What goes around comes around: the US climate-economic cycle*

Konstantin Boss, Alessandra Testa This is a preliminary draft: please do not cite or circulate

This draft: October 16, 2023

Abstract

We use a spatial data set of US temperatures in a factor-augmented VAR to quantify the contribution of the US economy to the long-term variation in temperatures over the past 70 years at 25%. However, not all expansionary shocks lead to warming: technology improvements decrease temperatures, whereas capital and labor supply shocks increase them. These effects occur rapidly, persistently and most visibly in eastern and southern states, where manufacturing and natural resource processing industries dominate. In turn, temperature shocks only lead to small contractions in aggregate GDP and can even be beneficial for the economy, when they predominantly hit the western states. If the detrimental effects of temperature warming induced by economic activity do not come around, expansions are only minimally larger.

Link to most recent version

Keywords: Factor-Augmented VAR, Climate Econometrics, Temperature Shocks, Frequency Domain Identification

JEL classification: C32, C38, Q54

*Boss: Universitat Autonoma de Barcelona (UAB) and Barcelona School of Economics, konstantin.boss@bse.eu; Testa: Università di Bologna, Collegio Carlo Alberto, and UAB, alessandra.testa@carloalberto.org. Boss acknowledges funding under the FPI grant PRE2020-093941 of the Ministerio de Trabajo y Economía Social in Spain. We would like to thank Luca Gambetti, Sarah Zoi, Marco Mazzali, and participants of the Bellaterra Macro Club for their very valuable comments.

1 Introduction

The rise in global socio-economic activity and the accompanying increase in anthropological greenhouse gas (GHG) emissions that characterized the past century are thought to be the dominant causes of global warming. Worldwide average surface temperatures have already increased by 1.1°C since the industrial revolution and are projected to increase by between 1.4°C and 4.4°C until 2100 (IPCC, 2023). In turn, temperature increases can lead to lower agricultural yields (Deschênes & Greenstone, 2007), more premature deaths (Barreca et al., 2015), and diminished productivity (Burke et al., 2015), resulting in potentially severe losses in welfare.

In this paper we develop an empirical framework for the United States (US) to study how economic activity affects temperatures and vice versa. We use a factor-augmented vector autoregression (FAVAR, Bernanke et al. (2005)) to model the dynamics of US temperatures on a $0.5° \times 0.5°$ spatial grid together with key macroeconmic aggregates. To disentangle the effect of human activity on temperatures from the effect of temperatures on human activity, we rely on the notion of structural shocks that is common in causal macroeconomic inference (Ramey, 2016). We identify three well-established economic shocks in the frequency domain along the lines of Forni et al. (2023). First, a technology shock is identified as the main contributor to low frequency variation in utilization-adjusted TFP similar to Dieppe et al. (2021). Second, conditional on the technology shock, we identify an investment shock in the spirit of Justiniano et al. (2010) as the main driver of business-cycle fluctuations in investment. Third, similar to Shapiro & Watson (1988) we identify a labor supply shock as the main driver of the low frequency component of hours worked, conditional on both the technology and the investment shock. We therefore target the main inputs of the neoclassical production function, as the emission of climate-altering gases is proportional to production in the structural climate-economic literature (Cai & Lontzek, 2019). The theoretical foundations for identifying structural temperature shocks in the empirical literature, on the other hand, are limited and often based on temperatures being contemporaneously unaffected by non-climatic shocks (see e.g. Donadelli et al. (2017) and essentially all single-equation models of the types discussed in Newell et al. (2021)). Instead of such exclusion restrictions, based on the spatial patterns of common temperature variation we observe for the US, we identify temperature shocks as the main drivers of temperature fluctuations in specific geographic areas, such as the west coast, the east coast, the Gulf region or the non-coastal states.

Our analysis allows us to make the following arguments: first, it is insufficient to rely on a single measure of national temperatures such as arithmetic or weighted averages, as is frequently done in the literature (Dell et al., 2012), (Burke et al., 2015), (Acevedo et al., 2020). This is because there is a lower bound of between four and six large shocks driving US temperatures. The average temperature taken alone reflects only variation in the Midwest region and neglects temperature changes in the economically important coastal areas and this geographic heterogeneity matters for the effect of temperatures on aggregate GDP, a crucial relationship for environmental policy-making. Second, we find evidence for a relationship between temperatures and socio-economic activity going mostly through changes in TFP. Pretis (2021) discusses the endogeneity issue arising in single equation regressions that relate economic outcomes to measures of temperatures, which are often used as instruments for climate change. We find that economic shocks affecting TFP also affect temperatures. Thus, any regression of an outcome affected by such TFP shocks, e.g. GDP, onto temperatures will uncover only a combination of the effect of economic and actual climate-related shocks. To avoid this issue, a control variable would need to purge the effect of the economic shock without removing the effect of the climatic shocks, which may be difficult to construct. We therefore agree with Pretis (2020) on the importance of using a systems approach rather than single equation models to study the linkages between climate variables and the economy and add the identification procedure discussed above as a way for determining the starting points for the causal chains in such systems.

In addition, we contribute the following new quantitative findings to the literature: first, on average, a quarter of the low frequency component of US temperatures can be attributed to the three economic shocks with technology shocks accounting for 14%, investment shocks for 8%, and labor supply shocks for 3%. In the east and south of the US, where manufacturing and natural resource processing are concentrated, the explained variation from technology shocks alone can be as high as 35%. High and medium cycle variations of temperatures, on the other hand, are not strongly explained by the economic shocks. The economic shocks have small, yet persistent effects on temperatures. While technology shocks decrease temperatures, investment shocks and labor supply shocks lead to geographically homogeneous warming, in the area of 0.01°C. Second, central US and east coast centered shocks of 1°C lead to mild losses of aggregate real GDP around $0.1\% - 0.13\%$, echoing the findings in Natoli (2023). However, shocks that predominantly affect temperatures on the west coast can have expansionary effects. We find them to lead to up to 0.29% higher GDP after an initial decrease of around 0.32%. This is because when increases in temperatures occur in the west, they are accompanied by decreases in the east. The net effect of this is positive for aggregate real GDP. Temperature shocks are not persistent for temperatures anywhere in the US. Third, we carry out a counterfactual exercise in which the expansionary economic shocks have minimal effect on temperatures, that is there is in essence no anthropological global warming. If this were the case, GDP would expand only fractionally more.

Comprehensive overviews of the climate-econometric literature are provided by Newell et al. (2021) and de Juan et al. (2022). We relate to and expand the literature that quantifies the effect of temperatures on the US economy. Studies in this area use mostly panel regressions without dynamic causal response estimates (e.g. Deryugina & Hsiang (2014), Colacito et al. (2019), Gourio & Fries (2020)) or aggregated measures of temperature shocks (e.g. Donadelli et al. (2017), Natoli (2023)). We combine dynamic effects together with a disaggregated approach, which allows us to consider several temperatures shocks rather than a single "climate shock" or instrument and show that this matters, as large temperature co-movements in the US can have both positive and negative effects. To the best of our knowledge we are the first to identify the causal effects of several specific economic shocks on temperatures. Kaufmann et al. (2013) discuss economic processes affecting climate forcing (and thus temperatures), but do not identify the stochastic processes explicitly. Empirical studies that compute the effects of economic shocks on US CO2 emissions are Khan et al. (2019) and Bennedsen et al. (2021), however, no connection to explicit temperature changes is made. Since the effect of economic activity on temperatures is not exclusively driven by GHG emissions, but also other gases and processes, Magnus et al. (2011) and Storelvmo et al. (2016) provide a breakdown of warming and cooling effects. We show that the cooling effect prevails for technology shocks, whereas other business cycle shocks lead to warming. From a methodological view our paper is closely related to Mumtaz & Marotta (2023) and Bastien-Olvera et al. (2022). The first one for the authors' use of a factor structure for temperature dynamics, the second one for the frequency domain decomposition of temperatures. While Mumtaz & Marotta (2023) use global data to characterize patterns of aggregate temperature movements, their study focuses on correlations with economic development indicators. We provide causal interpretations for the variations in temperature data and vice versa. Bastien-Olvera et al. (2022) regress GDP growth onto the low-frequency component of average temperatures extracted using a low-pass filter. However, as we show, this component is substantially affected by economic shocks, for which the authors do not control.

The rest of the paper is organised as follows: section 2 describes the temperature and economic data we use in the empirical model, section 3 introduces the model and explains the identification methodology, section 4 presents the findings, which are discussed in section 5, section 6 offers a counterfactual exercise to assess the cost of anthropological warming and section 7 concludes.

2 Data

Temperature data are obtained from the *Terrestrial Air Temperature and Precipitation* $1900 - 2017$ *Gridded Monthly* data set (Matsuura & Willmott, 2018) which provides monthly mean temperatures over land at 0.5×0.5 degree resolution for the entire globe. The authors compute the monthly average gridded data from daily weather station records, considering only stations for which no more than five daily data points in a given month are missing. The grid cell data are estimated from measurement station averages through spatial interpolation. Outliers and unrealistic values that might arise due to measurement error are removed by the authors.

$3,325$ of the grid points are located in the contiguous United States (i.e. excluding Alaska, Hawaii and the US territories). We aggregate the monthly data to quarterly frequency by taking the average over the three months in a quarter and seasonally adjust each time series using the `deseason()` function of the `MATLAB Climate Data Toolbox` Greene et al. (2019), which centers and linearly detrends each time series and then removes the climatology, i.e. the average of each given month in a year. In addition, we weight each grid point by the square root of the cosine of the latitude in the center of the cell. This is common practice in the literature that computes empirical orthogonal functions (EOFs) from climate data (Hannachi et al., 2007) and serves as a means to account for the arc of the earth which changes the size of degree-based grid cells further away from the equator relative to those that are closer to the equator. EOFs are in essence the loadings of the principal components computed for gridded climate data which can be used to detect patterns such as the El Niño Southern Oscillation (ENSO) (Erichson et al., 2020).

We use this method to summarize the information contained in the gridded land surface temperature data set. To determine the number of principal components we use the criterion of Alessi et al. (2010), which suggests between 8 and 17. For parsimony, we set the number of principal components to $r = 8$ and study the effect of picking $r = 17$ in a robustness exercise. Figure 1 shows that the time series for average US temperature and the first principal component from our data set are 96% correlated. In addition, Figure 2 shows that the first principal component – which carries the same signal as the average – explains temperature variation only in the Midwest of the US, important economic centres such as the coastal areas are much less well explained. We expect similar results to appear in other large countries of the world. Therefore, the information in average temperatures in covered by a single principal component, which is clearly insufficient to capture the full temperature dynamics of the US. Any approach using nationwide averages will miss important spatial temperature information.

Figure 1: Average temperatures in the US and first principal component. Correlation is 96%.

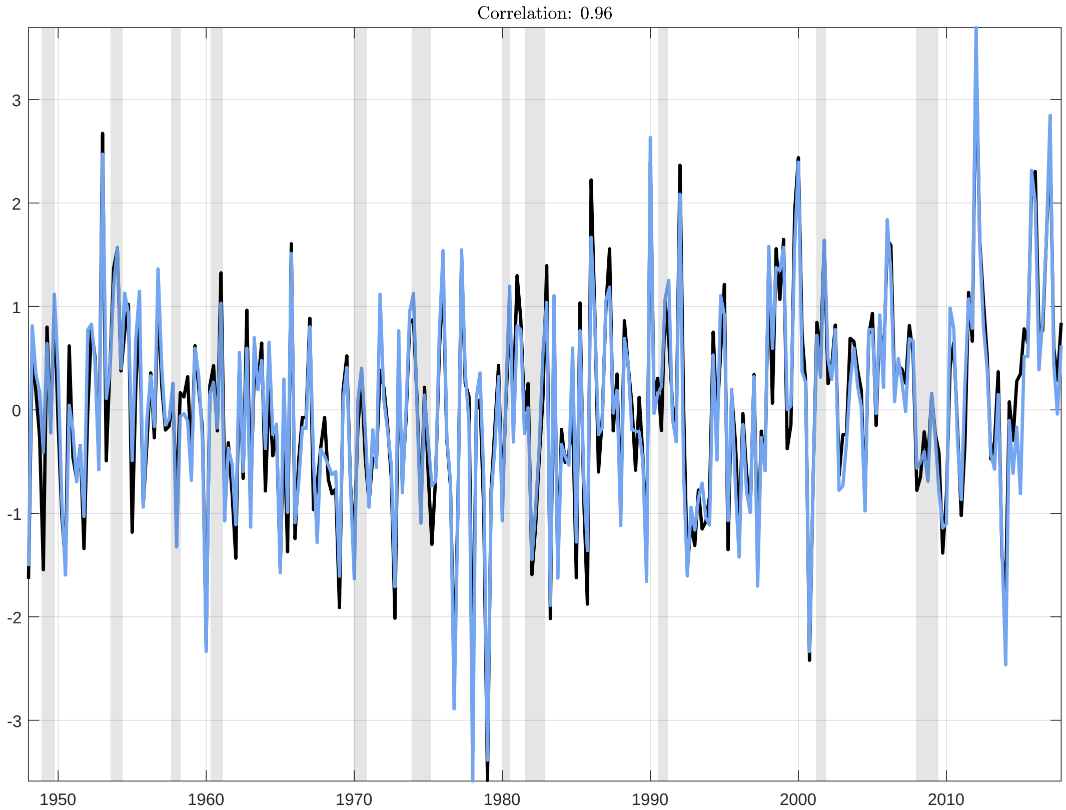
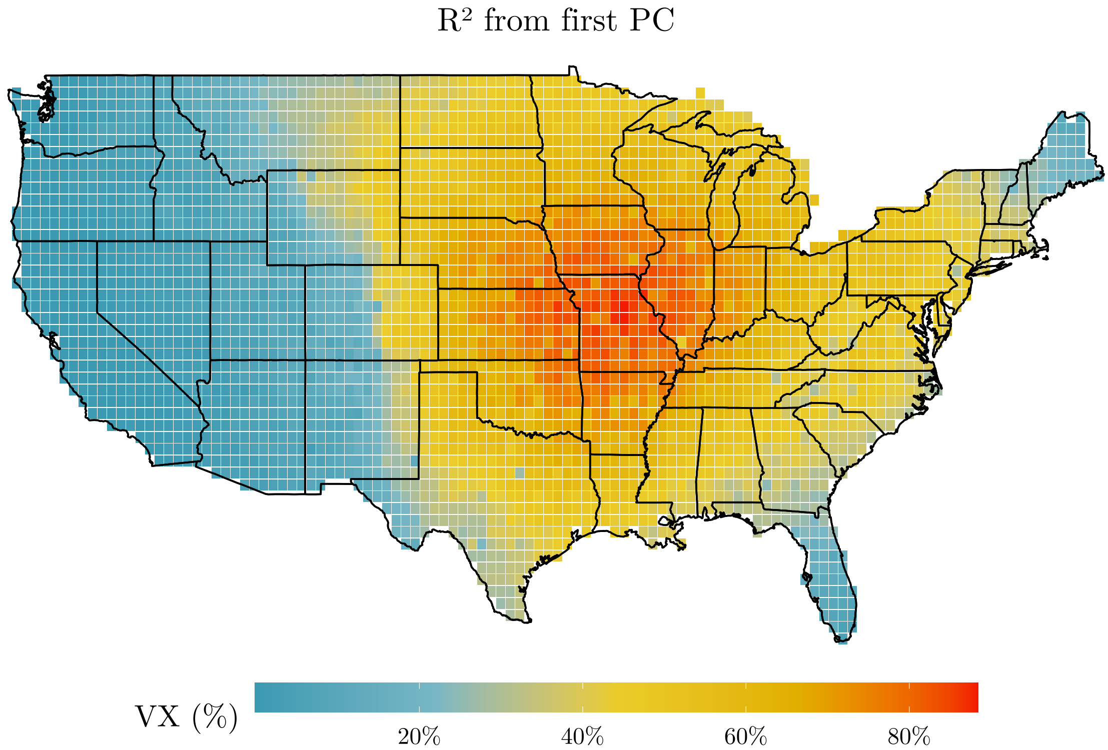
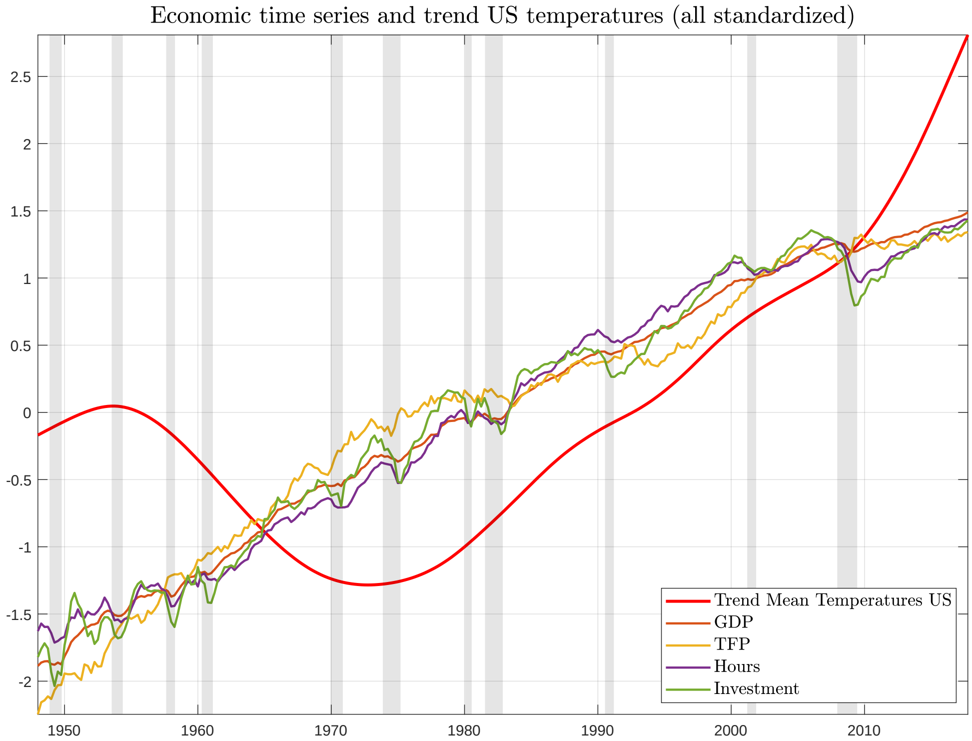


Figure 2: R^2 from regression of grid cell temperatures on first principal component.



