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Temperature and the U.S. economy: From demand to supply-side effects

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IES Working Paper 21/2025

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Temperature and the U.S. Economy: From Demand to Supply-Side Effects

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Abstract:
We examine how the macroeconomic effects of temperature shocks have evolved in the United States since 1947. Using a time-varying parameter vector autoregression with stochastic volatility estimated on monthly data, we document a structural shift in the propagation of temperature shocks. Before the 1980s, higher temperatures induced demand-like dynamics—output and prices rose together. Since the 1980s, responses have become supply-like: real activity declines persistently while prices rise on impact and turn negative thereafter. A sectoral decomposition confirms shifts in agriculture, manufacturing, and services, with the services sector the primary driver of recent GDP dynamics. Our results reveal that food, services, and energy prices drive most of the aggregate price adjustments, while core prices remain muted. Temperature shocks now explain a rising share of medium-run output and price variation, and greater ex-ante temperature uncertainty depresses equity valuations on impact. Overall, temperature shocks have become increasingly contractionary and inflationary in nature.

JEL: C22, E30, E32, Q54
Keywords: Temperature shocks, Time-varying VAR, US economy

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1 Introduction

The economic consequences of climate change have become an increasingly urgent concern for policymakers, central banks, and researchers worldwide.[1] In the United States, a key indicator of climate change—average surface temperature—has risen by roughly 1.25,°C since the 1950s, with the warming trend intensifying in recent decades. At the same time, greater climate variability and uncertainty have amplified the frequency and severity of extreme weather events (Diffenbaugh et al., 2017; IPCC, 2022). A growing body of evidence indicates that rising temperatures and heightened climate uncertainty pose significant risks to macroeconomic stability (Skidmore, 2022). Yet we know relatively little about whether the macroeconomic effects of temperature shocks have changed over time, and about their structural nature—specifically, whether they propagate primarily through demand-like or supply-like channels. This paper addresses two questions: (i) have the macroeconomic effects of temperature shocks evolved over the past eight decades, and (ii) do these shocks operate mainly through demand or supply mechanisms?

Most studies on the economic costs and benefits of climate change focus on relatively short time horizons—typically the past 30 to 40 years—and rely on low-frequency (annual) cross-country data. By contrast, we adopt a longer historical horizon and a higher-frequency perspective, analyzing how monthly temperature fluctuations have affected the U.S. economy since the mid-1940s. This approach substantially extends the temporal coverage and captures short-run macroeconomic dynamics that are often obscured in annual data. Beyond our two core questions, we also: (i) quantify the relative contribution of temperature shocks to overall macroeconomic fluctuations; (ii) document how sectoral GDP and price responses to temperature shocks have evolved across time; and (iii) assess the contemporaneous effects of temperature uncertainty—an ex ante risk measure based on conditional volatility—on key macroeconomic and financial variables.

To investigate these questions, we estimate a time-varying-parameter vector autoregression with stochastic volatility (TVP-VAR-SV).[2] In this framework, coefficient paths are allowed to evolve over time, capturing potential adaptation—the idea that the economy's response to a given temperature shock changes across decades—while time-varying shock variances and covariances capture shifts in the distribution of temperature shocks associated with climate change and rising uncertainty.[3] Nevertheless, we impose a conservative prior that favors constant coefficients and variances, centered on estimates from the late 1940s–1950s. Thus, *ex ante*, the model prefers time-invariant dynamics; any departure from it must be supported by the data and will appear as posterior evidence of statistically meaningful parameter change.

[1] Recent economic bulletins from major central banks—including the ECB (Fernandez and Parker, 2025) and the BIS (Ehlers et al., 2025)—underscore central banks' growing attention to the macroeconomic risks associated with climate-related shocks.

[2] Vector autoregressions are a workhorse in empirical macroeconomics; see Sims (1980); Christiano et al. (2005); Beaudry and Portier (2006); Brunnermeier et al. (2021).

[3] Because climate and macroeconomic series can exhibit trends, structural breaks, and heteroskedasticity, a TVP-VAR-SV provides a flexible, state-dependent framework for inference. This specification accommodates shifts in the underlying environment, yielding more reliable estimates. For instance, climate series (e.g., global and national temperatures) display strong trends and potential regime changes, while macro data feature breaks around episodes such as the 2008 financial crisis and the COVID-19 pandemic. There is substantial evidence that the volatility of macroeconomic shocks has changed over time—most notably declining from the Great Inflation to the Great Moderation; see McConnell and Perez-Quiros (2000); Cogley and Sargent (2005); Fernández-Villaverde and Rubio-Ramírez (2010).

Our contributions are threefold. First, we document statistically significant time variation in the macroeconomic effects of temperature shocks: the impulse responses of real GDP, CPI (and its subcomponents), real equity prices, real personal consumption, population, and the unemployment rate vary significantly across decades. This time variation reveals structural economic shifts in the propagation of temperature shocks. Before the 1980s, temperature shocks exhibit (positive) demand-like comovement—output and prices rise together—whereas in recent decades they appear (negative) supply-like—output falls while prices rise. At medium horizons (24–36 months), the median CPI response exceeds 2% before 1980 but turns negative post-1980s. For real GDP, the median response goes back to zero before the 1980s, and persistently decreases (on average, 2%) from the 1980s. The shift in the propagation of temperature shocks from demand to supply-type also broadly aligns with long-term trends in average temperature. Knappenberger et al. (2001) identify several distinct phases in U.S. temperature trends, noting that temperatures declined slightly from the 1940s through the late 1960s before beginning to rise in the 1970s. More recent evidence suggests that this warming trend has accelerated since the early 2000s. Similarly, Morice et al. (2021) provide evidence that temperature anomalies have risen markedly since 1980.

Second, to shed more light on transmission mechanisms, a sectoral decomposition of GDP to agriculture, manufacturing, and services shows dynamics broadly similar to aggregate output, documenting that the temperature shocks exhibit economy-wide consequences. Our results further indicate that temperature shocks influence various price indices, with the strongest effects observed for energy and food prices. Third, we find that higher *ex ante* temperature uncertainty depresses equity prices on impact, while showing no statistically significant effects on other macroeconomic variables, such as real GDP and CPI. Therefore, our research shows it may be worthwhile to examine not only on the first moment but also the second moment of temperature shocks.

Overall, our findings underscore the increasing economic and financial stability risks associated with rising temperatures. The progressively stronger adverse response to temperature shocks over time suggests that the U.S. economy has not fully adapted to a warming climate, consistent with the evidence reported for US by Burke and Emerick (2016) and Bakkensen and Mendelsohn (2016).

The rest of the paper is structured as follows. Section 2 reviews the existing literature on temperature, economic growth, and financial markets. Section 3 outlines the empirical approach and data. Section 4 presents the main findings. Section 5 explores robustness checks and extensions. Section 6 concludes. An Appendix with additional details on estimation framework and data follows.

2 Literature Survey

A growing body of research examines the relationship between climate-related shocks—ranging from extreme weather (rising temperatures, heavy precipitation, drought) to gradual changes (sea-level rise)–and economic activity (Barrage and Hsiang, 2024; Dell et al., 2014). For developing economies, numerous studies document sizable negative effects of weather shocks on economic growth (see Dell et al. (2012); Cashin et al. (2017); Mendelsohn et al. (2012); Horvath (2021); Acevedo et al. (2020)). By contrast, the aggregate evidence for advanced economies, including the United States, is mixed: some papers find limited or even positive effects (Cashin et al., 2017; Deschênes and Greenstone, 2007; Noy, 2009; Strobl, 2011), whereas others report negative short-

and long-run responses (Colacito et al., 2019; Kim et al., 2025; Burke and Leigh, 2010; Kahn et al., 2021; Bakkensen and Mendelsohn, 2016). We contribute by showing that the propagation of temperature shocks in the U.S. economy has shifted over time: before 1980, responses are demand-like (output and prices rise together), whereas in recent decades they are supply-like (output falls while prices rise), at both the aggregate and sectoral levels—implying materially time-varying effects. To obtain this result, we depart from the smooth-transition VAR of (Kim et al., 2025), which focuses on the macroeconomic effects of severe weather shocks in the United States. By contrast, our model studies the impact of temperature shocks and uses a conservative prior that tightly centers coefficients on early-sample estimates and imposes a close to zero dynamics on the parameter drift, allowing the data to reveal any evolution in coefficients or volatilities, without pre-imposing different regimes or thresholds.

Furthermore, the literature finds heterogeneous inflation responses to weather shocks across advanced and developing economies. In advanced economies, evidence points to short-lived, composition-driven price pressure rather than persistent headline inflation: hot summers lift food prices on impact, but medium-term effects on headline often fade or even turn slightly negative as demand softens (Faccia et al., 2021; Kotz et al., 2024). Lucidi et al. (2024) document an energy channel for six euro-area countries, whereby warmer temperature shocks reduce energy demand and exert moderate deflationary pressure. By contrast, Natoli (2023) show that temperature surprises decrease consumer prices via a slowdown in aggregate demand. Disaster episodes in rich economies similarly produce brief spikes—food after droughts and wildfires, energy after storms—without durable effects on core or headline inflation (Ehlers et al., 2025 for the U.S.; Beirne et al., 2024 for euro-area countries). In developing (hotter, lower-income) economies, both the size and persistence of price responses are stronger, with food driving most of the effect: panel-VAR and local-projection studies find that temperature shocks and climate disasters raise inflation for multiple quarters to years, especially where food shares are high and adaptation is limited (Mukherjee and Ouattara, 2021; Cevik and Jalles, 2023; Parker, 2018; Kotz et al., 2024). Evidence from the Caribbean documents sizable and persistent post-hurricane and flood price spikes concentrated in food and utilities (Heinen et al., 2019).

Literature also focuses on specific channel through which temperature and climate shocks affect the real economy: (i) labor productivity and labor supply (Graff Zivin and Neidell, 2014; Hsiang, 2010; Dell et al., 2012); (ii) cognition and workplace performance (Park et al., 2021); (iii) agriculture and food systems (Dell et al., 2012; De Winne and Peersman, 2018, 2021); (iv) energy demand/supply and power systems (Lucidi et al., 2024); (v) prices and inflation (food, energy, headline/core) (Parker, 2018; Heinen et al., 2019; Faccia et al., 2021; Kabundi et al., 2022; Kotz et al., 2024; Beirne et al., 2024); (vi) capital accumulation, infrastructure, and spatial reallocation (Burke et al., 2015; Desmet and Rossi-Hansberg, 2015); (vii) public budgets, adaptation, and financial intermediation (Mendelsohn et al., 2006; Botzen et al., 2019; Noy and duPont IV, 2018; Klomp, 2014; Berg and Schrader, 2012; Hosono et al., 2016; Schuwer et al., 2019); (viii) supply chains and trade (Parker, 2018); (ix) health and mortality (Burke et al., 2015); and (x) aggregate growth and social stability/conflict (Hsiang, 2010; Dell et al., 2012; Burke et al., 2015).

