end{bmatrix}, \quad Z_t = A_1 Z_{t-1} + \cdots + A_p Z_{t-p} + u_t \tag{2.3}$$

where p is the number of lags for VAR system.

In order to extract the hidden factors, principal component is used to compute the latent hidden factors F_t. Let X^r is a standardized $T \times N$ matrix consist of X_t observed vector of N variables for all $t \in T$, which is demeaned and divided by the standard deviations for each of N variables. Simple principal component analysis (PCA) finds the linear combinations $C_t = W'X_t^r$ from the standardized X_t^r. The number (rank) of principal component is chosen to be 3 and $p = 13$ is set, following Bernanke et al. (2005).

Note that the principal components extracted from the entire dataset $\hat{C}(F_t, Y_t)$ has the direct dependence on the variable of interest. Because the actual linear combinations implicit in the principal components are unknown, in order to remove such dependence, "slow-moving" variables are assumed not to be affected contemporaneously by the variable of interest for the identification purpose. This research follows the choice of "slow-moving" and "fast-moving" variables of Bernanke et al. (2005). Using only slow-moving variables, the principal components from only slow-moving variables F_t^s can be extracted from the slow variables. Using the principal components C_t from the entire dataset and the principal components from only slow-moving variables, the following regression equation is estimated:

$$\hat{C}_t = b_{F^s} \hat{F}_t^s + b_Y Y_t + e_t \tag{2.4}$$

and thereby $\hat{F}_t = \hat{C}_t - \hat{b_Y} Y_t$ can be constructed and aforementioned VAR equations can be recursively estimated as well. 10,000 simulation draws are used for the bootstrapping.

2.3 Data

The time frame used for this research is from 1978 March to 2024 February, for the climate data and monthly macroeconomic data series. Actuaries Climate Index (ACI) data is used as the variable of interest to capture the impact of climate change onto the wholesome macroeconomy of the United States represented by 123 monthly variables from Federal Reserve Economic Data (FRED). The start of the time frame of the data is chosen to be after 1975 considering the structural break of the ACI dataset analyzed in Won (2025), the date 1978 March is chosen to have oil price data included.

Table 2.1: Actuaries Climate Index (ACI) and monthly FRED-MD economic data

ACI	Actuaries Climate Index	$mean(T90_t^{std} - T10_t^{std} + P_t^{std} + D_t^{std} + W_t^{std} + S_t^{std})$
	High Temperature (*T90*)	Frequency of temperatures over the 90th percentile
	Low Temperature (*T10*)	Frequency of temperatures lower than the 10th percentile
	Precipitation (P)	Maximum rainfall across five consecutive days
	Dry Days (D)	Annual Maximum consecutive dry days
	Wind Speed (W)	Frequency of wind speed over 90th percentile
	Sea Level (S)	Sea level changes
FRED-MD	Monthly U.S. data	Monthly economic and finance data in 8 groups
	Group 1	Output and Income data
	Group 2	Labor Market data
	Group 3	Consumption and Orders data
	Group 4	Orders and Inventories data
	Group 5	Money and Credit data
	Group 6	Interest Rates and Exchange Rates data
	Group 7	Prices data
	Group 8	Stock Market data

Table 2.1 describes the categories of the Actuaries Climate Index (ACI) and the monthly macroeconomic data from Federal Reserve Economic Data (FRED-MD). ACI is an aggregate

measure built by American Academy of Actuaries et al. (2026) to represent the extremity in the climate change in the United States and Canada. This is an average of the volatilities of the temperature, precipitation, dry days, wind speed and sea level, measured in standard deviations of them. This Actuaries Climate Index (ACI) indicates the climate change in the United States as a single index. FRED-MD data contains many economic and finance variables in monthly frequency; this data are categorized in 8 different groups.

For the macroeconomic data, 2025-12-MD vintage of FRED-MD data is used for this research. In the tables in this Data section, "id" refers to the id number ordered in 2025-12-MD vintage of FRED-MD. Because of the update in the stream of monthly level data vintages, not all dataset are identical to the original FRED-MD paper from Federal Reserve Bank of St. Louis by McCracken and Ng (2015) or the published article version of McCracken and Ng (2016). Tables for the categorized monthly data are accompanied by the explanations about the difference between the original McCracken and Ng (2015) and the recent version used for this research. Unless they are specified as slow-moving variables, the variables are treated as fast-moving variables, following Bernanke et al. (2005).

Transformation methods for the stationarity of each of monthly variables are encoded as "tcode" and these methods follow the recommendation of Federal Reserve. Here, tcode=1 is no transformation, tcode=2 is Δx_t (difference), tcode=3 is $\Delta^2 x_t$ (double difference), tcode=4 is $\log(x_t)$ (log of variable), tcode=5 is $\Delta \log(x_t)$ (log difference), tcode=6 is $\Delta^2 \log(x_t)$ (double difference of log variable) and tcode=7 is $\Delta\left(\frac{x_t}{x_{t-1}} - 1.0\right)$ (difference of percentage change).

Table 2.2: Group 1: Output and Income data

	id	tcode	fred	description
1	1	5	RPI	Real Personal Income
2	2	5	W875RX1	Real personal income ex transfer receipts
3	6	5	INDPRO	IP Index
4	7	5	IPFPNSS	IP: Final Products and Nonindustrial Supplies
5	8	5	IPFINAL	IP: Final Products (Market Group)
6	9	5	IPCONGD	IP: Consumer Goods
7	10	5	IPDCONGD	IP: Durable Consumer Goods
8	11	5	IPNCONGD	IP: Nondurable Consumer Goods
9	12	5	IPBUSEQ	IP: Business Equipment
10	13	5	IPMAT	IP: Materials
11	14	5	IPDMAT	IP: Durable Materials
12	15	5	IPNMAT	IP: Nondurable Materials
13	16	5	IPMANSICS	IP: Manufacturing (SIC)
14	17	5	IPB51222s	IP: Residential Utilities
15	18	5	IPFUELS	IP: Fuels
	~~19~~	~~1~~	~~NAPMPI~~	~~ISM Manufacturing: Production Index~~
16	19	2	CUMFNS	Capacity Utilization: Manufacturing

Since 2016-06 vintage, ISM Manufacturing: Production Index (fred code: NAPMPI) has been removed from FRED-MD dataset.

The variables in the Group 1: Output and Income are taken as slow-moving variables following Bernanke et al. (2005).

Table 2.3: Group 2: Labor Market data

	id	tcode	fred	description
1	20	2	HWI	Help-Wanted Index for United States
2	21	2	HWIURATIO	Ratio of Help Wanted/No. Unemployed
3	22	5	CLF16OV	Civilian Labor Force
4	23	5	CE16OV	Civilian Employment
5	24	2	UNRATE	Civilian Unemployment Rate
6	25	2	UEMPMEAN	Average Duration of Unemployment (Weeks)
7	26	5	UEMPLT5	Civilians Unemployed - Less Than 5 Weeks
8	27	5	UEMP5TO14	Civilians Unemployed for 5-14 Weeks
9	28	5	UEMP15OV	Civilians Unemployed - 15 Weeks & Over
10	29	5	UEMP15T26	Civilians Unemployed for 15-26 Weeks
11	30	5	UEMP27OV	Civilians Unemployed for 27 Weeks and Over
12	31	5	CLAIMSx	Initial Claims
13	32	5	PAYEMS	All Employees: Total nonfarm
14	33	5	USGOOD	All Employees: Goods-Producing Industries
15	34	5	CES1021000001	All Employees: Mining and Logging: Mining
16	35	5	USCONS	All Employees: Construction
17	36	5	MANEMP	All Employees: Manufacturing
18	37	5	DMANEMP	All Employees: Durable goods
19	38	5	NDMANEMP	All Employees: Nondurable goods
20	39	5	SRVPRD	All Employees: Service-Providing Industries
21	40	5	USTPU	All Employees: Trade, Transportation & Utilities
22	41	5	USWTRADE	All Employees: Wholesale Trade
23	42	5	USTRADE	All Employees: Retail Trade
24	43	5	USFIRE	All Employees: Financial Activities
25	44	5	USGOVT	All Employees: Government
26	45	1	CES0600000007	Avg Weekly Hours: Goods-Producing
27	46	2	AWOTMAN	Avg Weekly Overtime Hours: Manufacturing
28	47	1	AWHMAN	Avg Weekly Hours: Manufacturing
	~~49~~	~~1~~	~~NAPMEI~~	~~ISM Manufacturing: Employment Index~~
29	119	6	CES0600000008	Avg Hourly Earnings: Goods-Producing
30	120	6	CES2000000008	Avg Hourly Earnings: Construction
31	121	6	CES3000000008	Avg Hourly Earnings: Manufacturing

The variables in the Group 2: Labor Market are taken as slow-moving variables following Bernanke et al. (2005).

Starting from 2016-06 vintage, ISM Manufacturing: Employment Index (NAPMEI) has been deleted from the FRED-MD dataset.

Table 2.4: Group 3: Consumption and Orders data

	id	tcode	fred	description
1	48	4	HOUST	Housing Starts: Total New Privately Owned
2	49	4	HOUSTNE	Housing Starts, Northeast
3	50	4	HOUSTMW	Housing Starts, Midwest
4	51	4	HOUSTS	Housing Starts, South
5	52	4	HOUSTW	Housing Starts, West
6	53	4	PERMIT	New Private Housing Permits (SAAR)
7	54	4	PERMITNE	New Private Housing Permits, Northeast (SAAR)
8	55	4	PERMITMW	New Private Housing Permits, Midwest (SAAR)
9	56	4	PERMITS	New Private Housing Permits, South (SAAR)
10	57	4	PERMITW	New Private Housing Permits, West (SAAR)

The variables in the Group 3: Consumption and Orders data are taken as fast-moving variables following Bernanke et al. (2005).

Table 2.5: Group 4: Orders and Inventories data

	id	tcode	fred	description
1	3	5	DPCERA3M086SBEA	Real personal consumption expenditures
2	4	5	CMRMTSPLx	Real Manu. and Trade Industries Sales
3	5	5	RETAILx	Retail and Food Services Sales
	~~60~~	~~1~~	~~NAPM~~	~~ISM: PMI Composite Index~~
	~~61~~	~~1~~	~~NAPMNOI~~	~~ISM: New Orders Index~~
	~~62~~	~~1~~	~~NAPMSDI~~	~~ISM: Supplier Deliveries Index~~
	~~63~~	~~1~~	~~NAPMII~~	~~ISM: Inventories Index~~
4	58	5	ACOGNO	New Orders for Consumer Goods
5	59	5	AMDMNOx	New Orders for Durable Goods
6	60	5	ANDENOx	New Orders for Nondefense Capital Goods
7	61	5	AMDMUOx	Unfilled Orders for Durable Goods
8	62	5	BUSINVx	Total Business Inventories
9	63	2	ISRATIOx	Total Business: Inventories to Sales Ratio
10	122	2	UMCSENTx	Consumer Sentiment Index

Real Personal Consumption expenditures (DPCERA3M086SBEA), Real Manufacturing and Trade Industries Sales (CMRMTSPLx) and Retail and Food Services Sales (RETAILx) are accounted as slow-moving variables just like Bernanke et al. (2005). Other variables in this group are orders, business inventories and expectation variables which are treated as fast-moving variables in Bernanke et al. (2005), and this research follows the same standard.

Starting in 2016-06 vintage, FRED-MD dataset has removed ISM: PMI Composite Index (NAPM), ISM: New Orders Index (NAPMNOI), ISM: Supplier Deliveries Index (NAPMSDI) and ISM: Inventories Index (NAPMII)

The variable ACOGNO is not used in the estimation due to missing data issue in early periods.

Table 2.6: Group 5: Money and Credit data

	id	tcode	fred	description
1	64	6	M1SL	M1 Money Stock
2	65	6	M2SL	M2 Money Stock
3	66	5	M2REAL	Real M2 Money Stock
	~~73~~	~~6~~	~~AMBSL~~	~~St. Louis Adjusted Monetary Base~~
4	68	6	TOTRESNS	Total Reserves of Depository Institutions
5	69	7	NONBORRES	Reserves of Depository Institutions
6	70	6	BUSLOANS	Commercial and Industrial Loans
7	71	6	REALLN	Real Estate Loans at All Commercial Banks
8	72	6	NONREVSL	Total Nonrevolving Credit
9	73	2	CONSPI	Nonrevolving consumer credit to Personal Income
	~~131~~	~~6~~	~~MZMSL~~	~~MZM Money Stock~~
10	123	6	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding
11	124	6	DTCTHFNM	Total Consumer Loans and Leases Outstanding
12	125	6	INVEST	Securities in Bank Credit at All Commercial Banks
13	67	6	BOGMBASE	Monetary Base: Total

Starting from 2020-01 vintage, St. Louis Adjusted Monetary Base (AMBSL) data has been replaced by Monetary Base: Total (BOGMBASE) data. MZM Money Stock (MZMSL) data has been removed since 2021-08 vintage due to discontinuation by the original source.

Table 2.7: Group 6: Interest Rates, Spreads and Exchange Rates data

	id	tcode	fred	description
1	77	2	FEDFUNDS	Effective Federal Funds Rate
2	78	2	CP3Mx	3-Month AA Financial Commercial Paper Rate
3	79	2	TB3MS	3-Month Treasury Bill
4	80	2	TB6MS	6-Month Treasury Bill
5	81	2	GS1	1-Year Treasury Rate
6	82	2	GS5	5-Year Treasury Rate
7	83	2	GS10	10-Year Treasury Rate
8	84	2	AAA	Moody's Seasoned Aaa Corporate Bond Yield
9	85	2	BAA	Moody's Seasoned Baa Corporate Bond Yield
10	86	1	COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS
11	87	1	TB3SMFFM	3-Month Treasury Minus FEDFUNDS
12	88	1	TB6SMFFM	6-Month Treasury Minus FEDFUNDS
13	89	1	T1YFFM	1-Year Treasury Minus FEDFUNDS
14	90	1	T5YFFM	5-Year Treasury Minus FEDFUNDS
15	91	1	T10YFFM	10-Year Treasury Minus FEDFUNDS
16	92	1	AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS
17	93	1	BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS
	~~101~~	5	~~TWEXMMTH~~	~~Trade Weighted U.S. Dollar Index: Major Currencies~~
18	95	5	EXSZUSx	Switzerland / U.S. Foreign Exchange Rate
19	96	5	EXJPUSx	Japan / U.S. Foreign Exchange Rate
20	97	5	EXUSUKx	U.S. / U.K. Foreign Exchange Rate
21	98	5	EXCAUSx	Canada / U.S. Foreign Exchange Rate
22	94	5	TWEXAFEGSMTHx	Nominal Advanced Foreign Economies U.S. Dollar Index

Starting from 2020-04 onwards, Trade Weighted U.S. Dollar Index: Major Currencies (TWEXMMTH) has been replaced by Nominal Advanced Foreign Economies U.S. Dollar Index (TWEXAFEGSMTHx).

The variables CP3Mx and COMPAPFFx are not used in the estimation due to missing data issue during pandemic periods.

Table 2.8: Group 7: Prices data

	id	tcode	fred	description
	~~106~~	~~6~~	~~PPIFGS~~	~~PPI: Finished Goods~~
	~~107~~	~~6~~	~~PPIFCG~~	~~PPI: Finished Consumer Goods~~
	~~108~~	~~6~~	~~PPIITM~~	~~PPI: Intermediate Materials~~
	~~109~~	~~6~~	~~PPICRM~~	~~PPI: Crude Materials~~
1	103	6	OILPRICEx	Crude Oil, spliced WTI and Cushing
2	104	6	PPICMM	PPI: Metals and metal products
	~~112~~	~~1~~	~~NAPMPRI~~	~~ISM Manufacturing: Prices Index~~
3	105	6	CPIAUCSL	CPI: All Items
4	106	6	CPIAPPSL	CPI: Apparel
5	107	6	CPITRNSL	CPI: Transportation
6	108	6	CPIMEDSL	CPI: Medical Care
7	109	6	CUSR0000SAC	CPI: Commodities
8	110	6	CUUR0000SAD	CPI: Durables
9	111	6	CUSR0000SAS	CPI: Services
10	112	6	CPIULFSL	CPI: All Items Less Food
11	113	6	CUUR0000SA0L2	CPI: All items less shelter
12	114	6	CUSR0000SA0L5	CPI: All items less medical care
13	115	6	PCEPI	Personal Cons. Expend.: Chain Index
14	116	6	DDURRG3M086SBEA	Personal Cons. Exp.: Durable goods
15	117	6	DNDGRG3M086SBEA	Personal Cons. Exp.: Nondurable goods
16	118	6	DSERRG3M086SBEA	Personal Cons. Exp.: Services
17	99	6	WPSFD49207	PPI: Final Demand: Finished Goods
18	100	6	WPSFD49502	PPI: Final Demand: Personal Consumption Goods
19	101	6	WPSID61	PPI: Processed Goods for Intermediate Demand
20	102	6	WPSID62	PPI: Unprocessed Goods for Intermediate Demand

Here, PPI refers to Producer Price Index (PPI) by Commodity types. From 2016-03 onwards, PPI: Finished Goods (PPIFGS), PPI: Finished Consumer Goods (PPIFCG), PPI: Intermediate Materials (PPIITM) and PPI: Crude Materials (PPICRM) have been replaced by PPI: Final Demand: Finished Goods (WPSFD49207), PPI: Final Demand: Personal Consumption Goods (WPSFD49502), PPI: Processed Goods for Intermediate Demand (WP-

SID61) and PPI: Unprocessed Goods for Intermediate Demand (WPSID62) respectively. Starting from 2016-06, ISM Manufacturing: Prices Index (NAPMPRI) has been deleted from the FRED-MD dataset.

The variables in Group 7: Prices are taken as slow-moving variables following the original paper of Bernanke et al. (2005).