The economic data we include are real GDP, real investment, nonfarm-business sector hours worked obtained from FRED and utilization adjusted TFP (from Fernald (2014)). All economic variables enter the model in log-levels to account for the possibility of co-integration among economic and climate variables pointed out in Pretis (2020). We have checked the model in per-capita terms and found no major difference. A detailed account of all the economic data used in this paper and their construction is given in the Appendix. The sample we use for estimation of the baseline model runs at quarterly frequency from 1948:Q1 to 2017:Q4. Figure 3 plots the economic data together with the trend in average US temperatures. Temperatures exhibit an initial decrease until around the 1970s after which they trend upwards. The series appear to share a common trend as of the 1970s, but diverge again after the Great Recession where the growth rate in temperatures speeds up.

Figure 3: HP-filtered trend in mean contiguous US temperatures ($\lambda = 160000$) and logarithmized economic time series. Shaded areas are NBER recessions. All data are centered and scaled to have zero mean and unit variance.



3 Econometric methodology

3.1 Reduced form data representation

Our estimation procedure is carried out in two steps, as in factor-augmented vector autoregressions (FAVAR) (e.g. Bernanke et al. (2005)) and dynamic factor models (DFM) (e.g. Forni et al. (2009)). These models have the advantage that they can accommodate data sets with many time series and allow for the straightforward identification of structural shocks and their propagation through the methods common in the literature on structural VARs (SVARs) (Ramey, 2016).

The model for the temperatures at grid cell i at time t is given by

$$T_{it} = \lambda_i Y_t + \eta_{it} \tag{1}$$

where T_{it} are the raw temperatures and η_{it} is the idiosyncratic component. The vector of loadings λ_i captures the sensitivity of temperatures at grid cell i to the aggregate variables in the vector $Y_t = [f_t, y_t]'$. We combine the principal components f_t of the temperature data with the selected set of economic variables y_t. The reduced form model for Y_t is a

VAR of lag order p:

$$A(L)Y_t = \mu + \epsilon_t, \quad \epsilon_t \sim WN(0, \Sigma) \tag{2}$$

where μ is a constant term, $A(L)$ is a matrix polynomial in the lag operator given by $A(L) = I - A_1 L - ... - A_p L^p$ and ϵ_t is a vector of reduced form white noise errors whose variance-covariance matrix is given by Σ. Treating the principal components f_t as observed, model (2) is efficiently estimated using OLS for each equation. The lag order is determined using the Akaike information criterion, which yields $p = 2$.

3.2 Semi-structural identification

To identify economic and temperature shocks we rely on structural identification techniques that have been proposed for the study of business cycles fluctuations in, among others, Angeletos et al. (2020) and Forni et al. (2023). It is most common to distinguish fluctuations of high frequency, business cycle frequency and low frequency. We adopt the following definition of frequency bands:

Table 1: Frequency bands adopted for identification.

Frequency	Low	Business Cycle	High	Full Spectrum
Quarters	> 40	$[6, 32]$	$(0, 6]$	$(0, \infty)$

The business cycle frequency is between 6 (1.5 years) and 32 quarters (8 years) as is common in the economic literature (Angeletos et al., 2020). This definition roughly coincides with medium cycles that are observable in climatic data as well. For example, ENSO influences global weather and occurs every 3-5 years and lasts for a year NOAA (2023). The higher frequencies coincide with the strongest fluctuations in our temperature data. This component is most similar to the types of weather shocks usually identified in the literature.

The reduced form VAR in (2) is assumed to admit a moving average (MA) representation given by

$$Y_t = c + C(L)\epsilon_t \tag{3}$$

where $C(L)$ is obtained by inverting $A(L)$. The structural representation (where we drop the constant term $c = C(L)\mu = C(1)\mu$ as it is immaterial for our identification strategy and the model dynamics) is given by

$$Y_t = C(L)SHu_t = D(L)Hu_t = K(L)u_t, \quad u_t \sim WN(0, I) \tag{4}$$

where $SS' = \Sigma$, $HH' = I$, and $u_t = H'S^{-1}\epsilon_t$. Identification of the structural shocks boils down to pinning down columns of the orthonormal matrix H. The impulse responses of the economic variables (subindex E) and of temperatures (subindex T) are then given by

$$IRF_E = D_E(L)H \tag{5}$$

$$IRF_T = \Lambda D(L)H \tag{6}$$

The notation $C_E(L)$ is shorthand for selecting the rows from each of the matrices in $C(L)$ which correspond to the entries of Y_t that belong to economic variables. Λ is the matrix containing the vectors of loadings λ_i for each grid cell.

3.2.1 Identification of economic shocks

We identify three economic shocks – a technology shock, an investment shock, and a labor supply shock. These are the three shocks that are proposed as the main business cycle drivers in Justiniano et al. (2010). To do this we follow the procedure described in Forni et al. (2023) which identifies shocks according to their contribution to the cyclical variances of key variables. Consider the structural representation of equation (4). The cyclical variance-covariance matrix of all variables in Y_t in the frequency band between $[\underline{\theta}, \bar{\theta}]$ is given by

$$V(\underline{\theta}, \bar{\theta}) = \int_{\underline{\theta}}^{\bar{\theta}} D(e^{-i\omega})D(e^{i\omega})'d\omega \tag{7}$$

where, for example, in the case of business cycle frequencies $[\underline{\theta}, \bar{\theta}] = [2\pi/32, 2\pi/6]$ and i is the imaginary constant $i = \sqrt{-1}$. In practice, $V(\underline{\theta}, \bar{\theta})$ can be obtained by computing the average over a grid of values between $\underline{\theta}$ and $\bar{\theta}$ and taking the real part of this average (or computing the inverse Fourier transform of the RHS in (7)). This returns the total variation of all variables in Y_t in the given frequency band as the diagonal elements of the matrix $V(\underline{\theta}, \bar{\theta})$. To identify a particular shock instead, we use a single column h of the orthonormal matrix H to obtain

$$\Psi(\underline{\theta}, \bar{\theta}) = \int_{\underline{\theta}}^{\bar{\theta}} D(e^{-i\omega})hh'D(e^{i\omega})'d\omega \tag{8}$$

which is the variation of all variables in the given frequency band stemming from the shock associated with column h. For our identification strategy, we want to target only specific variables in a given band, so we select the rows of D that correspond to these variables. Suppose, for example, TFP is ordered second in Y_t, then D_m for $m = 2$ would select the corresponding row. As shown in Forni et al. (2023), this can easily be extended for multiple targets. This is discussed in more detail for the case of temperature shocks where we make use of this technique. We want to find the shock which contributed the majority of fluctuations in the given band to our target variable, so the column h is identified as:

$$h = \arg\max \quad h' \left(\int_{\underline{\theta}}^{\bar{\theta}} D_m(e^{-i\omega})' D_m(e^{i\omega}) d\omega \right) h, \quad \text{s.t} \quad h'h = 1 \tag{9}$$

The h that solves this is the unit-length eigenvector corresponding to the largest eigenvalue of the matrix sandwiched in between h' and h in (9) (as shown for the time domain in (Uhlig, 2003)).

We first identify the technology as the main driver of low frequency variation in TFP as in Dieppe et al. (2021), which echoes the idea of Gali (1999) to identify technology shocks as the only long-run driver of labor productivity. Maximization does not imply that a single source is responsible for all long-run variation of TFP, but picks out the disturbance that contributes the most to its fluctuations. This method is shown to be robust to interference from other shocks that typically occurs in maximization approaches such as Barsky & Sims (2011). Conditional on the identified technology shock, we then proceed to identifying the investment shock as the main driver of investment over the business cycle. Justiniano et al. (2010) and Justiniano et al. (2011) show that such a shock can be interpreted as a shock to the marginal efficiency of capital, that is, how easily investment is converted to productive capital. The conditional shock is identified by finding another column of H, call it h_j:

$$\begin{aligned} h_j = \arg\max \quad & h_j' \left(\int_{\underline{\theta}}^{\bar{\theta}} D_m(e^{-i\omega})' D_m(e^{i\omega}) d\omega \right) h_j \\ \text{s.t} \quad & h_{tech}' h_j = 0 \quad \text{and} \quad h_j' h_j = 1 \end{aligned} \tag{10}$$

Finally, the labor supply shock is identified similarly to the TFP shock as the main driver of hours worked in the low frequency, but conditional on both the technology shock and the investment shock. This identification is inspired by Shapiro & Watson (1988) with an analogy to the relationship between Dieppe et al. (2021) and Gali (1999). It is easy to extend the maximization constraints in (10) to pin down this labor supply shock.

3.2.2 Identification of temperature shocks

We use a similar method as for the economic shocks to pin down temperature shocks. Conditional on the three economic drivers, we identify the maximizers of temperature fluctuations in our data set. Economic theory can inform the identification of economic shocks, whereas there is no clear guideline for the identifying traits of climate related shocks. For example, there is no mutually agreeable sign pattern in output, technology, hours or prices that should ensue from a temperature shock. Nor do zero restrictions using a recursive (Cholesky) or long-run neutrality (Blanchard-Quah) scheme seem appropriate, as these would have to hold at every temperature location in our data set, requiring an impossible number of zero responses to be enforced. Maximizing frequency variations of temperatures has the advantage of being statistically driven rather than theoretically and allows us to target many temperature series simultaneously rather than restricting individual variables. To do this we need to extend the above framework slightly. Call the IRFs of the temperature variables $\Omega(L) = \Lambda C(L)SH$ and collect the columns of H which identify the economic shocks in $H_E = [h_{tech}, h_{inv}, h_{lab}]$. Then the maximization program is the following:

$$\begin{aligned} h_{Tj} = \arg\max \quad & h'_{Tj} \left(\int_{\underline{\theta}}^{\bar{\theta}} \Omega_m(e^{-i\omega})' W \Omega_m(e^{i\omega}) d\omega \right) h_{Tj} \\ \text{s.t} \quad & h'_{Tj} H_E = [0,0,0]' \quad \text{and} \quad h'_{Tj} h_{Tj} = 1 \end{aligned} \tag{11}$$

As before, h_{Tj} is a single column of H and can be found as the eigenvector of the matrix in the quadratic form in (11). The matrix W is a weighting matrix which has on its diagonal the square roots of the standard deviations of the m targeted variables in the frequency band of interest. Given that all our data is measured in degree Celsius this is less of a concern, but is done for completeness.

We do not require the temperature shocks to be orthogonal to each other, only to the economic shocks. This is because the main identifying property these shocks have come from geography. Temperature fluctuations on the US West coast may be driven by other impulses than on the East coast. The targets and bands for identification are chosen as follows:

1. Maximize the low frequency temperature variation everywhere
2. Maximize the full spectrum temperature variation everywhere
3. Maximize the full spectrum temperature variation for the West coast (states that border the Pacific Ocean)
4. Maximize the full spectrum temperature variation for the East Coast (states that border the Atlantic Ocean)
5. Maximize the full spectrum temperature variation for the Gulf of Mexico states (Texas, Louisiana, Mississippi, Alabama, Florida)

6. Maximize the full spectrum temperature variation for non-coastal states

The choice is motivated by the geographical patterns we observe in the descriptive analysis below, which suggest important temperature commonalities in the Midwest, on the coastal regions, and the Gulf area. Moreover, the maximizer of low frequency temperature movements will likely pick up some non-US socio-economic shocks and the full-spectrum maximizer would be the closest to the temperature shock measured in an approach that uses average temperatures, only in this case it is purged of US economic activity.

4 Results

4.1 Descriptive results

We begin by summarizing the linkages between the US economy and temperatures through the lens of the model in (1) and (2). As a first exercise we determine the number of shocks which drive US temperatures. In the macroeconometric literature, such shocks are sometimes referred to as *deep shocks* (Forni et al., 2009). We do this by maximizing the full-spectrum fluctuations of all US temperature series without conditioning on other shocks. Notice that this is done on the spectral density matrix in (7) rather than the sample correlation matrix that is used for computation of the principal components. We repeat the same exercise and target the full spectrum of variation in the four economic variables to see how these shocks affect temperatures. The outcomes of this are reported in Tables 2 and 3.

Table 2: Cumulative cyclical variances explained by the first six shocks that maximize the full spectrum variation of temperatures at grid-cell level in the US. Rounded to two decimals.

	Low Frequencies						Business Cycles						High Frequencies					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Avg. Temp.	0.31	0.48	0.58	0.66	0.81	0.86	0.42	0.63	0.78	0.84	0.88	0.92	0.42	0.65	0.77	0.84	0.88	0.92
GDP	0	0.01	0.01	0.01	0.04	0.09	0	0.01	0.01	0.02	0.11	0.17	0	0.01	0.02	0.03	0.04	0.08
TFP	0	0.04	0.06	0.09	0.32	0.33	0	0.03	0.06	0.13	0.47	0.52	0.01	0.02	0.04	0.11	0.26	0.29
Hours	0	0.01	0.01	0.01	0.05	0.08	0	0.01	0.01	0.03	0.15	0.2	0.02	0.03	0.04	0.05	0.1	0.11
Investment	0	0.01	0.02	0.03	0.06	0.07	0	0.01	0.02	0.02	0.08	0.11	0	0.01	0.03	0.03	0.04	0.06

Table 3: Cumulative cyclical variances explained by the first six shocks that maximize the full spectrum variation of GDP, TFP, hours, and investment in the US. Rounded to two decimals.