Finally, a growing literature treats temperature uncertainty itself as an economically relevant state.[4] In global panels, higher *ex ante* temperature volatility is shown to *lower* average growth and

[4]Methodologically, using conditional volatility of residuals as a second-moment regressor follows standard

raise macro volatility, with the volatility trend increasing over the postwar period—in non-advanced economies (Alessandri and Mumtaz, 2025). Related evidence using intra-annual variability links hotter, more variable years to weaker productivity growth in advanced regions (Donadelli et al., 2021).

Financial markets also appear to price climate and temperature risks. Low-frequency temperature risk carries a negative elasticity for equity valuations in long-run risk frameworks and in the data (Bansal et al., 2016; Giglio et al., 2021; Hong et al., 2020). At higher frequencies, extreme-weather uncertainty raises option-implied volatility for exposed firms and shifts expected returns (Kruttli et al., 2025). Asset-pricing and survey evidence indicate that climate risk is salient for institutions and listed firms (Bolton and Kacperczyk, 2021; Krueger et al., 2020; Sautner et al., 2023), with spillovers beyond equities: climate exposure is capitalized into real estate and municipal finance (Bernstein et al., 2019; Painter, 2020). Sectorally, temperature variability and anomalies transmit to commodity and energy markets, providing additional pricing channels and near-term cash-flow risk (De Winne and Peersman, 2018, 2021). Taken together, the literature supports our empirical pattern—muted contemporaneous real effects in rich economies but a measurable, negative on-impact response of equity prices to temperature risk.

3 Data and Econometric Approach

This section describes the data and our empirical strategy. To analyze the effects of temperature shocks while allowing for potential structural change, we estimate a time-varying-parameter VAR with stochastic volatility (TVP-VAR-SV). We impose a conservative (shrinkage) prior that favors constant coefficients: the initial state of the parameter vector is centered on estimates from the late 1940s–1950s, and the state-innovation variances governing coefficient drift are set to be small. In other words, *ex ante,* the model prefers time-invariant dynamics; any departure from constancy must be supported by the data and will appear as posterior evidence of parameter change. This design aligns with our economic questions. First, have the macroeconomic effects of temperature shocks changed across decades? Second, do temperature shocks propagate more like supply or demand disturbances? By shrinking toward no time variation yet letting the data override that prior when warranted, the framework cleanly separates adaptation (time-varying coefficients) from changing shock distributions (time-varying volatilities). For this reason, we opt for a TVP-VAR-SV rather than a non-linear VAR as in Kim et al. (2025) because it allows us to set a prior that does not impose any evolution of coefficients and volatilities explicitly over time, hence it does not require ex-ante imposing a different distribution of parameters across the sample period.

3.1 Data: Sources, and Transformation

Data Sources. This paper employs a monthly dataset for the United States covering the period January 1947 to December 2023. The data are compiled from the following primary sources:

(i) Financial Data: Share price data are sourced from the OECD Main Economic Indicators database.[5]

(ii) Macroeconomic Data: Data for real gross domestic product (GDP), the consumer price

macro–finance practice (Mumtaz and Theodoridis, 2015, 2018; Alessandri and Mumtaz, 2019).

[5]The OECD series begins in 1957. To extend the series backward, we splice it with the S&P Composite Stock Price Index from Robert Shiller's dataset.

index (CPI) and its components (core, energy, services less energy, and food), real personal consumption, population, the unemployment rate, and the federal funds rate are obtained from the Federal Reserve Economic Data (FRED).

(iii) Climate Data: Gridded historical near-surface temperature data come from the CRU TS4.08 dataset (University of East Anglia and the UK National Centre for Atmospheric Science).

(iv) Sectoral Data: Value-added data for the agriculture, forestry, and fishing sector and for total manufacturing are collected from the FAOSTAT database, covering the period 1970–2022.

The baseline specification includes temperature, real GDP growth, and inflation. In extended versions of the model, we augment this system with a fourth variable—considering, one at a time, core CPI, energy CPI, services less energy CPI, food CPI, real personal consumption, population, unemployment, or the federal funds rate.

Transformations. The series not already available in the seasonally adjusted form are seasonally adjusted using JDemetra+ 2.2 -this software uses the following algorithm X-13ARIMA-SEATS. Additionally, GDP data is interpolated to obtain a monthly frequency.

Figures for the main variables are presented in Appendix B.

3.2 Model

We use a time-varying VAR model with stochastic volatility (TVP-VAR-SV) along the modelling lines of Benati and Mumtaz (2007) and Galí and Gambetti (2009). Let y_t denote the vector of n endogenous variables, which includes temperature, real GDP growth, and inflation. All variables are expressed in year-on-year growth rates, except for temperature, which enters the model in levels. Let us assume that y_t follows

$$y_t = A_{0,t} + A_{1,t}y_{t-1} + ... + A_{p,t}y_{t-p} + \epsilon_t = X_t'\theta_t + \epsilon_t \tag{1}$$

where ϵ_t is a Gaussian white noise vector of innovations with time-varying covariance matrix Σ_t, $A_{0,t}$, is a vector of time-varying intercepts and $A_{i,t}$, are matrices of time-varying coefficients, $i = 1, ..., p$. Let $A_t = [A_{0,t}, A_{1,t}, ..., A_{p,t}]$, and $\theta_t = vec(A_t^{'})$ being the stacking column operator. The VAR coefficients are assumed to evolve as random walk

$$\theta_t = \theta_{t-1} + \nu_t, \tag{2}$$

where ν_t is a Gaussian white noise vector with covariance Ω, and independent of ϵ_t at all leads and lags. The innovation variance is decomposed as $\Sigma_t = F_t D_t F_t'$, where F_t is a lower triangular matrix with ones on the main diagonal and D_t a diagonal matrix. Let σ_t be a column vector that contains the diagonal elements of $D_t^{1/2}$ and let λ_t be a vector containing all the elements of F_t^{-1} below the diagonal, stacked by rows. Their law of motion are as follows

$$log\ \sigma_t = log\ \sigma_{t-1} + \varepsilon_t, \tag{3}$$

$$\lambda_t = \lambda_{t-1} + \psi_t, \tag{4}$$

where ε_t and ψ_t are Gaussian white noise vectors with zero mean and variance Ξ and Ψ, respectively. We assume that Ψ has a block diagonal structure, i.e., all the covariances between coefficients

belonging to different equations are zero, and that Ξ is diagonal;

$$\Psi = \begin{bmatrix} S_1 & 0_{1\times 2} & \cdots & 0_{1\times(n-1)} \\ 0_{2\times 1} & S_2 & \ddots & 0_{2\times(n-1)} \\ \vdots & \ddots & S_i & 0_{i\times(n-1)} \\ 0_{(n-1)\times 1} & \cdots & 0_{(n-1)\times i} & S_{(n-1)} \end{bmatrix}, \; \Xi = \begin{bmatrix} \tilde{\sigma}_1 & 0 & \cdots & 0 \\ 0 & \tilde{\sigma}_2 & \ddots & \vdots \\ \vdots & \ddots & \tilde{\sigma}_i & \vdots \\ 0 & \cdots & 0 & \tilde{\sigma}_n \end{bmatrix}.$$

Finally, we assume that ν_t, ε_t and ψ_t are all mutually independent. We assume that the vector of reduced-form VAR innovations ϵ_t is a linear transformation of the vector of underlying "structural" shocks, $\boldsymbol{u}_t$, satisfying $E\{\boldsymbol{u}_t\boldsymbol{u}_t'\} = \mathbf{I}$ for all t. Thus, we assume $\epsilon_t = \mathbf{C}_t\boldsymbol{u}_t$ for all t for some nonsingular matrix $\mathbf{C}_t$ satisfying $\mathbf{C}_t\mathbf{C}_t' = \Sigma_t$.

3.3 Priors and Estimation

We follow standard practice in the time-varying parameters Bayesian VAR literature (e.g., Primiceri (2005); Galí and Gambetti (2009); Benati and Mumtaz (2007); Baumeister and Peersman (2013)), we impose independent priors on the initial states and covariance matrices. Priors for the states are Normal, while those for the precision matrices are Wishart or Gamma distributed. The prior hyperparameters are calibrated using the posterior median of a time-invariant VAR with two lags estimated on the first 120 observations (1947m1–1958m12), following the dummy-observation approach of Bańbura et al. (2010).

For estimation, we implement a Gibbs sampler, iterating across the conditional posterior distributions of the parameters and states. We retain 500 draws from a total of 31,500 iterations, after a conservative burn-in and thinning procedure. Convergence diagnostics (see Appendix C) indicate that the algorithm performs satisfactorily. Full details on the prior specification, hyperparameter calibration, and estimation procedure are reported in Appendix A.

3.4 Identification

In traditional growth-climate regressions, the climate system (temperatures) is typically treated as an exogenous driving force. By contrast, our nonlinear VAR framework allows for a multivariate dynamic interaction between climate and macroeconomic variables. Specifically, temperature (T_t) can influence economic activity, and inflation, while also responding endogenously to changes in these variables.[6] The reduced-form model can be estimated without imposing restrictions on these interactions. However, as with any VAR, additional assumptions are required to make causal statements. Our baseline identification strategy assumes that macroeconomic shocks do not exert contemporaneous effects on temperatures. In other words, unexpected changes in output, or inflation may influence future temperatures, but not within the same period (the same month). This recursive scheme is consistent with the view that feedbacks from the economy to the climate system occur gradually rather than instantaneously (e.g., via emissions and technological change). Similar assumptions have been used in related climate–economy VAR studies (see, the identification sections in Kim et al. (2025); Alessandri and Mumtaz (2025)). Notice that this restriction does not rule out the possibility that long-run economic trends influence climate outcomes, but only that such effects materialize with a delay.

[6] This choice reflects the premise that economic activity contributes to climate change with a delay; see, for example, Stern (2008).