Table 2.9: Group 8: Stock Market data

	id	tcode	fred	description
1	74	5	S&P 500	S&P's Common Stock Price Index: Composite
	~~81~~	~~5~~	~~S&P: indust~~	~~S&P's Common Stock Price Index: Industrials~~
2	75	2	S&P div yield	S&P's Composite Common Stock: Dividend Yield
3	76	5	S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio
4	126	1	VIXCLSx	CBOE Volatility Index: VIX

Starting from April 2024, S&P:industrials data has been removed from all FRED-MD vintages. CBOE Volatility Index: VIX (VIXCLSx) has been added to the FRED-MD dataset since December 2021.

2.4 *Empirical Results and Discussions*

This section provides the impulse response analyses of major macroeconomic variables from the climate change shock represented by Actuaries Climate Index data. Each of impulse response contains 90% confidence intervals that are shown as dotted blue lines.

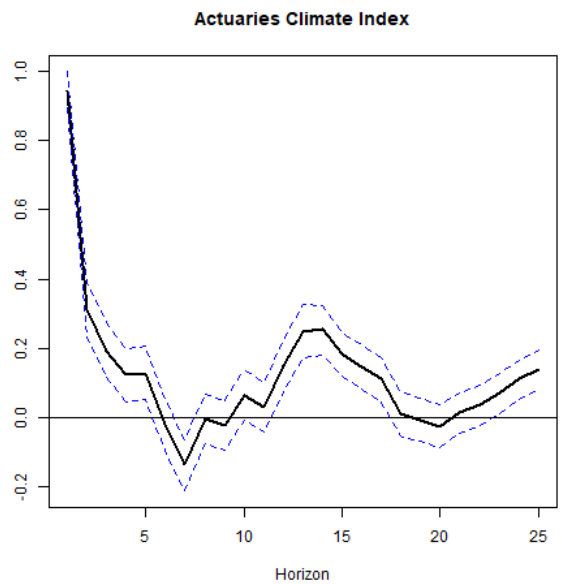


Figure 2.1: Self-Impulse Response of Actuaries Climate Index

Figure 2.1 shows one standard deviation shock of the Actuaries Climate Index (ACI) for the impulse response functions of variables including itself. Once there comes a positive shock, it quickly drops down until 7-months ahead horizon. But later in the periods, it goes up again until about 14-months horizon afterward. Such reaction is partially due to the chosen number of lags to be 13 following Bernanke et al. (2005), and this response shows the seasonal aspects of the climate data. For instance, the shock from a certain month would drop for next 6-7 months because time goes towards completely opposite season, but as it approaches back to 12 months it goes back to the same season as the initial shock, resulting a similar shock as the initial one just with a dampened magnitude, in this case about one quarter of the initial shock.

It is noteworthy to mention that the wide and growing confidence intervals in the impulse response functions of macroeconomic variables are due to the modeling feature because the model handles more than 100 variables at the same time and these enormous number of variables are entangled and affect each other. Such wide confidence intervals are also present in the original paper of Bernanke et al. (2005) and this is typically common in models which use very large number of variables like this.

Because the observable series are standardized prior to factor extraction from the principal component analysis, the units of the impulse responses are expressed in standardized units of the transformed variables relative to their historical volatility in terms of standard deviations, rather than in original units of the variables such as percent or level index points. This normalization is useful because it places variables measured in very different units on a common scale, and therefore it allows a relative comparison of responsiveness across different macroeconomic series.

2.4.1 Output and Income

Figure 2.2 shows the impulse response functions of the major macroeconomic variables of Group 1: Output and Income dataset: Real Personal Income (top) and Industrial Production (bottom) from one standard deviation ACI climate change shock. These impulse response functions have very wide and growing confidence intervals as they move toward further horizon, making them difficult to see the median percentile of the impulse response functions which are the main results. In order to deal with such issue, the zoomed version of the impulse response function that shows the median of the impulse response is provided on the right, and the explanation is based on the main median impulse response results.

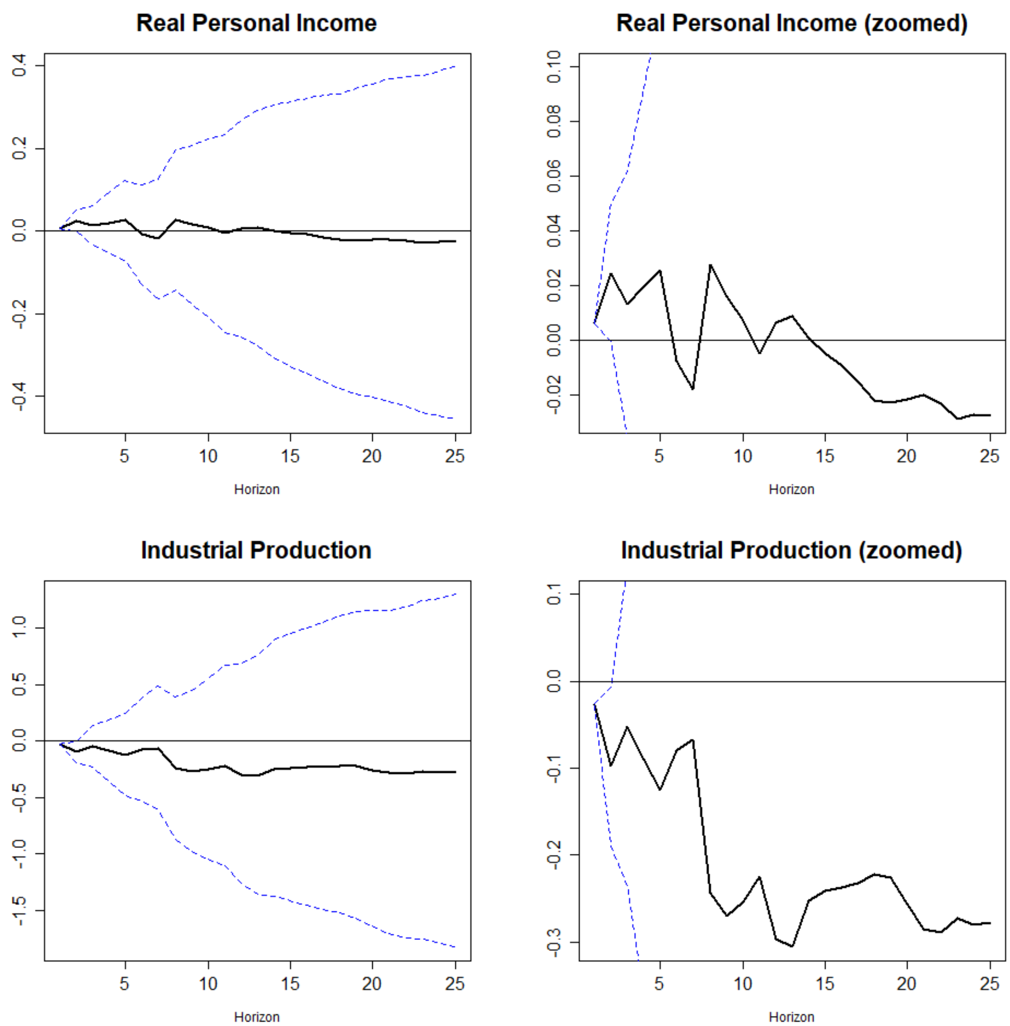


Figure 2.2: Income and Output

In **Figure 2.2**, Real Personal Income and Industrial Production are are statistically insignificant at 90% level in their impulse responses from the climate change shock. Note that even though they are insignificant, there is a tendency that the industrial production declines directly but real income is staggering for 12 months and then drops, suggesting income is stickier than the output production.

2.4.2 Labor Market

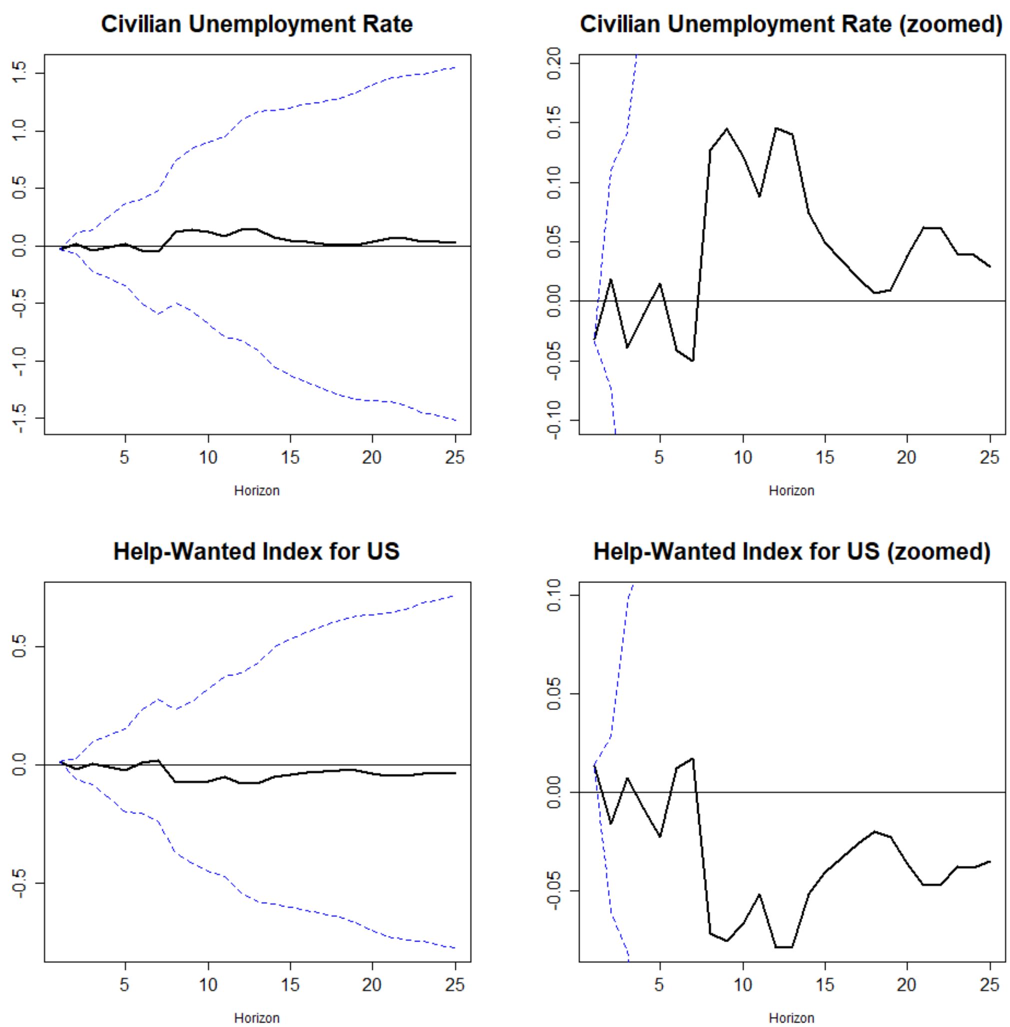


Figure 2.3: Labor Market: Unemployment Rate and HWI

Figure 2.3 shows the impulse response function of unemployment rate and the help-wanted index for the United States from the climate shock. Help-Wanted Index serves as an indicator of labor demand and hiring intent from employer perspective. Note that the unit of these impulse response is relative to the standard deviations of the variables. Therefore although the units of the unemployment rate and help-wanted index for US are different, the unit of the impulse responses are standardized and therefore direct comparison is made possible. Although they are statistically insignificant, the increase in the median impulse responses of the unemployment rate and the decrease in the help-wanted index for US can be seen in the graph, suggesting the climate change shock would increase the unemployment and reduce the job-posting: extensive labor market tightening.

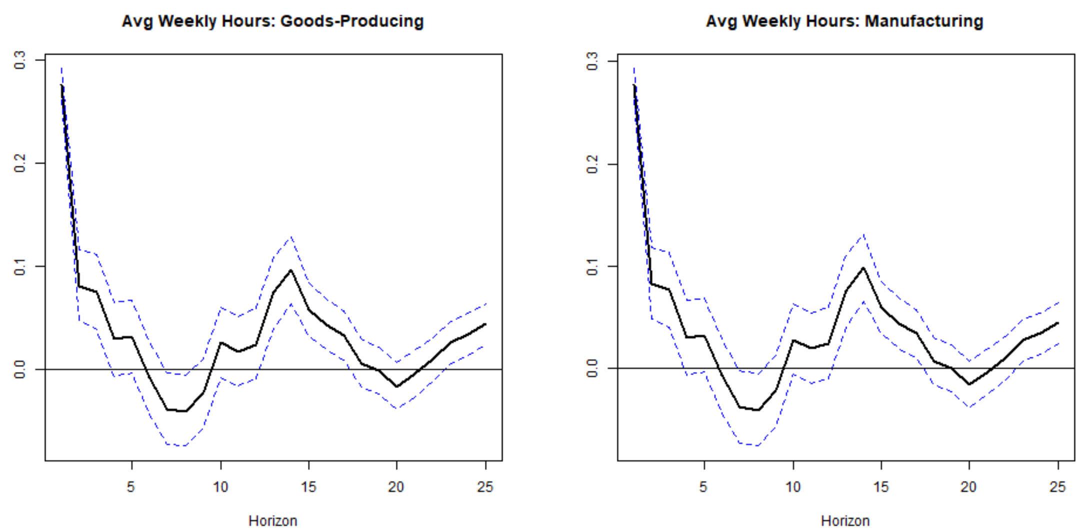


Figure 2.4: Labor Market: Avg Weekly Hours

Figure 2.4 shows the impulse response of the average weekly hours in goods-producing and manufacturing sectors from a climate shock. These average weekly hours variables have an increase from the climate shock at 90% significance level. These average weekly hours variables are intensive margin of the labor market and together with the extensive margin labor market variables in **Figure 2.3**, the evidence suggests the climate shock impact the intensive margin of the labor market more than the extensive counterpart. In other words, climate shock could have insignificant impact on firing and hiring, but the uncertainty from the climate change is likely to make existing labors work more hours.

2.4.3 Housing Market

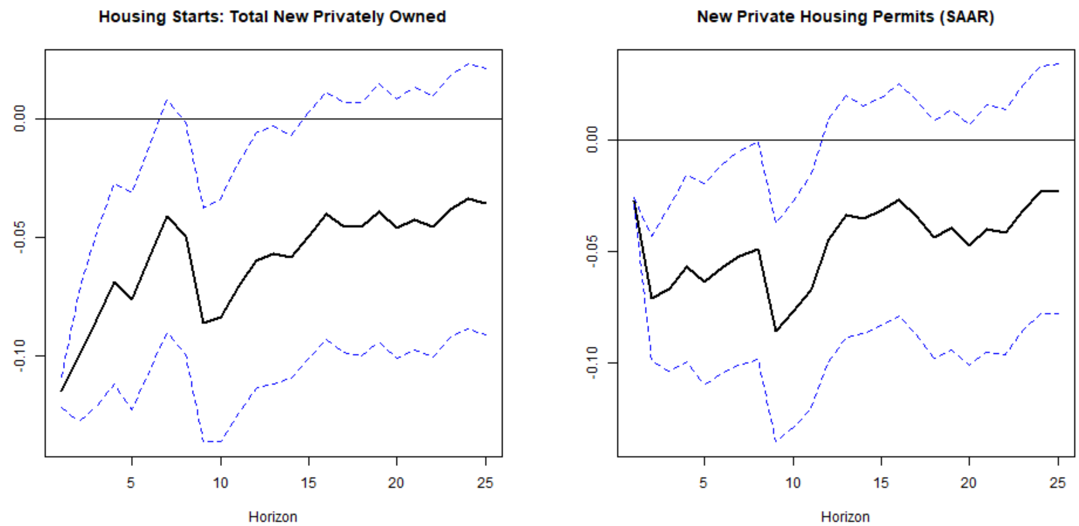


Figure 2.5: Housing Market

Figure 2.5 shows the impulse responses of new housing starts and permits in the united states from one standard deviation climate change shock. They are both negative and statistically significant at 90% level up to 5 months, suggesting the climate change shock induces negative responses to housing starts and housing permits. It is noteworthy to mention that the initial response of the housing starts is about the double of the magnitude of that of housing permits. This one-to-one comparison is made possible because the unit of the impulse responses is standardized to the point relative to standard deviation of the variable. Greater magnitude in the impulse response in housing start than in permit suggests the physical dimension of the housing market is affected by the climate shock more - almost twice more - than the paperwork side of it.

2.4.4 Orders and Inventories

Figure 2.6 shows the impulse responses of the key variables in Group 4: Orders and Inventories: Real Personal Consumption Expenditure (top), Real Manufacturing and Trade Industries Sales (middle), and Retail and Food Services Sales (bottom).

All of Real Personal Consumption, Real Manufacturing and Trade Industries Sales and Retail and Food Services Sales are statistically insignificant at 90% level in their impulse response functions from one standard deviation climate change shock. Although they are not statistically significant, the median impulses show interesting characteristics that fit to general economic sense. They all have generally negative responses from the climate change shock, and Real Personal Consumption and Retail and Food Services Sales decreases from the initial period, where Real Manufacturing and Trade Industries Sales staggers for 7 months, suggesting different level of stickiness in macro-variables. Manufacturing and Trade Industries show more staggering behavior than the Retail and Food Services where the drop in impulse response is instant and direct. Real Personal Consumption declines in its impulse response as well, but it is not as instant as the Retail and Food Services. The magnitudes of three impulses are comparatively similar, where Real Manufacturing and Trade Industries Sales have the least move in magnitude.

