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Essays in Applied Time Series Econometrics

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Essays in Applied Time Series Econometrics

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ESSAYS IN
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To my son, Edoardo.

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CONTENTS

PREFACE

This doctoral thesis exploits time series data to investigate two relevant topics in the macroeconomic and macroeconometric literature: financial instabilities and climate change.

In the first chapter, I develop a new monthly financial systemic stress indicator (FSSI) for 20 major economies, and I investigate the international transmission of financial shocks from the United States (US) to the other countries in the sample. The findings show a significant global rise in financial stress following US shocks, with emerging economies being more affected. Additionally, US economic slowdowns have a delayed but substantial impact on the financial stability of most countries in the sample.

In the second chapter, co-authored with Konstantin Boss, we use a factor-augmented VAR to investigate the contribution of the US economy to fluctuations in temperatures since 1940. This econometric framework allows to disentangle natural from anthropogenic sources of temperature variation. We show that socio-economic activity has been responsible for around 25% of the long-term temperature variation in the US.

In the third chapter, co-authored with Konstantin Boss, we provide new evidence on the time-varying effects of temperature shocks on the economic activity of the US. Using a TVC-VAR model, we document that temperature shocks of the same size have triggered less severe economic responses in recent decades, suggesting increased adaptation to rising temperatures.

Chapter 1

INTERNATIONAL TRANSMISSION OF US FINANCIAL SHOCKS

Alessandra Testa

Abstract: This paper examines the international transmission of financial shocks from the United States to 20 major economies. The analysis employs a novel monthly financial systemic stress indicator, constructed for a broad set of advanced and emerging markets. Using quarterly data from 1995 to 2020, I first estimate financial shocks originating in the United States, and then incorporate these into country-specific vector autoregressive (VAR) models to assess the cross-border spread of financial stress. The findings reveal a significant global increase in financial stress following an unexpected shock in the United States, with the effect being more pronounced in emerging economies. Additionally, the results indicate that economic slowdowns in the United States have a delayed but substantial impact on the financial stability of most countries in the sample.

Keywords: Financial stress index, macro-financial linkages, emerging market economies.

JEL classification: E32, E44, F36, G01, G10.

1 INTRODUCTION

The 2008 global financial crisis (GFC) highlighted the importance of measuring and monitoring financial stress. The crisis in the United States (US), initially triggered by the subprime mortgage crisis, resulted in a deterioration of financial conditions and severe economic recession worldwide. While industrialised countries were directly exposed to the turmoil, emerging countries were not immune to the associated shocks and were also negatively affected (Baur, 2012). The GFC demonstrated that financial shocks may disrupt business cycles, and the economy may enter a vicious cycle in which financial and economic distress reinforce each other (Miglietta and Venditti, 2019). Before the GFC the potential impact of financial shocks were vastly underestimated since central banks were primarily focused on price stability. There has been renewed interest in recent years on the impact of financial crisis on the real economy and in cross-border spillovers of financial instability and recession. Addressing these issues is crucial for short-term monetary policy and financial regulation. This paper investigates the transmission of financial stress from the US to advanced and emerging market economies.

There is no agreed definition of financial stress in the literature. Nevertheless, it seems that past financial crises have characteristic symptoms that can occur individually or together. (Altınkeski et al., 2022)

Yao et al. (2020) define a financial crisis as a period of high *systemic* financial stress in which shocks spill over to the real economy, leading to recession. An increase in financial stress is generally associated with an interruption of financial markets' normal functioning, with a sudden increase in uncertainty and risk, large shifts in asset prices and the increased fragility of the banking sector (Hakkio and Keeton, 2009; Balakrishnan et al., 2011).

Identifying periods of high financial stress is often challenging due to the complexity of the financial system. Many studies measure the instability of individual market segments, often using a single variable to capture market-specific-stress symptoms. For instance, indices of option price volatility, such as the VIX, which is considered a "fear gauge", are used as an indicator of stress in the financial market (Chavleishvili and Kremer, 2021). However, these standard individual measures make it complicated to disentangle whether instability arising in one segment reflects idiosyncratic or systemic stress.

More precise measurements of financial stress should account for different sources of risks and vulnerabilities. Studies emphasise the importance of accounting for the degree of interdependence among financial markets and the co-movement and contagion of financial sector variables (see e.g. Hollo, Kremer and Lo Duca, 2012; Chatterjee et al., 2017; Kisten, 2020). Interconnectedness is generally related to the concept of systemic stress since the more financial stress is interconnected among market segments, the more widespread the financial turmoil. Accordingly, several studies propose financial stress indexes that quantify the aggregate level of stress by aggregating several variables into a single statistic.

In their pioneering work, Illing and Liu (2006) develop a daily financial stress index for Canada, proposing several approaches to aggregating indices of financial instability into a composite indicator. Relying on a Bank of Canada survey, the authors identify the set of variables and specifications that best capture the most stressful events. Hakkio and Keeton (2009) at the Federal Reserve Bank of Kansas City construct a monthly financial stress indicator(FSI), known as the KCFSI and employ principal component (PC) analysis to aggregate eleven daily financial market indices; each index is weighted employing the loadings to the first PC. A similar methodology is employed by Kliesen and Smith (2010). Yiu et al. (2010) and Cardarelli, Elekdag and Lall (2011) construct monthly FSIs computed by averaging various standardised market-based indices with variance-equal weighting for 17 advanced economies and Hong Kong. The European Central Bank periodically publishes its Composite Indicator of Systemic Stress (CISS). This indicator, originally proposed by Hollo, Kremer and Lo Duca (2012), is based on 15 market-based measures of financial stress aggregated by applying basic portfolio theory to account for their cross-correlations. The real-time nature of this indicator permits its use as a macroprudential tool to monitor financial stress. Dovern and van Roye (2014) construct a monthly indicator for 20 major economies through a simple aggregation of six indices of financial instability for each.