4 Empirical results

This section first documents the time-varying effects of temperature shocks on real GDP growth and inflation. We then assess the quantitative importance of these shocks for macroeconomic fluctuations through forecast error variance decompositions

4.1 The evolution of the effect of temperature shocks over time

Figure 1 presents the impulse responses of average temperatures, and cumulative impulse responses of real GDP growth, and inflation to an unanticipated 1°C increase in the average temperature level. The shock is normalized to a one-degree Celsius impact increase to ensure comparability across the sample periods. Responses are computed for horizons from impact (1 month) to 6, 12, 24, and 36 months, allowing for an analysis of the dynamic effects over different epochs. This analysis reveals a fundamental shift in the nature of temperature shocks and their macroeconomic transmission.[7]

Temperature dynamics. The first column of Figure 1 shows the response of temperature to its own shock. By construction, the shock induces an immediate 1°C increase on impact. A key finding is the stark contrast in the shock's persistence across time. From the 1950s to 1980, the temperature innovation was largely transitory, dissipating completely within six months. However, from the 1980s onward, an identical size shock exhibits significant persistence, with elevated temperatures enduring for 12 to 24 months. Furthermore, this persistence has grown over recent decades. The growing persistence over time indicates a structural change in the climate system's propagation mechanism. Plausible channels include: First, thermal inertia from oceanic heat uptake plays a critical role; the oceans have absorbed a substantial fraction of historical CO_2 emissions, creating a vast reservoir of heat that is gradually released back into the atmosphere, thereby sustaining temperature anomalies (Abraham et al., 2022; Stallinga, 2023; Lee et al., 2025). Furthermore, the long atmospheric lifespan of greenhouse gases like CO_2 and methane enhances radiative forcing, increasing the atmosphere's heat-trapping capacity and leading to sustained warming (Masson-Delmotte et al., 2021; Sherwood et al., 2020). Another contributing factor involves changes in atmospheric dynamics, as a weakening polar vortex and alterations to jet stream patterns can cause weather regimes to become more persistent, leading to prolonged temperature anomalies (Francis and Vavrus, 2015; Coumou et al., 2015). The confluence of these mechanisms explains the observed trend toward more persistent temperature innovations.

[7] To establish whether time-variation in the parameters is a feature of the data in a formal way, we follow Cogley and Sargent (2005). Despite the tight prior imposed, the trace of the prior variance-covariance matrix, Ω_0, is 2 times smaller than the 16% percentile of the posterior; thus, the sample points towards greater time variation in the parameters than that of the prior selected. See Table 1 in Appendix B. Furthermore, to strengthen the evidence of time variation in parameters, we conduct an analysis similar to that proposed by Cogley et al. (2010). This exercise involves scatter plots of the draws of parameters capturing the impulse responses of the different variables to the temperature shocks at different horizons (on impact, and at six and thirty-six months ahead), as shown in Figures 14, and 15 in Appendix B. Each horizon compares the draws at two points in time: 1949m3 vs 2023m2, 1960m11 vs 1985m8 and 1977m5 vs 1990m3, respectively. For example, if the impact impulse response function of GDP to a temperature shock had remained relatively stable over time, the parameter combinations from early in the sample (e.g., 1949m3) and later (e.g., 2023m2) would cluster near the 45-degree line. However, this is not observed for the shock at any horizon. The figures demonstrate six instances where combinations of parameters deviate significantly from the 45-degree line, reinforcing our conclusion that key parameters have likely evolved over time.

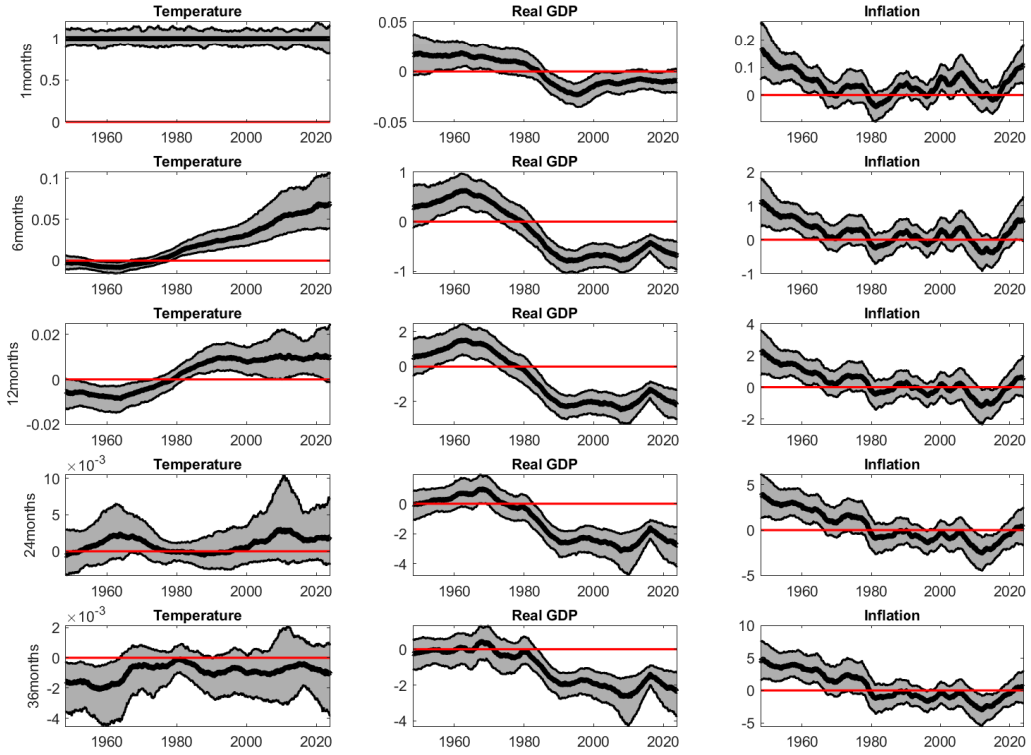

Figure 1: Time-varying effect of temperature shocks on GDP growth, and inflation: cumulative responses at different horizons

Note: Evolution of impulse responses of average temperatures, and cumulative impulse responses of real GDP growth and inflation to a temperature shock at specific horizons - impact, 6, 12, 24, 36 months - over time, median, 16% and 84% percentiles.

Real activity. The response of real GDP to a temperature shock has undergone a pronounced structural shift over the past decades. Two distinct phases are evident. In the mid-20th century (1950s–1970s), a temperature shock had a modest positive effect on output. From the 1980s onward, the response has turned increasingly and persistently negative. This evolution is particularly evident at longer horizons. The 36-month response has grown significantly more negative in recent decades, indicating that economic costs of temperature anomalies have become more persistent. This pattern aligns with theoretical models positing non-linear climate damages, where economic costs accelerate with rising temperatures (Burke et al., 2015; Pindyck, 2021). The extended negative effects suggest that temperature shocks now induce more permanent structural damages, likely through channels such as persistent supply chain disruptions, energy system strains, and declines in labor productivity (Colacito et al., 2019; Kim et al., 2025; Amiot, 2025). The findings confirm that climate change has transitioned from a neutral-positive factor (before the 1980s) to a significant macroeconomic burden, with recent effects consistent across global and regional studies (Hsiang, 2010; Dell et al., 2012).

Prices. The response of the price level to a temperature shock also shifts across periods. Before 1960, a 1°C shock produced a positive and statistically significant effect on prices at short horizons, suggesting that temperature shocks initially operated like demand expansions. After 1960, however,

the on-impact response became insignificant, and by the early 2000s the immediate response turned modestly positive again. This shift implies that the nature of the shock has evolved: whereas earlier it resembled a positive demand shock (raising both GDP and prices), more recently it has begun to resemble a negative supply shock (lowering GDP while raising prices). At the 24–36 month horizon, the pattern reverses relative to the pre-1980 era: the pre-1980 median CPI response exceeds 2 % and is significant in most years, whereas post-1980 the median response is negative and significant only in the 2010s. In other words, recent decades exhibit short-run inflationary but medium-run deflationary pass-through— coinciding with depressed output. These results differ from much of the literature, which typically reports positive medium-term effects of climate change on prices, in the medium-run, especially in developing economies. Our findings are more consistent with Cevik and Jalles (2023), who document deflationary impact of climate shocks in economies with greater fiscal and institutional capacity. They are also broadly aligned with Ciccarelli et al. (2024), who find that temperature shocks in the euro area tend to reduce inflation, except during the summer months. To better delineate the underlying drivers of these aggregate dynamics, a more granular investigation is provided in Section 5, including additional channels—equity prices, core CPI, energy CPI, services CPI (excluding energy), food CPI, personal consumption, population, unemployment, and the federal funds rate.

Overall, the impulse responses reveal a regime shift in both climate persistence and macroeconomic propagation. Temperature shocks that were short-lived and expansionary before 1980 have become more persistent, output-contracting, and medium-run disinflationary since the 1990s. The combination of negative output effects and ambiguous price effects complicates the standard policy trade-off. Since, stabilizing the economy in the presence of climate shocks will likely require a rethinking of conventional macroeconomic stabilization tools.

4.2 The importance of the temperature shock

To quantify the contribution of temperature shocks relative to other disturbances, we compute variance decompositions. Figures 2, 3, and 4 display the median fraction of forecast error variance in GDP, consumer prices, and average temperature that is explained by temperature shocks across horizons and time-periods.

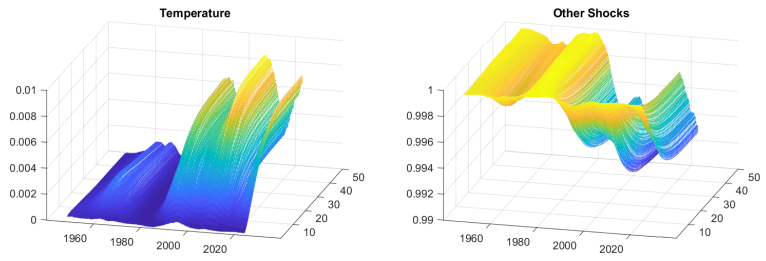

Figure 2: Variance Decomposition of GDP

Note: These figures represent the fractions explained by temperature shocks and the sum of other shocks of real GDP across time and horizons base on the median of each time period.

For real GDP, the median contribution of temperature shocks was negligible before the 1980s,

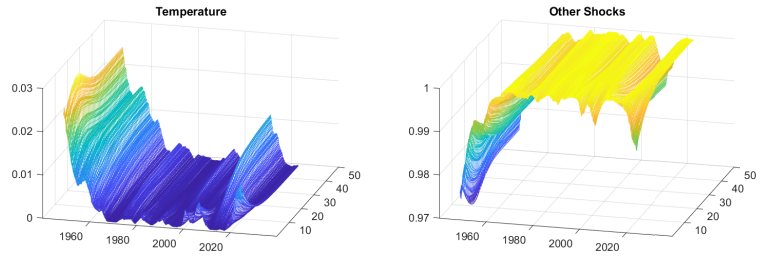

Figure 3: Variance Decomposition of Consumer Prices

Note: These figures represent the fractions explained by temperature shocks and the sum of other shocks of consumer prices across time and horizons base on the median of each time period.

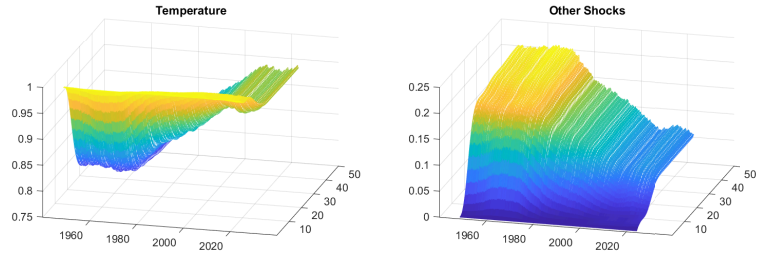

Figure 4: Variance Decomposition of Temperatures

Note: These figures represent the fractions explained by temperature shocks and the sum of other shocks of temperatures across time and horizons base on the median of each time period.

accounting for only about 0.2% of GDP variance at a 36-month horizon. Since the 1990s, however, this share has increased more than fivefold to nearly 1%, suggesting that temperature fluctuations are emerging as a meaningful source of medium-run variation in economic activity. This result indicates that the U.S. economy has grown increasingly vulnerable to climate-related disturbances in recent decades.

