Climate Change and the large set of US macroeconomic variables: FAVAR approach

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Abstract

This study implements Factor Augmented VAR (FAVAR) model to research how the climate change shock represented by Actuaries Climate Index (ACI) could impact on a large set of 123 monthly macroeconomic variables from 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.

The main findings of this research is in twofold. Firstly, this study presents the climate change and its impact to a comprehensive set of US macroeconomic variables. It 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.

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 macroeconomic variables and the 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 or Ridge estimator. Such merit can be easily utilized in policy recommendation, monitoring tool and macroeconomic forecasting.

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1 Introduction

This research studies 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 fairly 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, Jones, and Olken, 2014; 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, Jones, and Olken, 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, Gupta, and Çepni (2022), Liao, Sheng, Gupta, and Karmakar (2024), Sheng, Gupta, and Cepni (2024), Kim, Matthes, and Phan (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. 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** provides the econometric model framework for the Factor Augmented VAR (FAVAR) model used for the estimation. **Section 3** describes the data used: the monthly-frequency US macroeconomic data and the Actuaries Climate Index (ACI). **Section 4** presents main empirical results and discussion. **Section 5** concludes.

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

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

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

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{2}$$

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

$$Z_t = \begin{bmatrix} F_t \\ Y_t \end{bmatrix}, \quad Z_t = A_1 Z_{t-1} + \cdots + A_p Z_{t-p} + u_t \tag{3}$$

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:

$$\hat{C}_t = b_{F^s} \hat{F}_t^s + b_Y Y_t + e_t \tag{4}$$

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.

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 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 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, Canadian Institute of Actuaries, Causalty Actuarial Society, and Society of Actuaries (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: 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 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 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 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 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 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 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 (WPSID61) 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 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.

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.

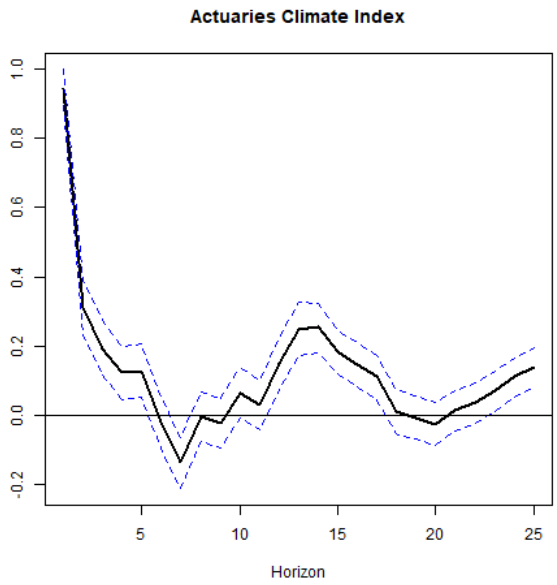

Figure 1: Self-Impulse Response of Actuaries Climate Index

Figure 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.

4.1 Output and Income

Figure 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.

In **Figure 2**, Real Personal Income and Industrial Productionare 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.