	Low Frequencies						Business Cycles						High Frequencies					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Avg. Temp.	0.02	0.23	0.3	0.32	0.39	0.46	0.01	0.02	0.05	0.06	0.14	0.24	0	0.01	0.03	0.04	0.1	0.19
GDP	0.91	0.93	0.99	1	1	1	0.76	0.86	0.93	0.99	0.99	0.99	0.81	0.85	0.89	0.94	0.94	0.97
TFP	0.33	0.97	1	1	1	1	0.11	0.87	0.93	0.98	1	1	0.33	0.81	0.85	0.91	0.95	0.97
Hours	0.78	0.96	0.98	1	1	1	0.54	0.96	0.97	0.99	1	1	0.47	0.84	0.9	0.95	0.97	0.98
Investment	0.88	0.93	0.96	1	1	1	0.62	0.77	0.77	0.99	1	1	0.48	0.56	0.57	0.91	0.93	0.99

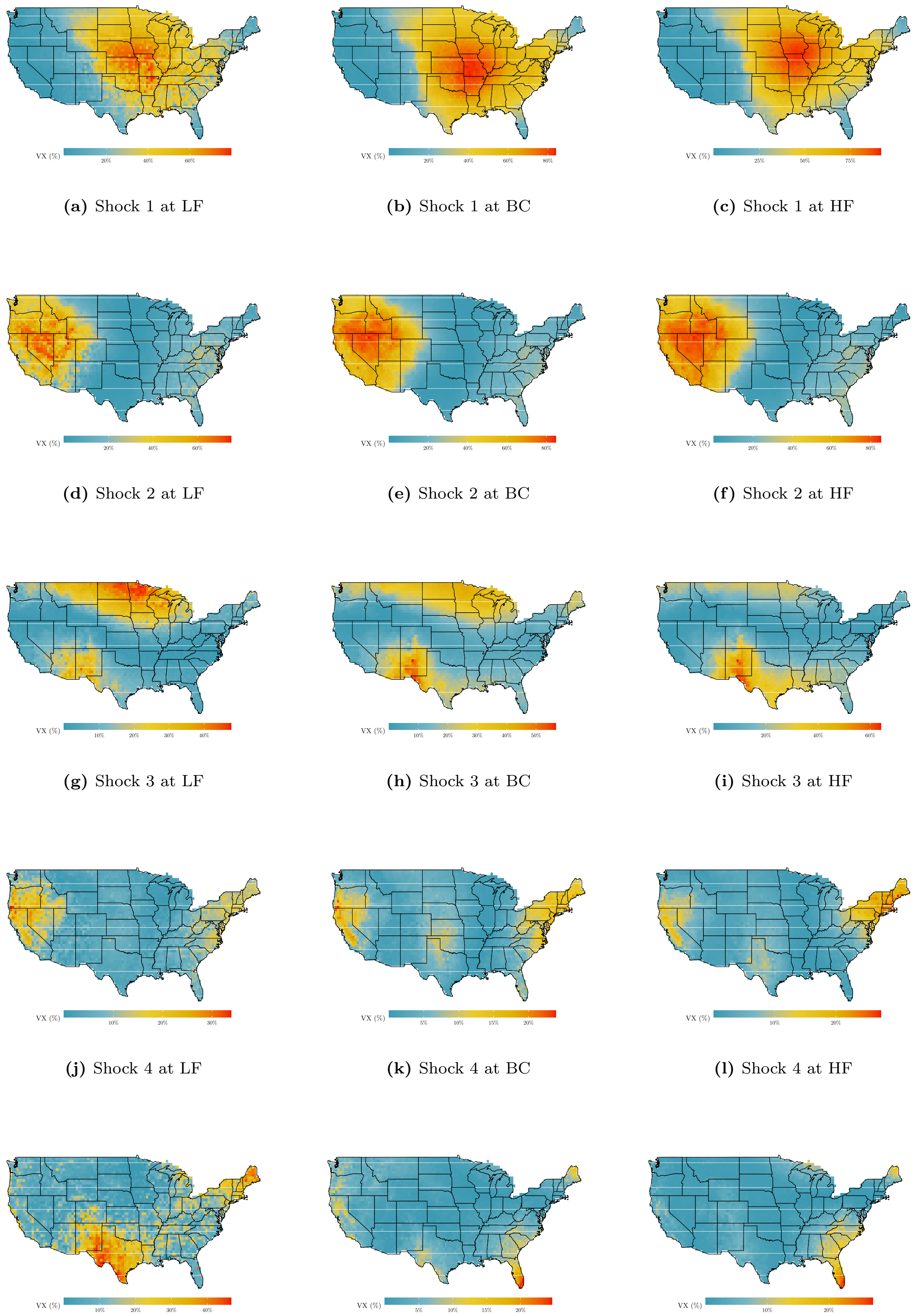
Two important new findings emerge from these tables. First, the common variation in US temperatures requires at least five shocks to reach more than 80% explained cyclical variance at all frequencies. After the fifth shock, the improvement in explained variance in any of the three bands of interest from adding another shock is below 5%. This number constitutes a lower bound for the actual number of exogenous temperature drivers, as the shocks here are not structurally identified, other than being mutually orthogonal variance maximizers. Based on this result, reducing the effects of temperatures on economic aggregates to a single variable such as a (weighted) average, as is frequently done in the literature, is implausible.

Second, there is a connection between temperature and economic variation, mostly through TFP. The fifth temperature variance maximizer is responsible for a sizable share of TFP variation at all frequencies, particularly at the low and medium end of the spectrum. This seems intuitive: the low frequencies are related to the trend in the temperature data and it is commonly believed that anthropological forces have contributed to this trend in the past half century. Since technology is an important ingredient for economic growth, we should expect it to correlate with the lower frequency components of temperatures. Moreover, we observe that, in line with the literature (e.g. Forni et al. (2023)), two shocks appear sufficient to capture a large share of the cyclical variation in key aggregate economic variables. In the low frequency and business cycle bands, hours, investment, and GDP are largely driven by the same shock, yet TFP is not. This echos the findings of Angeletos et al. (2020) who also demonstrate a disconnection between TFP and business cycle fluctuations of GDP. Interestingly, investment fluctuations of high frequency appear to require more than three shocks to be accurately explained. Finally, we see that the second shock, which especially drives long-run TFP is responsible for a large increase in the explained variance of average US temperatures.

While these descriptive results report only the variation in average US temperatures, our model allows us to disaggregate the effects down to the grid cell level. This is presented in Figure 4 for the five temperature variance maximizers and in Figure 5 for the first four economic maximizers. As is visible from the spatial distribution of explained variances in Figure 4, the first shock is unsurprisingly strongly related with the first principal component of the temperature data – it is centered in the Midwest region of the US. The second shock is mostly responsible for variation on the West coast and the third shock picks up signals more strongly near the Canadian and Mexican borders. This result is partly due to the imposition of orthogonality of the shocks and commonly observed in the study of EOFs (Hannachi et al., 2007). For the economic maximizers, on the other hand, we note that the primary driver of low freqeuncy variation hardly has any impact on US temperatures. Effects are stronger for the second, third and fourth shokcs that are more related to TFP and investment.

We take the following lessons from this descriptive section: first, it seems reasonable to distinguish shocks by geographic criteria, such as a heartland and a coastal shock, with a distinction between west and east coast also warranted. Second, imposing orthogonality for these shocks may create artificial geographical patterns. We therefore choose to condition only on the economic shocks and treat the temperature shocks one-by-one, without imposing that they themselves be mutually orthogonal. Third, there is a clear connection between the economy and temperatures. However, the descriptive exercise does not permit us to tell apart the respective source of the fluctuation. Is the variation in temperatures due to climatic or economic shocks? What part of GDP variation is truly due to climatic shocks and which part just masquerades interference from economic shocks? These questions go back to the cyclical nature of the climate-economic system and we need the structural identification exercise explained in the preceding section for an answer.

Figure 4: Cyclical temperature variation explained in each grid cell in the US from the first five shocks which maximize temperature variation over the full frequency spectrum.



(a) Shock 1 at LF

(b) Shock 1 at BC

(c) Shock 1 at HF

(d) Shock 2 at LF

(e) Shock 2 at BC

(f) Shock 2 at HF

(g) Shock 3 at LF

(h) Shock 3 at BC

(i) Shock 3 at HF

(j) Shock 4 at LF

(k) Shock 4 at BC

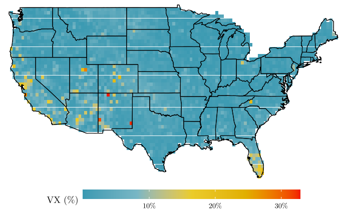
(l) Shock 4 at HF

(m) Shock 5 at LF

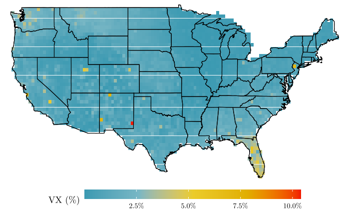
(n) Shock 5 at BC

(o) Shock 5 at HF

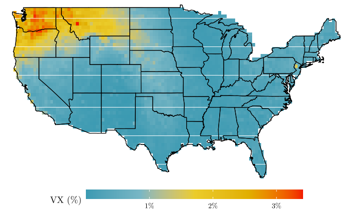
Figure 5: Cyclical temperature variation explained in each grid cell in the US from the first four shocks which maximize the economic variables' variation over the full frequency spectrum.



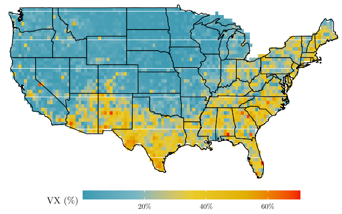
(a) Shock 1 at LF



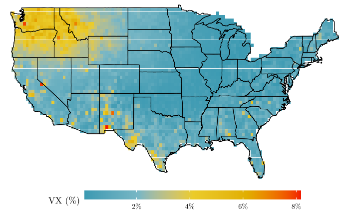
(b) Shock 1 at BC



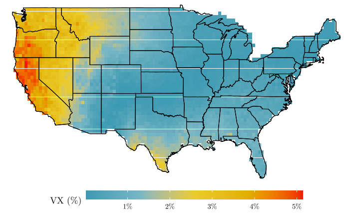
(c) Shock 1 at HF



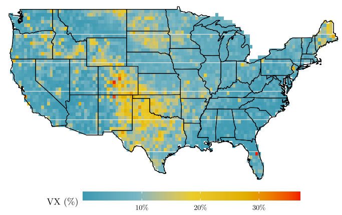
(d) Shock 2 at LF



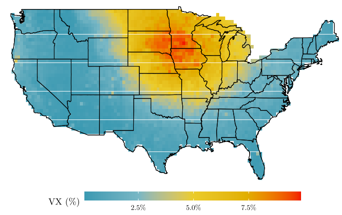
(e) Shock 2 at BC



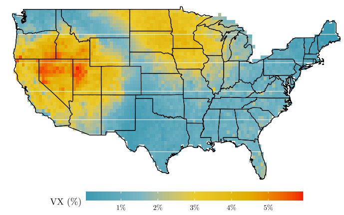
(f) Shock 2 at HF



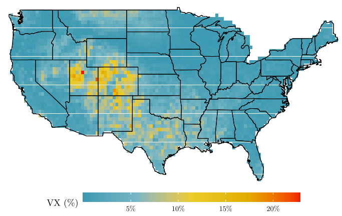
(g) Shock 3 at LF



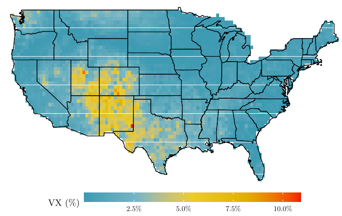
(h) Shock 3 at BC



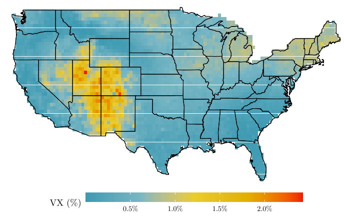
(i) Shock 3 at HF



(j) Shock 4 at LF



(k) Shock 4 at BC



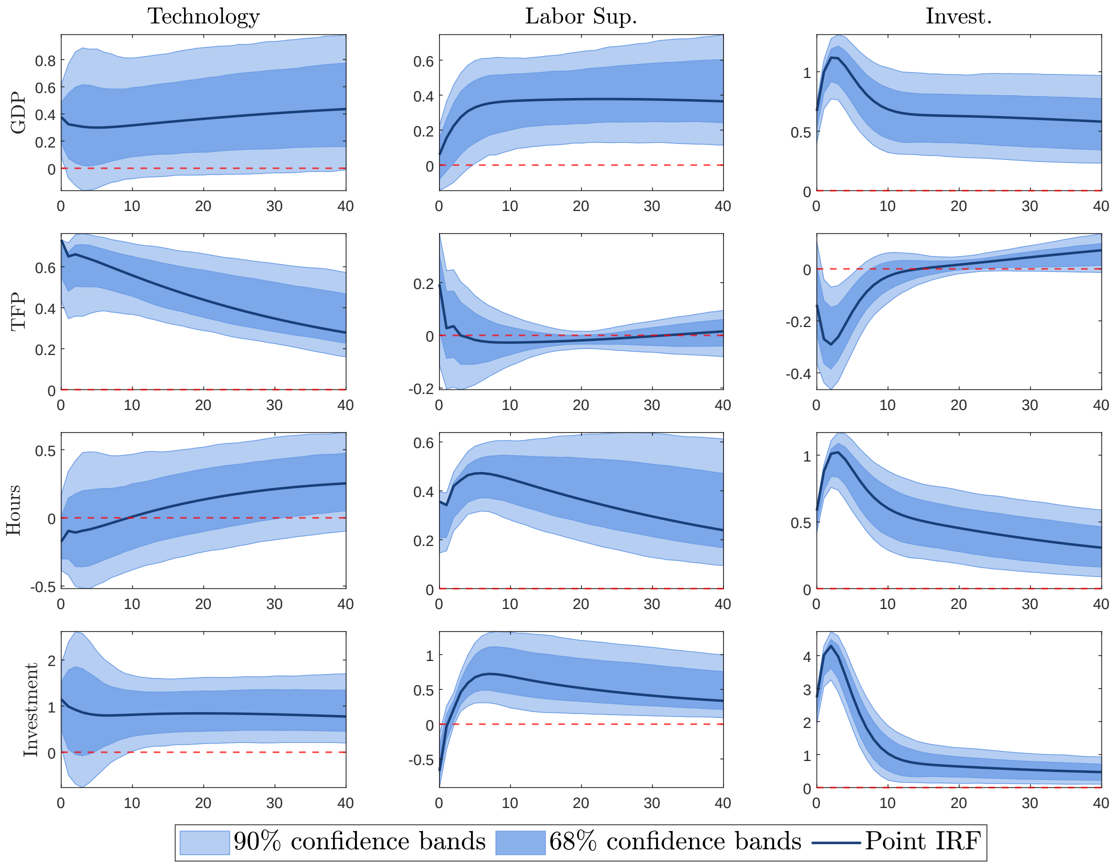
(l) Shock 4 at HF

4.2 Semi-structural results

4.2.1 Economic shocks

We begin by discussing the effects of the economic shocks on the economic variables. This is done to confirm that our identification procedure is indeed successful in selecting technology, labor supply, and investment related shocks as described in the macroeconomic literature. The impulse response functions for this are reported in Figure 6.

Figure 6: Impulse response functions for the three structural economic shocks. Shaded areas are bootstrapped 68% and 90% confidence bands.

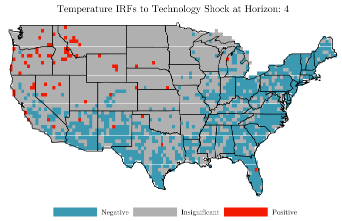


First, the technology shock leads to an immediate increase in TFP which is accompanied by an expansion of real GDP of around 0.4%. Hours initially decline (although this is statistically insignificant) and investment increases. These results are very similar to those found in Dieppe et al. (2021), who use labor productivity in a spectral identification exercise with a different VAR specification. Second, the labor supply shock leads to a slowly-building increase in output of around 0.3%, a mildly hump-shaped response of hours after an initial increase and an initial reduction in investment which is replaced by labor as an input to production. The TFP response is almost entirely insignificant, which is partially a result of conditioning on the technology shock. The slow-building GDP response is consistent with other studies that identify labor supply shocks such as Foroni et al. (2018) (for the US) and Peersman & Straub (2009) (for the euro area). The responses of hours and GDP are in line with the paper of Shapiro & Watson (1988), which we have used as motivation for the identification strategy. Lastly, the investment shock creates hump-shaped expansions in investment, hours and GDP and a hump-shaped decline in TFP. These responses are in line with the motivating paper of Justiniano et al. (2011). The decrease in TFP is also observed in Ben Zeev & Khan (2015) (although in their paper the response is insignificantly different from zero) for investment-specific technology shocks. We take these results as evidence that our proposed identification strategy can indeed correctly pick out empirically valid impulse responses in a joint identification framework, even though the identification approach is entirely built on spectral identification and does not exactly copy the approaches in the originally proposed papers.

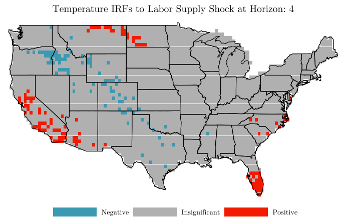
Next, we describe the responses of US temperatures to the three expansionary economic shocks, a key result of this paper. It is important to note that the impact reactions (near impulse response horizon $h = 0$) of temperatures across the US to the shocks are difficult to measure accurately due to the high volatility of the temperature time series' as opposed to the macroeconomic aggregates. We therefore prefer to not interpret temperature responses to economic shocks near the impact. The graphs in Figure 7 show the following picture: the technology shock has a cooling effect on temperatures in the east and the south of the US. Importantly, as the impulse horizon increases, the effect dissipates almost everywhere, which suggests that eventually, cooling and warming offset each other. The effect is persistently significant at the 68% confidence level even after 10 years. The investment shock leads to increases in temperatures almost in the entire US after 10 years, after initially dominating in California, Arizona, near the Canadian border, and in the east. Finally, a similar pattern emerges for the labor supply shock, although the initial temperature responses are less pronounced compared to the investment and technology shocks. As far as the magnitudes of the responses are concerned, they range between -0.03 and 0.01 °C (technology shock), -0.01 and 0.02 °C (labor supply shock) and -0.01 and 0.02 °C (investment shock)[1].