In contrast, the influence of temperature shocks to consumer price dynamics follows a distinct pattern. In the early part of the sample, temperature shocks accounted for between 2 and 3% of cpi variance at both short and long horizons. Between 1980 and 2000, however, their variance share fell sharply, becoming largely insignificant. This pattern shifted again after 2000 when temperature shocks explained roughly 1.5% of price fluctuations at longer horizons.

Finally, we examine the contribution of temperature shocks to average temperature fluctuations. We find that at the beginning of the sample these forces accounted for up to 20% of longer-horizon temperature variation. Over time, their explanatory share has declined to about 5% in the past two decades, while the contribution of temperature shocks at longer horizons has risen steadily to nearly 95%. This decline in the role of other shocks may be linked to reductions in total and per capita CO_2 emissions since the early 2000s.[8] Importantly, these findings confirm that identified temperature shocks explain the bulk of the variance in average temperatures at longer horizons. This outcome validates the identification strategy used, following Kim et al. (2025) and Alessandri

[8]See CO_2 emissions data in https://ourworldindata.org/co2-and-greenhouse-gas-emissions.

and Mumtaz (2025), which restricts contemporaneous interactions but allows longer-run economic trends to influence climate dynamics.

5 Model extensions

While the baseline model provides a comprehensive assessment of temperature shocks on two core macroeconomic variables—real GDP and CPI, additional extensions allow us to refine and expand our understanding of these relationships. First, we conduct a sectoral decomposition of temperature shocks across agriculture, manufacturing, and rest of the economy (services) to identify differential vulnerabilities and clarify the mechanisms through which climate shocks propagate through the macroeconomy. Second, to better understand the macroeconomic effects—particularly on CPI—we extend the model to include equity prices, core CPI, energy CPI, services CPI (excluding energy), food CPI, personal consumption, population, unemployment, and the federal funds rate. Third, we incorporate temperature volatility as an exogenous variable, recognizing that the unpredictable component of climate dynamics poses distinct risks beyond direct temperature shocks. We then examine the immediate impact of volatility shocks on both the baseline and extended set of variables.

5.1 The role of temperature shocks on specific economic sectors

Changes in average temperature can affect economic activity through multiple channels. To better understand the mechanisms underlying the aggregate GDP results, we extend the analysis to the sectoral level—agriculture, manufacturing, and the rest (services)—from 1970 to 2022. Specifically, we estimate three separate time-varying structural VARs, each including three variables: temperature, a sector-specific activity measure, and inflation. Sectoral activity is defined as the product of the sector's share in overall GDP and the level of aggregate GDP.[9] This approach allows us to capture sectoral dynamics while maintaining consistency with the aggregate macroeconomic framework.

Figure 10 reports the cumulative impulse responses at horizons of impact (month 0), 6, 24, and 36 months for three sectors: (i) agriculture (including forestry and fishing), (ii) manufacturing, and (iii) the remainder of the economy (primarily services, construction, and retail). The figure highlights how sectoral vulnerabilities to temperature shocks have changed over time and how these sector-specific responses contribute to the aggregate GDP patterns discussed above.

A key insight from Figure 10 is that prior to 1980, all three sectors generally exhibited a positive output response to a 1°C temperature shock—likely reflecting moderate warming benefits (e.g., for agriculture) or reduced energy demand for heating. From the mid-1980s onward, however, sectoral responses became statistically insignificant or turned negative across the board. This shift is most pronounced at the 24–36-month horizon.

Starting with the agricultural sector, responses to a 1°C temperature shock were positive in earlier decades, particularly at longer horizons. This likely reflects periods where warming benefited crop yields. For example, Mendelsohn et al. (2006) argue that moderate warming in high-income, temperate regions can initially raise agricultural output by extending growing seasons and reducing

[9] We use annual data on sectoral GDP shares (agriculture, manufacturing, and services). For each year, we assume the share remains constant across months, and multiply it by the monthly level of aggregate GDP to construct monthly sectoral activity.

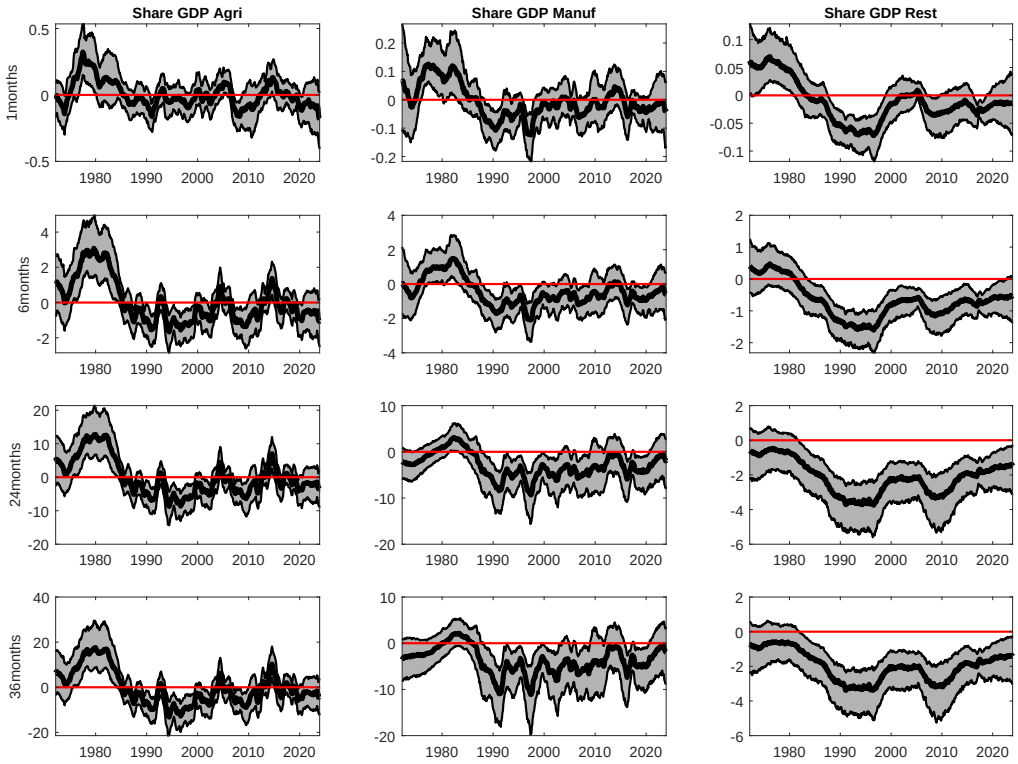

Figure 5: The Effect of Temperature on US Economic Sectors: Cumulative Responses at Different Horizons

Note: Evolution of cumulative impulse responses of sector's activity (agriculture, manufacturing and rest of the economy) to a temperature shock at specific horizons - impact, 6, 24, 36 months - over time, median, 16% and 84% percentiles.The cumulative impulse responses for each sector are estimated separately.

frost risk. However, from the late 1980s to the 1990s, the responses turned negative at the 6-, 24-, and 36-month horizons, suggesting that higher and more extreme temperatures increasingly eroded productivity and yields. The median negative effect in the mid-1990s was about 10%. This finding is consistent with a large body of evidence showing nonlinear temperature effects on U.S. agriculture, where yields decline sharply beyond critical heat thresholds (Schlenker and Roberts, 2009). Similarly, Burke and Emerick (2016) analyze U.S. agricultural outcomes using long-difference estimates over the 1980–2000 period. They find that extreme heat imposed sizable losses on crop productivity and farm revenues, and show that there is little evidence that adaptation had offset these adverse effects during the studied period. Nevertheless, since the late 1990s, we find that the 24- and 36-month responses have been statistically indistinguishable from zero. This may reflect increased adaptation, shifts in crop selection, technological improvements, or the stabilization of temperature shocks at the regional level.

In the case of manufacturing, short-term responses to a 1°C temperature shock were slightly positive prior to 1980. From the 1980s onward, however, the effects became insignificant, and by the 1990s turned negative at medium-run horizons, particularly at the 6-, 24-, and 36-month horizons. This shift can be attributed to the growing impact of heat stress on worker productivity, which has been widely documented. Graff Zivin and Neidell (2014) show that extreme heat reduces labor productivity, especially in physically demanding industries but also in climate-exposed man-

ufacturing industries, where high temperatures increase fatigue and reduce efficiency. In addition, elevated temperatures impair cognitive function, lowering productivity (Park et al., 2021).

Finally, the remainder of the economy (primarily services, construction, and retail)—which represents the largest share of U.S. GDP—has become increasingly vulnerable to climate shocks since the 1980s. In earlier decades, this sector exhibited a positive initial response to temperature shocks. However, since the 1980s, the responses have turned persistently negative, likely driven by reduced labor productivity, higher cooling costs, and shifts in consumer demand. The figure shows negative and sustained effects at longer horizons. These results are consistent with Colacito et al. (2019), who document that rising temperatures disproportionately affect the U.S. service sector, particularly in warmer regions, through lower output, weaker consumer spending, and reduced business activity.

Overall, the sectoral decomposition confirms that before 1980s, temperature shocks had a positive effect on output. Since then, however, all three sectors have shifted toward increasingly insignificant or negative responses, with the most persistent declines observed in services. Because services and related industries (including construction and retail) account for the largest share of the economy, their negative response at longer horizons largely explains the aggregate GDP downturn following temperature shocks in recent decades. This structural change underscores the growing importance of climate-related vulnerabilities across both goods-producing and service-oriented sectors of the U.S. economy.

5.2 Temperature and Prices in Detail

In this subsection, we further investigate the baseline macroeconomic effects, with particular emphasis on CPI dynamics. To this end, we extend the model by including additional variables—one at a time—into the system: real equity prices, core CPI, energy CPI, services CPI (excluding energy), food CPI, personal consumption, population, the unemployment rate, and the federal funds rate. All variables enter in year-on-year growth rates, except for the unemployment rate, which enters in first differences, and the federal funds rate, which enters in levels.

Figure 6 reports the cumulative impulse responses of equity prices, core CPI, energy CPI, and services CPI (excluding energy), while Figure 7 presents the corresponding responses of food CPI, personal consumption, population, the unemployment rate, and the federal funds rate to an unanticipated 1°C increase in average temperature. All responses are computed at horizons of impact (1 month), 6, 24, and 36 months.