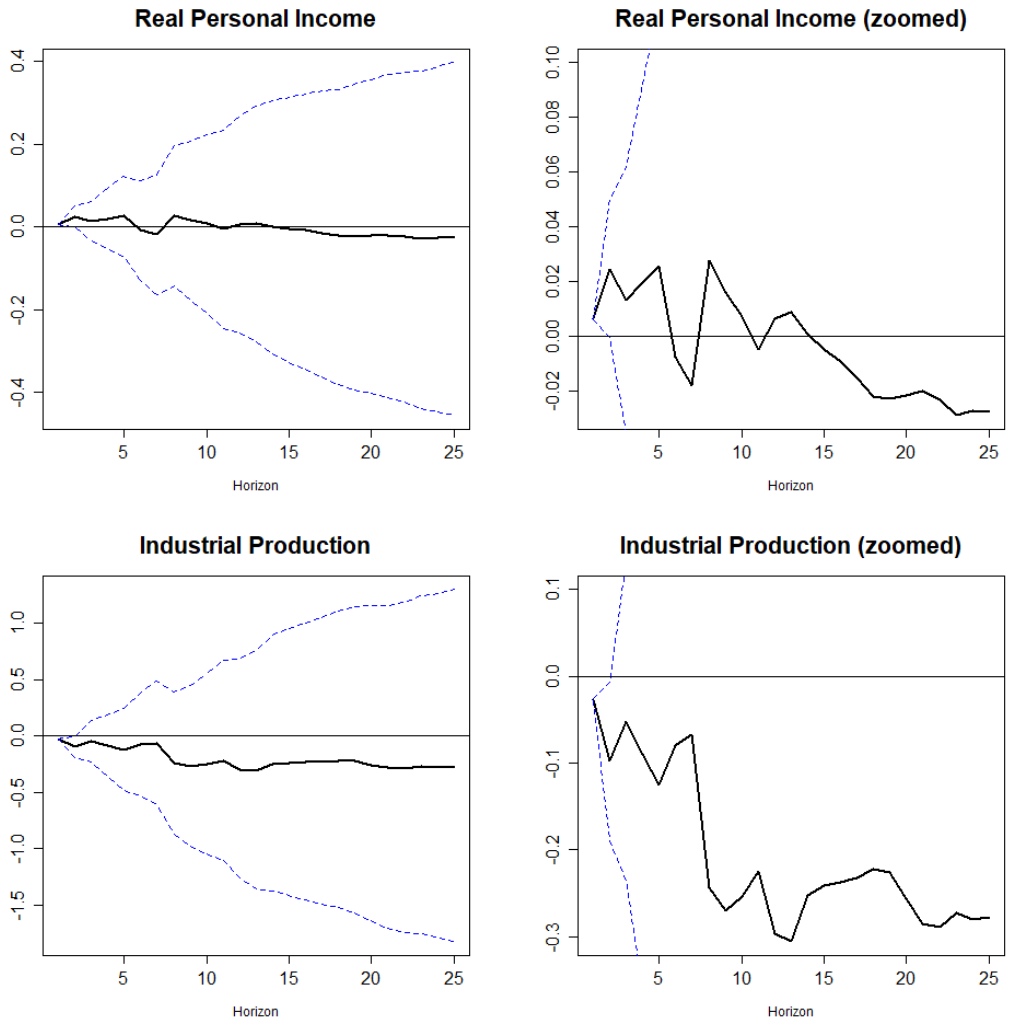

Figure 2: Income and Output

4.2 Labor Market

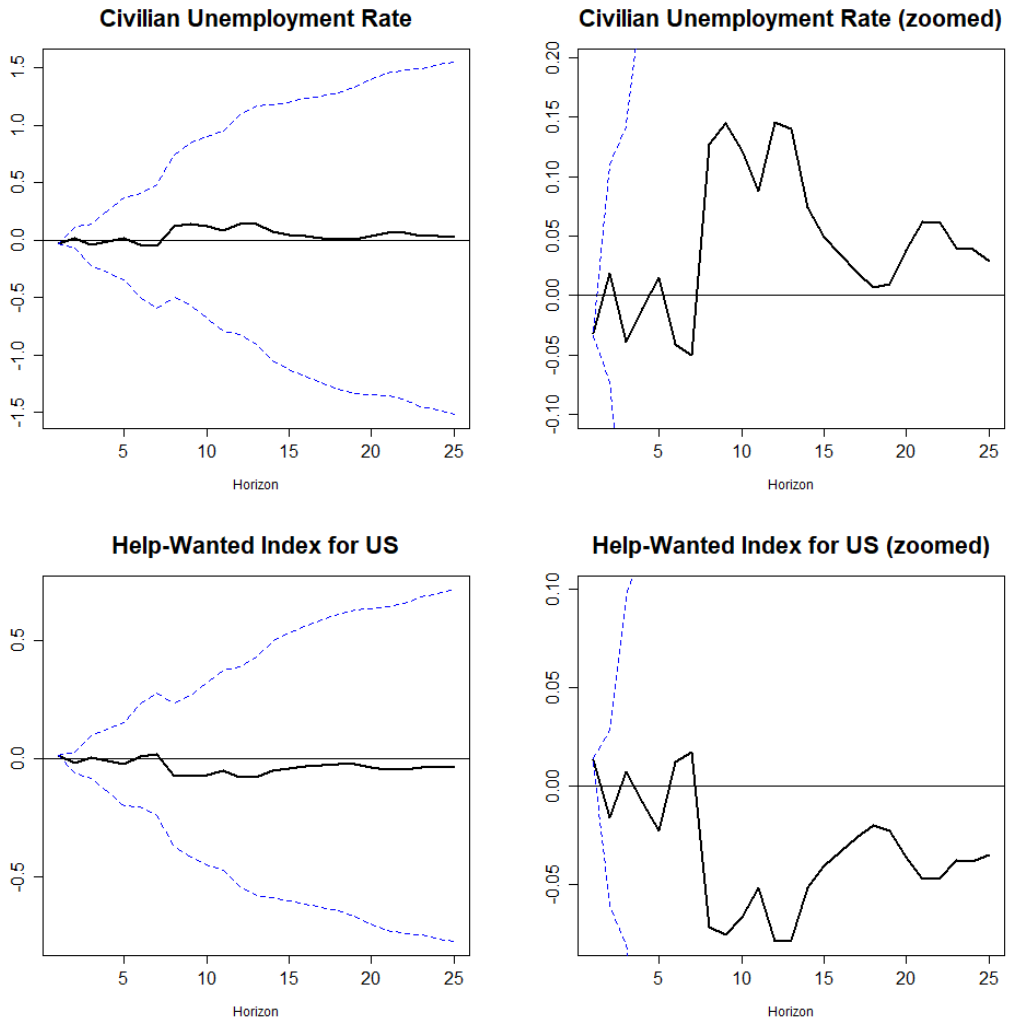

Figure 3: Labor Market: Unemployment Rate and HWI

Figure 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.