[1] These values are computed across all horizons and grid cells as a single standard deviation around the mean response for each of the three shocks.

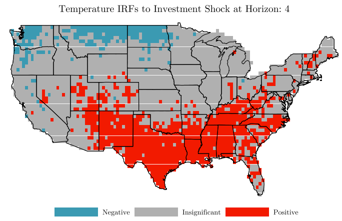
Figure 7: Grid cell temperature IRFs at given horizons in response to the three economic shocks.



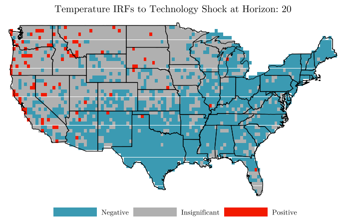
(a) Tech. shock after 1 year



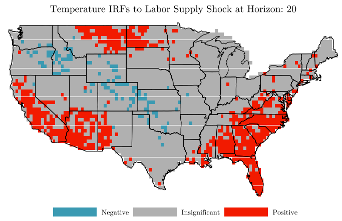
(b) Lab. sup. shock after 1 year



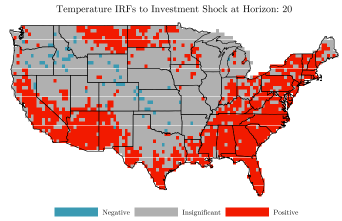
(c) Inv. shock after 1 year



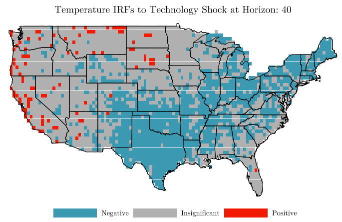
(d) Tech. shock after 5 years



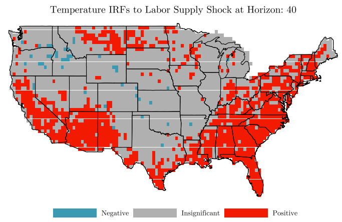
(e) Lab. sup. shock after 5 years



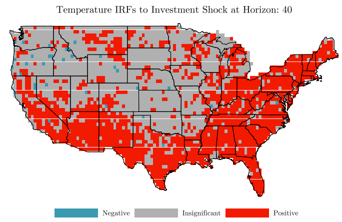
(f) Inv. shock after 5 years



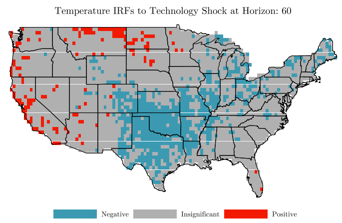
(g) Tech. shock after 10 years



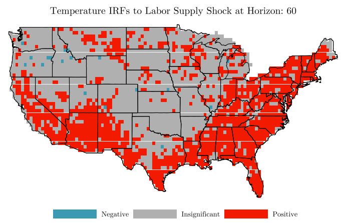
(h) Lab. sup. shock after 10 years



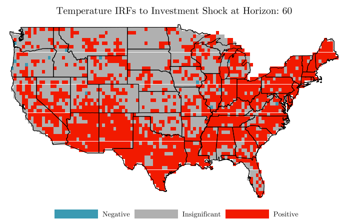
(i) Inv. shock after 10 years



(j) Tech. shock after 15 years



(k) Lab. sup. shock after 15 years



(l) Inv. shock after 15 years

Next, we report the relative importance of each of the three economic shocks in explaining average temperature movements, as well as the fluctuations of our economic variables at low, business cycle, and high frequencies.

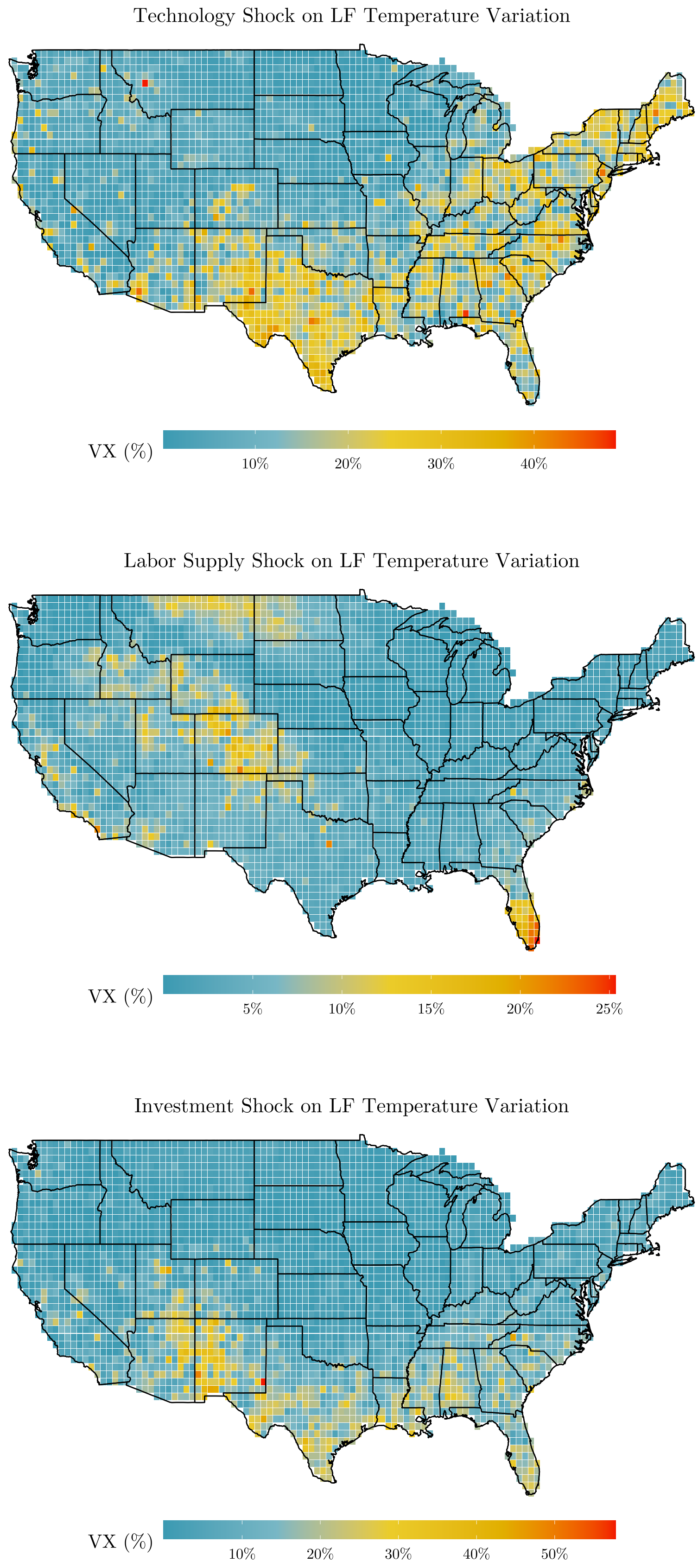
Table 4: Individual cyclical variances explained by the three identified economic shocks over the three frequency bands. Numbers in parentheses are the 90% confidence bands associated with the percentage above. Rounded to two decimals.

	Low Frequencies			Business Cycles			High Frequencies		
	Tech.	Lab. Sup.	Invest.	Tech.	Lab. Sup.	Invest.	Tech.	Lab. Sup.	Invest.
Avg. Temp.	0.14	0.03	0.08	0.01	0.01	0.01	0.01	0.01	0
	(0.05,0.34)	(0.03,0.14)	(0.05,0.19)	(0.01,0.06)	(0.01,0.06)	(0.02,0.06)	(0.01,0.05)	(0.01,0.05)	(0,0.03)
GDP	0.2	0.16	0.52	0.13	0.07	0.68	0.29	0.09	0.48
	(0.01,0.74)	(0.02,0.46)	(0.13,0.71)	(0.02,0.51)	(0.02,0.25)	(0.3,0.75)	(0.05,0.67)	(0.02,0.33)	(0.14,0.62)
TFP	0.93	0	0.03	0.69	0.02	0.2	0.72	0.1	0.05
	(0.72,0.99)	(0,0.07)	(0,0.12)	(0.26,0.86)	(0.01,0.18)	(0.03,0.43)	(0.3,0.75)	(0.01,0.25)	(0.02,0.16)
Hours	0.11	0.29	0.6	0.07	0.13	0.78	0.19	0.22	0.51
	(0.02,0.57)	(0.11,0.55)	(0.16,0.76)	(0.02,0.37)	(0.06,0.22)	(0.42,0.81)	(0.05,0.5)	(0.07,0.35)	(0.19,0.58)
Investment	0.33	0.1	0.57	0.04	0.03	0.91	0.17	0.1	0.62
	(0.04,0.73)	(0.02,0.36)	(0.16,0.79)	(0.01,0.33)	(0.01,0.08)	(0.6,0.92)	(0.05,0.39)	(0.03,0.16)	(0.3,0.67)

Taken together the three economic shocks explain around 25% of the low frequency movement of temperatures. Technology and investment shocks contribute the most (14% and 8% respectively), labor supply shocks contribute less (3%). We conclude from this that a non-negligible share of the trend- and long-cycle component of temperatures is caused by anthropological activity in the United States. The economic shocks are not important sources of average short-term temperature fluctuations, which we take as evidence for such fluctuations as being mostly of natural or non-US causes. The three shocks also appear to be reasonable choices to explain business cycle fluctuations in the economy. Together they account for 88% of the BC variation in GDP, 91% of the variation in TFP, 98% of the variation in hours, and 98% of the variation in investment.

The spatial distribution of explained variances of the three shocks is presented in Figure 8. Given that there is hardly any variance arising at medium and short frequencies, we report this only for the low frequency. Patches of relevant fluctuations are observable in all three cases. For the technology shock, variances explained are around 35% in the east and in the south, particularly in Texas. For the investment and the labor supply shocks, the patterns emerge predominantly in the south and in the corridor across Colorado, Wyoming, and Idaho, for which the labor supply shock was cooling. explained variances for the investment shock are locally larger than 40% in some areas in the south, while they are lower in the case of the labor supply shock.

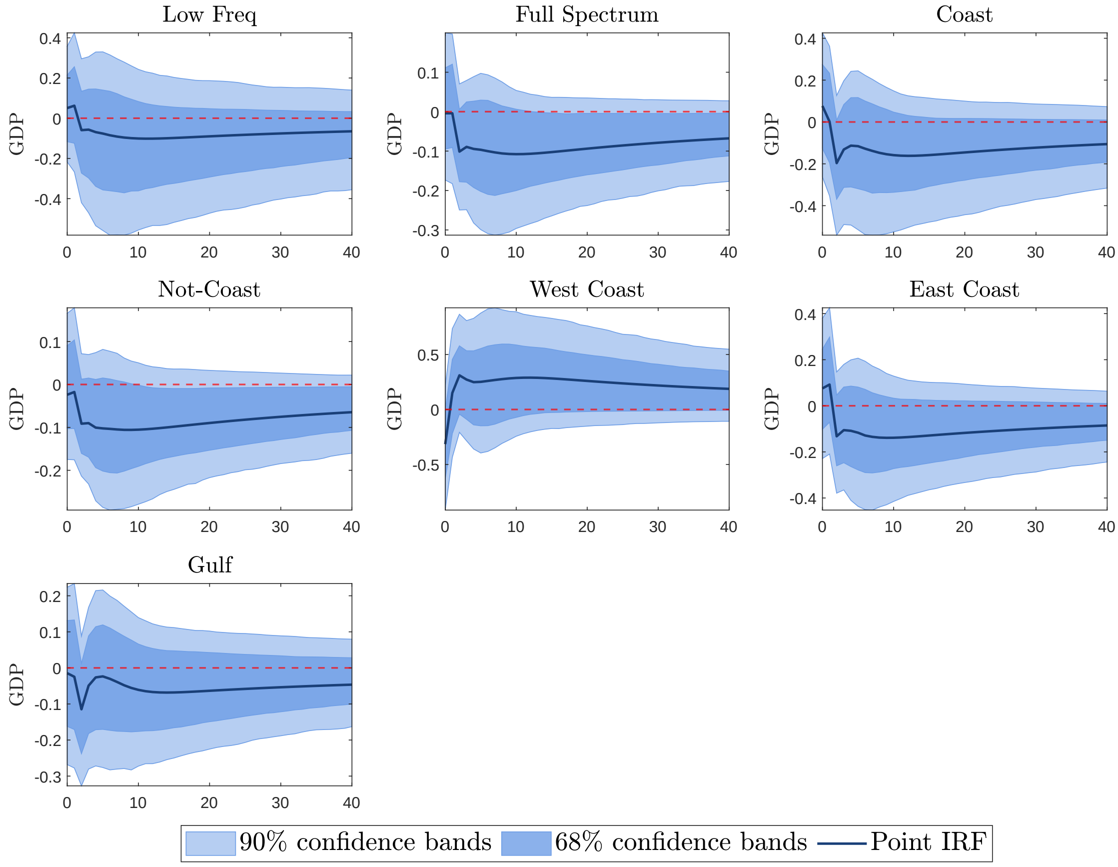
Figure 8: Grid cell level cyclical variation explained at low low frequencies from the three economic shocks.



4.2.2 Temperature shocks

Next, we turn to the effects of the temperature shocks that are identified as described in section 3. For ease of interpretation we have normalized all shocks such that the impact response in average temperatures is scaled to 1 degree Celsius, as is customary. We are primarily concerned with the effect of temperature changes on GDP as all other economic variables were used for identification purposes. Figure 9 summarizes the resulting IRFs.

Figure 9: Impulse response functions for the different temperature shocks. Shaded areas are bootstrapped 68% and 90% confidence bands.

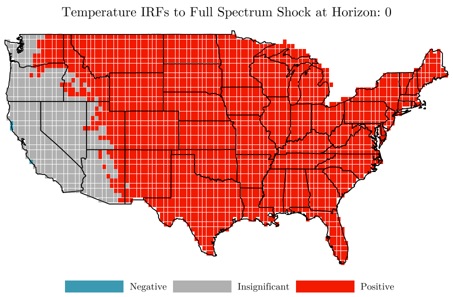


All of the identified shocks lead to small and persistent GDP contractions between 0.1% and 0.2% except for the shock that hits primarily the West coast of the US. The confidence bands are always very close to the zero line. This result is consistent with the majority of the literature, which finds substantial uncertainty involved in the estimates of temperature shocks in the US, see for example Newell et al. (2021) and Nath et al. (2023), who find nearly zero effect for countries with an average temperature around 10 degrees Celsius such as the US. Negative effects of temperature shocks in the range of 0.1% are also found in Natoli (2023) (although using an instrumental variable approach) and slightly more negative impacts are documented in Colacito et al. (2019), while Dell et al. (2012) found insignificant effects of temperatures on rich countries' output.

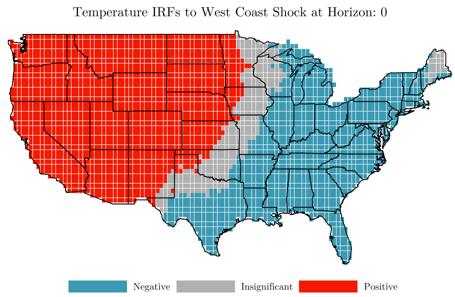
The results that these papers obtain are consistent with the shock in our set, which maximizes temperature variation in the entire US over all frequency bands. However, we can go beyond this based on our conclusion that more than one shock is required to capture US temperature variation. In fact, without imposing orthogonality for this exercise, the West coast shock is only 2% correlated with the low-frequency maximizer, 3% with the full spectrum maximizer, and a relatively low 33% with the East coast shock. Interestingly, it produces a comparatively sizable expansion in aggregate GDP (although this is statistically insignificant). This effect would either be lost entirely or mixed into average results obtained through the usual econometric techniques. As Table 4 suggests, the share of variation in the economic variables from temperature movements are very small, which is why we choose not to report them here.

For illustration of the spatial distribution of impulse responses, we focus on the full spectrum maximizer for temperatures everywhere and the west coast shock. These two shows are only 3% correlated, without the imposition of orthogonality. Figure **??** shows the signs of the responses. Clearly, the full spectrum maximizer without geographical constraints raises temperatures everywhere except for the west coast. The shock which drives temperatures up on the west coast, simultaneously decreases them in the east. Due to the scaling of the average temperature to equal 1°C, the positive responses outweigh the negative ones. Both of these shocks are quantitatively important for temperature variations (38% and 16% on average respectively over all frequency bands). Importantly, we find no evidence of significant persistence in either of the temperature shocks considered here. After around three years, all effects on temperatures turn insignificant.