Equity prices. The response of the stock market to a temperature shock is more transitory than that of real GDP. On impact, equity prices are not statistically different from zero, but they turn negative and significant at short horizons (2–4 months ahead, not shown here). After the fifth month, the effect begins to fade, and by the sixth month (second row) the response is only marginally significant. These results align with the post-1980 contraction observed in real GDP, but in contrast to output, the effects of temperature shocks on equity markets are entirely short-lived.

Core CPI. The response of CPI excluding energy and food to a temperature shock is not statistically different from zero at any horizon. This suggests that the aggregate CPI effects of temperature shocks are (primarily) transmitted through volatile components—namely energy and

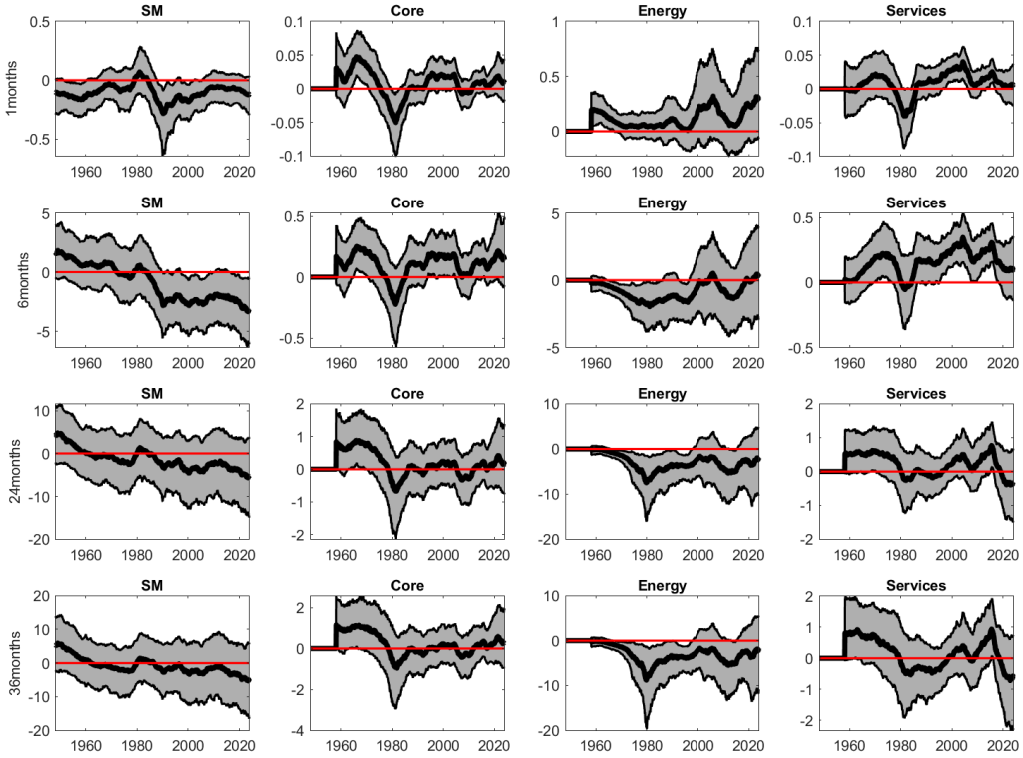

Figure 6: Time-varying effect of temperature shocks on additional variables

Note: Evolution of cumulative impulse responses of equity prices (SM), core CPI, energy CPI, services CPI to a 1ºC temperature shock at specific horizons - impact, 6, 24, 36 months - over time, median, 16% and 84% percentiles. The cumulative impulse responses for each variable are estimated separately.

food prices—rather than through the broader basket of core goods and services.

Energy CPI. The immediate response of energy prices to a temperature shock is positive across all time periods, but the associated uncertainty bands are wide, rendering the estimates statistically insignificant. This short-run positive effect likely reflects upward pressure on fuel and utility costs, for instance due to increased air-conditioning demand. The median impact is generally larger after the 1990s, coinciding with the growing prominence of the service sector and higher energy consumption. Shortly after the initial impact, however, the cumulative response turns negative. At horizons of 24–36 months, the median response is predominantly negative (around –5% on average after the 1960s), though again surrounded by considerable uncertainty. This pattern reinforces the broader narrative that the transmission of temperature shocks has shifted over time from demand-side to supply-side: energy prices tend to overshoot upward on impact—likely as households and firms adjust to higher temperatures—but at longer horizons they decline, reflecting the contractionary effects of weaker real GDP.

Services CPI (excluding energy). The response of service prices to a temperature shock illustrates the heterogeneity across CPI subcomponents. In this case, a positive on-impact effect emerges only after the 1990s. The response continues to rise in the months following the shock and becomes statistically significant, with an average increase of about 0.25%, in the post-1990 period. At longer horizons (24–36 months), however, the median response reverts toward zero, signaling

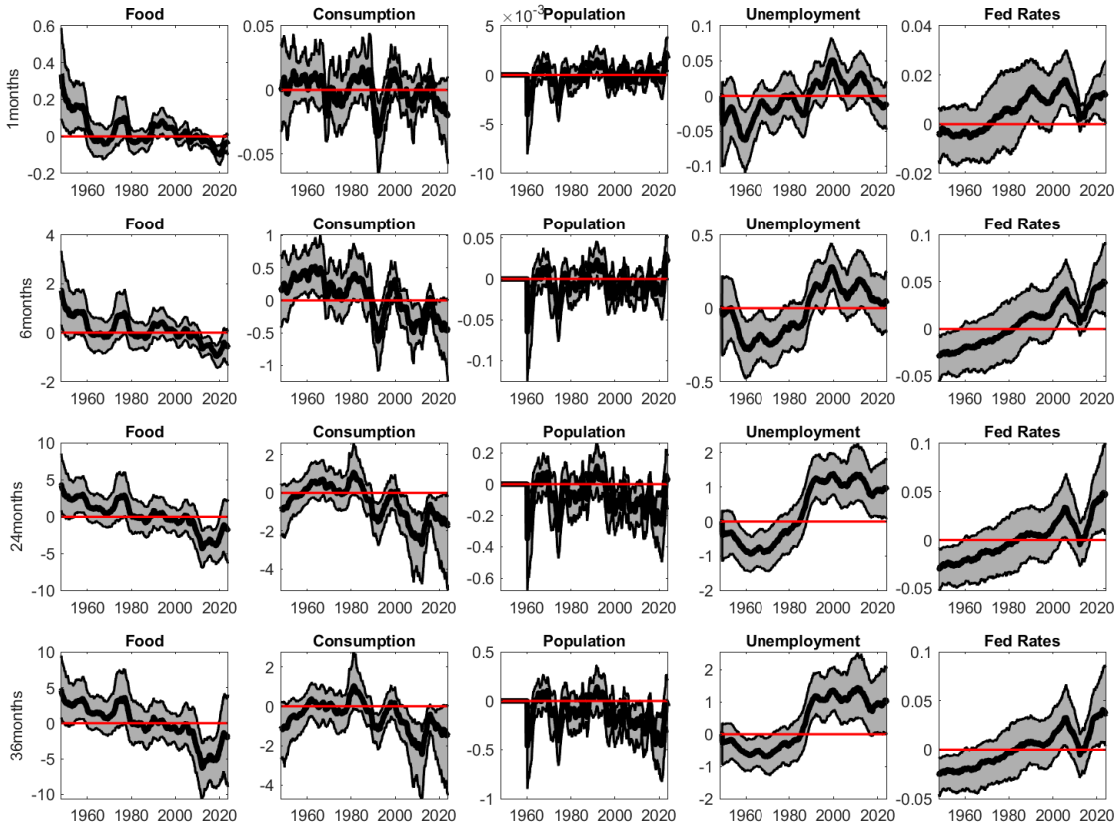

Figure 7: Time-varying effect of temperature shocks on additional variables

Note: Evolution of cumulative impulse responses of food CPI, personal consumption, population, unemployment, and the federal funds rate to a 1ºC temperature shock at specific horizons - impact, 6, 24, 36 months - over time, median, 16% and 84% percentiles. The cumulative impulse responses for each variable are estimated separately.

deflationary effects.

Food CPI. The overall response of food prices to a temperature shock resembles that of aggregate CPI, but with greater volatility. Prior to the 1980s, the on-impact response is positive and tends to increase at longer horizons, albeit with substantial uncertainty. At 24–36 months, the median response in this earlier period is around 2–3%. In contrast, in the most recent period (post-2000), the 24–36 month response is negative and highly significant, with food prices declining by roughly 5%. Food therefore appears to be one of the most influential components driving the decline in aggregate CPI at longer horizons in recent decades.

Personal consumption. The response of personal consumption to a temperature shock highlights a demand channel behind the decline in aggregate prices and its subcomponents. On impact, consumption does not respond significantly in any time-period. However, within the first 12 months, dynamics similar to those of real GDP emerge. Prior to the 1980s, consumption increases significantly between 7 and 13 months ahead, while after the 1980s the response turns negative. At horizons of 24–36 months, the negative response becomes more pronounced, reducing personal consumption by about 1% on average, whereas the earlier positive effects converge toward zero. We interpret these results as evidence of a demand-contraction channel underpinning the aggregate

price response to temperature shocks.

Population. The response of population to a temperature shock is zero on impact across all periods and remains so up to the 12-month horizon. Beyond that, population gradually declines in the post-2000 period, reaching an average loss of 0.2–0.3% at 36 months ahead. These findings are consistent with Bilal and Rossi-Hansberg (2023), who show in a dynamic spatial model that heat waves reduce population through two channels: lower productivity and diminished amenities (direct disutility from living in hotter areas). Similarly, Boustan et al. (2020) find that severe disasters increase out-migration rates at the county level by 1.5%.

Unemployment. The response of the unemployment rate to a temperature shock mirrors the dynamics of real GDP and personal consumption. Prior to the 1980s, unemployment declines by about 0.75% at the 24-month horizon, before converging back toward zero by 36 months. After the 1980s, however, the pattern reverses: unemployment rises by roughly 1.25% at 24 months and remains persistently elevated at 36 months. These results underscore the broader narrative that the transmission of temperature shocks has shifted over time from demand-side to supply-side: prices move upward on impact, while unemployment decreases, but after 1980s both, unemployment and prices increase, reflecting the contractionary supply effects.

Federal funds rate. The response of the federal funds rate to a temperature shock is positive on impact after the 2000s and remains relatively persistent up to 36 months ahead. However, in economic terms the effect is relatively negligible: the rate increases by only about 5 basis points, equivalent to one-fifth of a typical 25 basis point policy adjustment.