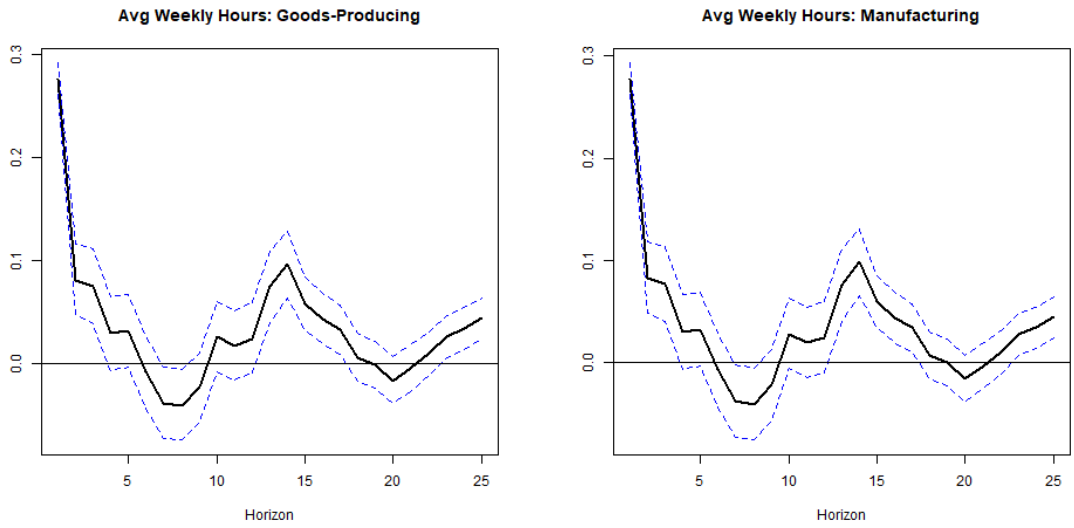

Figure 4: Labor Market: Avg Weekly Hours

Figure 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 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.

4.3 Housing Market

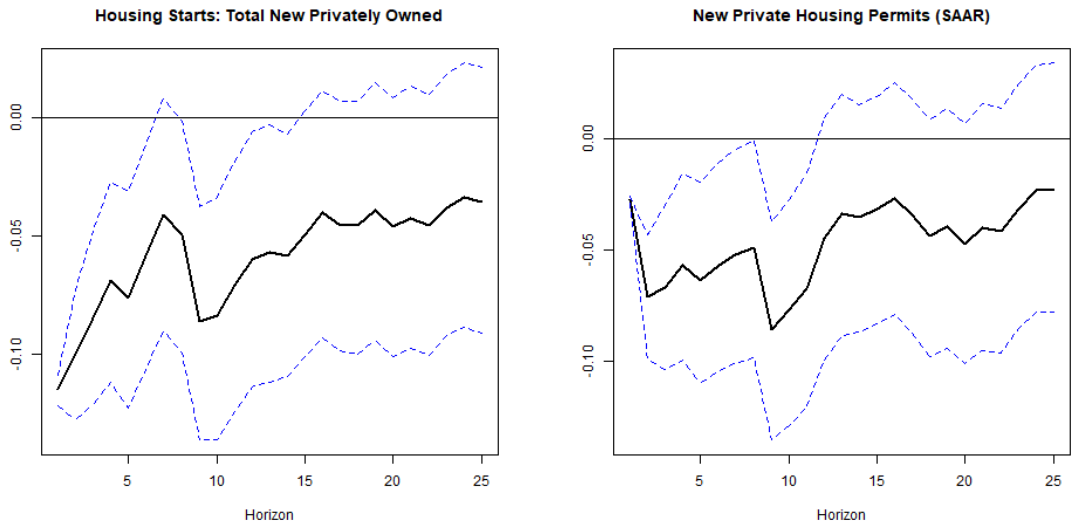

Figure 5: Housing Market

Figure 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 reponses 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.

4.4 Orders and Inventories

Figure 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.