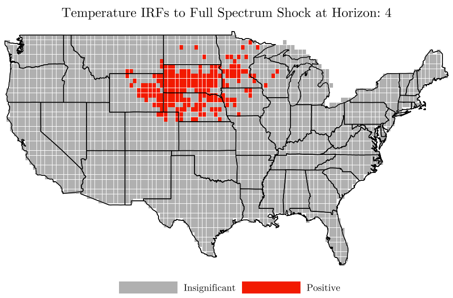
Figure 10: Grid cell temperature IRFs at given horizons in response to the full spectrum and the west coast temperature shocks.



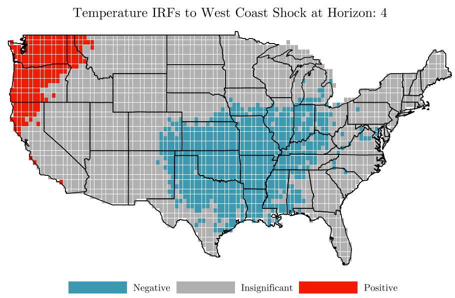
(a) Full spectrum shock on impact



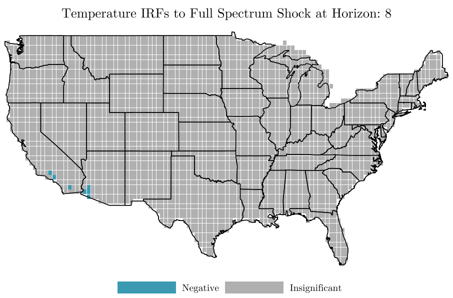
(b) West coast shock on impact



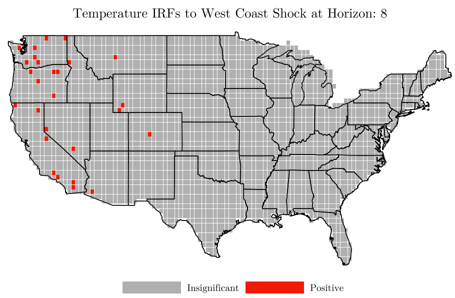
(c) Full spectrum shock after 1 year



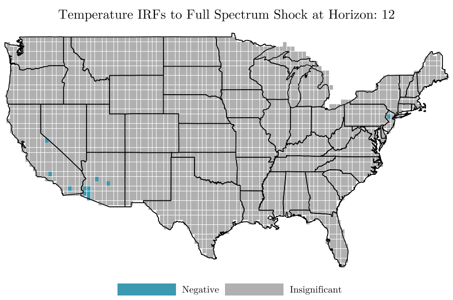
(d) West coast shock after 1 year



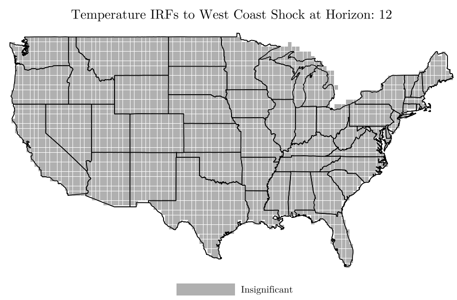
(e) Full spectrum shock after 2 years



(f) West coast shock after 2 years



(g) Full spectrum shock after 3 years



(h) West coast shock after 3 years

To summarize the semi-structural results, we see that economic sources, especially technology and investment shocks, are locally important drivers of temperature variations. They lead to noticeable decreases (technology) and increases (investment, labor supply) in temperatures that persist for many years and are noticeable even relatively shortly after the initial shock. Treating temperatures as unaffected by anthropological forces even in the short run can thus lead to confounding causal effects, especially when annual data is used as is customary in the literature. Moreover, it is important to distinguish the effects of temperature shocks on aggregate GDP by the geographical location of the epicentre of the shock. If the west coast is predominantly affected, GDP may be unaffected or even increase, while shocks in the rest of the country lead to small contractions. This is important for assessing the damages of climate change which are fed into models used for policy decisions.

5 Discussion

We now discuss the main results presented before. First, the documented effects of the three economic shocks on temperatures across the US warrant closer inspection. The connection between economic activity and temperatures runs through the emission and storage of climate-active gases. Magnus et al. (2011) decompose the temperature effect of anthropogenic gas emissions into warming – through the emission of GHGs, most prominently CO2 – and cooling – through aerosol emissions, most prominently SO2. CO2 is a well-mixing gas, which spreads through the Earth's atmosphere over time. Moreover, Zickfeld & Herrington (2015) suggest that CO2 emission impulses can lead to notable warming even relatively quickly – 93% of the warming effect materializes within 10 years after emission. SO2, on the other hand, leads to the creation of a solar radiation effect, which blocks incoming solar waves from entering the atmosphere, thus leading to net cooling. Magnus et al. (2011) argue that this effect is more pronounced on a local, rather than a global scale. Both warming and cooling effects are sizable at the global scale.

Technology shocks induce cooling in parts of the US east and south. Therefore, the solar radiation effect from aerosol emissions outweighs the heating effect from GHG emissions at these locations. The geographical pattern coincides with the location of important parts of the American manufacturing and natural resource processing industries[2] as highlighted in Figure 11. Additionally, as shown in Figure 11, these areas are also centres of CO2 and SO2 emissions. This supports the hypothesis that cooling is driven largely by the local effect from aerosol emissions. It is also possible that technological improvements,

[2]The source for this is BEA Table CAGDP2, downloadable from `https://apps.bea.gov/regional/downloadzip.cfm`. We exclude government enterprises from the data set and display only the industry which has the highest contribution to county-level nominal GDP in 2017.

especially towards the end of the sample, allow emission-neutral expansions. In the absence of long quarterly time series for GHGs and aerosols, we are careful to push this point, but Khan et al. (2019) provide evidence that neutral technology shocks have insignificant effects on CO2 emissions.

Figure 11: Main industries by county are computed as the biggest contributors to nominal GDP without government enterprises in 2017 from BEA data.

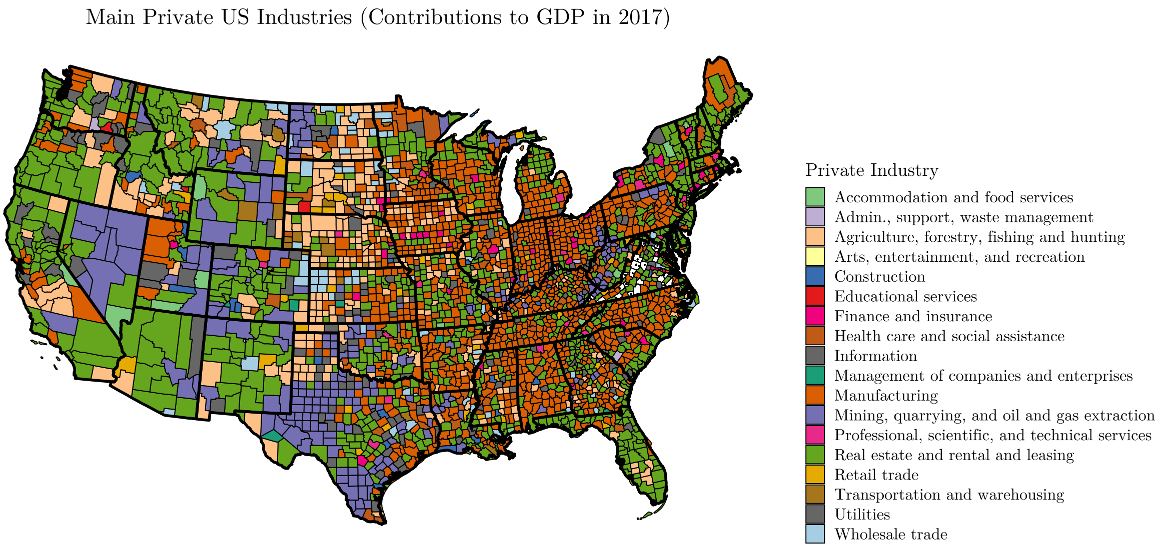
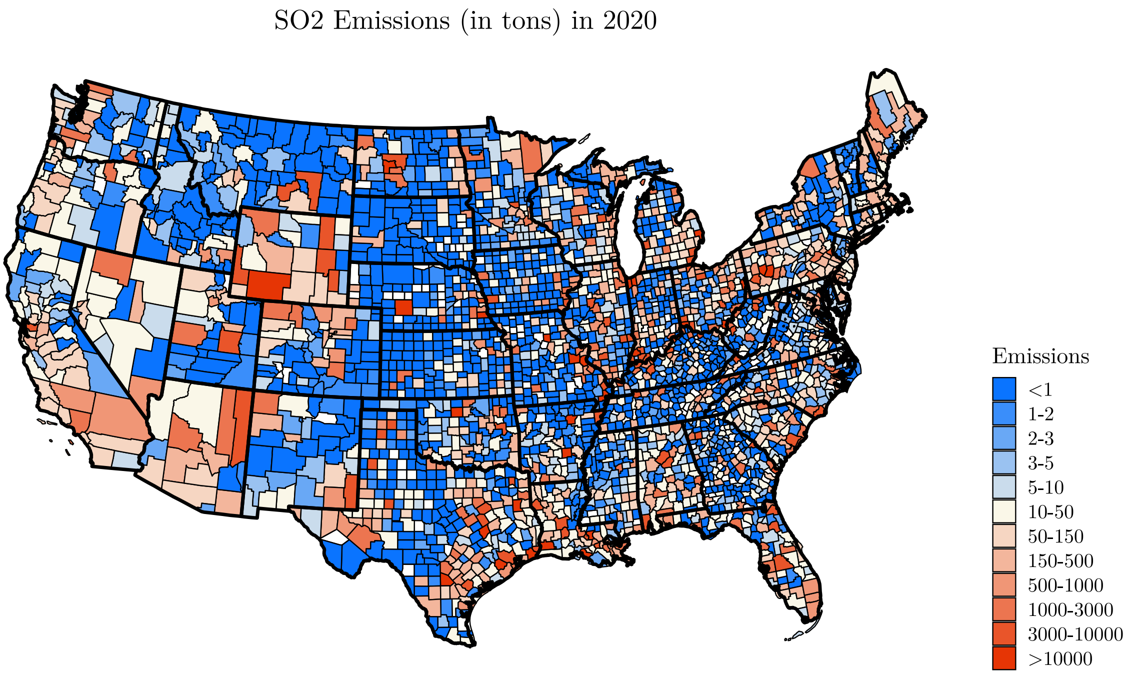
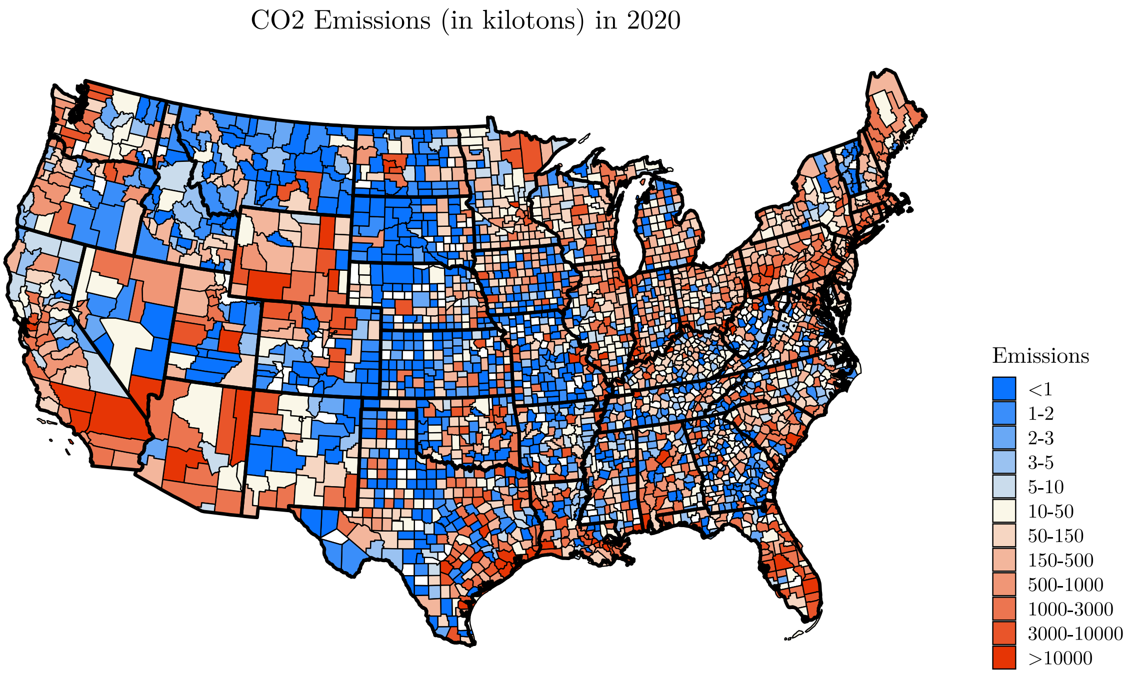


Figure 12: SO2 and CO2 emissions are computed by aggregating the EPA's NEI 2020 data set for site-specific emissions at the county level (data retrievable from `https://www.epa.gov/air-emissions-inventories/2020-national-emissions-inventory-nei-data`). These include emissions from fossil fuel combustion, industrial processes and biomass (e.g. wildfires), but exclude *onroad* emissions.