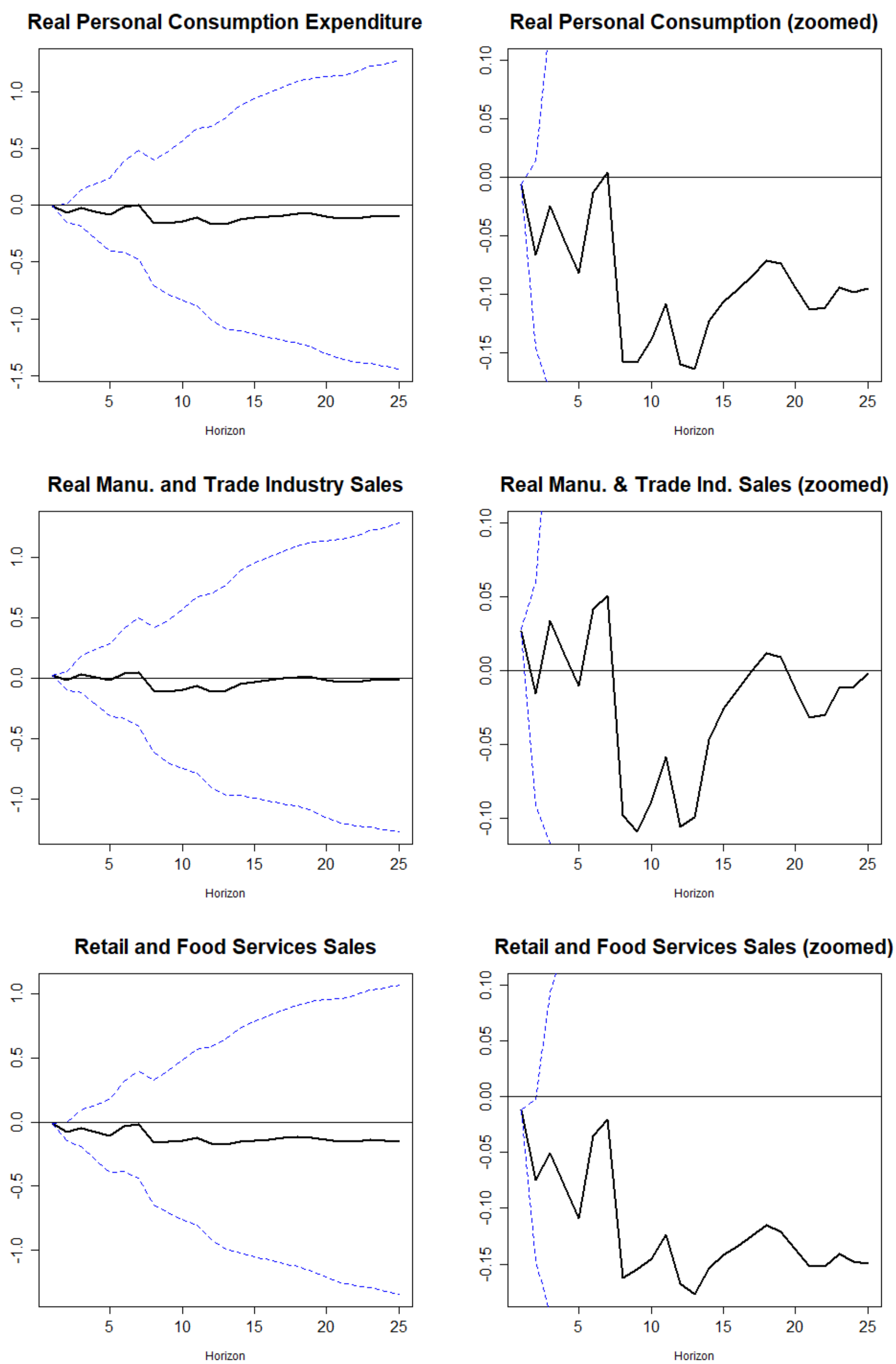


Figure 2.6: Orders and Inventories

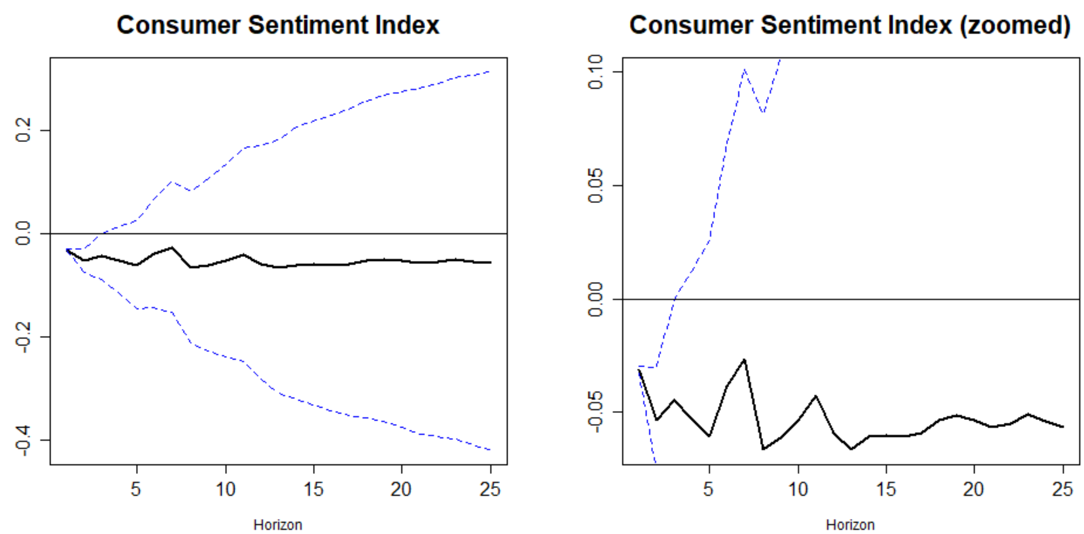


Figure 2.7: Consumer Sentiment Index

Figure 2.7 shows the impulse response function of the consumer sentiment index from the climate shock. Consumer sentiment index is from University of Michigan, representing how optimistic consumers are about the economy and their finances.

Consumer sentiment index drops as a response from the climate shock and this decrease is statistically significant at 90% level for a short period of time of 2-3 months. This evidence suggests the climate change shock decreases the consumer optimism in the United States. The magnitude of such decline does not seem to change much for long periods after, suggesting the consumer optimism decrease due to climate shock does not restore nor worsens easily.

2.4.5 Money, Stock Market and Spreads

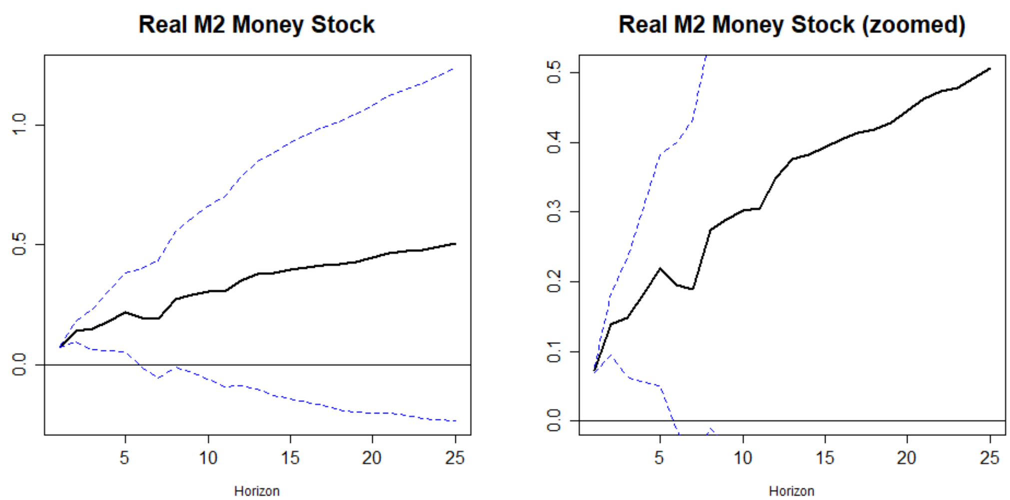


Figure 2.8: Money Market: Real M2 Money Stock

Figure 2.8 shows an increase in the Real M2 Money Stock in its impulse response from a climate change shock, which is statistically significant at 90% up to 5 months horizon. This evidence suggests more circulation of money could be induced from a climate shock; possible explanation for it could be the economy in general requires more money circulated to deal with the potential damage and uncertainty. This possibility is consistent to the disaster literature that explains the disaster like hurricane induces a sharp loss in output but there comes subsequent reconstructions and recoveries; which would require more circulation of money in the economy.

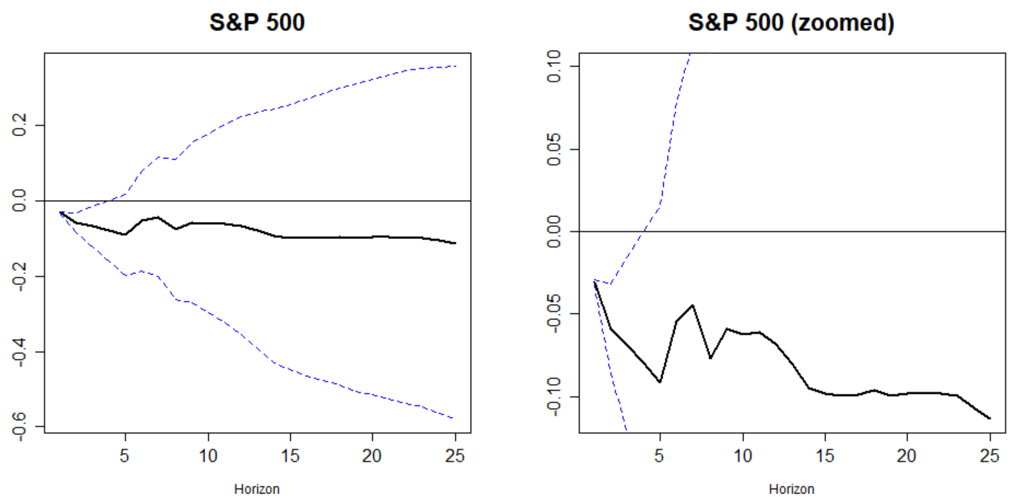


Figure 2.9: Stock Market: S&P 500

Figure 2.9 shows a decrease in the S&P500 index of the US stock market in its impulse response function from a climate change shock, which is statistically significant up to 3 months horizon. It is quite clear that the increase in uncertainty due to climate change shock would work negatively to the stock market in general, although initial statistical significance starts to fade away quickly as time goes by.

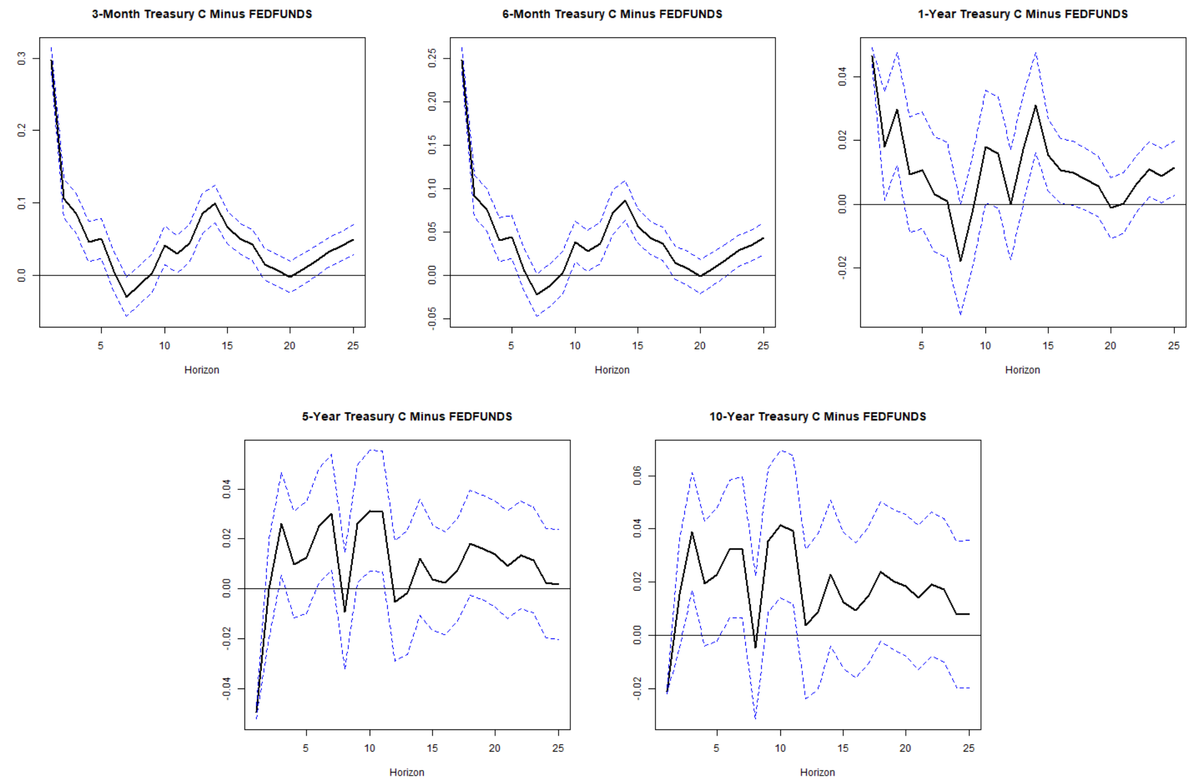


Figure 2.10: Treasury spreads

Figure 2.10 shows the impulse responses of the short-term (3-month, 6-month & 1-year) and long-term (5-year & 10-year) treasury spreads from the climate change shock. Climate change is more costly and the impact is sizable to 3-month than it is to 6-month and to 1-year compared to their standard deviations. Also, there exist a change in pattern that the short-term spreads have initial positive impulse responses where long-term spreads have negative initial impulse responses.

This is consistent with other related studies that find the climate change vulnerability and the level of resilience impact significantly on the probability of sovereign debt default (Cevik & Jalles, 2022a) and the cost government borrowing (Cevik & Jalles, 2022b); in the economic story that in short-term, the climate change vulnerability is huge and such

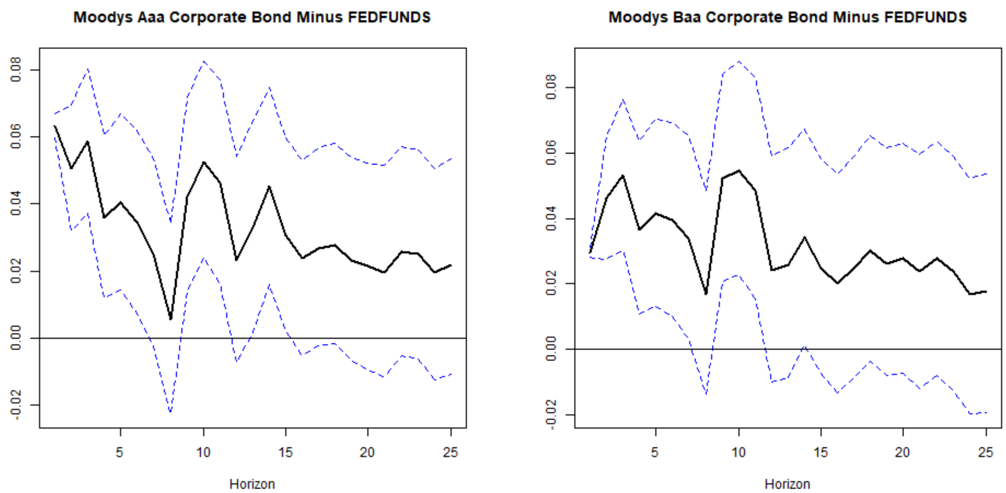


Figure 2.11: Corporate Bond Spreads

uncertainty may not be solved until the maturity, leading to positive and significant impulse responses. Whereas in long-term, the uncertainty could likely be solved by the maturity so it could work like a safe haven asset.

Figure 2.11 shows the impulse responses of corporate bond spreads from the climate change shock. They are positive and statistically significant at 90% level until 5-months horizon, suggesting that their characteristics are akin to that of short-term treasury spreads than that of long-term ones. The initial response magnitude is about 0.06 for Aaa spread and 0.03 for Baa spread, which are similar to that of 1 year treasury spread, suggesting corporate bond spreads behave most likely to 1 year of treasury bond.

2.4.6 Prices

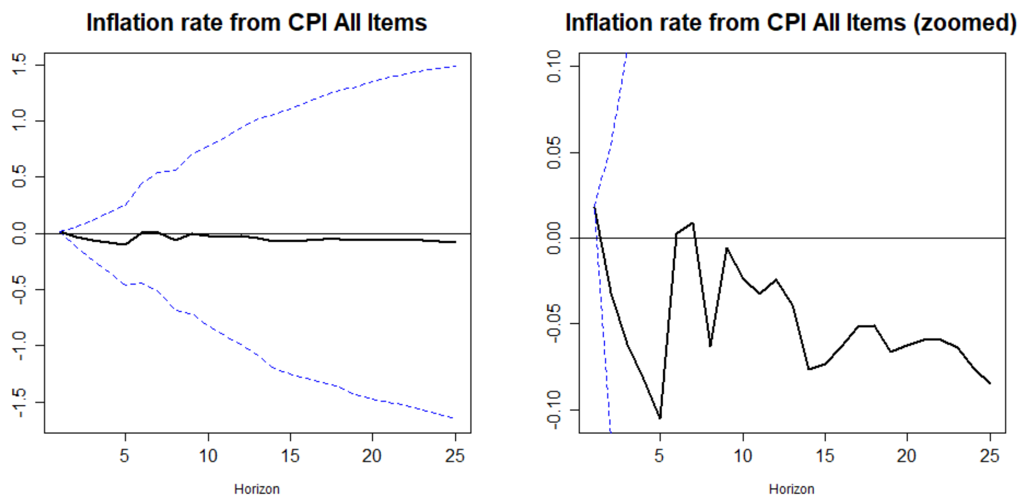


Figure 2.12: Inflation Rate from CPI: All Items

Figure 2.12 shows the impulse response of the inflation rate from the climate change shock. Although it is statistically insignificant at 90%, it is noteworthy to mention that the impulse response is negative. In order to examine this issue, the impulse responses of six sub-categories of the Consumer Price Indices: Apparel, Transportation, Medical Care, Commodities, Durables, and Services are presented in **Figure 2.14** and **Figure 2.13**.