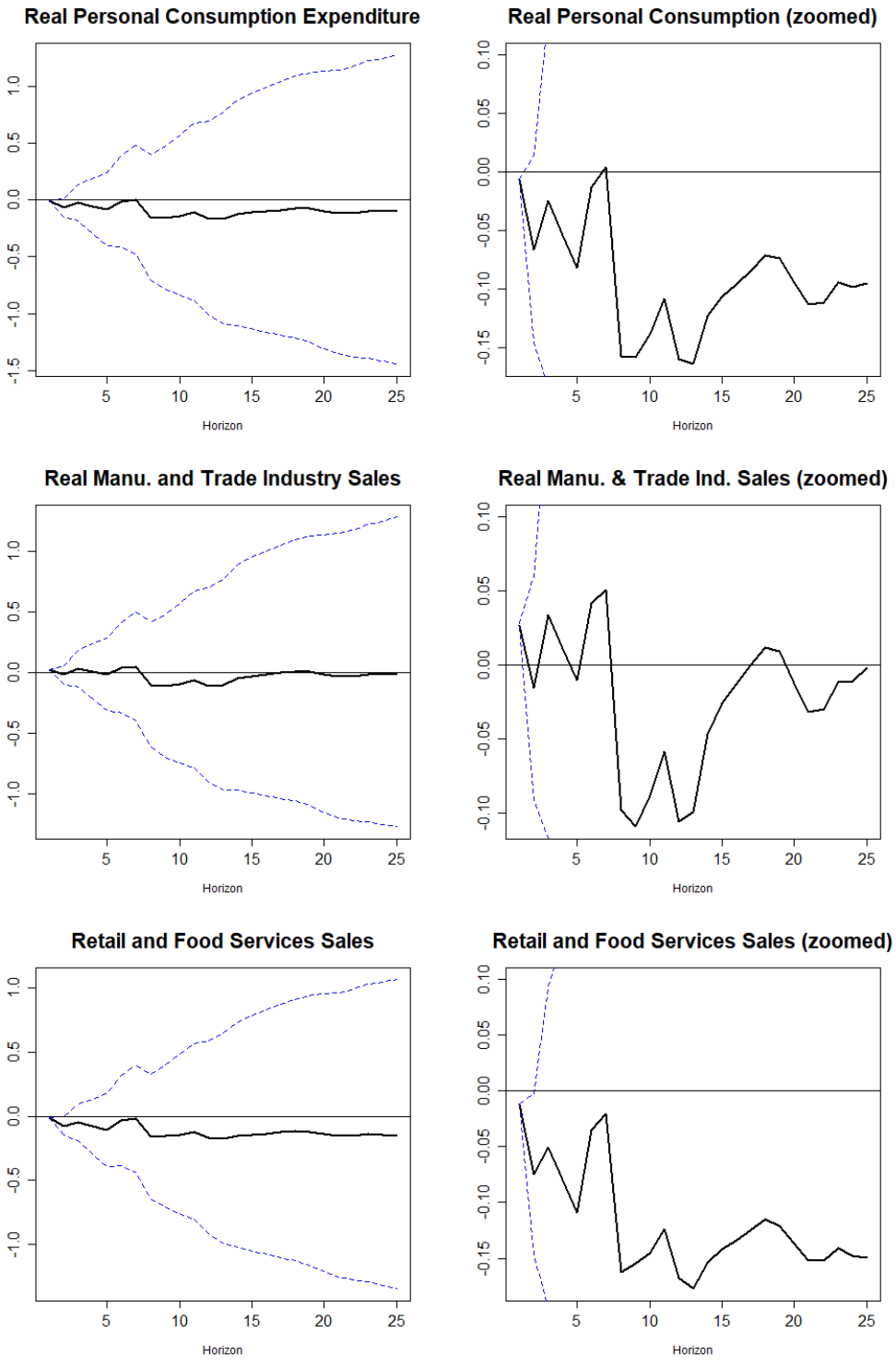

Figure 6: Orders and Inventories

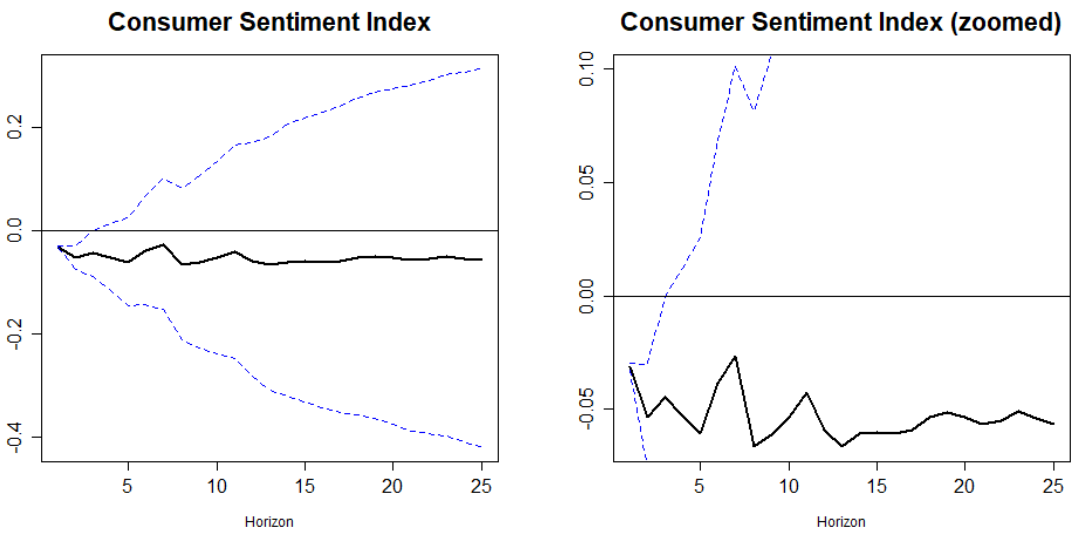

Figure 7: Consumer Sentiment Index

Figure 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.

4.5 Money, Stock Market and Spreads