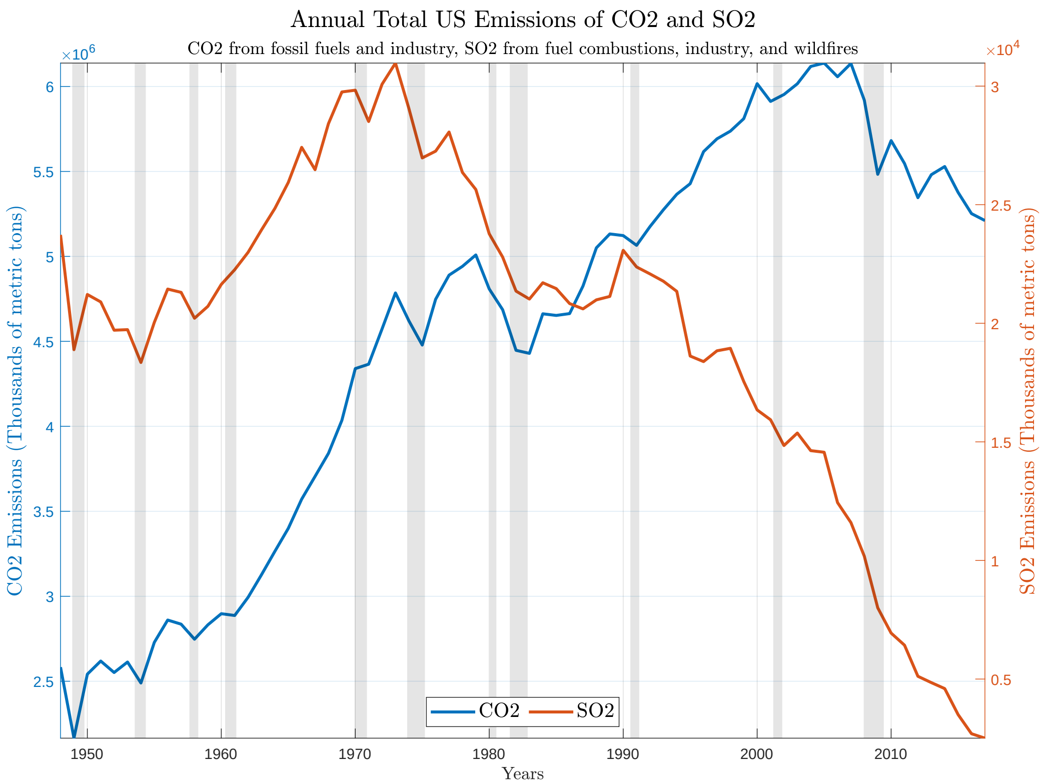
(a) SO2 emissions 2020



(b) CO2 emissions 2020

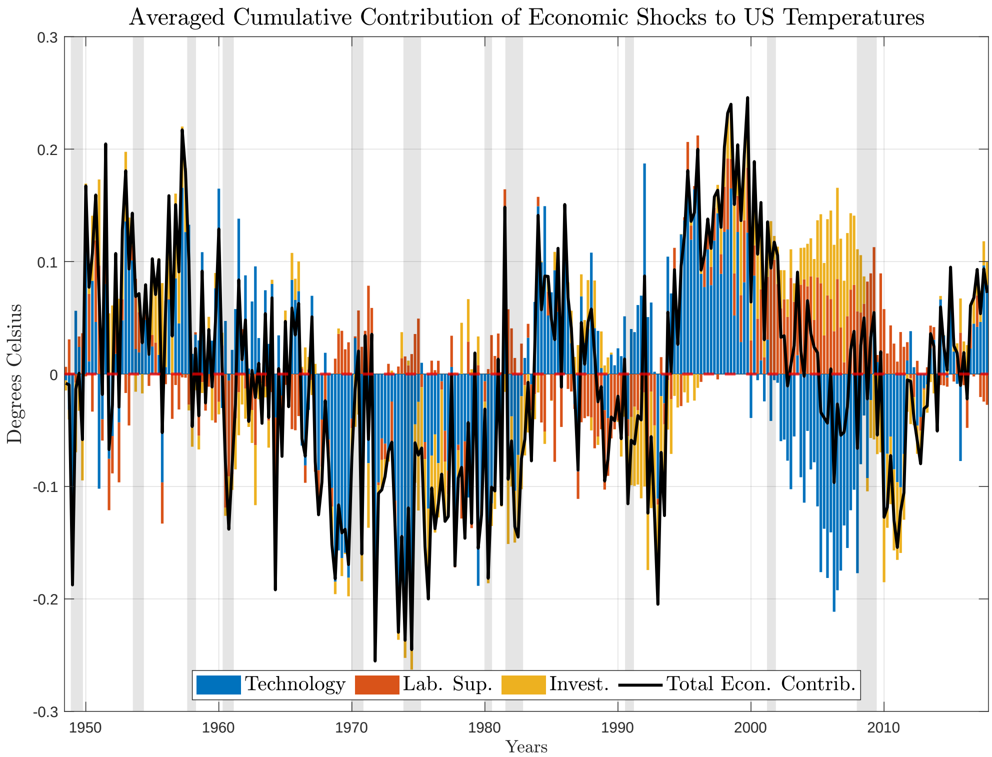
Why does this not also happen for the investment and labor supply shocks, if all three lead to sustained increases in production and hence emissions? On the one hand, Khan et al. (2019) identify investment-specific shocks as the main driver of CO2 emissions. On the other hand, in 1970 the *US Clean Air Act* was amended to require the installation of specialized industrial equipment, such as *SO2 scrubbers*, to reduce aerosol emissions drastically. Figure 13 shows the trends in CO2 emissions and SO2 emissions for the US, which have opposite trends as of 1970.

Figure 13: Annual time series of SO2 and CO2 emissions for the US. The data for CO2 are retrieved from `https://ourworldindata.org/co2-emissions`, the data for SO2 are from Smith et al. (2011) until 1990 and from then on from the EPA (`https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data`).



Installing these scrubbers is likely captured by our investment shock. Thus, such shocks lead to reductions in aerosols and simultaneous increases in CO2 emissions, both of which are net warming. Labor supply shocks, in the literature, are a strong driver of changes in the labor force participation rate (Foroni et al., 2018) and other demographic factors, which affect GHG emissions positively through the *Kaya identity*. Labor market participation in the US has experienced a well-documented slowdown after increasing steadily until around the year 2000. This implies a positive correlation with CO2 emissions, which also trend downwards in the last 10-15 years of our sample, which is suggestive of am induced warming effect. Figure 14 shows that until 1970, the economic shocks' joint contribution led to a decline in temperatures, as hypothesized, likely driven through the strong effect on aerosol emissions. As of 1970, economic activity started to increase average temperatures as aerosol emissions were decreased and CO2 emissions (and other GHGs) continued to increase. There is a negative trend starting around the year 2000 where CO2 emissions cease to grow and a small plateau for SO2 emissions is reached. This continued until the recovery of the Great Recession and is driven by reductions in temperatures after positive technology shocks in that period, potentially improving climate-neutral productive capacity. The economic expansion leading up t the crisis on the other hand is accompanied by an increase in temperatures from investment and labor supply shocks. We find this to support our interpretation of the temperature effects of economic shocks to be strongly related to the change in trend in aerosol emissions combined with the continued release of GHGs through much of the 1980s and 1990s.

Figure 14: Average historical contributions of the three economic shocks to US temperatures. The contribution to a single series is computed as the sum of the historical decomposition: $T_{it}^{HD} = \lambda_i' \sum_{s=1}^{3} \sum_{j=0}^{t-1} h_{s,j}' u_{s,t-j}$, for all $t = 1, ..., T$ of the sample.



Second, we turn to the discussion of the different effects of west coast centered temperature shocks and the other weather shocks we have identified. We focus on the full spectrum maximizer as a representative of the other shocks. Increases in temperatures can reduce output in almost every industry as productivity decreases Colacito et al. (2019) and mortality increases Carleton et al. (2022), but these effects tend to be more pronounced for industries that are less able to shield their productive processes from climate factors, such as agriculture and construction. The broad scale temperature increase that follows the full spectrum shock affects almost the entire US and this essentially all industries. As shown in Colacito et al. (2019), there are very few industries that benefit from higher temperatures, such as utilities which face higher energy demand, for instance, to operate air conditioning systems. The magnitude of temperature effects is estimated to be highest for agriculture, forestry,and fishing as well as insurance. The west coast shock leads to increased temperatures on the west coast, but declines in temperatures in the east. In our linear model, decreasing temperatures should be expected to be beneficial for output. The increases in the west do not appear to offset this positive effect. Hsiang et al. (2017) provide estimates of the projected geographical distribution of climate effects for the US. They calculate a gain in agriculture from increased temperatures in the north-west of the country and project overall total damages to concentrate in the south-east of the US, whereas the north-western states experience positive effects from warming. The largest damages from temperature increases go through excess mortality in their study. This is a large factor especially in the already warmer southern states, for which we observe cooling after the west coast shock. In sum, the warming effect of the full spectrum shock is in line with an aggregate reduction in GDP as many sectors all over the country are negatively affected by higher temperatures and mortality should be expected to increase. For the west coast shock, temperature increases in the north-west have been shown to be net positive. Together with the cooling observed for the east and south that is good for productivity and lowers mortality, this leads to an aggregate gain in US GDP.

Finally, we want to address a few shortcomings of our approach. First, temperatures, especially at low frequencies, are driven not only by US shocks, but also economic activity elsewhere on the planet, so this is likely still present in our low frequency temperature maximizer. We believe our approach can be extended to a global setting, where we can control for the main drivers of output globally before considering aggregate temperature shocks. Second, we cannot clearly trace out the response of climate-active gases to the economic shocks to complement the findings for net temperature changes that follow. There may be an important change in the transmission mechanism coming from the amendment of the Clean Air Act in 1970. We are not aware of sufficiently long enough quarterly frequency data for these emissions to be included in our empirical framework. Third, our estimates of shock responses are averages over the 1948-2017 sample, computed in a linear model. There is good evidence that the transmission of temperature shocks is non-linear (Burke et al., 2015) or state-dependent Nath et al. (2023). As temperatures increase globally, positive shocks push up already high temperatures even more, which may be more severe for the economy than shocks occurring at lower average temperatures. Tipping points may play a substantial role for the propagation for shocks Cai & Lontzek (2019). We hope to combine the modeling and identification approach of this paper with such extensions in future work.

6 Counterfactual

We run a counterfactual exercise loosely inspired by Mountford & Uhlig (2009) and McKay & Wolf (2023). The question we want to answer is *"How would the GDP responses to the economic shocks change, if there were no intermediate effect on temperatures?"* This is an important question for the distinction between the effects of *global warming* as opposed to the effects of *weather shocks*. We have argued that the temperature shocks we have identified in the previous section belong to the latter category, as they are causally unrelated to (at least US) economic activity. We understand anthropological global warming as the component of temperatures that is substantially caused by the economic shocks we have identified. Economic damages (or benefits) from global warming materialize because temperatures endogenously change after the shock. The conditions for socio-economic activity become endogenously less (or more) favourable, both in the short and in the long run[3]. Since exogenous increases in temperatures lead to reductions in GDP almost everywhere, we expect shocks that produce warming to lead to less favorable conditions, which then implies costs that would be absent if there were no climatic feedback.

McKay & Wolf (2023) discuss an application of their counterfactual methodology, where several monetary policy shocks are used to implement a new policy rule, under which an investment specific technology shock produces different effects compared to the observed data. Instead, we use several weather shocks to implement a zero response in temperatures, which leads to potentially different outcomes in GDP for the economic shocks of this paper. The authors argue that the counterfactual is robust to the Lucas critique, essentially because the shocks which implement the counterfactual path of the targeted variable (in their case nominal rates, for us temperatures) only occur on impact, but are such that the desired path obtains thereafter. This is just a single surprise and agents have no reason to expect it or change their view of the world in anticipation of more such shocks. Mechanically, to exactly implement the desired path – in our case a zero temperature response for 60 periods everywhere in the US – would require 60 shocks *per grid cell*, a number which is obviously not available. The solution consists in finding a combination of a few available (and distinct) shocks that minimizes the deviation from the desired path across the US according to a squared loss function. In the context of our climate-economic model, this implies the following steps: first, identify the three economic shocks as before and find the conditional temperature maximizers everywhere in the US. We use five shocks for this, the maximizers of high- and business cycle frequencies as these are better described as weather shocks due to less interference from economic

[3]Of course there are damages that stem from the release of toxic gases themselves, not the implied warming, as documented in Carleton et al. (2022) and Deschenes (2022), for example. We do not zero out these effects in the counterfactual.

shocks, US-based or international. Collect the associated columns of H in the matrix H_c. Call the structural responses of Y_t to these shocks $P(L) = D(L)H_c$. Second, for a given economic shock vector u^E, find the corresponding temperature shocks u^T which minimize the responses of temperatures over the horizons $j = 1, ..., J$ at all locations $i = 1, ..., N$. u^E is in our case a 3×1 vector whose elements are zeros except for a one in the position of the current shock of interest. Third, recompute the implied IRFs. Formally, we ideally want to achieve:

$$\Lambda P_j^E u^E + \Lambda P_j^T u^T = \mathbf{0}_N \quad \forall j$$

where the superscript E implies picking the columns related to the economic shocks and analogously for T. That is, the response to all shocks in the system described by H_c of temperatures everywhere should be zero at all impulse response horizons. This is not possible, because there are $N \times J$ conditions and far fewer shocks. Therefore, we solve a least-squares problem which minimizes the error e_j between the temperature IRFs with and without u^T:

$$\Lambda P_j^E u^E + \Lambda P_j^T u^T = e_j \quad \forall j$$

The objective is then to minimize the sum of the sums of squared errors over all grid cells and all horizons:

$$\hat{u}^T = \underset{u^T}{\arg\min} \quad \sum_{j=0}^{J} e_j' e_j = \underset{u^T}{\arg\min} \quad \sum_{j=0}^{J} (P_j^E u^E + \Lambda P_j^T u^T)'(P_j^E u^E + \Lambda P_j^T u^T) \tag{12}$$

The closed form solution of this is given by

$$\hat{u}^T = -\left(\sum_{j=0}^{J} \left(\Lambda P_j^T\right)' \left(\Lambda P_j^T\right) \right)^{-1} \left(\sum_{j=0}^{J} \left(\Lambda P_j^T\right)' \left(\Lambda P_j^E u^E\right) \right) \tag{13}$$

We can then compute the counterfactual IRFs (IRF_c) to the economic shock of interest that occurs simultaneously with the weather shocks that implement the desired path of US temperatures as best as possible from $IRF_c = P(L)[u^E, \hat{u}^T]'$.

Figure 15: Counterfactual IRFs of real GDP to the three economic shocks with temperature responses across the US muted to zero.

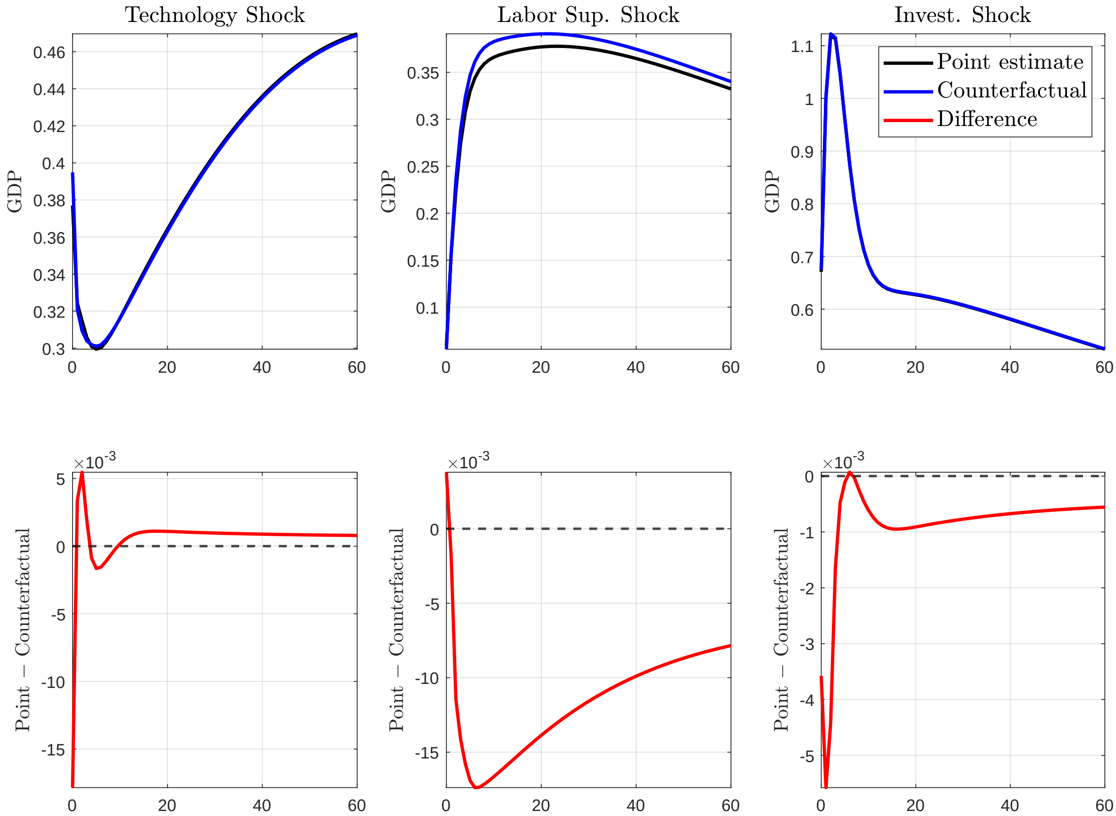


Figure 15 reports the results of this exercise. The differences in the paths are very small, in the order of -0.0078% for the labor supply shock, -0.0006% for the investment shock and essentially 0.0008 for the technology shock after 15 years. Given that the temperature IRFs after the expansionary shocks are already very close to zero, the shocks necessary to bring them even closer are quite small, around 10% , 7%, and 4% of a standard deviation for the respective shocks. Nevertheless, the signs of the differences suggest that if there were no spillback from temperature changes into the economy after an expansionary shock, output would generally be higher than what we measure in the true data. A policy that was able to achieve this outcome would still (in non-discounted terms) save between 1 (investment shock) and 1.4 (labor supply) billion dollars if the shock occurred in 2017. Importantly this is not the same as computing the savings implied by avoiding the emission of climate-active gases. This would require mitigation technologies to zero out the total emissions implied by the economic expansion. Rather, our counterfactual only speaks to a situation where natural circumstances are such that the effect from the emission of climate-active gases is offset on temperatures. Such Lucas critique robust counterfactuals offer interesting potential for assessing, for example, the cost of implementing mitigation policies that are able to nullify emissions after an economic expansion or the technology improvements necessary for perfect adaptation to a given climate shock.

Ciccarelli & Marotta (2021) make strides in this direction using a similar methodology. We aim to explore this further in the future.