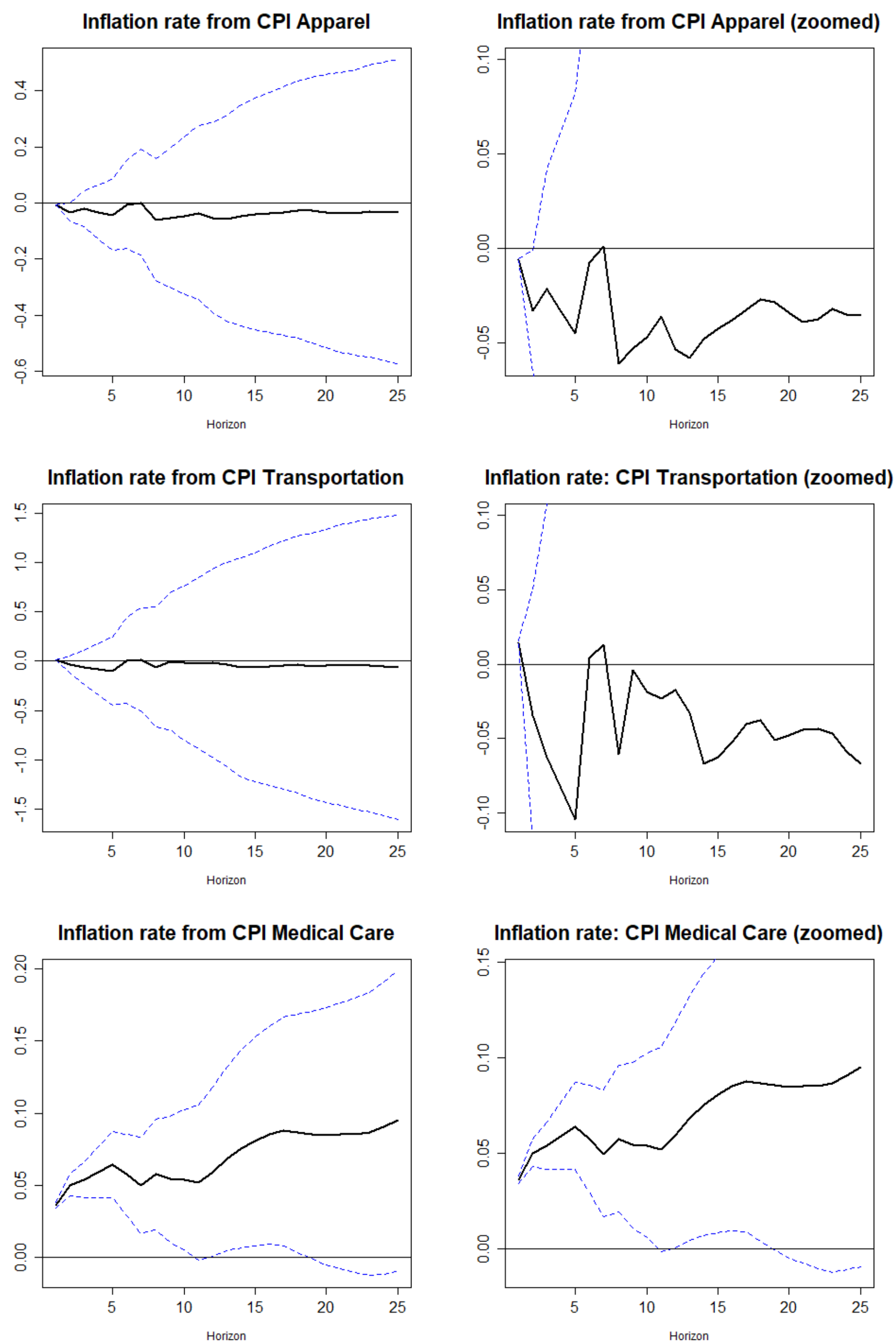


Figure 2.13: Inflation Rate from CPI: Apparel, Transportation and Medical Care

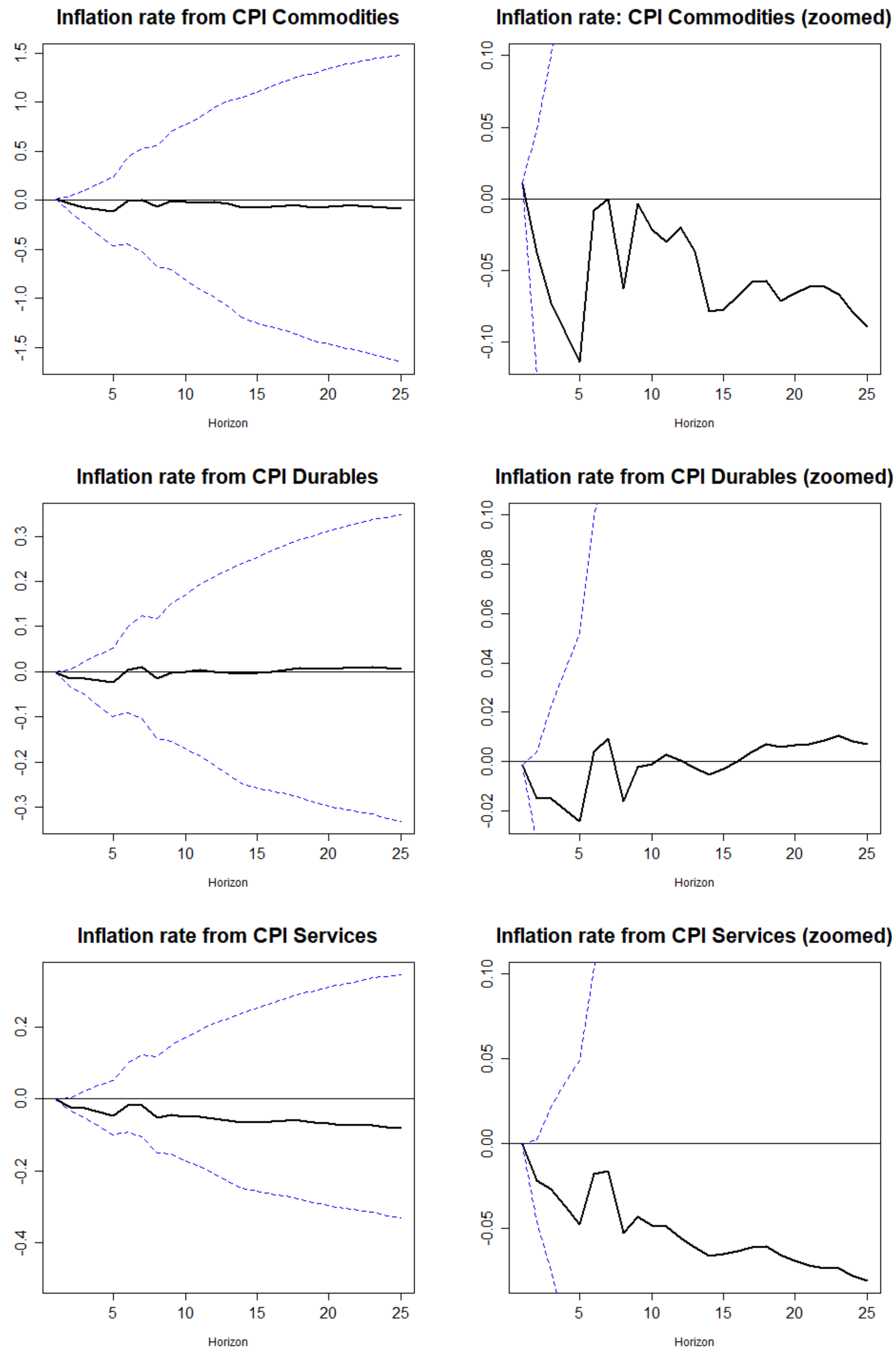


Figure 2.14: Inflation Rate from CPI: Commodities, Durables and Services

Figure 2.14 and **Figure 2.13** present more specified sub-categories of Consumer Price Indices. Except for CPI: Medical Care which is positive, growing and conspicuously significant for 10-months horizon, sub-categories of CPI are generally statistically insignificant at 90% level in blue dotted lines.

Cevik and Jalles (2024) reports the heterogeneity of climate shocks to inflation using panel data of 1970-2020 periods, presenting temperatures result in lower inflation globally. In advanced economies, the inflation increases from the temperature shock in its impulse response unlike the global sample, but the drought shock and storm shock lead to negative impulse responses of inflation.

The models using small number of real variables such as Kim et al. (2025) and Won (2025) present a positive impulse response of inflation rate from a climate change shock represented by ACI data. The FAVAR approach in this research is very different in the modeling as there exist many "fast-moving" monetary and financial variables that could influence to the impact of climate shock to inflation rate which is one of most monitored economic measure. The models using real variables only are generally for policy recommendations about the size of impact of a shock without government or market intervention, whereas FAVAR model incorporate the intervention of the government and the market through the rich dataset. Therefore the impulse responses of the inflation here, although they are mostly statistically insignificant except medical care, could be attributed to the dataset covers the relevant market intervention and government policies after observing the climate change, leading to the controlled inflation.

Recall the typical reduced-form Phillips curve such that:

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t + \gamma s_t$$

where π_t represents the inflation at time t, $E_t\pi_{t+1}$ is the inflation expectation at time t for time $t + 1$ inflation, x_t is the output gap that measures the difference between the actual economic output and its maximum potential, representing the demand pressure, and s_t is the cost-pushing supply side disturbance.

A climate change shock can potentially affect all of the expectation, demand pressure and cost-push effect. On the one hand, the climate shock may raise the production costs in general and increase the price level. On the other hand, the climate shock may depress the aggregate demand and lower income and investments and may also trigger a governmental response, all of which tend to reduce inflation.

This result could be related to "Fed Information Effect" such that the market interprets an unexpected rate hike as a signal from the Federal Reserve acting on superior information about positivity in the economic growth, leading to a higher, not lower, inflation expectations (Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018). Likewise, the observed climate shock could trigger financial and monetary reactions first before the sticky price variables move, and the belief of the economy, that the US government will do something about it, could lead the response of the inflation to an opposite in sign to what standard macroeconomic models predict. This conjecture is coherent to the heterogeneity of different inflation responses from the climate shock across different countries in the world because the levels of government competence would be different.

2.4.7 *Discussions*

Factor Augmented VAR model suggests an alternative variable selection method apart from traditional Ridge estimator or LASSO (Least Absolute Shrinkage and Selection Operator) model. This alternative is particularly meritorious because unlike rather mechanical models like LASSO, the significance of the variables in the impulse response from a certain shock naturally convey more economic stories.

In this research, for example, the intensive margin of the labor market, housing market represented by housing starts and permits, real M2 stock, S&P500 in stock market, treasury spreads especially short-term ones, corporate spreads and inflation rate for medical bills are statistically significant at 90% level in their impulse response functions from the climate change shock, at least for first several months. This method of selection can serve as a monitoring tool that tells which sectors and/or variables are more likely to be impacted by the climate change through the responses, and this feature is not something mechanical regularization methods offer.

This advantage can be easily extended to policy recommendation. For instance, the intensive margin of the labor market such as working hours should be more of a focus in the topic of climate change and its impact to labor market. Intensive margins of the labor market, and 3-months and 6-months short term treasury spreads seem to be more closely-related to the climate change shock represented by the Actuaries Climate Index in their shape in the impulse responses so this information can be utilized in an analysis about more and directly impacted sectors and variables from the climate change.

2.5 Conclusion

This research implements Factor Augmented VAR (FAVAR) model to study how the climate change shock represented by Actuaries Climate Index (ACI) could impact on a large set of 123 macroeconomic variables from Federal Reserve Economic Data. The rich macroeconomic dataset allows to present the impact of climate change shock on every sector of entangled US macroeconomy.

The main findings of this research is in two parts. Firstly, this research encompasses the climate change and its impact to a comprehensive set of US macroeconomic variables. It presents that there exist significant impacts of the climate change shock on: the working hours in goods-producing and manufacturing sectors in the US labor market, housing starts and permits in national level, real M2 money stock, S&P500 in US stock market, treasury and corporate spreads, and the inflation in medical care sector.

Secondly and correspondingly, these results can be used as an alternative measure for the variable selection method that conveys richer economic stories about which of macro sectors are more prone to climate change. As the selection of significantly impacted variables are chosen via impulse responses from the climate shock, it offers a different setting to commonly used variable selection methods such as LASSO. Such merit can be easily utilized in policy recommendation, monitoring tool and macroeconomic forecasting.

Chapter 3

GLOBAL OIL PRICE CHANGE AND ITS IMPACT ON SOUTH KOREAN MACROECONOMY

3.1 Introduction

Since the seminal work of Sims (1980), Vector Autoregression (VAR) model has been a workhorse model for analyzing macroeconomic dynamics. In particular, the dynamic impacts of the oil price changes on the macroeconomy have been intensively studied, especially the different facades of the oil price change shock and how such variety in characteristics can impact economy differently.

Since the price began to be chosen by the oil market not directly by OPEC as of the year 1985 (Mabro, 2006), substantial number of literature address the macroeconomic responses from the oil price disturbances. Whilst the earlier studies focused on documenting the adverse macroeconomic effects of the oil price increases, subsequent steam of research has presented the transmission mechanism cannot be understood properly without distinguishing the characteristics of oil price movements (Kilian, 2009a; Kilian, 2009b; Peersman and Van Robays, 2009; Kilian, 2014). This stream of literature on the macroeconomic effects of the oil price change has been evolved from the models using a certain cutoff threshold (Edelstein and Kilian, 2007; Herrera and Pesavento, 2009) or estimating decade by decade (Blanchard & Gali, 2007) to more general time-varying parameter model frameworks that allow to see the dynamic effects of the oil price change on macroeconomy.

Since the pioneering work of Baumeister and Peersman (2013), the Bayesian Time-Varying Parameter model has been extensively used for studying how the oil price change propagates to macroeconomy in different countries and economy settings (Baumeister and Kilian, 2016; Boufateh and Saadaoui, 2021). This research implements a Bayesian Time-Varying Parameter Structural VAR with Stochastic Volatility (TVP-SVAR-SV) model framework following Primiceri (2005) and Nakajima (2011). This Time-Varying Parameter model has been used by the earlier research about the oil price shock and its impact on the South Korean macroeconomy by Cha (2018), but there is a substantial change in the responses of the Korean economy from the global oil price shock after the earlier work.

Baumeister, Leiva-León, and Sims (2024) presents the higher frequency of the data and consequent construction of weekly state-level indices are especially valuable for situations where the policy is effective but only lasts for a short period of time, for example for a few weeks. Likewise, the impact of the oil price shock that is significant but lasts for only few months can be only visible in monthly level data frequency, not in quarterly level frequency. Earlier study of Cha (2018) allows time-variation in model parameters, but the quarterly data it uses could miss certain short term effect that is strongly meaningful but lasts for only short period of time.

The contribution of this research is in twofold. Firstly, this research presents the global oil price change shocks increases the South Korean inflation, but it also increases the industrial output and decreases the unemployment rate in South Korea in one-month ahead impulse responses. Such increase in the industrial output and related labor market benefits are consistent to the literature presenting that the oil price change shock that is demand-driven can improve the economic growth, especially for exporting countries in Asia. (Lee and Song, 2009; Cunado, Jo, and de Gracia, 2015; Arsalane and Kim, 2024) This is because the increase in global real economic activities outweighs the damages from the increase in costs from the oil shock. This is not only due to Asia specific setting because the economic impacts of the oil price change shocks have been declined over time because of the globalization, because these oil shocks are recycled when the oil-exporting countries imports more goods and services from oil-importing countries, and the massive growth of the shale oil industry in the United States brought a structural shift (Baumeister & Kilian, 2016).

Secondly and perhaps more importantly, this research finds the switch in the initial impulse response of the industrial output of South Korea from the oil price change shock. One-month ahead impulse response is positive, just like the analysis about the boost from the rise in global economic activities can benefit South Korean output, but the initial zero-period impulse response declines and it becomes negative from the year 2014. Such change can be attributed to the changing relationship between China-Korea trade; South Korea has been a beneficiary of the Chinese economic growth but it is becoming less complementary and more competitive over time (Choi and Xu, 2020; Yi and Kim, 2024). The change in the initial response of the output captures such changing dynamics of Korean economy, especially contemporaneous to the oil shock in particular.

The remainder of this research proceeds as follows. **Section 3.2** presents the economic model framework for the Time-Varying Parameter model used for the estimation. **Section 3.3** describes the data, including the global oil price change variable and the key macroeconomic variables of South Korea: inflation rate, industrial production as output variable, and the unemployment rate. **Section 3.4** provides the main empirical findings. Finally **Section 3.5** concludes.

3.2 Model

This section shows the model used to estimate the changing impacts of the global oil price change onto the South Korean key macroeconomic variables. For the estimation, the Bayesian Time-Varying Parameter model with the Stochastic Volatility model of Nakajima (2011), with the structural change matrix A_t that changes across the time periods, is used. Note that because the econometric model used for the estimation is the same to Chapter 1, the flow of this model section of Chapter 3 is the same to that of Chapter 1. But for the sake of completeness of each chapter as a single research paper, the model is re-written again.