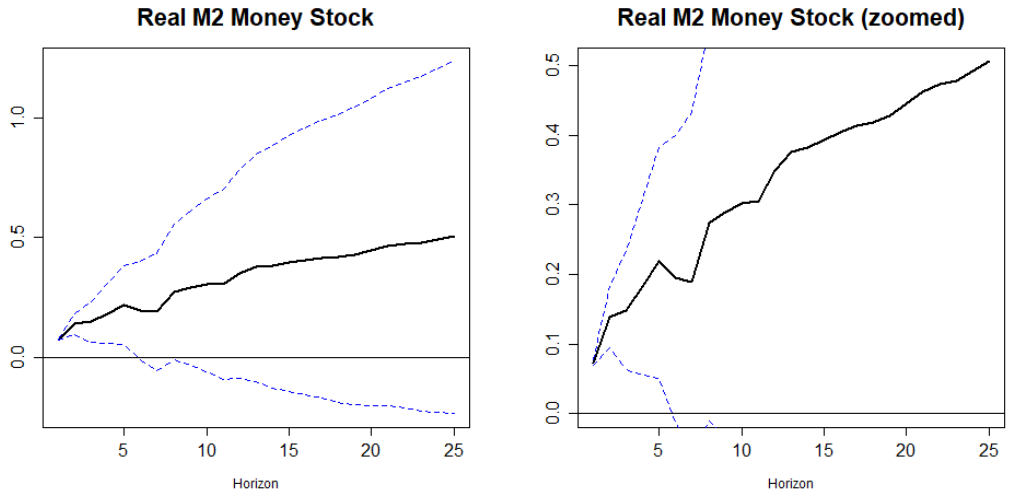

Figure 8: Money Market: Real M2 Money Stock

Figure 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.

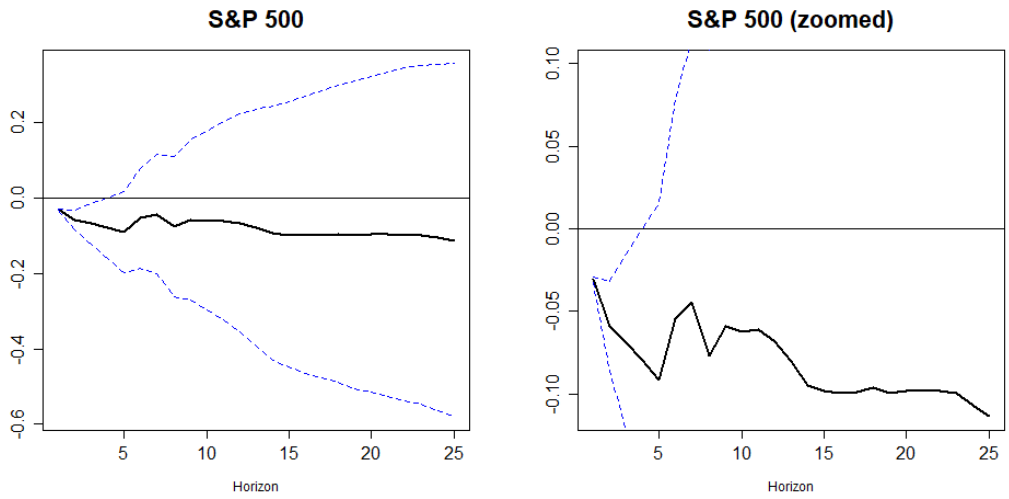

Figure 9: Stock Market: S&P 500

Figure 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.