7 Conclusion

We propose to model a joint climate-economic system to investigate the effect of economic shocks on temperatures in the US and vice versa. Using the principal components of a large, gridded data set of US temperatures we show that five shocks are necessary to accurately reflect temperature variations of different frequencies everywhere in the contiguous US. We show that a clear connection between economy and temperatures exists, which is mostly driven by changes in TFP. We identify three economic shocks, arguably responsible for a bulk of business-cycle and long-term variation in the US economy and thus emissions of climate-active gases – a technology shock, a labor supply shock, and an investment shock. Identification in the frequency domain allows us to mix medium term and long-term identification assumptions. Together these shocks account for around 25% of the low frequency component of US temperatures. Investment shocks increase temperatures on average, technology shocks decrease them, suggesting that growth without warming may be possible through technological improvements and giving a significant role to aerosol emissions together with GHG emissions. Labor supply shocks have a less pronounced effect on temperatures. On the other hand, we show that temperature changes that affect primarily the US West coast lead to economic expansions, as they are accompanied by decreasing temperatures in the east and south. Shocks raising temperatures elsewhere are mildly recessionary. We conclude by proposing a counterfactual exercise, through which we assess by how much output would react if temperature shocks are recombined to minimize any endogenous temperature response in the US. We find that for the labor supply shock and the investment shock output would be higher in the absence of temperature feedback. However, in monetary terms, the gains from cutting the link between the economy and temperatures (not gas emissions!) is minimal for the US, suggesting that it has been well adapted to climate feedback in the past.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. (2020). The effects of weather shocks on economic activity: what are the channels of impact? *Journal of Macroeconomics*, *65*, 103207.

Alessi, L., Barigozzi, M., & Capasso, M. (2010). Improved penalization for determining the number of factors in approximate factor models. *Statistics & Probability Letters*, *80*(23-24), 1806–1813.

Angeletos, G.-M., Collard, F., & Dellas, H. (2020). Business-cycle anatomy. *American Economic Review*, *110*(10), 3030–70.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., & Shapiro, J. S. (2015). Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. *American Economic Review*, *105*(5), 247–251.

Barsky, R. B., & Sims, E. R. (2011). News shocks and business cycles. *Journal of monetary Economics*, *58*(3), 273–289.

Bastien-Olvera, B. A., Granella, F., & Moore, F. C. (2022). Persistent effect of temperature on gdp identified from lower frequency temperature variability. *Environmental Research Letters*, *17*(8), 084038.

Bennedsen, M., Hillebrand, E., & Koopman, S. J. (2021). Modeling, forecasting, and nowcasting us co2 emissions using many macroeconomic predictors. *Energy Economics*, *96*, 105118.

Ben Zeev, N., & Khan, H. (2015). Investment-specific news shocks and us business cycles. *Journal of Money, Credit and Banking*, *47*(7), 1443–1464.

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (favar) approach. *The Quarterly journal of economics*, *120*(1), 387–422.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239.

Cai, Y., & Lontzek, T. S. (2019). The social cost of carbon with economic and climate risks. *Journal of Political Economy*, *127*(6), 2684–2734.

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., ... others (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, *137*(4), 2037–2105.

Ciccarelli, M., & Marotta, F. (2021). Demand or supply? an empirical exploration of the effects of climate change on the macroeconomy.

Colacito, R., Hoffmann, B., & Phan, T. (2019). Temperature and growth: A panel analysis of the united states. *Journal of Money, Credit and Banking*, *51*(2-3), 313–368.

de Juan, A., Poncela, P., Rodríguez-Caballero, V., & Ruiz, E. (2022). Economic activity and climate change. *arXiv preprint arXiv:2206.03187*.

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

Deryugina, T., & Hsiang, S. M. (2014). *Does the environment still matter? daily temperature and income in the united states* (Tech. Rep.). National Bureau of Economic Research.

Deschenes, O. (2022). The impact of climate change on mortality in the united states: Benefits and costs of adaptation. *Canadian Journal of Economics/Revue canadienne d'économique*, *55*(3), 1227–1249.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review*, *97*(1), 354–385.

Dieppe, A., Francis, N., & Kindberg-Hanlon, G. (2021). The identification of dominant macroeconomic drivers: coping with confounding shocks. *ECB Working Paper, No. 2021/2534*.

Donadelli, M., Jüppner, M., Riedel, M., & Schlag, C. (2017). Temperature shocks and welfare costs. *Journal of Economic Dynamics and Control*, *82*, 331–355.

Erichson, N. B., Zheng, P., Manohar, K., Brunton, S. L., Kutz, J. N., & Aravkin, A. Y. (2020). Sparse principal component analysis via variable projection. *SIAM Journal on Applied Mathematics*, *80*(2), 977–1002.

Fernald, J. (2014). A quarterly, utilization-adjusted series on total factor productivity. *Federal Reserve Bank of San Francisco Working Paper, No. 2012/19*.

Forni, M., Gambetti, L., Antonio, G., Sala, L., & Soccorsi, S. (2023). An american macroeconomic picture. *mimeo*.

Forni, M., Gambetti, L., & Sala, L. (2014). No news in business cycles. *The Economic Journal*, *124*(581), 1168–1191.

Forni, M., Giannone, D., Lippi, M., & Reichlin, L. (2009). Opening the black box: Structural factor models with large cross sections. *Econometric Theory*, *25*(5), 1319–1347.

Foroni, C., Furlanetto, F., & Lepetit, A. (2018). Labor supply factors and economic fluctuations. *International Economic Review*, *59*(3), 1491–1510.

Francis, N., & Ramey, V. A. (2009). Measures of per capita hours and their implications for the technology-hours debate. *Journal of Money, credit and Banking*, *41*(6), 1071–1097.

Gali, J. (1999). Technology, employment, and the business cycle: do technology shocks explain aggregate fluctuations? *American economic review*, *89*(1), 249–271.

Gourio, F., & Fries, C. (2020). Adaptation and the cost of rising temperature for the us economy.

Greene, C. A., Thirumalai, K., Kearney, K. A., Delgado, J. M., Schwanghart, W., Wolfenbarger, N. S., ... Blankenship, D. D. (2019). The climate data toolbox for MATLAB. *Geochemistry, Geophysics, Geosystems*. Retrieved from `https://doi.org/10.1029/2019GC008392` doi: 10.1029/2019GC008392

Hannachi, A., Jolliffe, I. T., & Stephenson, D. B. (2007). Empirical orthogonal functions and related techniques in atmospheric science: A review. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *27*(9), 1119–1152.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., ... others (2017). Estimating economic damage from climate change in the united states. *Science*, *356*(6345), 1362–1369.

IPCC. (2023). *Ar6 synthesis report: Climate change 2023.* Retrieved from `https://www.ipcc.ch/report/sixth-assessment-report-cycle/`

Justiniano, A., Primiceri, G. E., & Tambalotti, A. (2010). Investment shocks and business cycles. *Journal of Monetary Economics*, *57*(2), 132–145.

Justiniano, A., Primiceri, G. E., & Tambalotti, A. (2011). Investment shocks and the relative price of investment. *Review of Economic Dynamics*, *14*(1), 102–121.

Kaufmann, R. K., Kauppi, H., Mann, M. L., & Stock, J. H. (2013). Does temperature contain a stochastic trend: linking statistical results to physical mechanisms. *Climatic change*, *118*, 729–743.

Khan, H., Metaxoglou, K., Knittel, C. R., & Papineau, M. (2019). Carbon emissions and business cycles. *Journal of Macroeconomics*, *60*, 1–19.

Kilian, L. (1998). Small-sample confidence intervals for impulse response functions. *Review of economics and statistics*, *80*(2), 218–230.

Kim, H. S., Matthes, C., & Phan, T. (2021). Extreme weather and the macroeconomy. *Available at SSRN 3918533*.

Magnus, J. R., Melenberg, B., & Muris, C. (2011). Global warming and local dimming: The statistical evidence. *Journal of the American Statistical Association*, *106*(494), 452–464.

Matsuura, K., & Willmott, C. J. (2018). Terrestrial air temperature: 1900–2017 gridded monthly time series. *University of Delaware, Newark, DE*. Retrieved from `http://climate.geog.udel.edu/~climate/html_pages/download.html#T2017`

McKay, A., & Wolf, C. K. (2023, September). What can time-series regressions tell us about policy counterfactuals? *Econometrica*, *91*(5), 1695–1725.

Mountford, A., & Uhlig, H. (2009). What are the effects of fiscal policy shocks? *Journal of applied econometrics*, *24*(6), 960–992.

Mumtaz, H., & Marotta, F. (2023). *Vulnerability to climate change. evidence from a dynamic factor model* (Tech. Rep.).

Nath, I. B., Ramey, V. A., & Klenow, P. J. (2023). *How much will global warming cool global growth?* (Tech. Rep.). Working paper.

Natoli, F. (2023). The macroeconomic effects of temperature surprise shocks. *Available at SSRN 4160944*.

Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The gdp-temperature relationship: implications for climate change damages. *Journal of Environmental Economics and Management*, *108*, 102445.

NOAA. (2023). *What are la niña and el niño and why do they matter?* Retrieved from `https://www.ipcc.ch/report/sixth-assessment-report-cycle/`

Peersman, G., & Straub, R. (2009). Technology shocks and robust sign restrictions in a euro area svar. *International Economic Review*, *50*(3), 727–750.

Pretis, F. (2020). Econometric modelling of climate systems: The equivalence of energy balance models and cointegrated vector autoregressions. *Journal of Econometrics*, *214*(1), 256–273.

Pretis, F. (2021). Exogeneity in climate econometrics. *Energy Economics*, *96*, 105122.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. *Handbook of macroeconomics*, *2*, 71–162.

Shapiro, M. D., & Watson, M. W. (1988). Sources of business cycle fluctuations. *NBER Macroeconomics annual*, *3*, 111–148.

Smith, S. J., van Aardenne, J., Klimont, Z., Andres, R. J., Volke, A., & Delgado Arias, S. (2011). Anthropogenic sulfur dioxide emissions: 1850–2005. *Atmospheric Chemistry and Physics*, *11*(3), 1101–1116.

Storelvmo, T., Leirvik, T., Lohmann, U., Phillips, P. C., & Wild, M. (2016). Disentangling greenhouse warming and aerosol cooling to reveal earth's climate sensitivity. *Nature Geoscience*, *9*(4), 286–289.

Uhlig, H. (2003). What drives gnp? *Unpublished manuscript, Euro Area Business Cycle Network*.

Zickfeld, K., & Herrington, T. (2015). The time lag between a carbon dioxide emission and maximum warming increases with the size of the emission. *Environmental Research Letters*, *10*(3), 031001.

8 Appendix

8.1 Data construction

We follow Angeletos et al. (2020) in constructing the economic variables.

Table 5: Economic Data Sources and Transformations

Data	FRED Mnemonic	Frequency/Transformation
Real gross domestic product per capita	A939RX0Q048SBEA	Q
Real Gross domestic product	GDPC1	Q
Share of GDP: gross private domestic investment	A006RE1Q156NBEA	Q
Share of GDP: personal consumption expenditures: durable goods	DDURRE1Q156NBEA	Q
Nonfarm business sector: average weekly hours	PRS85006023	Q
Employment Level	CE16OV	M2Q (EoP)
Total factor productivity (annualized Q-Q growth rate)	dTFPu (from Fernald)	Q
Relative price of investment	from Angeletos et al. (2020)	Q

The variables enter the model as follows:

1. **Real GDP:** $\log(GDPC1) \times 100$
2. **Real investment:** $\log((DDURRE1Q156NBEA + A006RE1Q156NBEA) \times GDPC1) \times 100$

3. **Hours:** $\log(PRS85006023 \times CE16OV) \times 100$

4. **TFP:** $\text{cumsum}(dTFPU/400) \times 100$

5. **Population:** $GDPC1/A939RX0Q048SBEA$

6. **Relative price of investment:** See description in Angeletos et al. (2020), Online Appendix G.5

7. **Labor productivity:** $\frac{GDPC1}{PRS85006023 \times CE16OV}$

For checks, the variables real GDP, real investment, and hours can be transformed to per capita units by dividing by the population level as computed above before taking logs.

8.2 US census regions

We distinguish the following census regions according to `https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf`:

- East North Central (Illinois, Indiana, Michigan, Ohio, and Wisconsin)
- East South Central (Alabama, Kentucky, Mississippi, and Tennesse)
- Middle Atlantic (New Jersey, New York, and Pennsylvania)
- Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming)
- New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont)
- Pacific (Alaska, California, Hawaii, Oregon, and Washington)
- South Atlantic (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, Washington, D.C., and West Virginia)
- West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota)
- West South Central (Arkansas, Louisiana, Oklahoma, and Texas)

8.3 Bootstrap procedure

We compute confidence bands for the IRFs and the cyclical variances using the following bootstrap procedure:

1. Use (2) to generate a new vector Y_t by bootstrapping from the reduced form residuals.
2. Use the method of Kilian (1998) to correct the bias of the OLS estimates.
3. Use Λ to recompute the common component of temperatures, ΛY_t, and add the original idiosyncratic component, η_{it}, to get a new data set of US temperatures.
4. On this new data set, estimate $r = 8$ principal components, and re-estimate a bootstrap Λ^B.
5. Estimate the FAVAR in (2) again with $p = 2$
6. Identify the shocks sequentially, compute IRFs and the cyclical variances
7. Repeat this $1,500$ times to obtain bootstrap distributions of the IRFs and the cyclical variances.
8. Find the quantiles of the bootstrap distributions to get the 68% and 90% intervals.

8.4 Robustness checks

To test the sensitivity of our results to the underlying assumptions we conduct the following robustness checks:

1. Changing the number of temperature factors:
We have used a statistical criterion to determine the number of factors to be extracted from the gridded temperature data set and opted for $r = 8$ in our preferred specification for parsimony. The upper bound recommended by the criterion was $r = 17$, which we test. In this case we set $p = 1$ according to the BIC.

2. More lags:
Our results concern mostly the low frequency components of temperatures. There may be reason to believe that this is inaccurately reflected in our model if the lag length is very short. In the baseline specification we had used $p = 2$. We increase this to $p = 4$ as a check. Given the frequentist approach to estimation, results become quite erroneous for even larger lag orders.

3. Sub-sample analysis:
We have used data between 1948 and 2017. The trend in temperatures that is usually attributed to human influence becomes visible in our data as of around 1970. We repeat our exercise by excluding the first 22 years from the sample. We re-estimate the recommended numbers of factors and lags to be $r = 9$ (ABC criterion lower bound) and $p = 1$ (BIC) in that case.

4. Maximizing long-run IRFs instead of variances:
An alternative to maximizing variances is represented by maximizing the long-run IRF of TFP (and hours). This is used, for example, in Forni et al. (2014). Since the connection between the economy and temperatures appears to run largely through TFP, correct identification of the technology shock is crucial.

5. Variables in per capita terms:
Long-run economic dynamics may be affected by demographic sources (Francis & Ramey, 2009) which we are not taking explicitly into account in our baseline specification. Population changes are an important source of emission variations according to the *Kaya identity*. We therefore check, whether expressing the economic variables GDP, hours and investment in per capita terms changes our results.

6. Labor productivity instead of TFP:
Our technology shock is identified by maximizing the low frequency component of TFP, an approach inspired by Dieppe et al. (2021). The authors use labor productivity instead. We test how changing this important variable affects our conclusions. We compute labor productivity as the ratio of real GDP to hours worked using the variable definitions as described in the appendix.

7. Targeting the relative price of investment:
We target investment variations to obtain the investment shock in the baseline specification. Taking the results in Justiniano et al. (2010) and Justiniano et al. (2011) as a basis, this should identify a shock to the marginal efficiency of capital, or the efficiency of transforming investment to productive capital. Khan et al. (2019) also argue that investment specific technology shocks are important drivers of emissions. They use the relative price of investment (RPI) for identification rather than investment itself. We test robustness of our results to changing the variable to the RPI. The RPI we use is directly taken from publicly available data from Angeletos et al. (2020).

Robustness results:
Figures 16 and 17 show the IRFs for average US temperatures to the economic shocks.

Since robustness checks 1-5 leave the set of economic variables unchanged, but 6 and 7 do not, we split the presentation of the results into two plots, the former reporting the results for the stable set of economic variables and the latter those where the identifying variables are changed. The most significant differences arise when we change the sub-sample to post 1970, as then the technology shock leads to positive temperature responses and similarly when we change to using labor productivity instead of TFP for identification of the technology shock. This seems to suggest that the change in trend in the baseline sample from 1948-2017 affects the sign of the TFP response. Kim et al. (2021) investigate the time-varying responses of US output to temperature shocks. Here it seems like the reverse relationship – economic shocks on temperatures – could require explicit modeling of time-varying effects as well. We leave this for future research.

Figure 16: Impulse response functions of US average temperatures to economic shocks for robustness checks 1-5.