The Time-Varying Parameter Structural VAR model is defined as:

$$A_t y_t = F_0 + F_1 y_{t-1} + \cdots + F_p y_{t-p} + \nu_t \quad \text{where} \;\; \nu_t \sim N(0, \Sigma_t \Sigma_t') \tag{3.1}$$

where y_t is the $k \times 1$ vector of observed variables, F_0 is $k \times 1$ dimensional intercept, A_t is $k \times k$ structural matrix to present the simultaneous relations and $F_1, \ldots, F_s$ are $k \times k$ coefficient parameter matrices. The standard deviation of the structural error ν_t is defined in the matrix 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 matrix A_t represents the simultaneous relationships of the observed variables to the structural shock terms. This matrix is constructed to have recursive ordering identification, assuming the lower-triangular structural matrix A_t such that:

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

A_t is invertible so we can re-write the **Equation (3.1)** into a reduced form:

$$y_t = B_0 + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t \tag{3.2}$$

where $u_t = A_t^{-1}\nu_t$ is a reduced form error and $B_i = A_t^{-1}F_i$ for $i = 1, \ldots, p$ lags. Stacking the row elements of the B_i's provides the coefficients β which is a $(k + k^2p) \times 1$ vector. Stacking the variables with the lags, $X_t = I_k \otimes (1, y_{t-1}, \ldots, y_{t-p})$ where $\otimes$ is the Kronecker product, **Equation (3.2)** can be re-written as:

$$y_t = X_t\beta + A_t^{-1}\Sigma_t\varepsilon_t \quad \text{where } \varepsilon_t \sim (N, I_k) \tag{3.3}$$

There is a reduced form error term $u_t = A_t^{-1}\nu_t = A_t^{-1}\Sigma_t\varepsilon_t$ because $\nu_t \sim N(0, \Sigma_t\Sigma_t')$ and $\varepsilon_t \sim N(0, I_k)$. Making the coefficients term to be Time-Varying Parameter β_t gives **Equation 3.3** to be the model of Time-Varying Parameter Structural VAR with Stochastic Volatility:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t \quad t = p+1, \ldots, n \tag{3.4}$$

Note that here the coefficients β_t, structural parameters A_t and the variance of the error Σ_t are all time-varying. Following Primiceri (2005) and Nakajima (2011) the parameter estimates are assumed to behave as random walk process:

$$\begin{cases} \beta_{t+1} \sim N\left(\beta_t, \Sigma_{\beta_0}\right) \\ a_{t+1} \sim N\left(a_t, \Sigma_{a_0}\right) \\ h_{t+1} \sim N\left(h_t, \Sigma_{h_0}\right) \end{cases} \tag{3.5}$$

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

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

The distribution of the prior is assumed to be the i-th diagonal elements of the variance-covariance matrices: $(\Sigma_\beta)^2_i \sim IG(20, 0.0001)$, $(\Sigma_\alpha)^2_i \sim IG(4, 0.0001)$, $(\Sigma_h)^2_i \sim IG(4, 0.0001)$ following Nakajima (2011). The initial values are set as $\mu_{\beta_0} = \mu_{\alpha_0} = \mu_{h_0} = 0$ and $\Sigma_{\beta_0} = \Sigma_{\alpha_0} = \Sigma_{h_0} = 10 \times I$. This estimation is done with the Markov Chain Monte Carlo (MCMC) process that discards first 5,000 burn-ins. And then it draws 20,000 samples after burn-ins, in total there are 25,000 sample draws for the estimation.

3.3 Data

The estimation of the impacts of the global oil price shock into the South Korean macroeconomy is conducted with four variables: the percentage change in global crude oil price, the percentage change in monthly South Korean inflation rate, the percentage change in South Korean production output and the percentage change in South Korean unemployment rate from January 2001 to November 2023. All Data are available in, and retrieved from the FRED database of Federal Reserve Bank of St. Louis. **Figure 3.1** presents the plots of the global oil price change and the change in macroeconomic variables aforementioned.

Top-Left figure of **Figure 3.1** shows the graph for the change in global oil price (o), which generally shows a mean-reverting behavior with zero mean with a noticeable COVID-19 shock in the year 2020. FRED code for the Global price of WTI Crude Oil is POILWTIUSDM and this is the oil price data used for the estimation. WTI oil refers to West Texas Intermediate Crude Oil, which is one of three benchmark crude oil data: West Texas Intermediate from the USA, Brent Blend from the Atlantic and Dubai Crude from the Persian Gulf.

Top-right figure of **Figure 3.1** shows the graph for the percentage change in South Korean inflation (p). For the inflation variable, Consumer Price Index All Items Total for Korea is used and the FRED code for this inflation data is KORCPALTT01IXNBM. South Korea is a small country that the difference between the price levels in the rural ares and urban areas is relatively small. Therefore the representativeness of the wholesome inflation should outweigh its potential weakness in usage.

Bottom-Left figure of **Figure 3.1** depicts the graph for the percentage change in the production output (x). The production output is measured by the index for the Production, Sales, Work Started and Orders Production Volume Economic Activity Industry (Except

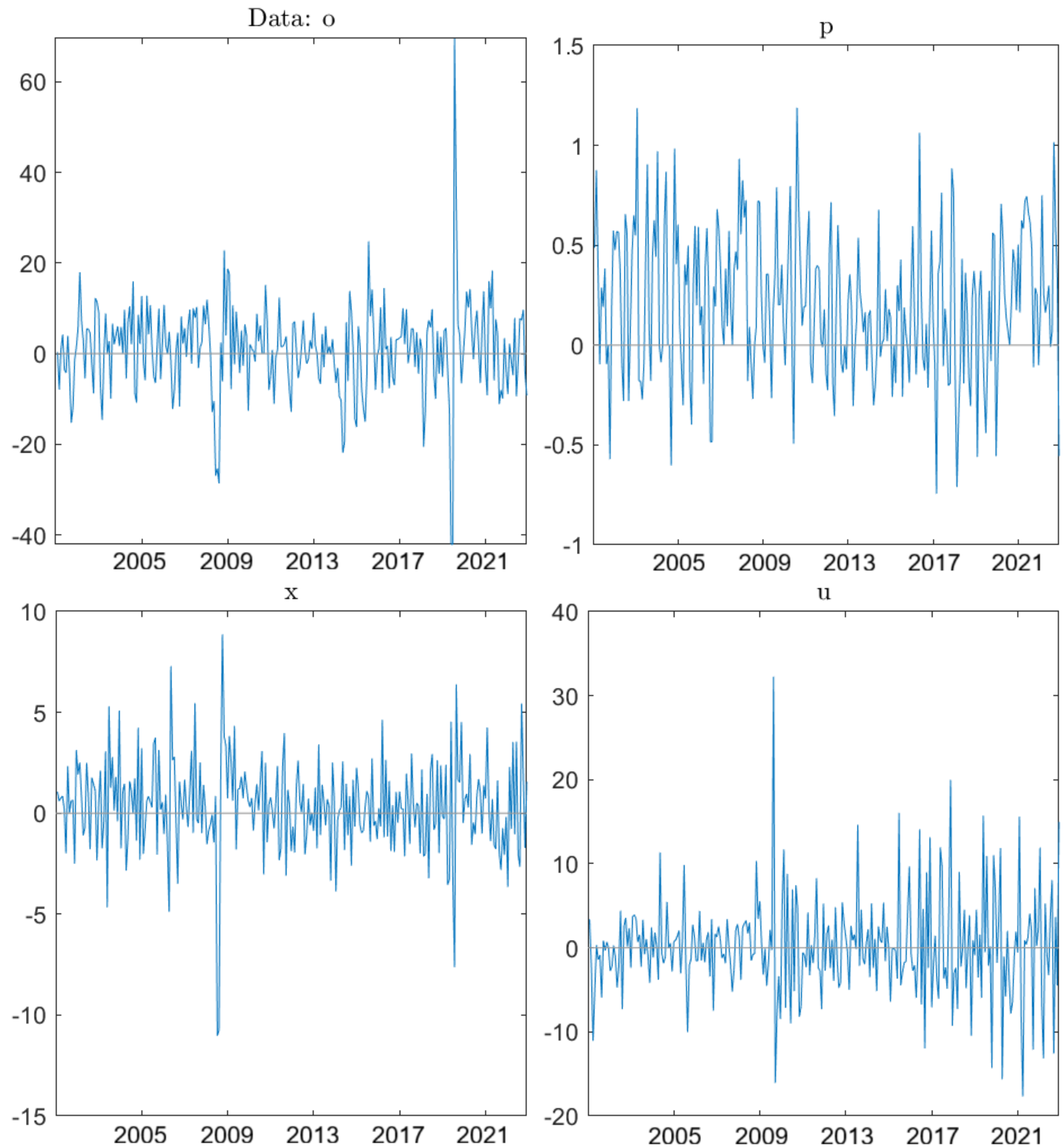


Figure 3.1: Plots for the change in Global Oil price (o), Korean Inflation rate (p), Korean Output (x) and Korean Unemployment rate (u)

Construction) for Korea, which is a monthly level frequency data akin to Industrial Production index. The FRED code for this output data is KORPROINDMISMEI. Alike the industrial production index of the USA data serves as a monthly frequency proxy data for the GDP data, this data should serve the same purpose.

Bottom-right figure of **Figure 3.1** shows the graph for the percentage change in the unemployment rate in South Korea (u). The rate of unemployment is measured by the Harmonized Unemployment Monthly Levels Aged 25 and over All Persons for Korea, with the FRED code of LFHUADTTKRM647S. In South Korea there is a mandatory military service for male citizens and high education fever of Korean culture leads to a representative labor to hold a bachelor's degree. Because of the military service the age 25 is typically the age when people with a bachelor's degree find their first full-time job in South Korea, and the South Korean unemployment data is surveyed to take account for such factor.

It is noteworthy to mention again that the unit of these monthly variables are percent change. For instance the global oil price swings somewhere between -20 to 20 except the COVID-19 periods, meaning that -20 to 20 percent changed from the previous month. These are in percent term (%) not in numeric term (for example 0.2 in numeric is 20 percent), so the stochastic volatility represented by the variance could be quite large in number.

3.4 Estimation Results

Table 3.1: Bayesian Information Criterion and the choice of lag

	$p = 1$	$p = 2$	$p = 3$	$p = 4$	$p = 5$	$p = 6$
BIC	179044.23	203877.34	208248.98	280175.36	228940.27	332983.76

Here p denotes the number of lags in the VAR model

Table 3.1 shows the Bayesian Information Criterion (BIC) for the choice of the lag in the VAR modeling. Lower number in the information criterion is a preferred model, and here the number of lag to be chosen with the lowest BIC value is $p = 1$; therefore the VAR estimation in this research is conducted with $p = 1$ lag. Typically, the choice of lag in the VAR modeling is usually $p = 2$. However, in this research the chosen number of lag is $p = 1$ not just because it is the best fit from the information criterion but also $p = 2$ suggests the lack of stochastic volatility in oil market which should be a false result.

Table 3.2: Selected parameter estimates of the model with two lags ($p = 2$)

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	0.0018	0.0028
$(\Sigma_a)_1$	0.0040	0.0007	0.0029	0.0057
$(\Sigma_h)_1$	**0.0071**	**0.0047**	0.0036	0.0171
$(\Sigma_h)_2$	0.0055	0.0016	0.0034	0.0090

Note: Mean denotes posterior means; Stdev means standard deviations

Table 3.2 shows the selected variances of the coefficient β_t parameters in the model with the number of VAR lags to be two ($p = 2$). Note that the estimates $(\Sigma_h)_1$ refers to the stochastic volatility term for the global oil price change. This estimate is statistically insignificant as the standard deviation value 0.0047 is too high in comparison to its mean value of 0.0071. For instance, at 95% significance level this estimate is statistically insignificant.

This statistically insignificant result of $(\Sigma_h)_1$ from **Table 3.2** reinforces the choice of lag to be $p = 1$ not $p = 2$, because the change in the global oil price is known heteroskedastic and therefore the stochastic volatility term of the oil price change is expected to be non-zero. The insignificance above shows the heteroskedasticity of the oil price change is not distinguishable from the value of zero, so the model should not be used as it lacks enough justification.

Table 3.3: Selected parameter estimates from the model with one lag ($p = 1$)

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	0.0018	0.0029
$(\Sigma_a)_1$	0.0040	0.0007	0.0029	0.0057
$(\Sigma_h)_1$	0.1721	0.0509	0.0781	0.2806
$(\Sigma_h)_2$	0.0054	0.0015	0.0034	0.0090

Note: Mean denotes posterior means; Stdev denotes standard deviations

Table 3.3 shows the posterior estimates for the selected parameter from the TVP-SVAR-SV model with $p = 1$ lag. Note that the selected variances of the coefficients in the model are all statistically significant at 95% significance level, suggesting that the true model specification parameters would really be time-varying. $(\Sigma_\beta)_1$ and $(\Sigma_\beta)_2$ are the variance estimates of the β coefficients: the intercept and the first own-lag of the global oil price change variable. The terms $(\Sigma_h)_1$ and $(\Sigma_h)_2$ indicate the stochastic volatility of the global oil price change variable and the inflation. $(\Sigma_\alpha)_1$ is the structural estimate presenting the contemporaneous impact of the global oil price change to the Korean inflation.

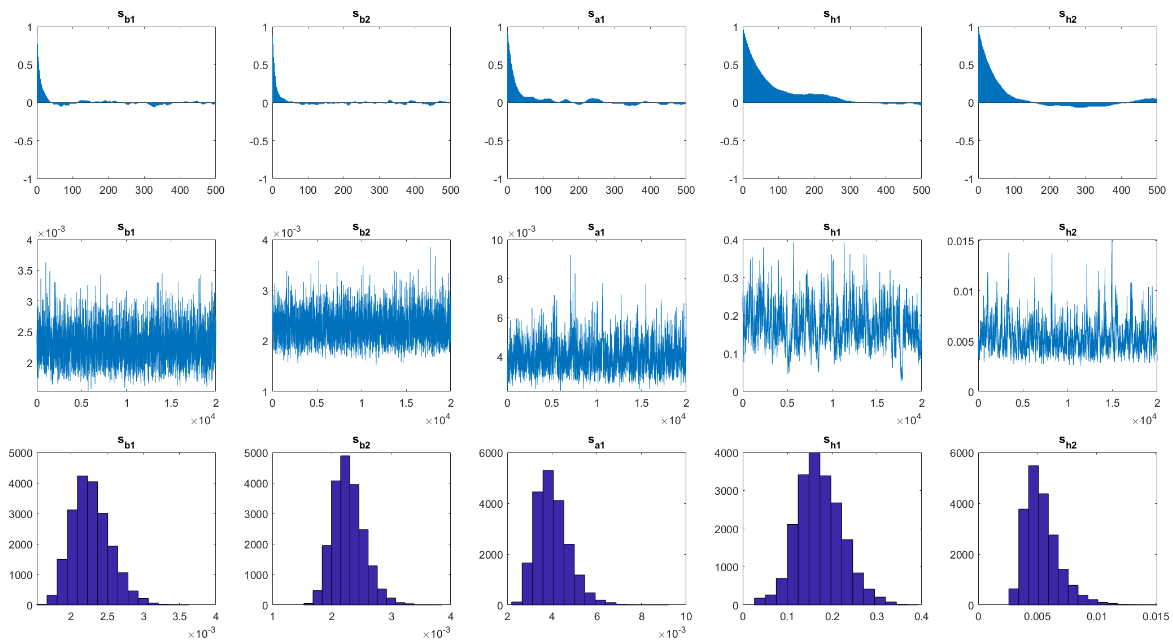


Figure 3.2: Sample Autocorrelation, Sample Path and Posterior Densities

Figure 3.2 shows the sample autocorrelation (top figure), sample path (middle figure) and posterior densities for the selected parameters (bottom figure) shown in **Table 3.3**. Note that this Time-Varying Parameter model assumes the random walk processes of the parameters for the transition of the parameters as time goes by. The sample autocorrelation graphs drop fairly quickly for those selected parameters, and the sample path graphs show nice stable behavior. The posterior densities of the selected parameters are nicely modal as well.

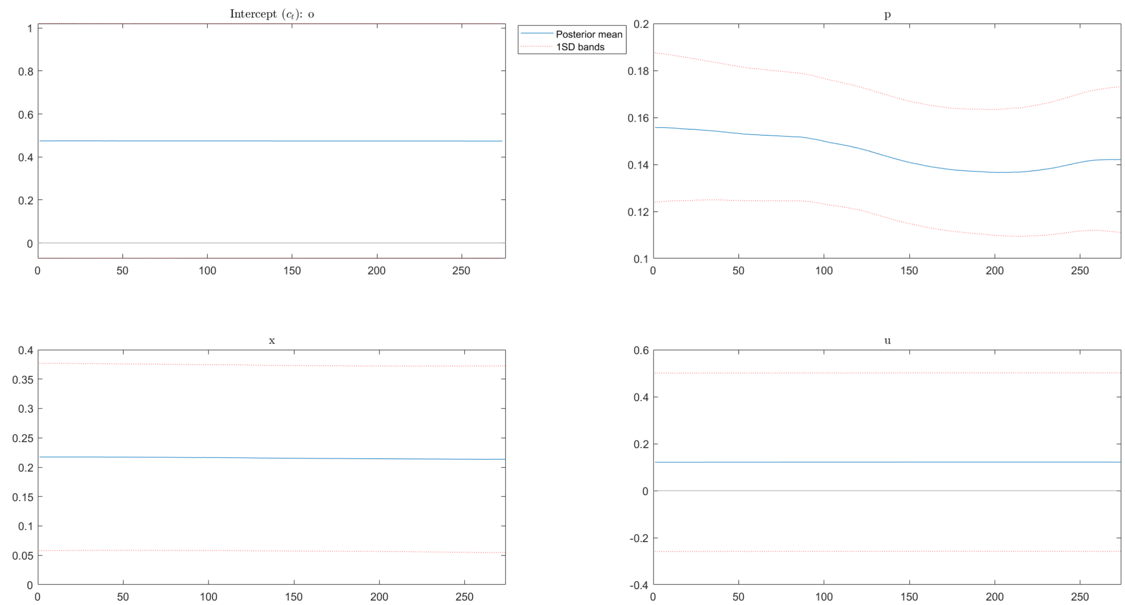


Figure 3.3: Intercept terms of the variables

Figure 3.3 presents the intercept terms of the four variables used in the estimation: percentage change in the global crude oil price (o) in top-left panel, the percentage change in the South Korean inflation rate (p) in top-right panel, the percentage change in South Korean production output (x) in bottom-left panel, and the the percentage change in South Korean unemployment rate (u) in bottom-right panel. Out of four variables, only inflation rate has a statistically significant inflation rate, suggesting growing inflation base of South Korea.