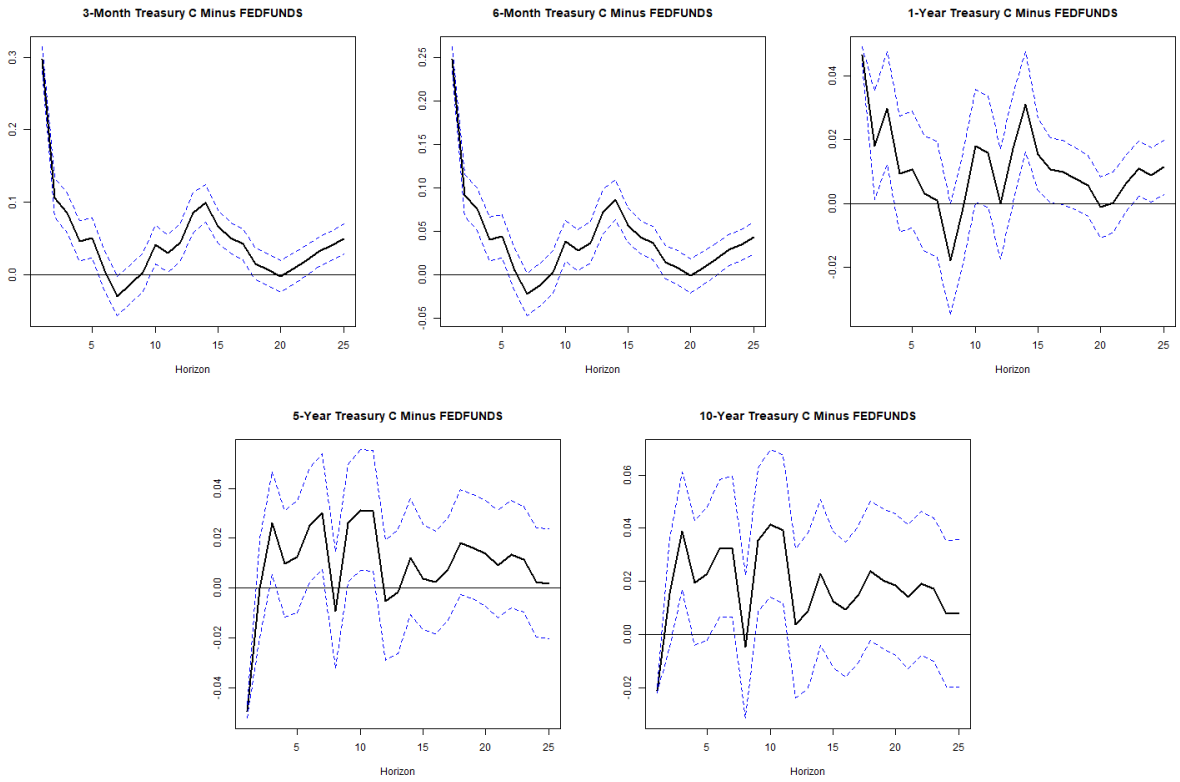

Figure 10: Treasury spreads

Figure 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 and Jalles, 2022a) and the cost government borrowing (Cevik and Jalles, 2022b); in the economic story that in short-term, the climate change vulnerability is huge and such 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.

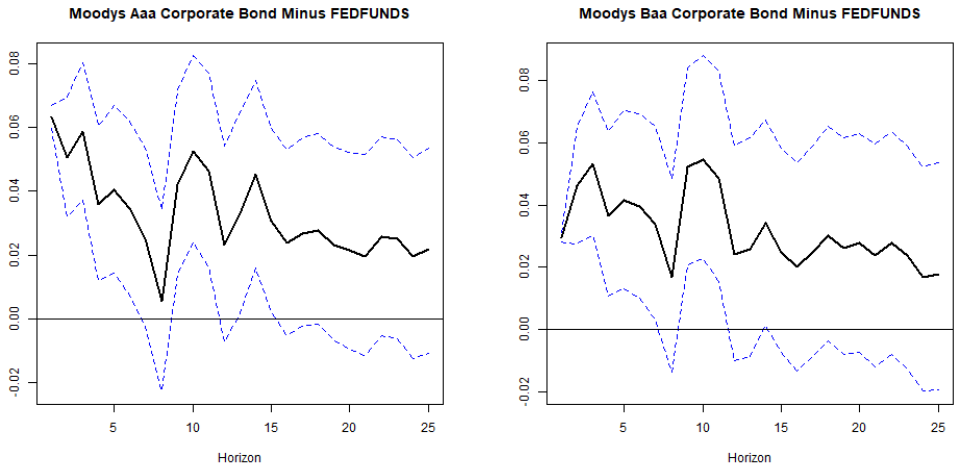

Figure 11: Corporate Bond Spreads

Figure 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.