5.3 Temperature Uncertainty

In this section, we study a distinct dimension of climate risk—temperature uncertainty—and its contemporaneous effects on macroeconomic aggregates (real GDP growth, CPI inflation, equity prices, core CPI, energy CPI, services CPI ex energy, food CPI, real personal consumption, population, the unemployment rate, and the federal funds rate). Following Alessandri and Mumtaz (2025), we measure *ex ante* temperature risk as the one-step-ahead conditional variance of the innovation in monthly average temperature,[10] i.e., the variance of the component of temperature changes that is not predictable from information available at $t-1$. Intuitively, this is a second-moment shock: it alters the dispersion of the temperature distribution and, via standard uncertainty channels, can generate first-order real and financial effects.

Empirically, we augment the TVP-VAR-SV from Section 3 by including the *ex ante* temperature-risk measure as a predetermined, exogenous regressor. Our set-up differs from Alessandri and Mumtaz (2025) in three aspects. First, we do not specify a VAR for volatility states: temperature volatility does not co-move endogenously with other macro volatilities in our system. Second, the first-moment parameters are allowed to evolve over time, accommodating changes in macroeconomic transmission. Third, we focus on U.S. (local) temperature uncertainty rather than a global aggregate. To keep the state space parsimonious, we exclude lags of the temperature-risk measure and disallow cross-equation interactions among volatilities. Consequently, our evidence pertains to impact (contemporaneous) effects of temperature uncertainty rather than its dynamic propagation; we view this as a conservative design that isolates high-frequency risk channels.

[10] Using the conditional volatility of residuals as a proxy for uncertainty is standard in the macro–finance literature; see, among others, Mumtaz and Theodoridis (2015, 2018); Alessandri and Mumtaz (2019).

Figure 8 reports the contemporaneous responses of macroeconomic aggregates to a 1% increase in *ex ante* temperature risk. We find no statistically significant impact on most real or price variables on impact. By contrast, equity prices (SM) decline on impact, with statistically significant effects prior to the 2000s; over the full sample, the median contemporaneous response is about a 0.5% decrease. Although our focus is on impact effects, this pattern is consistent with asset-pricing evidence that climate risk is priced in the cross-section of returns (e.g., Bansal et al. (2016); Bolton and Kacperczyk (2021); Hong et al. (2020); Giglio et al. (2021)) and with survey/earnings-based evidence on the salience of climate risk for institutional investors and listed firms (e.g., Krueger et al. (2020); Sautner et al. (2023)). Finally, we do not find that *ex ante* temperature risk materializes into lower GDP growth on impact, in line with Alessandri and Mumtaz (2025), who document negligible contemporaneous GDP effects for rich countries even as global temperature uncertainty is associated with global output declines elsewhere.

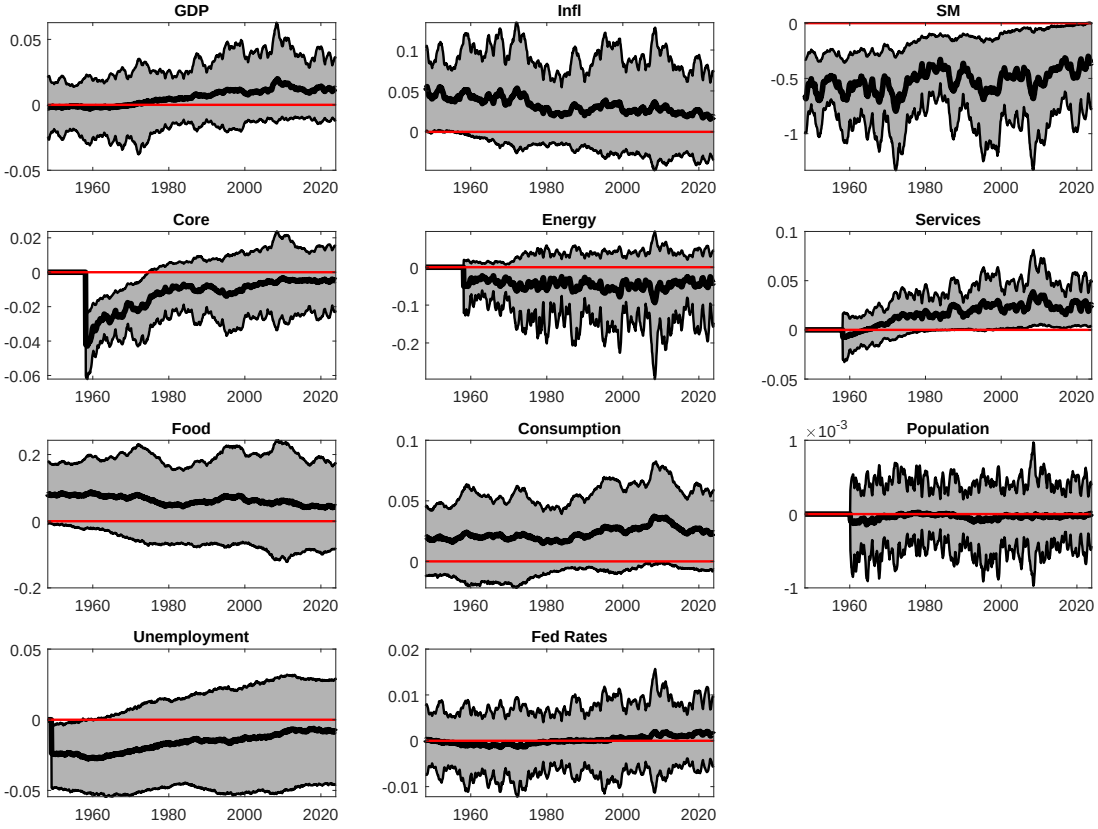

Figure 8: Time-varying effect of *ex ante* temperature-risk shocks

Note: Evolution over time of contemporaneous responses of real GDP growth, CPI inflation, equity prices, core CPI, energy CPI, services CPI ex energy, food CPI, real personal consumption, population, the unemployment rate, and the federal funds rate to a 1% ex ante *temperature-risk shock, median, 16% and 84% percentiles.*

6 Concluding Remarks

This paper offers a time-varying perspective on the macroeconomic effects of temperature shocks in the U.S. economy from 1947 to 2023. Using a time-varying parameter vector autoregression model with stochastic volatility that *ex ante* imposes time-invariant dynamics, we uncover structural

shifts in how temperature fluctuations propagate through the economy.

The paper makes three main contributions. First, it documents significant time variation in the macroeconomic effects of temperature shocks: impulse responses of real GDP, CPI (and subcomponents), equity prices, consumption, population, and unemployment differ markedly across decades. The results reveal a clear structural shift. Before the 1980s, temperature shocks resemble demand-like disturbances—output and prices rise together, with the CPI increasing by more than 2% at 24–36 months while GDP reverts—whereas in recent decades they resemble supply shocks, with GDP declining persistently (around -2% at 36 months) and the CPI response fading to mildly negative by 24–36 months.

Second, a sectoral decomposition shows that these state-dependent dynamics are broad-based but heterogeneous across agriculture, manufacturing, and services, highlighting where and when temperature shocks most strongly affect real activity. The results further indicate that temperature shocks influence various price indices, with the largest effects concentrated in energy and food prices, confirming their economy-wide reach. Third, we provide new evidence on temperature uncertainty: higher *ex ante* temperature risk depresses equity prices on impact (about -0.5% for a one-percent risk increase in the full sample, with stronger effects before 2000) while leaving contemporaneous real activity and prices statistically unchanged.

Overall, our findings suggest that the channels through which climate affects the macroeconomy have shifted over time: the same temperature disturbance can propagate differently across eras. Future work could extend this framework to (i) multi-country settings to compare transmission across income groups and (ii) micro-to-macro linkages that trace firm- and household-level adjustments underlying the aggregate responses.

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A Priors Specification and Estimation

Following Galí and Gambetti (2009), Benati and Mumtaz (2007), Primiceri (2005), and Baumeister and Peersman (2013) we assume that the covariance matrices Ω, Ξ, and Ψ and the initial states, θ_0, λ_0 ,and $\log \sigma_0$, are independent. The prior distributions for the initial states are normally distributed, and the prior distributions for Ω^{-1} and Ψ_i^{-1} are Wishart; the diagonal elements of Ξ^{-1} are Gamma. More precisely,

$$\begin{aligned}
\theta_0 &\sim N\left(\hat{\theta}, \hat{\mathcal{V}}_\theta\right) \\
\log \tilde{\sigma}_0 &\sim N\left(\log \hat{\tilde{\sigma}}, 10 \times \mathcal{I}_n\right) \\
\lambda_{i0} &\sim N\left(\hat{\lambda}_i, \hat{\mathcal{V}}_{\lambda_i}\right) \\
\Omega^{-1} &\sim W\left(\underline{\Omega}^{-1}, \underline{\rho}_1\right) \\
\Psi_i^{-1} &\sim W\left(\underline{\Psi}_i^{-1}, \underline{\rho}_{2i}\right) \\
\Xi_{i,i}^{-1} &\sim G\left(\frac{0.01^2}{2}, \frac{1}{2}\right)
\end{aligned}$$

where $W(\mathbf{S}_W, d_W)$ denotes a Wishart distribution with scale matrix $\mathbf{S}_W$ and degrees of freedom d_W; $G(\mathbf{S}_G, d_G)$ denotes a Gamma distribution with scale matrix $\mathbf{S}_G$ and degrees of freedom d_G, and $\mathbf{I}_n$ is a $n \times n$ identity matrix where n is the number of variables in the VAR.

Prior means and variances of the Normal distributions are calibrated using a time invariant VAR with 2 lags, employing the first 120 observations (1947m1-1958m12). To define priors for the VAR coefficients ($\mathcal{A}^{(j)}$) we follow Bańbura et al. (2010) in implementing the dummy observation approach (Doan et al. (1984); Sims and Zha (1998)).[11] We set $\hat{\theta}$ and $\hat{\mathcal{V}}_\theta$ equal to their posterior mode.

Let $\hat{\Sigma}$ be the covariance matrix of the residuals, $\hat{\epsilon}_t$, from the initial time-invariant VAR. We apply the same decomposition discussed in the text $\hat{\Sigma} = \hat{F}\hat{D}\hat{F}'$ and set $\log \hat{\sigma}_0$ equal to the vector containing the elements of the diagonal matrix $\hat{D}$, $\hat{\lambda}_i$ are the i-th row elements of the lower triangular matrix $\hat{F}^{-1}$, and $\hat{\mathcal{V}}_{\lambda_i}$ are the absolute value of the i-th row elements of the lower triangular matrix $\hat{F}^{-1}$ times 4.

We parametrize diffuse scale matrices as follows $\underline{\Omega} = \underline{\rho}_1 \left(0.0035 \times \hat{\mathcal{V}}_\theta\right)$, $\underline{\Psi}_i = \underline{\rho}_{i,2} \left(0.001 \times |\hat{\lambda}_i|\right)$. The degrees of freedom for the priors on the covariance matrices: Ω^{-1}, $\underline{\rho}_1$ is set equal to the number of rows $\underline{\Omega}^{-1}$ plus twenty. Note that the chosen degrees of freedom and the 0.0035 scaling applied to $\hat{\mathcal{V}}_\theta$ jointly imply that, a priori, we impose a relatively tight prior on the degree of time variation in the model's autoregressive parameters. Ψ_i^{-1}, $\underline{\rho}_{i,2}$ are set equal to the number of rows $\underline{\Psi}_i^{-1}$ plus one.