Figure 3.4 shows the stochastic volatility terms estimated from the TVP-SVAR-SV model for all four variables: the percentage change in the global crude oil price (o), South Korean inflation (p), South Korean production output (x) and South Korean unemployment rate (u). They represent the variance of the structural error terms for the variables. Note that large numbers of these variables are because the unit of the variables is in percent

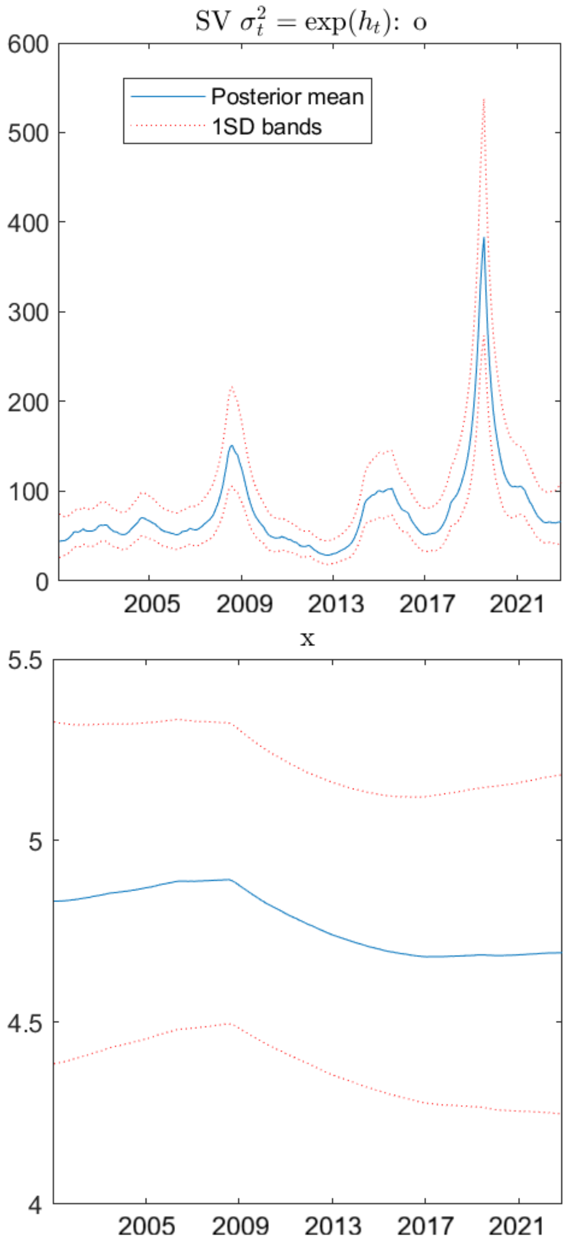


Figure 3.4: Stochastic Volatility terms of the variables

change and variances are standard deviations squared. For example the value of 400 of the stochastic volatility $\sigma^2_{o,t}$ has its standard deviation of 20, and 20 percent in oil price change is not an impossible number. The inflation (p) and output (x) are quite steady in values, where unemployment rate (u) is growing. These statistically significant values of stochastic volatilities suggest that there exist time-variations in the structural errors of the global oil price change, Korean inflation, Korean output and Korean unemployment. Unemployment in particular, is growing in its time-varying variance, suggesting an increase in uncertainty of the Korean labor market.

Impulse Response Analysis

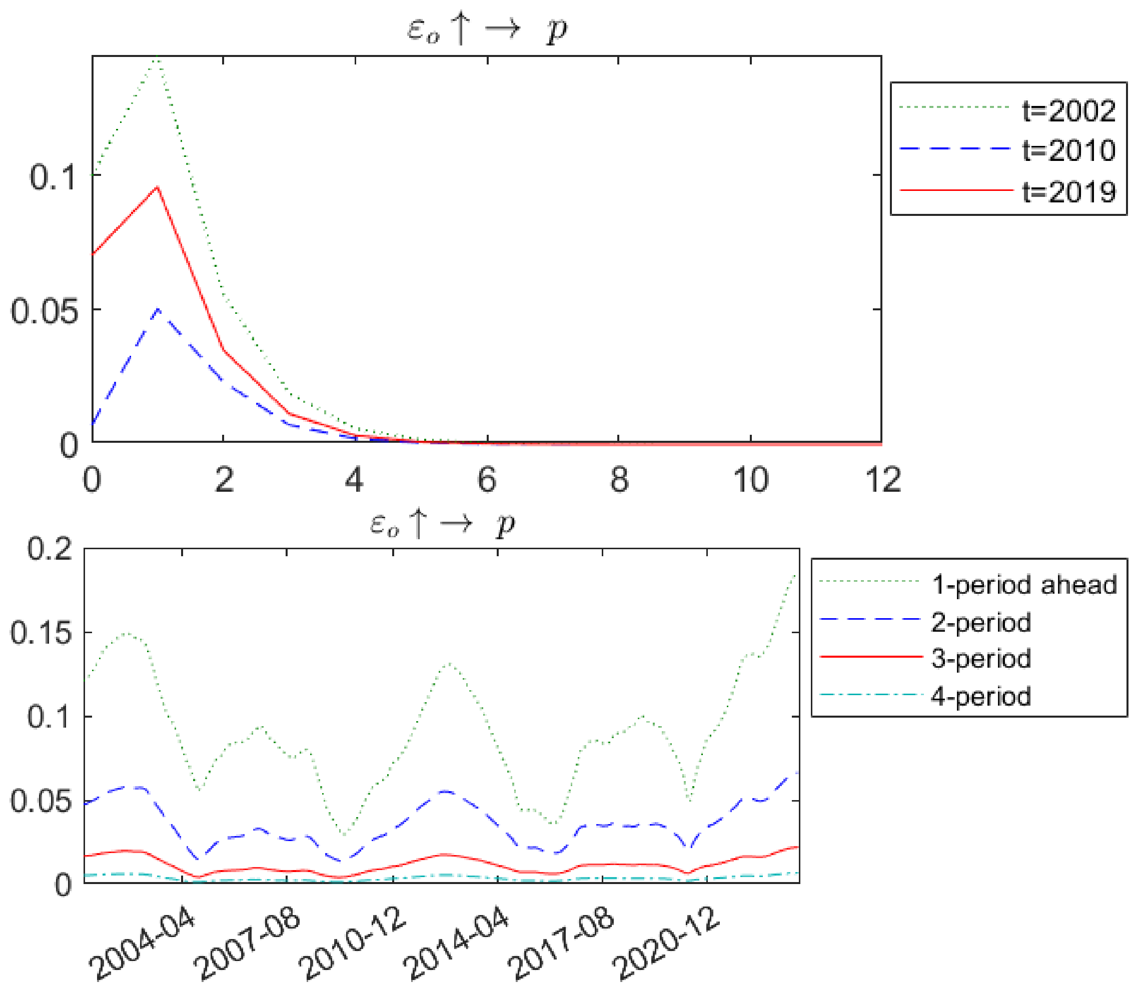


Figure 3.5: Time-Varying impulse responses of the Global Oil Price shock to Inflation

Figure 3.5 shows the time-varying impulse response functions of the Korean inflation when there is one standard deviation global oil price change shock. Top figure of **Figure 3.5** shows the periodic impulse responses at year 2002, 2010 and 2019. Bottom figure of **Figure 3.5** presents the time-variation of the impulse response across the time horizon, with the impulse responses of 1-month to 4-months ahead from the shock.

The result at the top figure shows that global oil price change shock increases the inflation rate in Korea initially, and the impact is amplified in 1-month ahead and then decays over. The high inflationary impact in year 2002 has gone down in year 2010; in year 2019 there is an increase in the size of the impact compared to year 2010 but it is lesser than year 2002. In the bottom figure, there are humps in the time-variation of the 1-month ahead impulse responses suggesting a cyclical aspect of the oil price effects to the inflation rate. For all time horizon, the oil price change shock is impactful but it only lasts for very short period of time.

Figure 3.6 presents the time-varying impulse response functions of the Korean output from one standard deviation global oil price change shock. Top figure represent the periodic impulse responses at year 2002, 2010 and 2019. Bottom figure shows the horizontal impulse responses of 1-month ahead to 4-months ahead from the initial oil price change shock across the time. The top figure shows that the initial oil price change shock impacts in the year 2002 and 2010 are positive and very similar in their magnitude, about 0.4 percent. However the initial impact seems to change dramatically in year 2019 to negative sign. In the bottom figure, 1-month ahead impulse responses in all time periods are positive where this impact decays very quickly in next periods, suggesting the impact on the output is lasting only for very short time.

These results suggest that the global oil price change shock has a positive impact on Korean output, in other words suggesting an increase in Korean output. While an increase in the price level leading to an increase in output sounds strange, this is a possible scenario for an exporting country like South Korea. Oil price shock that is demand-driven could boost economic growth because of the increased industrial production arising from the rise in the global real economy; this characteristics had been documented in Asian countries (Lee and Song, 2009; Cunado et al., 2015; Arsalane and Kim, 2024). The initial shock changes its sign

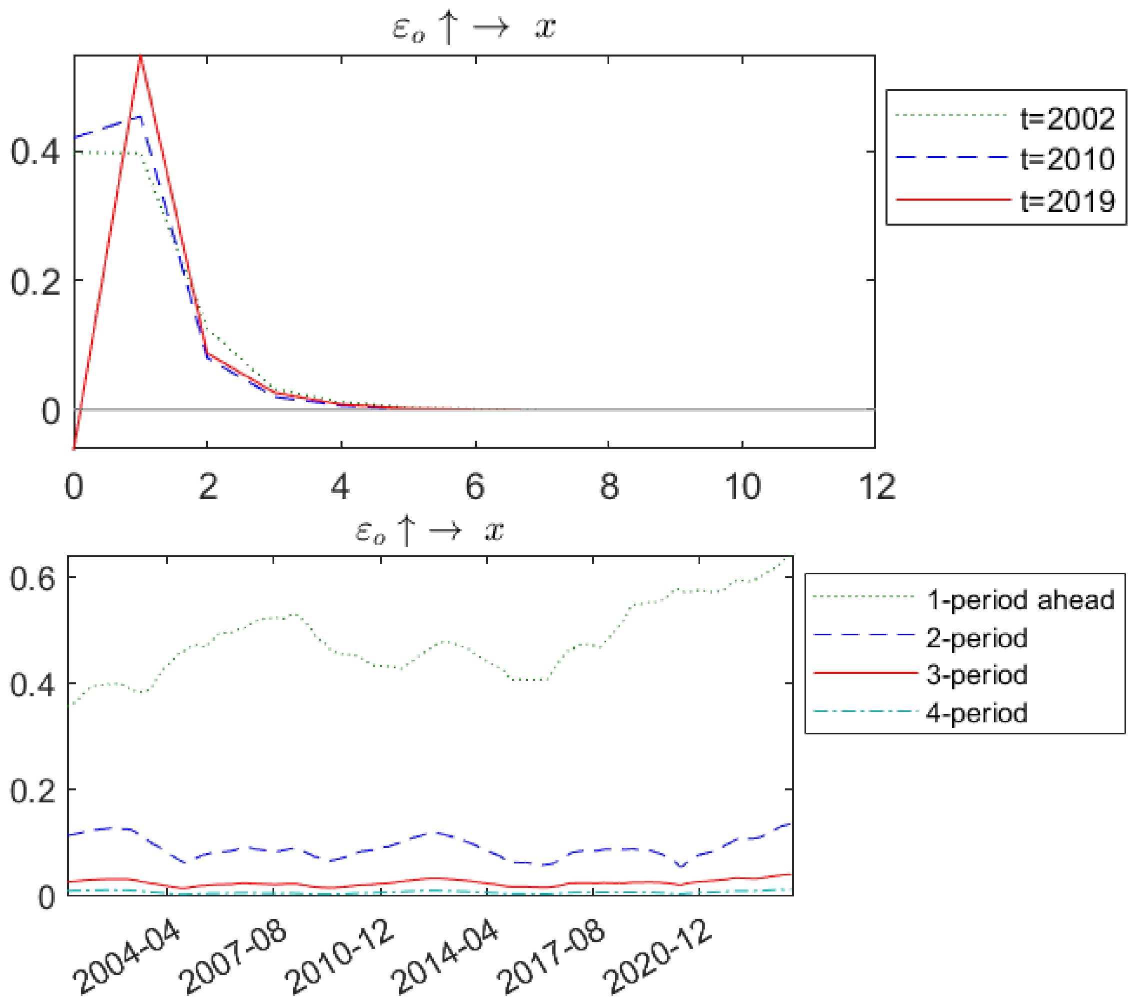


Figure 3.6: Time-Varying impulse responses of the Global Oil Price shock to Output

in the year 2019 compared to the previous results from the year 2002 and 2010, suggesting that there is a change in the characteristics of the initial impact from the global oil price change onto Korean industrial output in the decade 2010s.

Figure 3.7 shows the time-varying impulse response functions of the Korean unemployment from the global oil price change shock. Top figure represent the periodic impulse responses at year 2002, 2010 and 2019. Bottom figure shows the horizontal impulse responses

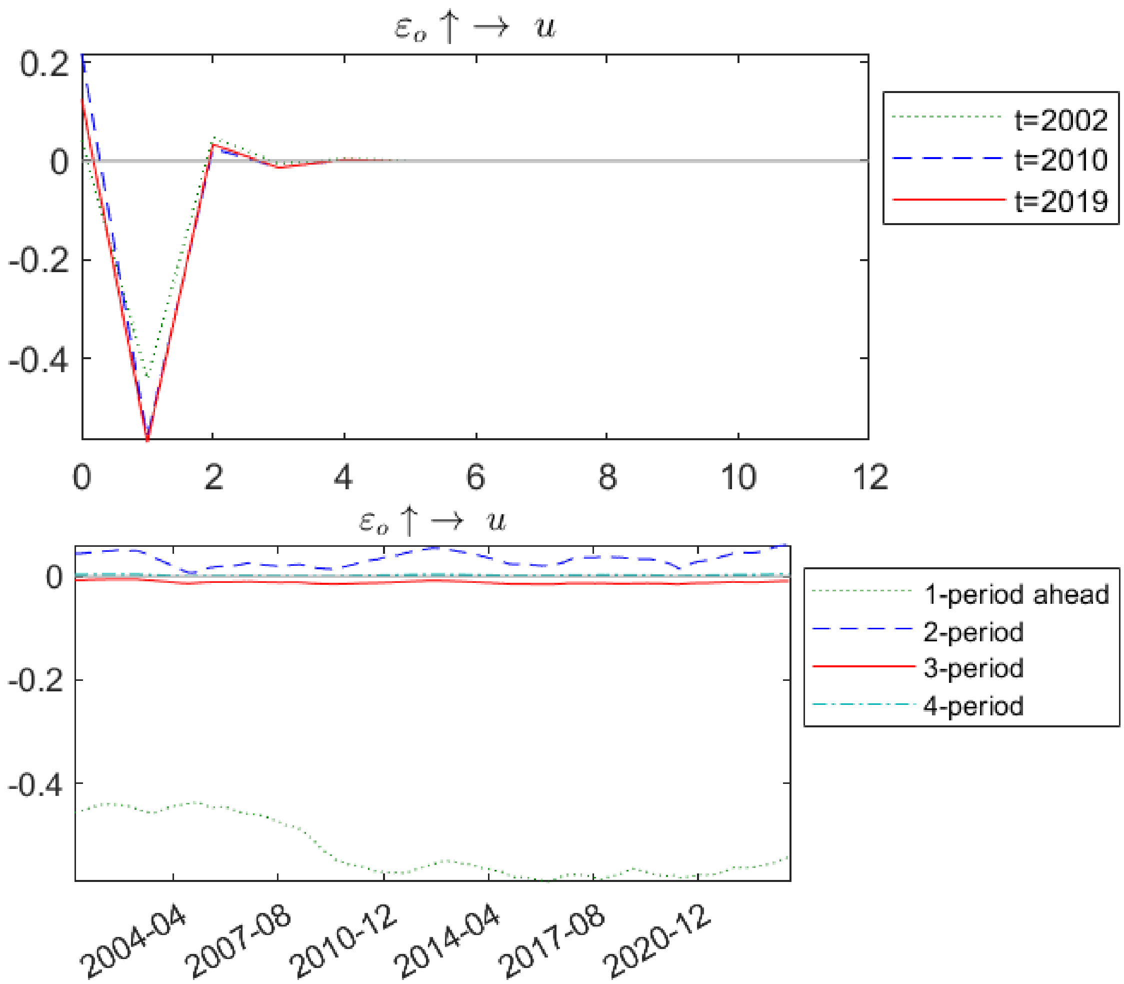


Figure 3.7: Time-Varying impulse responses of the Global Oil Price shock to Unemployment

of 1-month ahead to 4-months ahead from the initial oil shock across the time. Top figure of **Figure 3.7** shows that general positive initial impact from the global oil price change onto Korean unemployment, suggesting an initial increase in unemployment. This comes with a significant reduction in the unemployment rate change, suggesting a temporal stimulation of the labor market. Linking with the output result, the temporal employment stimulus in Korea could be from the surge of the global economic activities that leads to an increase in industrial production of Korea as it is an exporting country. Bottom figure shows that the size of the decrease in the unemployment rate change in 1-month ahead period gradually increases in its size. This labor market stimulus, however, only lasts for short period of time of one month, and from 2-months onward the effects become negligible.

Change in the Initial response over the time periods

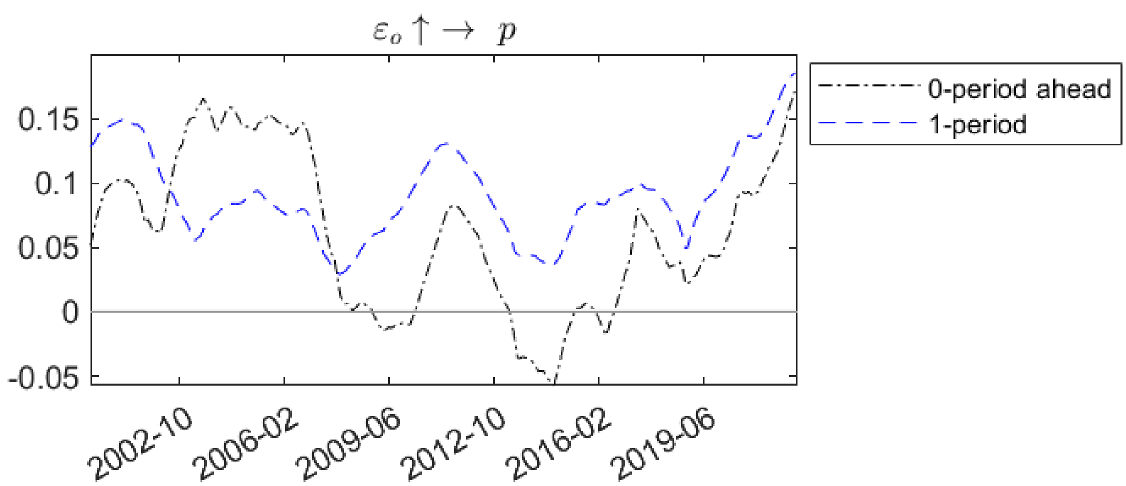


Figure 3.8: Initial horizontal Impulse Response of the Global Oil Price shock to Inflation

Figure 3.8 shows the change in the initial responses of South Korean inflation from the global oil price change shock. There is a change in the response that from the year 2002 to 2008, the zero-period contemporaneous response of the inflation from the global oil price change had been greater than the one-month ahead impulse response. This high impact and then dampening behavior switches in later periods after, as one-month ahead impulse response of the inflation rate is amplified from the initial zero-period response from the global oil price change shock. Note that the amplification gap shrinks as it comes to 2020s.