4.6 Prices

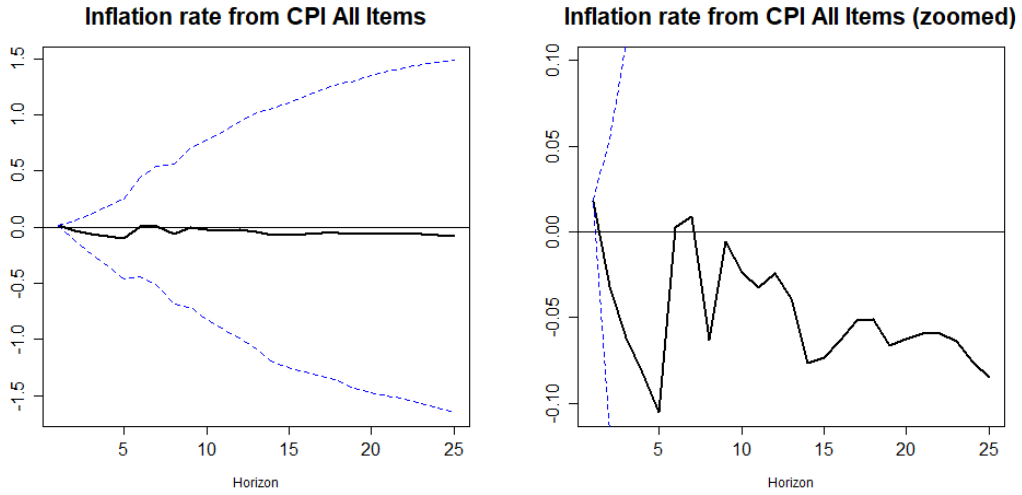

Figure 12: Inflation Rate from CPI: All Items

Figure 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 14** and **Figure 13**.