The VAR is estimated with two lags. To simulate the posterior distribution of the hyperparameters and the states conditional on the data, we use a Markov-Chain Monte Carlo (MCMC) algorithm, the Gibbs sampler, which works in an iterative way along the lines described in Primiceri (2005), Galí and Gambetti (2009), Benati and Mumtaz (2007), Baumeister and Peersman (2013). Each iteration is done in four blocks: the coefficients θ^T; the simultaneous relations λ^T; the variances

[11] More specifically, we assume Normal priors on the parameters controlling the dynamics of the VAR. One hyper parameter controls the overall tightness of the prior on the VAR coefficients which we set $\tau = 0.1$ following Bańbura et al. (2010).

σ^T, where the superscript T refers to the whole sample; and the hyperparameters—the elements of Ω, Ψ and the Ξ. Posteriors for each block of the Gibbs sampler are conditional on the observed data y^T and the rest of the parameters drawn at previous steps.

The steps are:

step 1: $p(\theta^T|y^T, \lambda^T, \sigma^T, \Omega, \Psi, \Xi)$,

step 2: $p(\lambda^T|y^T, \theta^T, \sigma^T, \Omega, \Psi, \Xi)$,

step 3: $p(\sigma^T|y^T, \theta^T, \lambda^T, \Omega, \Psi, \Xi)$,

step 4: $p(\Omega|y^T, \theta^T, \lambda^T, \sigma^T, \Psi, \Xi)$, $p(\Psi|y^T, \theta^T, \lambda^T, \sigma^T, \Omega, \Xi)$, $p(\Xi|y^T, \theta^T, \lambda^T, \sigma^T, \Omega, \Psi)$,

and involves drawing a subspace of coefficients conditional on a specific realization of the remaining coefficients and then utilizing this realization in the conditional densities of the remaining coefficients. Under specified regularity conditions and following a burn-in period, iterations through these four steps yield draws from the joint density. See appendix B of Galí and Gambetti (2009) or Baumeister and Peersman (2013), for details of the Gibbs sampler algorithm. In the estimation, we use all observations starting from 1947m1. We perform 31,500 repetitions. We discard the first 19,000 draws and keep one for every 25 of the remaining 12,500 draws to break the autocorrelations of the draws. Appendix C plots the draws' inefficiency factors, which assess the satisfactory converge of the MCMC algorithm.

B Supplementary Tables and Figures

The figure shows the time-series evolution of the main variables used in the analysis.

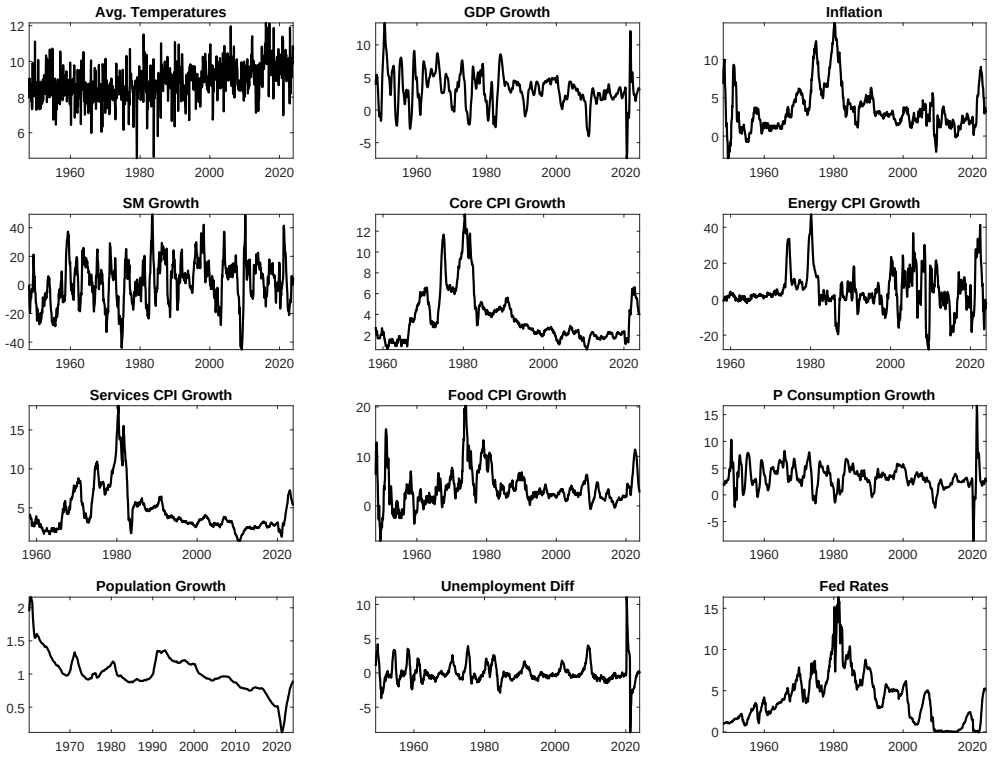


Figure 9: Evolution of variables over time

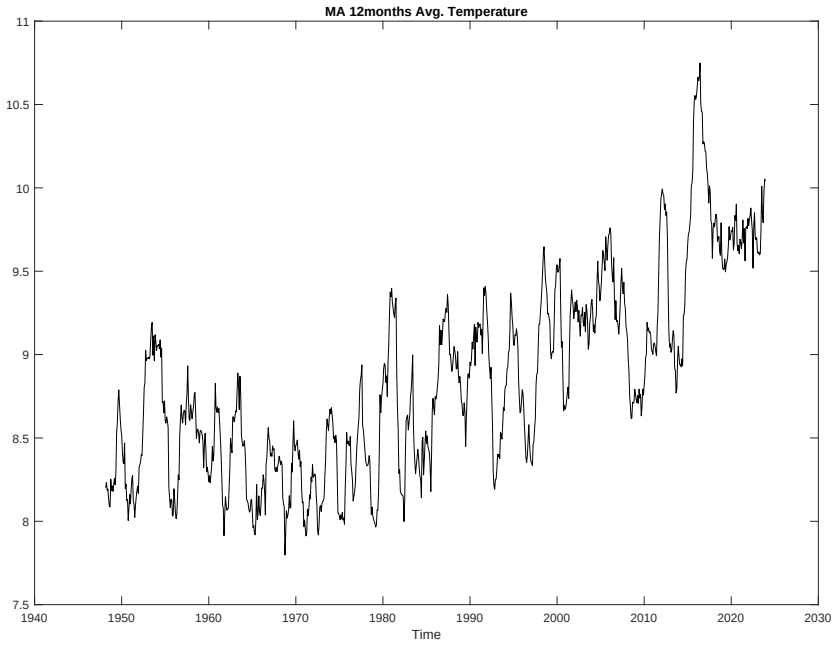


Figure 10: Twelve month moving average evolution of average U.S. temperatures

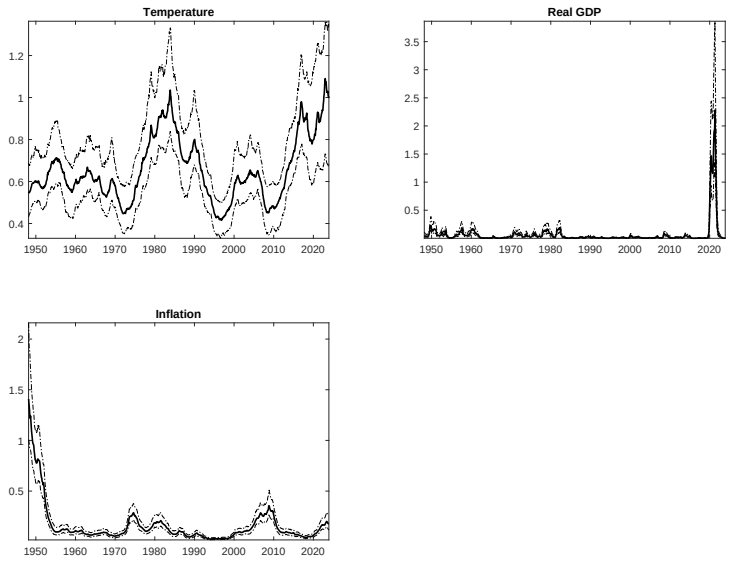


Figure 11: Stochastic volatility

Note: Residual time-varying variances, median, 16% and 84% percentiles.

C Convergence of the Markov chain Monte Carlo algorithm

This section of the appendix assesses convergence of the Markov chain Monte Carlo algorithm in the baseline application. Following Primiceri (2005), we assess the convergence of the Markov chain by inspecting the autocorrelation properties of the ergodic distribution's draws. In order to judge how well the chain mixes, common practice is to look at the draws' inefficiency factors (IF) for the posterior estimates of the parameters. Specifically, that is the inverse of the relative numerical efficiency measure of Geweke et al. (1991), i.e., the IF is an estimate of $(1 + 2\sum_{i=1}^{\infty} \rho_i)$, where ρ_i is the i-th autocorrelation of the chain. In this application, the estimate is performed

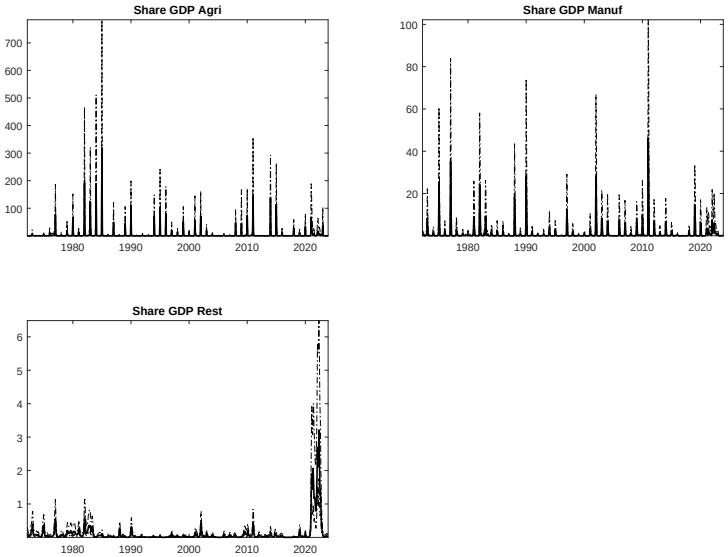


Figure 12: Stochastic volatility sectors

Note: Residual time-varying variances, median, 16% and 84% percentiles.