Figure 3.9 shows the change in the initial responses of South Korean industrial output from the global oil price change. One-month after impulse response continues to be positive and it seems to be growing over time, which is consistent to the explanation of **Figure 3.6**

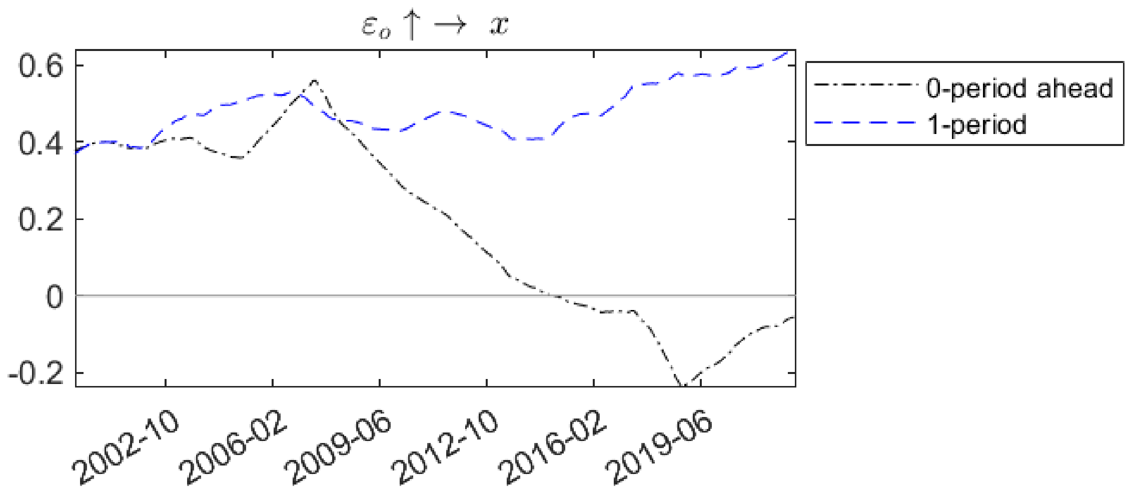


Figure 3.9: Initial horizontal Impulse Response of the Global Oil Price shock to Output

and its related previous literature about demand-driven oil price shock stimulating Korean economy. However, there exists a meaningful turn-over of the initial impulse response of the South Korean industrial output from the global oil price change shock from year 2008. This turnover in trend continues to decline and it reaches to negative from the year 2014.

This result is coherent to the study of the changing industry dynamics of the Asian countries and the how the demand-driven characteristics of oil shock can affect them. Choi and Xu (2020) documents a boost in Korean manufacturing industry due to increased Chinese demand for Korean intermediaries and capital goods. But this Korea-China trade relationship has become less complementary and more competitive over time (Yi & Kim, 2024). The turnover in the zero-period response provides one evidence about the changing dynamics of Korean industry: China is catching up the global economic status of South Korea, therefore in the initial response the negative energy cost component seems to dominate the positive global demand increase component of the oil-price led innovation of the South Korean industry.

3.5 Conclusion

This research implements Time-Varying Parameter model to study the changing impacts of the global oil price change on key macroeconomic variables: inflation rate, industrial output and unemployment rate in South Korea. The dynamic impacts of oil price change shock are indeed time-varying across decades, and such time-variational changes are prominent even after accounting for the stochastic volatility terms of the macroeconomic variables.

The main findings of this study is in twofold. Firstly, this paper finds the global oil price change shocks generally increase the South Korean inflation, increase the South Korean industrial output and decrease the unemployment in one-month ahead period. The increase in the industrial output and related benefits in labor market represented by the decrease in unemployment rate is consistent to the existing literature about Asian economy that the demand-driven oil price shock can boost economic growth because exporting countries in Asia benefit more from the increase in global real economic activities than the harms from the increase in costs.

Secondly, this research finds the shift in the initial impulse response of the Korean industrial output from the global oil price change shock. Although the one-month ahead impulse response is positive and growing which is coherent to the boost by increase in global demand aforementioned, the zero-period impulse response of the Korean output decline since 2007 and it switches to negative from 2014. This swift can be attributed to the rise in Chinese economy that changing characteristics of Korea-China trade can be visible in the contemporaneous effect from the global oil price change, i.e. the contemporaneous harms from an increase in cost due to increase in oil price are starting to dominate the benefits from the increase in Chinese demand and the global economic stimulation. Therefore this research serves as a alarm for South Korean industry.

REFERENCES

Alessandri, P., & Mumtaz, H. (2021). The macroeconomic cost of climate volatility. *arXiv preprint arXiv:2108.01617*.

American Academy of Actuaries, Canadian Institute of Actuaries, Causalty Actuarial Society, & Society of Actuaries. (2026). *Acturaries climate index.*

Arsalane, S., & Kim, Y. M. (2024). Macroeconomic impact of oil shocks. *Journal of Economic Integration*, *39*(4), 899–920.

Bai, J., Li, K., & Lu, L. (2016). Estimation and inference of favar models. *Journal of Business & Economic Statistics*, *34*(4), 620–641.

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of applied econometrics*, *18*(1), 1–22.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, *124*(1), 105–159.

Baumeister, C., & Kilian, L. (2016). Lower oil prices and the us economy: Is this time different? *Brookings Papers on Economic Activity*, *2016*(2), 287–357.

Baumeister, C., Leiva-León, D., & Sims, E. (2024). Tracking weekly state-level economic conditions. *Review of Economics and Statistics*, *106*(2), 483–504.

Baumeister, C., & Peersman, G. (2013). Time-varying effects of oil supply shocks on the us economy. *American Economic Journal: Macroeconomics*, *5*(4), 1–28.

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy:

a factor-augmented vector autoregressive (favar) approach. *The Quarterly journal of economics*, *120*(1), 387–422.

Blanchard, O. J., & Gali, J. (2007). *The macroeconomic effects of oil shocks: Why are the 2000s so different from the 1970s?* National bureau of economic research Cambridge, Mass., USA.

Boufateh, T., & Saadaoui, Z. (2021). The time-varying responses of financial intermediation and inflation to oil supply and demand shocks in the us: Evidence from bayesian tvp-svar-sv approach. *Energy Economics*, *102*, 105535.

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–140.

Campbell, J. R., Evans, C. L., Fisher, J. D., Justiniano, A., Calomiris, C. W., & Woodford, M. (2012). Macroeconomic effects of federal reserve forward guidance [with comments and discussion]. *Brookings papers on economic activity*, 1–80.

Cevik, S., & Jalles, J. (2024). Eye of the storm: The impact of climate shocks on inflation and growth. *Review of Economics*, *75*(2), 109–138.

Cevik, S., & Jalles, J. T. (2022a). An apocalypse foretold: Climate shocks and sovereign defaults: Cevik s., jalles jt. *Open Economies Review*, *33*(1), 89–108.

Cevik, S., & Jalles, J. T. (2022b). This changes everything: Climate shocks and sovereign bonds∗. *Energy Economics*, *107*, 105856.

Cha, K. (2018). Time-varying effects of oil shocks on the korean economy. *Environmental and Resource Economics Review*, *27*(3), 495–520.

Choi, J., & Xu, M. (2020). The labor market effects of the china syndrome: Evidence from south korean manufacturing. *The World Economy*, *43*(11), 3039–3087.

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of political Economy*, *113*(1), 1–45.

Cogley, T., & Sargent, T. J. (2001). Evolving post-world war ii us inflation dynamics. *NBER macroeconomics annual*, *16*, 331–373.

Cunado, J., Jo, S., & de Gracia, F. P. (2015). Macroeconomic impacts of oil price shocks in asian economies. *Energy Policy*, *86*, 867–879.

D'Agostino, A., Gambetti, L., & Giannone, D. (2013). Macroeconomic forecasting and structural change. *Journal of applied econometrics*, *28*(1), 82–101.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature*, *52*(3), 740–798.

Dias, D. A., & Duarte, J. B. (2019). Monetary policy, housing rents, and inflation dynamics. *Journal of Applied Econometrics*, *34*(5), 673–687.

Dietz, S., Gollier, C., & Kessler, L. (2018). The climate beta. *Journal of Environmental Economics and Management*, *87*, 258–274.

Dyurgerov, M. B., & Meier, M. F. (2000). Twentieth century climate change: evidence from small glaciers. *Proceedings of the National Academy of Sciences*, *97*(4), 1406–1411.

Edelstein, P., & Kilian, L. (2007). The response of business fixed investment to changes in energy prices: A test of some hypotheses about the transmission of energy price shocks. *The BE Journal of Macroeconomics*, *7*(1).

Golosov, M., Hassler, J., Krusell, P., & Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, *82*(1), 41–88.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, *32*(1), 1–26.

Hallegatte, S. (2008). An adaptive regional input-output model and its application to the assessment of the economic cost of katrina. *Risk Analysis: An International Journal*, *28*(3), 779–799.

Hassler, J., & Krusell, P. (2018). Environmental macroeconomics: the case of climate change. In *Handbook of environmental economics* (Vol. 4, pp. 333–394). Elsevier.

Herrera, A. M., & Pesavento, E. (2009). Oil price shocks, systematic monetary policy, and the "great moderation". *Macroeconomic Dynamics*, *13*(1), 107–137.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, *8*(1), 43–75.

Hsiang, S. M., & Jina, A. S. (2014). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones* (Tech. Rep.). Cambridge, MA: National Bureau of Economic Research.

Kilian, L. (2009a). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American economic review*, *99*(3), 1053–1069.

Kilian, L. (2009b). Oil price shocks, monetary policy and stagflation. *CEPR Discussion Papers*(7324).

Kilian, L. (2014). Oil price shocks: Causes and consequences. *Annu. Rev. Resour. Econ.*, *6*(1), 133–154.

Kim, H. S., Matthes, C., & Phan, T. (2025). Severe weather and the macroeconomy. *American Economic Journal: Macroeconomics*, *17*(2), 315–341.

Lee, J., & Song, J. (2009). *Nature of oil price shocks and monetary policy* (Tech. Rep.). Cambridge, MA: National Bureau of Economic Research.

Liao, W., Sheng, X., Gupta, R., & Karmakar, S. (2024). Extreme weather shocks and state-level inflation of the united states. *Economics Letters*, *238*, 111714.

Mabro, R. (2006). *Oil in the 21st century: issues, challenges and opportunities.* Oxford

University Press, USA.

McCracken, M. W., & Ng, S. (2015). Fred-md: A monthly database for macroeconomic research. *FRB St. Louis Working Paper*(2015-12).

McCracken, M. W., & Ng, S. (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, *34*(4), 574–589.

Meehl, G. A., Hu, A., & Santer, B. D. (2009). The mid-1970s climate shift in the pacific and the relative roles of forced versus inherent decadal variability. *Journal of Climate*, *22*(3), 780–792.

Nakajima, J. (2011). Time-varying parameter var model with stochastic volatility: An overview of methodology and empirical applications. *Monetary and Economic Studies*, 107–142.

Nakamura, E., & Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics*, *133*(3), 1283–1330.

Nordhaus, W. D. (1991). To slow or not to slow: the economics of the greenhouse effect. *The economic journal*, *101*(407), 920–937.

Nordhaus, W. D. (1993). Optimal greenhouse-gas reductions and tax policy in the "dice" model. *The American Economic Review*, *83*(2), 313–317.

Ojeda-Castillo, V., Murillo-Tovar, M. A., Hernández-Mena, L., Saldarriaga-Noreña, H., Vargas-Amado, M. E., Herrera-López, E. J., & Díaz, J. (2024). Tropospheric no2: Anthropogenic influence, global trends, satellite data, and machine learning application. *Remote Sensing*, *17*(1), 49.

Peersman, G., & Van Robays, I. (2009). Oil and the euro area economy. *Economic Policy*, *24*(60), 603–651.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy.

The Review of Economic Studies, *72*(3), 821–852.

Ramanathan, V., & Feng, Y. (2009). Air pollution, greenhouse gases and climate change: Global and regional perspectives. *Atmospheric environment*, *43*(1), 37–50.

Roberts, M. J., & Schlenker, W. (2013). Identifying supply and demand elasticities of agricultural commodities: Implications for the us ethanol mandate. *American Economic Review*, *103*(6), 2265–2295.

Romer, C. D., & Romer, D. H. (2000). Federal reserve information and the behavior of interest rates. *American economic review*, *90*(3), 429–457.

Roth Tran, B., & Wilson, D. J. (2025). The local economic impact of natural disasters. *Journal of the Association of Environmental and Resource Economists*, *12*(6), 1667–1704.

Sheng, X., Gupta, R., & Çepni, O. (2022). The effects of climate risks on economic activity in a panel of us states: The role of uncertainty. *Economics Letters*, *213*, 110374.

Sheng, X., Gupta, R., & Cepni, O. (2024). Time-varying effects of extreme weather shocks on output growth of the united states. *Finance Research Letters*, *70*, 106318.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1–48.

Smets, F., & Wouters, R. (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American economic review*, *97*(3), 586–606.

Stock, J. H., & Watson, M. W. (2005). *Implications of dynamic factor models for var analysis.* National Bureau of Economic Research Cambridge, Mass., USA.

Stock, J. H., & Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In *Handbook of macroeconomics* (Vol. 2, pp. 415–525). Elsevier.

Won, S. (2025). Climate change and the us macroeconomy: Bayesian time-varying parameter approach with stochastic volatility. *Available at SSRN 5210616*.

Won, S. (2026). Climate change and the large set of us macroeconomic variables: Favar approach. *Available at SSRN 6567378*.

Yamaka, W., Lomwanawong, S., Magel, D., & Maneejuk, P. (2022). Analysis of the lockdown effects on the economy, environment, and covid-19 spread: lesson learnt from a global pandemic in 2020. *International Journal of Environmental Research and Public Health*, *19*(19), 12868.

Yamamoto, Y. (2019). Bootstrap inference for impulse response functions in factor-augmented vector autoregressions. *Journal of Applied Econometrics*, *34*(2), 247–267.

Yamamoto, Y., & Hara, N. (2022). Identifying factor-augmented vector autoregression models via changes in shock variances. *Journal of Applied Econometrics*, *37*(4), 722–745.

Yi, Y., & Kim, E. (2024). Is shanghai a rival to seoul? analysis on complementary and competitive relationships in trade. *Papers in Regional Science*, *103*(6), 100050.

Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of business & economic statistics*, *10*(3), 251–270.

Appendix A

APPENDIX FOR CLIMATE CHANGE AND THE US MACROECONOMY: TIME-VARYING PARAMETER APPROACH WITH STOCHASTIC VOLATILITY

A.1 Simultaneous Relations

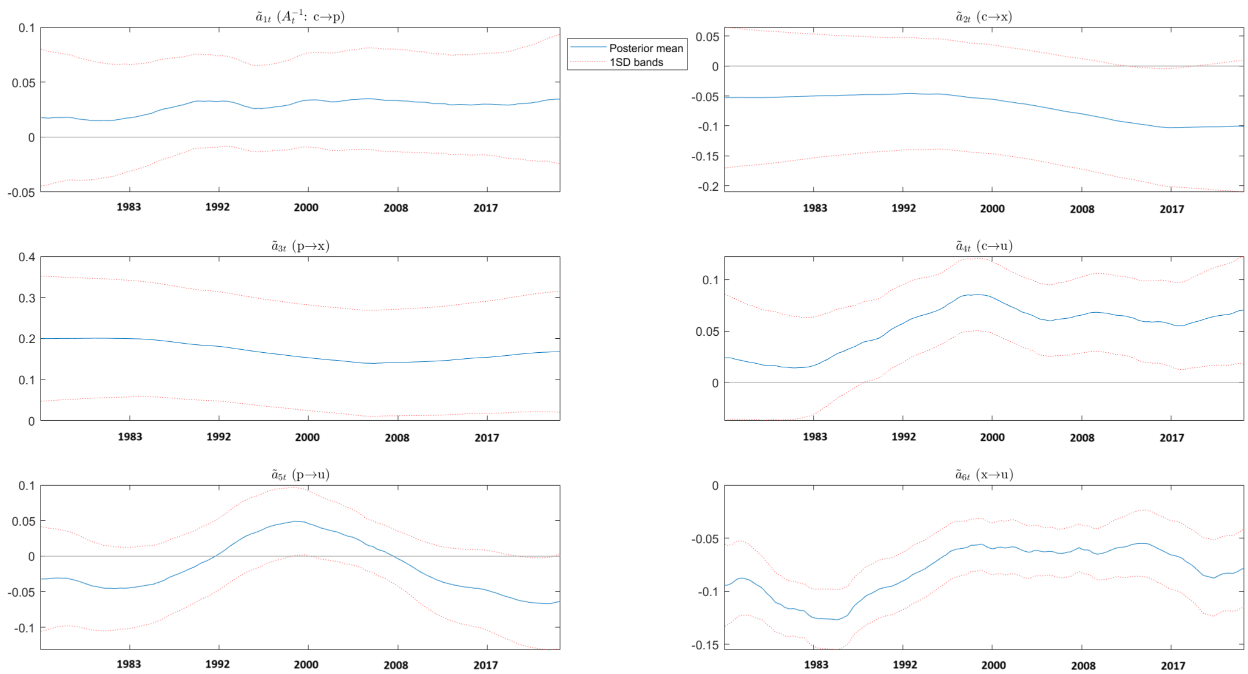


Figure A.1: Coefficients of Simultaneous Relations

Figure A.1 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 simultaneous 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.