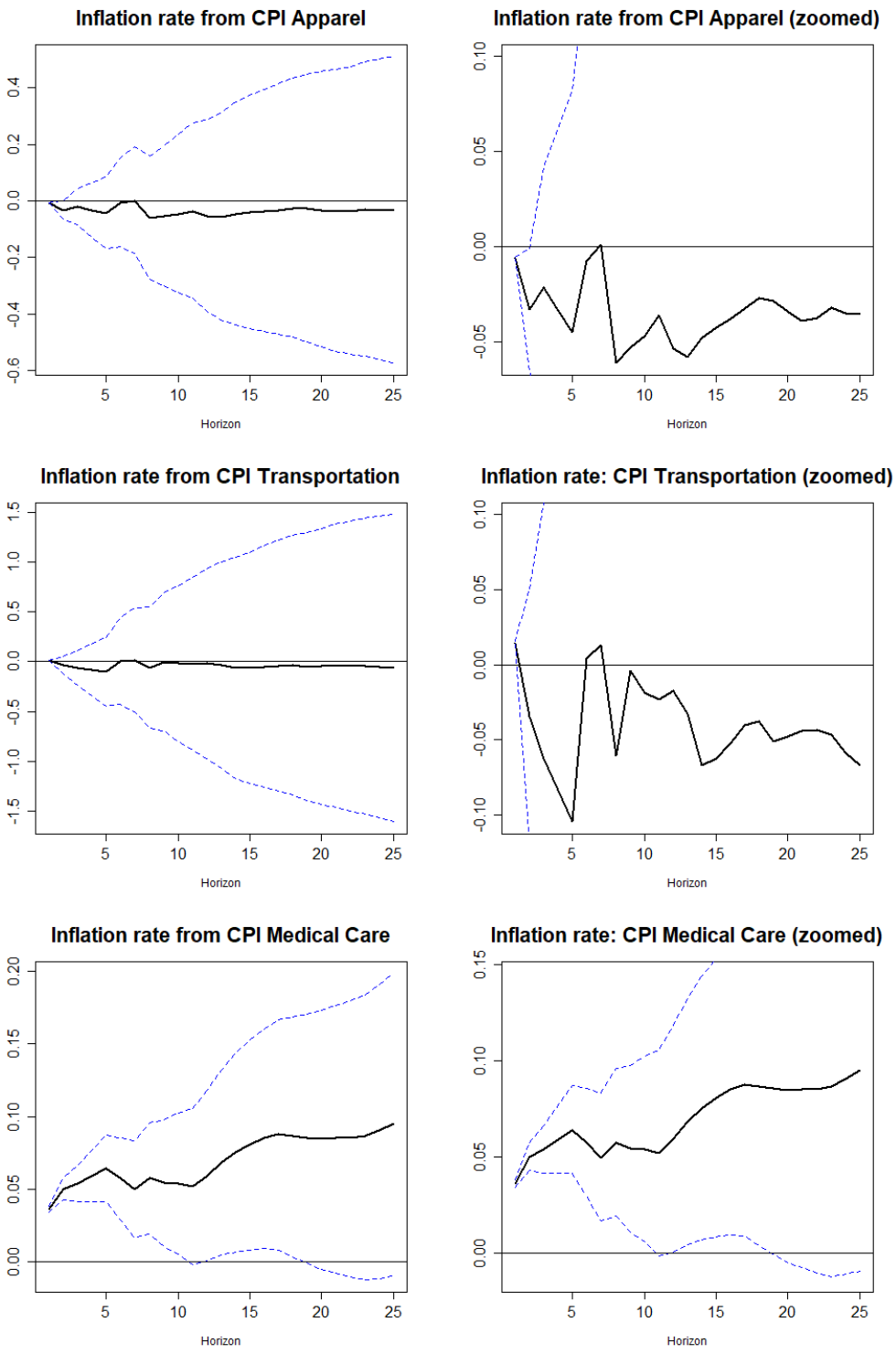

Figure 13: Inflation Rate from CPI: Apparel, Transportation and Medical Care

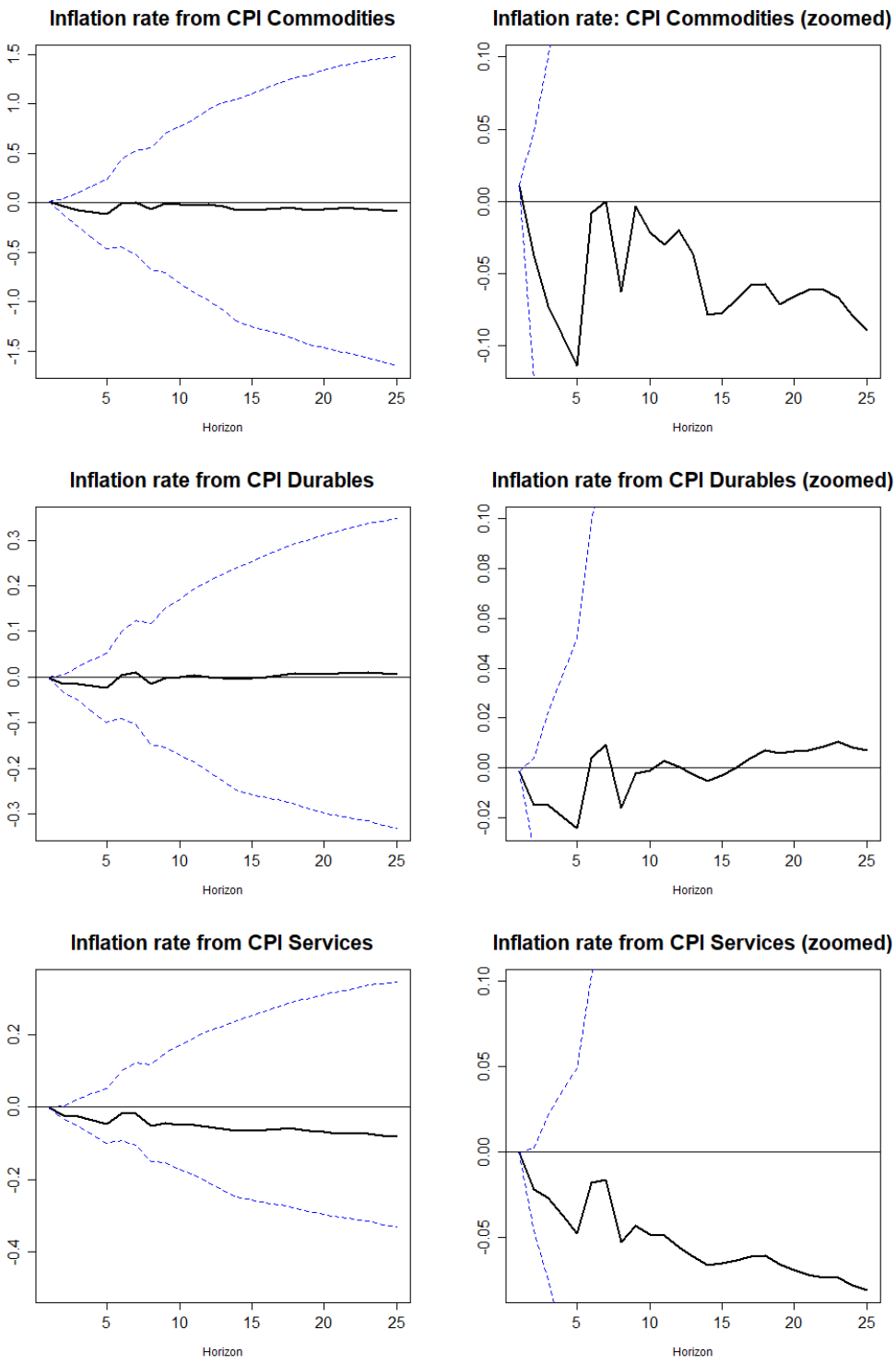

Figure 14: Inflation Rate from CPI: Commodities, Durables and Services

Figure 14 and **Figure 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 modelling 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, Evans, Fisher, Justiniano, Calomiris, and Woodford, 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.

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 meritful 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.

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 or Ridge estimator. Such merit can be easily utilized in policy recommendation, monitoring tool and macroeconomic forecasting.

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