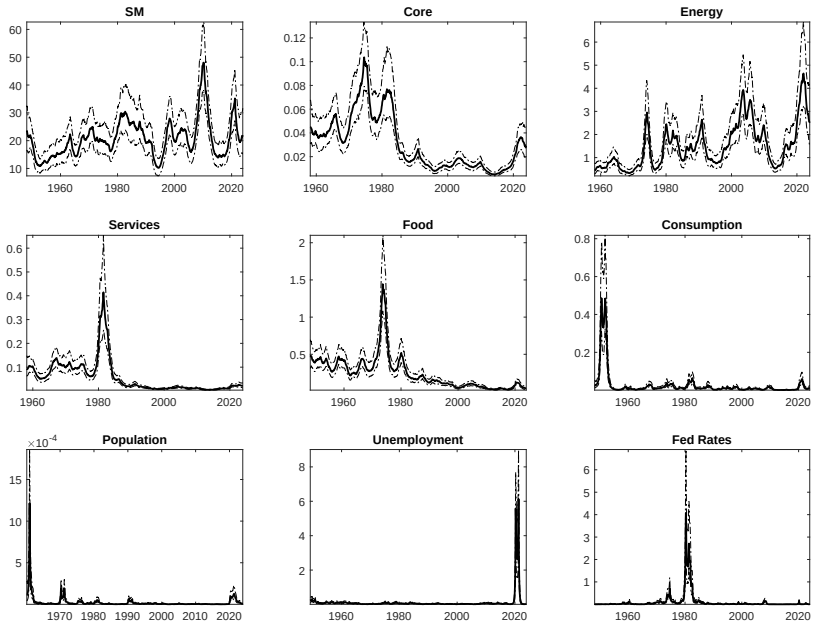


Figure 13: Stochastic volatility extension model

Note: Residual time-varying variances, median, 16% and 84% percentiles.

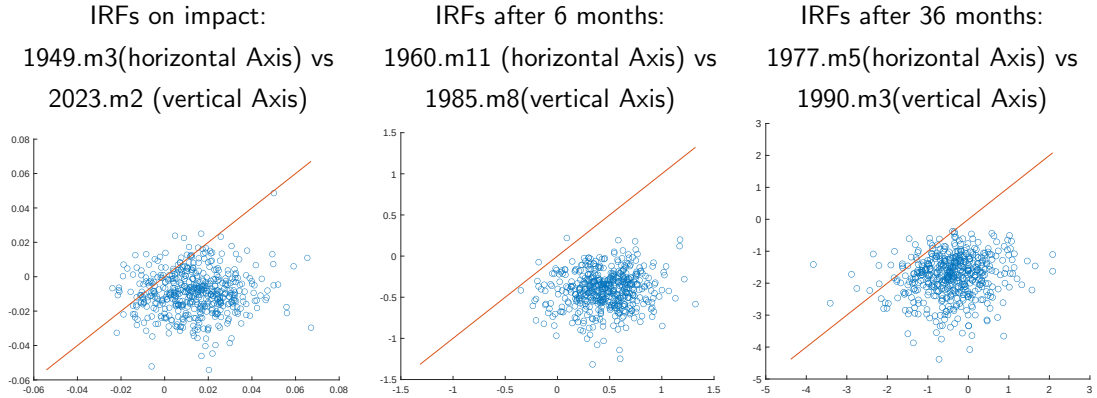
using a Parzen window.[12] Figure 16 plots a complete description of the characteristics of the chain, which is provided for the different sets of parameters. Θ_t: time-varying coefficients of the VAR; Ω: (hyperparameters) elements of the covariance matrix of Θ_t; λ_t: time varying simultaneous relations; σ_t: time varying volatilities; Ψ, Ξ: (hyperparameters) elements of the covariance matrix of λ_t and σ_t. As stressed by Primiceri (2005), values of the IFs below or around twenty are regarded as satisfactory, meaning that the densities for the parameters are well behaved. We made many

[12]For inefficiency factors, see Section 6.1 of Giordani et al. (2011).

16% perc.	50% perc.	84% perc.	trace(Ω_0)
0.0017	0.0024	0.0037	8.6862e-04

Table 1: Trace test

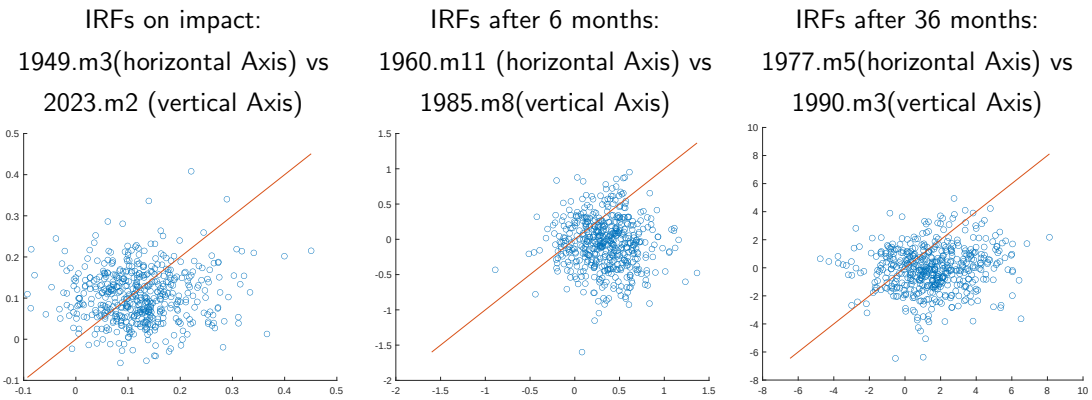
Note: The three columns in the figures represent the 16%, 50%, and 84% percentiles of the posterior distribution for the trace of the variance-covariance matrix associated with the error term in the VAR parameter dynamics. The trace of the prior variance-covariance matrix is displayed in the fourth column. Echoing the analysis by Cogley and Sargent (2005), the observation that the trace of the prior variance-covariance matrix falls below the 16% percentile suggests evidence of time-varying behavior in the VAR parameters. This indicates that the sample exhibits a greater degree of time variation in the parameters compared to the prior assumptions.



Notes: Joint distribution for posterior impulse responses of real GDP after impact, six and thirty-six months to a temperature shock, comparing the periods 1949.m3 (horizontal axis) versus 2023.m2 (vertical axis), 1960.m11 (horizontal axis) versus 1985.m8 (vertical axis), 1977.m5 (horizontal axis) versus 1990.m3 (vertical axis).

Figure 14: Impulse Response functions of real GDP to a temperature Shock

robustness checks for prior specifications and the length of the chain with the main results not being affected significantly.



Notes: Joint distribution for posterior impulse responses of prices after impact, six and thirty-six months to a temperature shock, comparing the periods 1949.m3 (horizontal axis) versus 2023.m2 (vertical axis), 1960.m11 (horizontal axis) versus 1985.m8 (vertical axis), 1977.m5 (horizontal axis) versus 1990.m3 (vertical axis).

Figure 15: Impulse Response functions of prices to a temperature Shock

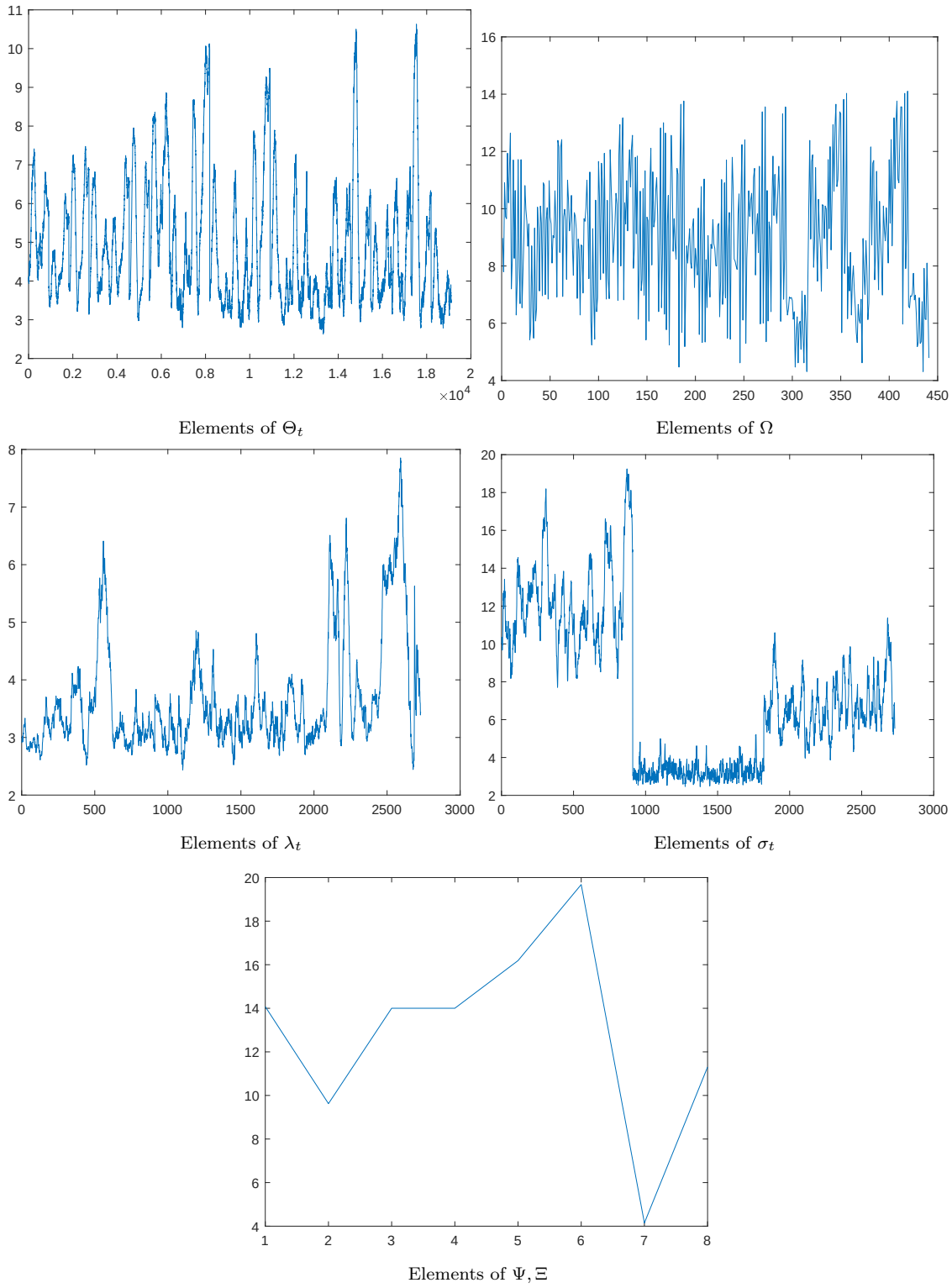


Figure 16: Summary of the distribution of the Inefficiency Factors for different sets of parameters and hyperparameters

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