A.2 3D Impulse Responses of the U.S. macroeconomy

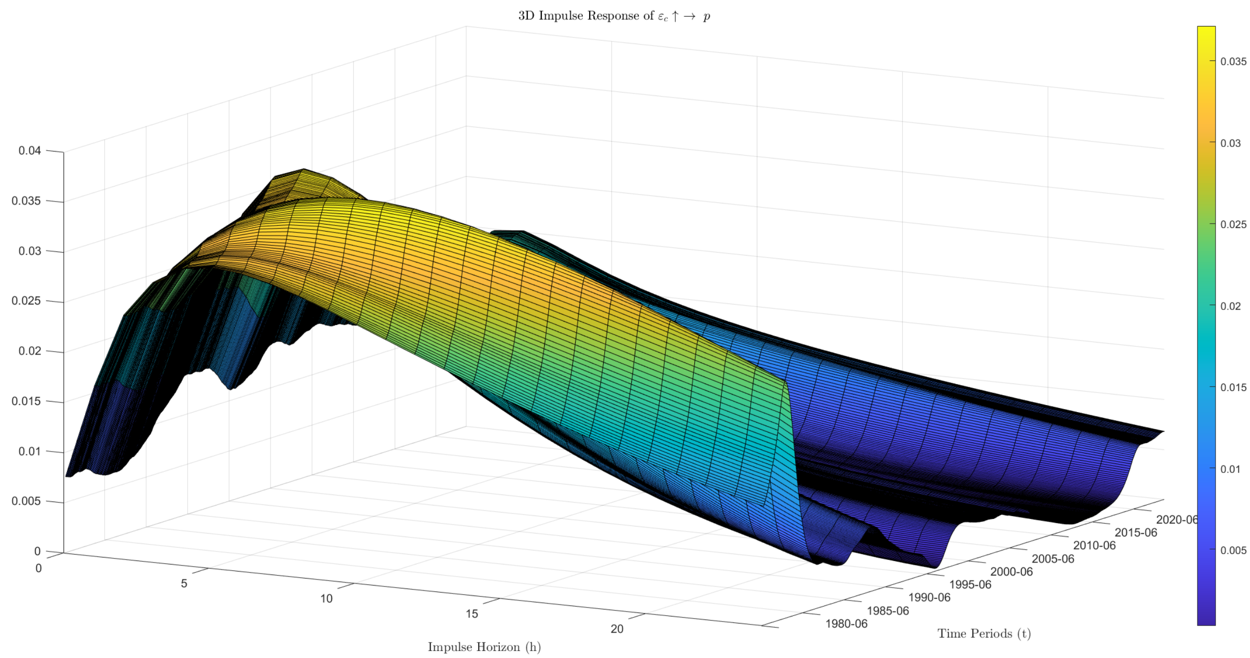


Figure A.2: 3D impulse response of the climate shock to inflation

Figure A.2 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 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 1.8** of Chapter 1.

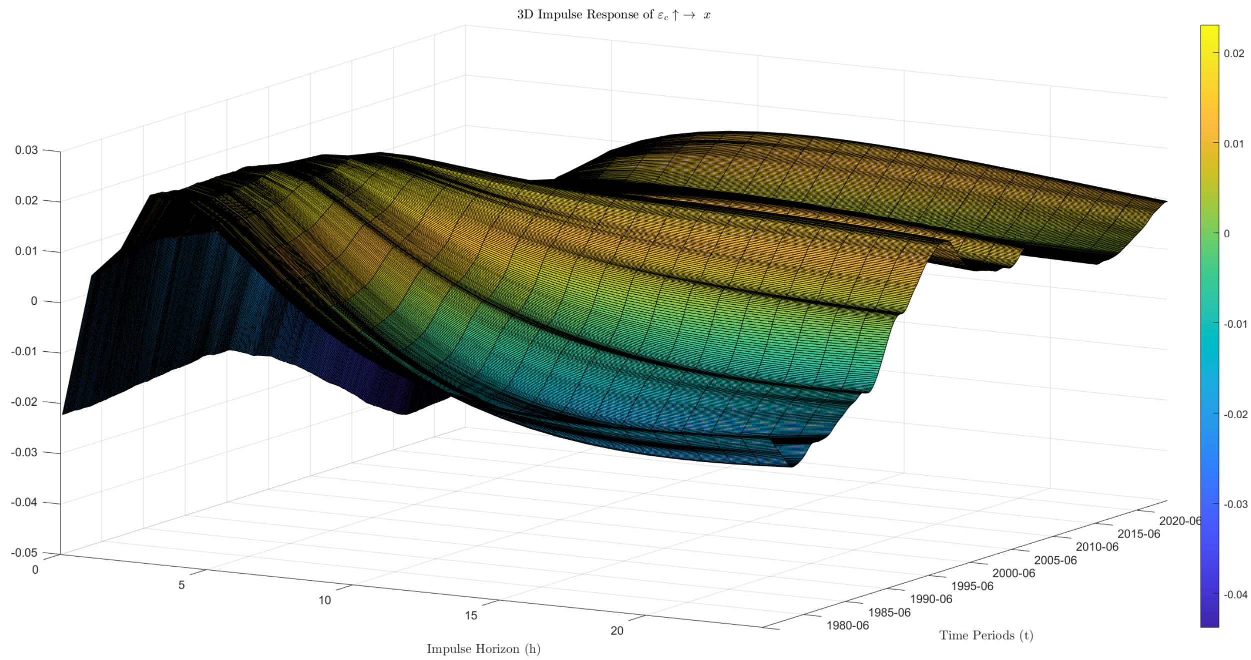


Figure A.3: 3D impulse response of climate shock to output

Figure A.3 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 1.9** of Chapter 1.

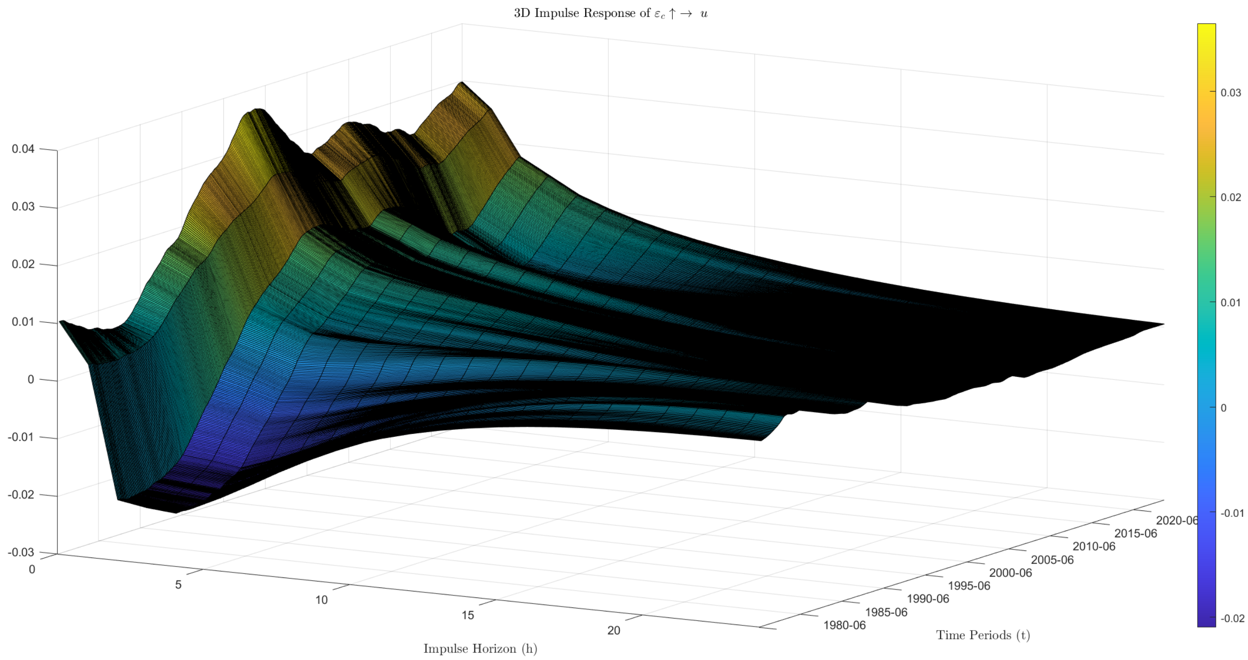


Figure A.4: 3D impulse response of climate shock to unemployment

Figure A.4 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 1.10** of Chapter 1.

Appendix B

APPENDIX FOR GLOBAL OIL PRICE CHANGE AND ITS IMPACT ON SOUTH KOREAN MACROECONOMY

3D Impulse Responses of Korean macroeconomic variables

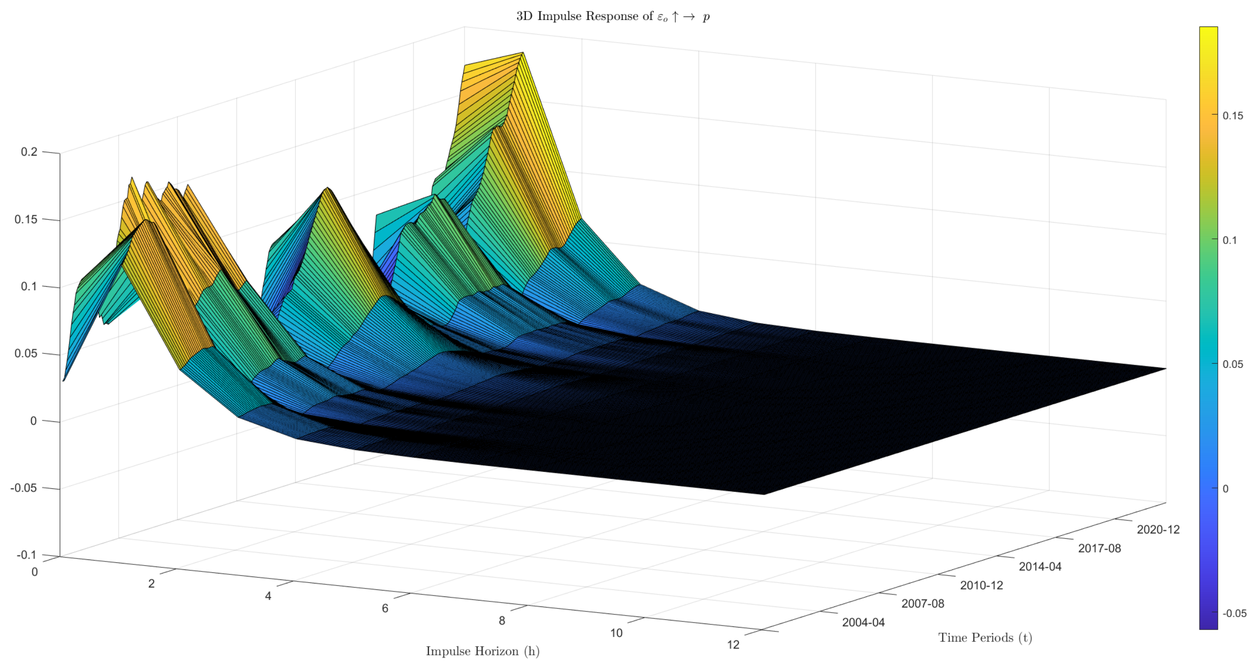


Figure B.1: 3D Impulse Response of the Oil Price shock to Inflation

Figure B.1 shows the 3-dimensional impulse response function of the oil price change shock to Korean inflation. Because of Time-Varying Parameter (β_t) in the econometric specification, the model can generate the impulse response horizon for all point of time periods. This 3D graph shows two different types of impulse responses altogether. Slicing this graph through the time horizon gives the impulse response function at a chosen point of time. Cutting through the period gives the periodic impulse response function over the time period, for instance 1-month ahead impulse responses for all time periods. Two different impulse response of the global oil price change shock to Korean inflation are shown in **Figure 3.5** of Chapter 3.

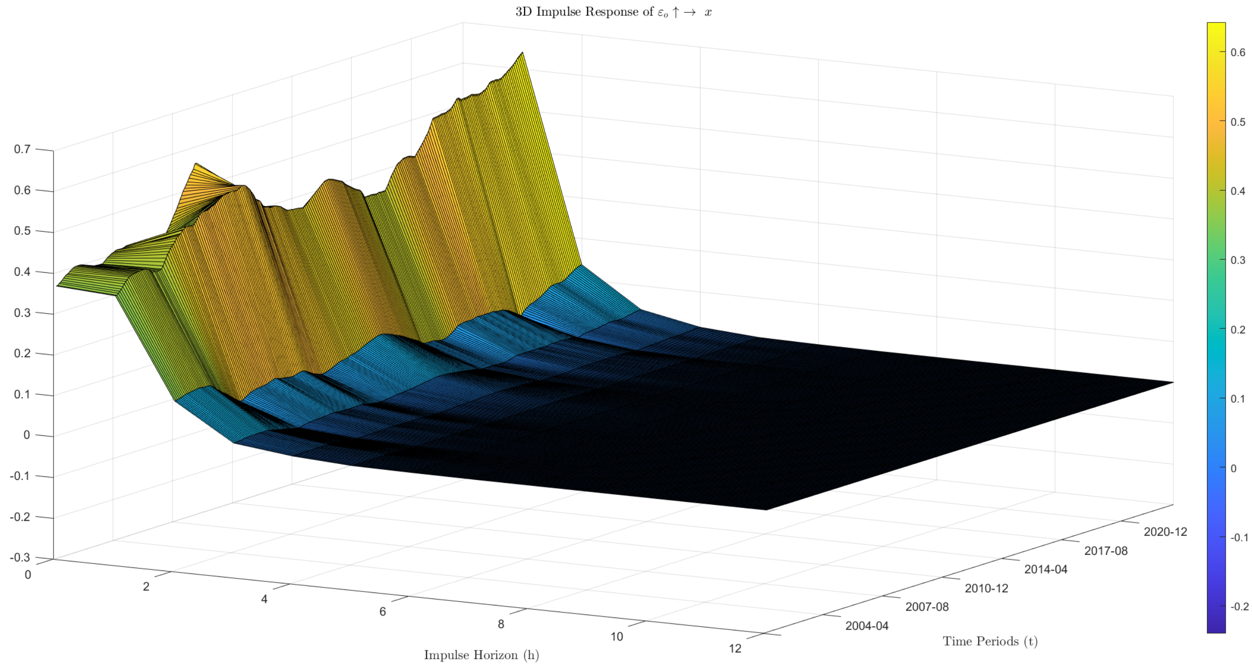


Figure B.2: 3D Impulse Response of the Oil Price shock to Output

Figure B.2 shows the 3D impulse response function of the oil price change shock to Korean output. Both of horizontal and periodic impulse response functions of Korean output from the global oil price change shock sliced from this 3D graph are presented in **Figure 3.6** of Chapter 3.

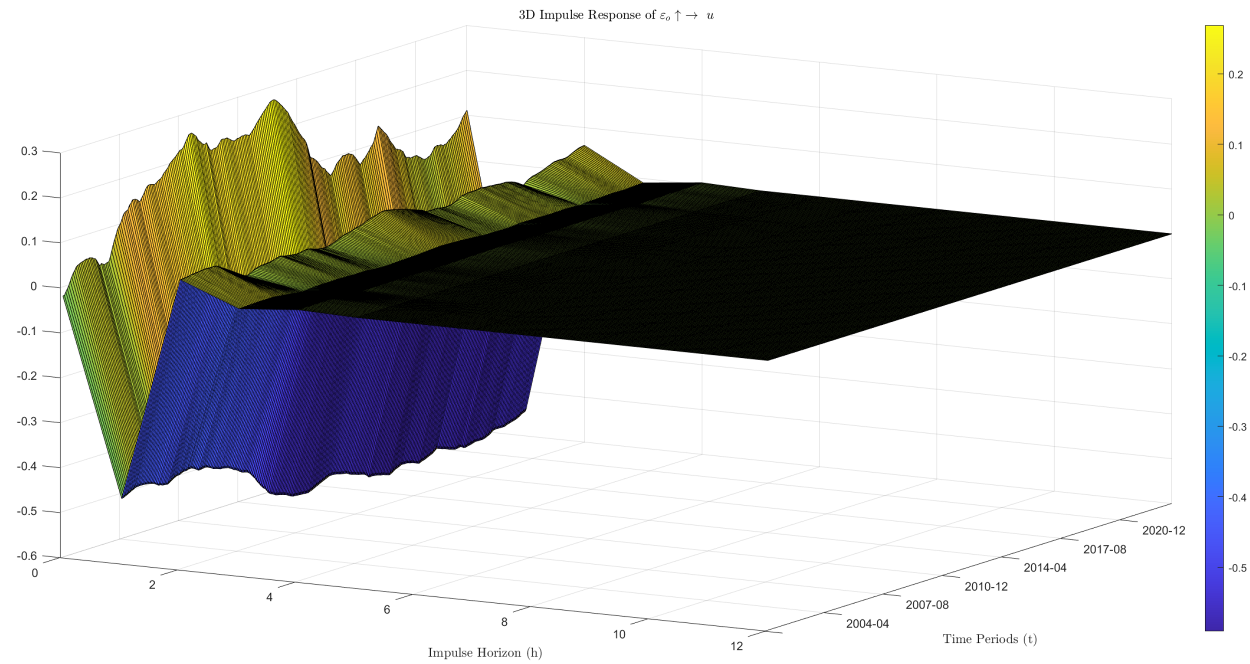


Figure B.3: 3D Impulse Response of the Oil Price shock to Unemployment

Figure B.3 shows the 3D impulse response function of the oil price change shock to Korean unemployment rate. The time-varying impulse responses in both horizontal and periodic facades of Korean unemployment rate is shown in **Figure 3.7** of Chapter 3.