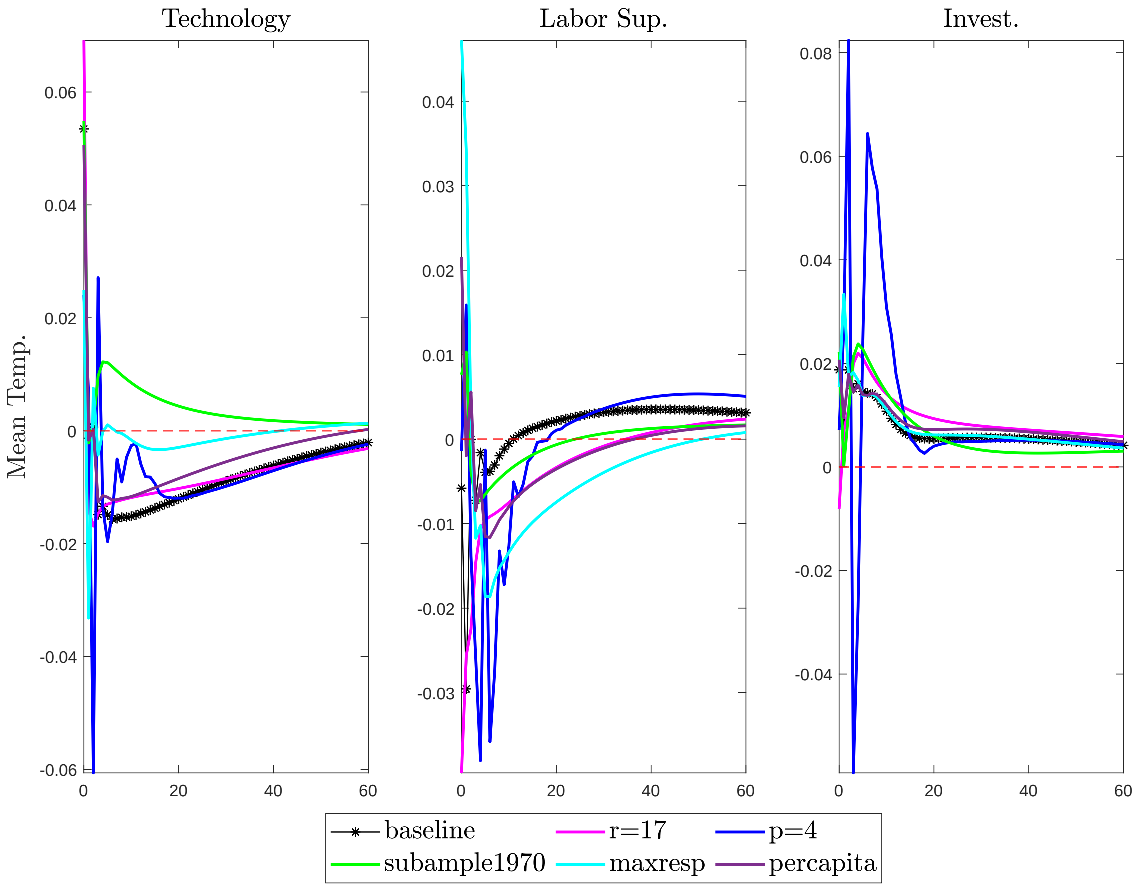
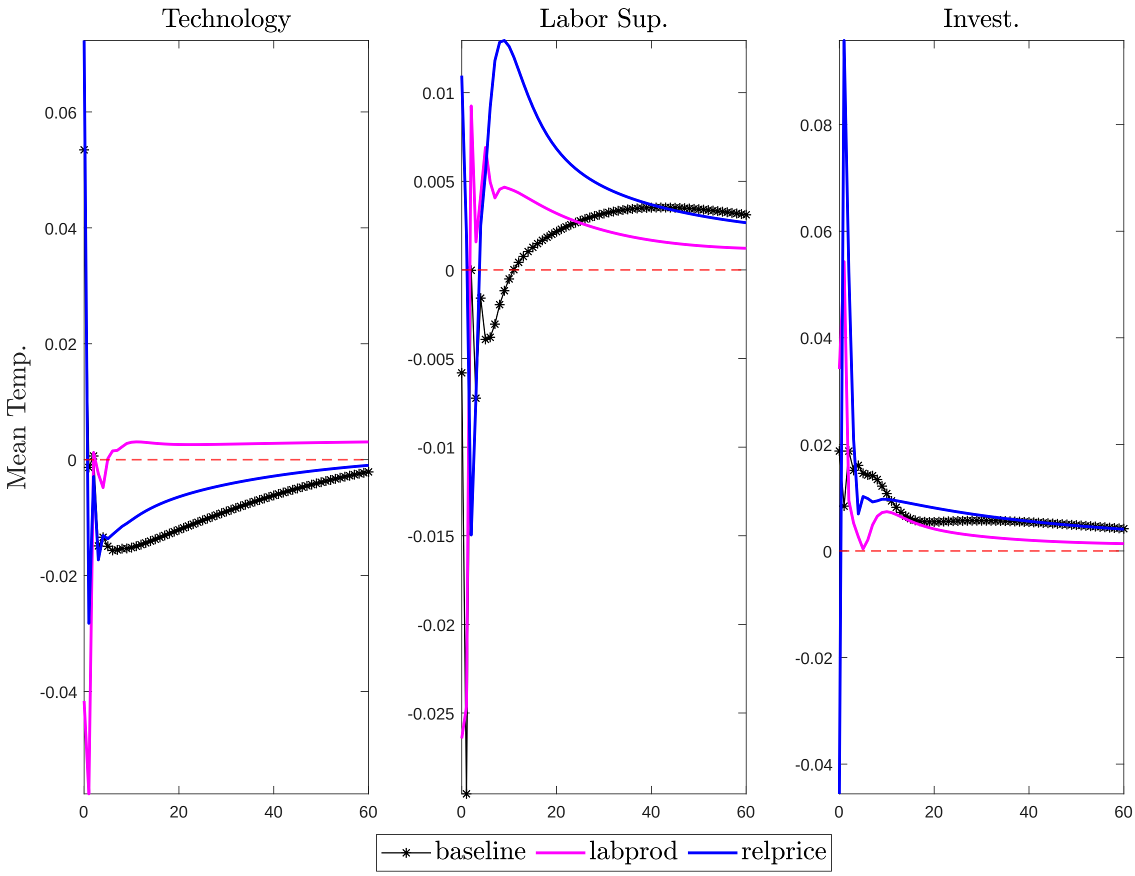


Figure 17: Impulse response functions of US average temperatures to economic shocks for robustness checks 6 and 7.



Figures 18 and 19, on the other hand, report the IRFs of real GDP to the different temperature shocks for all seven robustness checks. We observe that changing the number of temperature principal components or the number of lags has negligible effects on the IRFs compared to our baseline specification. The same goes for taking the variables in per capita terms. Changes in the responses of GDP to the temperature shocks are slightly more pronounced if we use labor productivity instead of TFP or the maximal response identification strategy to obtain the technology shock and then condition the temperature shocks on it. All in all, the baseline specification lies roughly in the middle of the IRFs under the different robustness checks. We leave the robustness check IRFs of the economic variables to the economic shocks in the Appendix since the only minor difference arises when using the response maximization approach over the cyclical variance maximization approach.

Figure 18: Impulse response functions of GDP to temperature shocks for robustness checks 1-5.

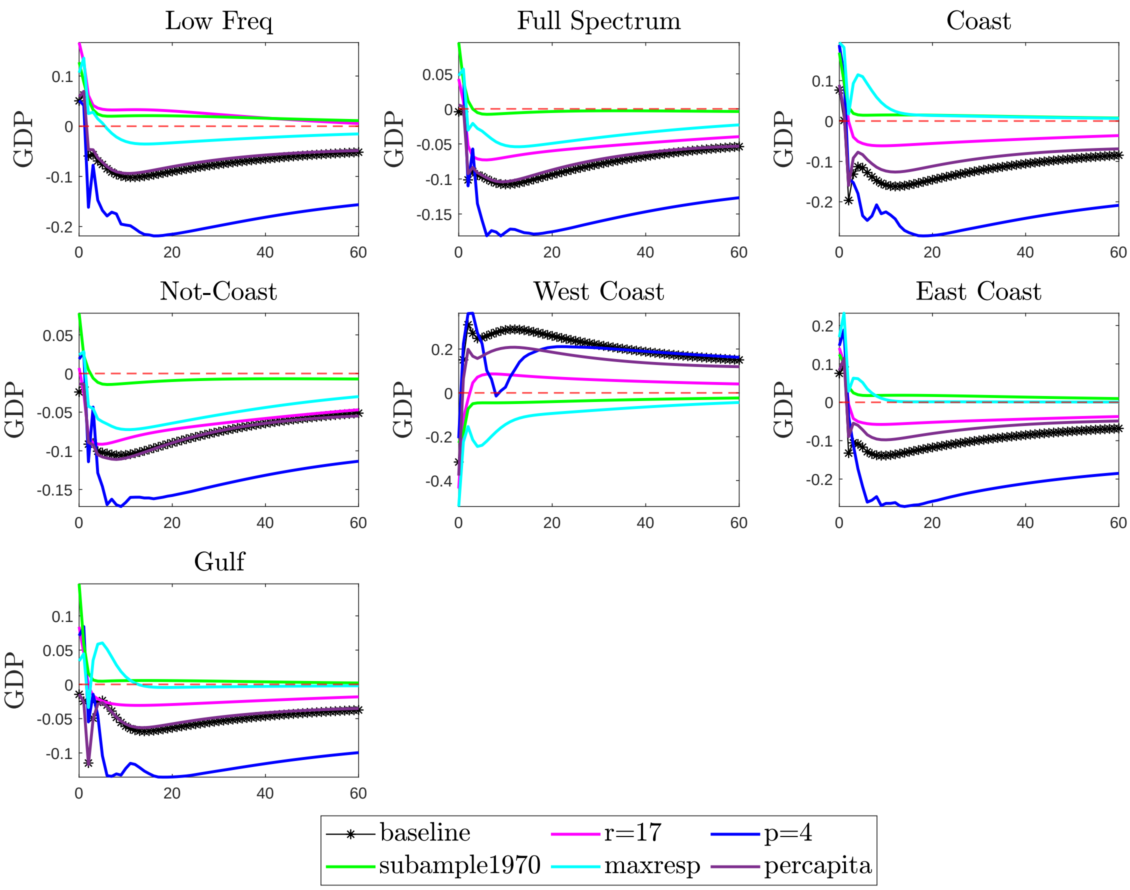


Figure 19: Impulse response functions of economic variables to economic shocks for robustness checks 6 and 7.

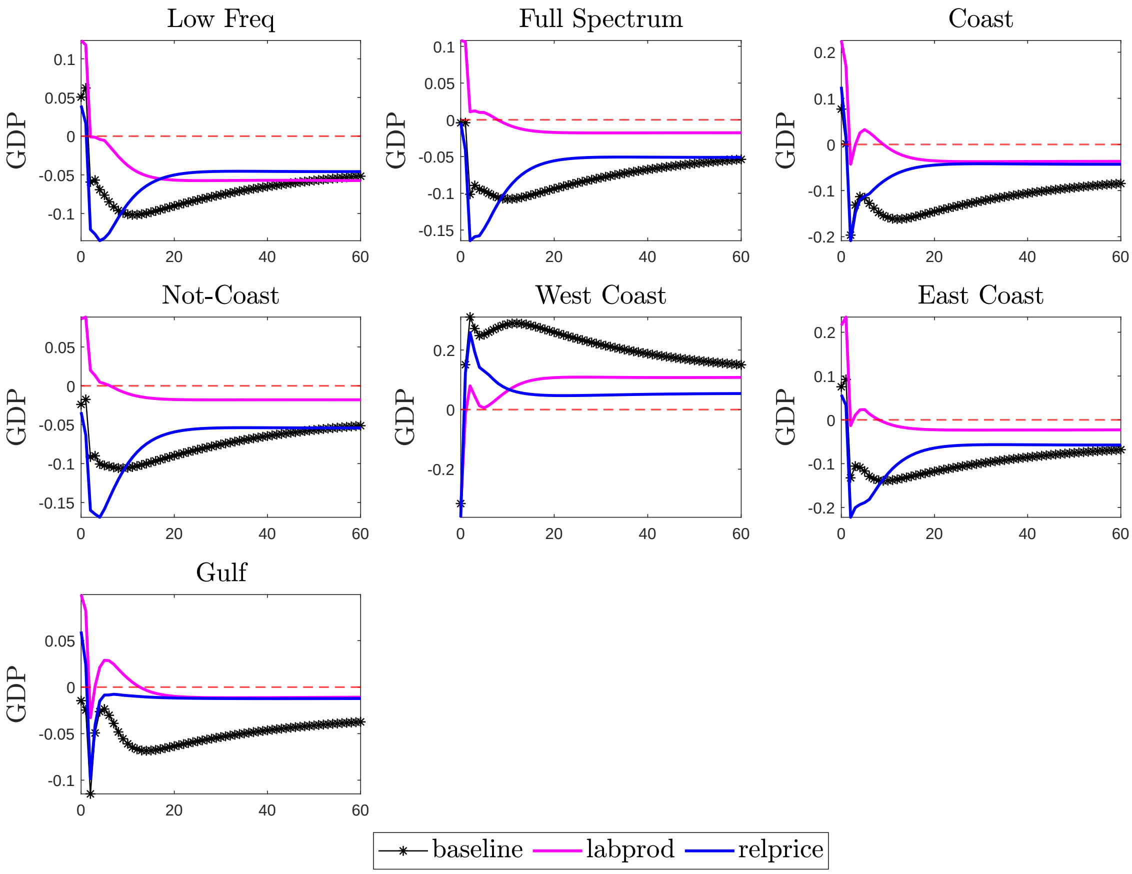


Figure 20: Impulse response functions of economic variables to economic shocks for robustness checks 1-5.

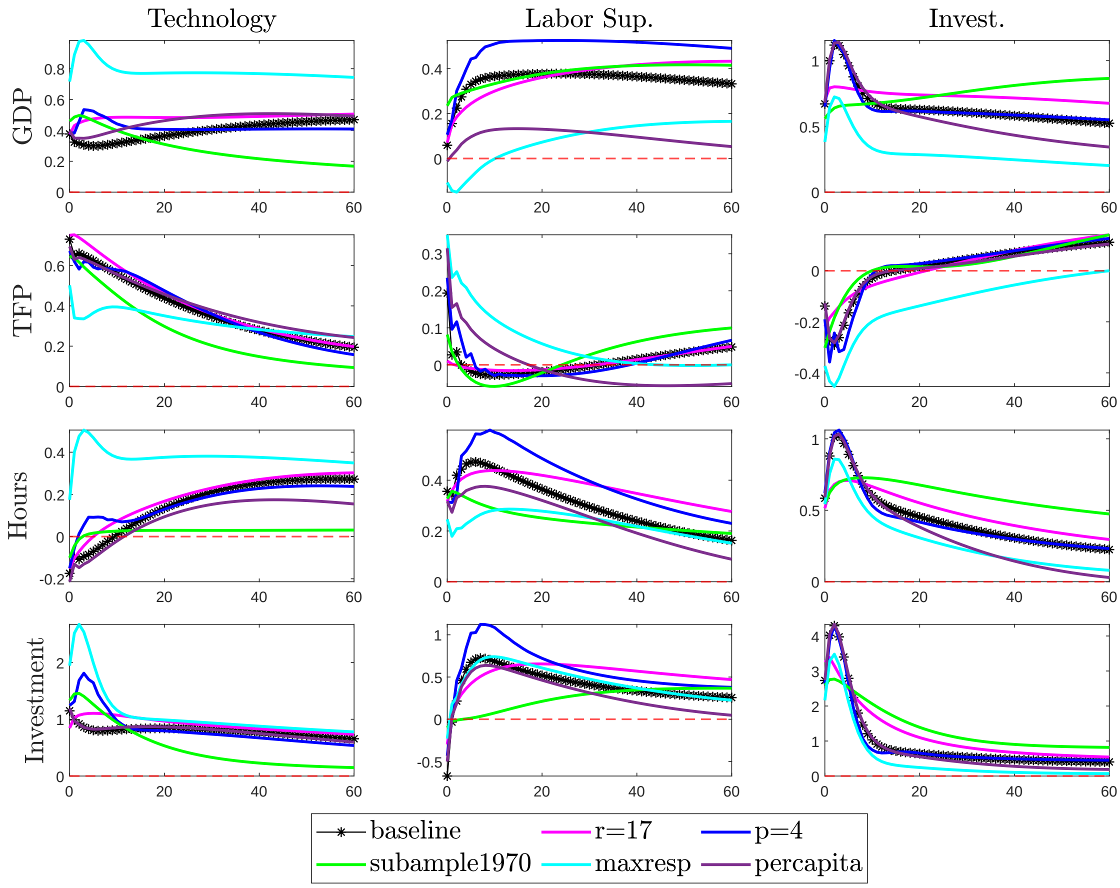


Figure 21: Impulse response functions of economic variables to economic shocks for robustness checks 6 and 7.