While many indices have been proposed to measure financial stress in advanced economies, scant attention has been paid to emerging markets. Balakrishnan et al. (2011) construct an aggregated FSI to analyse the passage of financial crises from advanced to emerging economies. Kisten (2020) develops an index to monitor financial instabilities in South

Africa, Yao et al. (2020) construct the first FSI for China, and Truong et al. (2022) set up early warning indicators for a set of Asian countries.

This paper contributes to long-standing research on interactions between the economic and financial sectors. One strand of this literature examines the relationship between financial stress and economic activity. For example, in their foundational study, Bernanke (1983) analyses the impact of the Great Depression on the US macroeconomy. Davig, Hakkio et al. (2010) find that the US economy fluctuates between financial stress regimes; financial stress has a greater impact on economic activity under the 'distressed regime' than under normal conditions. Gilchrist and Zakrajšek (2012) show that shocks to their innovative excess bond premium caused significant and protracted contractions in US economic activity and reduced short and long-term risk-free rates. Mallick and Sousa (2013) study the real effects of financial stress on the Eurozone, showing that an unexpected monetary policy contraction worsens financial stress conditions and sudden increases in financial instability increases the demand for expansionary policies. In the aftermath of the GFC there have been many papers that have tackled the impact of financial conditions on the real economy and the output costs of financial crisis (see e.g. Barkbu, Eichengreen and Mody, 2012; Schularick and Taylor, 2012; Hartmann et al., 2015).

Another line of research explores the transmission of financial stress between countries. Evgenidis and Tsagkanos (2017) employ a threshold-vector auto-regression (VAR) model to analyse the spread of a negative financial shock in the US to the Eurozone. Dovern and van Roye (2014) estimate a global VAR model to show the business-cycle effects and international transmission of financial stress and Altınkeski et al. (2022) consider the bilateral transmission of financial stress between the US and the Eurozone.

Although there is a rapidly growing literature on the transmission of financial instabilities, few studies take a global perspective. I contribute to the literature on financial stress in several ways. First, I develop a new country-specific financial systemic stress indicator (FSSI) for a large set of advanced and emerging economies. This study complements the existing literature by providing a broad and comparable high-frequency measure of systemic stress allowing for a more systematic analysis of stress transmission among advanced and emerging countries. Second, the empirical investigation here sheds light on the transmission of financial shocks from the US to advanced and emerging countries.

I propose a two-step identification strategy. Using a monthly VAR model for the US, I identify the financial shock following the scheme in Gilchrist and Zakrajšek (2012) and then assess its international transmission using the estimated US financial shock in country VARs. Finally, I extend the baseline model to explore whether an economic slowdown in the US impacts the financial stability of other countries.

I find that a financial shock in the US has substantial spillovers worldwide and that, on average, emerging economies are more affected than advanced countries. Increased financial stress in the US quickly transmits internationally, leading to a hump-shaped FSSI response for most of the countries in the sample. Results from the extended framework show that an economic slowdown in the US causes considerable financial instability in some countries, although the extent of financial stress is smaller outside the US.

The remainder of the paper is organised as follows. In Section 2, I describe the conceptual framework for analysing systemic financial stress and then proceed to construct the FSSI. In Section 3 I analyse how financial shocks are transmitted internationally, and set out my conclusions in Section 4.

2 Financial Systemic Stress Indicator

2.1 Theoretical Background

The data and methodologies selected to construct an indicator of financial instability must account for the insights offered by economic theory and historical crises. Despite the growing literature on its measure, there is still no commonly accepted and precise definition of financial stress.

Hollo, Kremer and Lo Duca (2012) note that financial stress may be defined as the amount of systemic risk which has already materialised. In turn, systemic risk has been described as the risk of experiencing a powerful systemic event that can have adverse effects on several systemically important intermediaries or markets and, as “the risk of a disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy" (ECB, 2009; IMF-BIS-FSB, 2009). Systemic stress can thus be interpreted as an ex post measure of systemic risk, and the FSSI can be seen as a coincident financial (in)stability

indicator (Chavleishvili and Kremer, 2021).
What remains to be determined are the main symptoms associated with crises in the financial market. An increase in financial stress is generally associated with an interruption of the normal functioning of financial markets, a sudden rise in uncertainty and risk, significant shifts in asset prices and the increased fragility of the banking sector (Hakkio and Keeton, 2009; Balakrishnan et al., 2011). Existing studies emphasise the importance of accounting for the degree of interdependence among financial markets and the comovement and contagion of financial sector variables (e.g. Hollo, Kremer and Lo Duca, 2012; Chatterjee et al., 2017; Kisten, 2020). Interconnectedness and systemic stress are related; the more financial stress flows among interconnected market segments, the more widespread the financial turmoil. Recent attempts to develop indicators emphasise that in attempting to capture the systemic nature of financial stress, it is crucial to account for instabilities in different segments of the financial market and to identify periods in which more than one segment is under stress.
The FSSI developed in this paper is a modified version of the CISS by Hollo, Kremer and Lo Duca (2012) and aims to capture the broad and systemic nature of financial stress based on six input variables that capture instabilities in four segments of the financial market: stocks, bonds, foreign exchange and banking. The variables are transformed into relative ranks through cumulative distribution function (CDF) transformation and then aggregated into the final indicator by computing the cross-product of all the transformed variables weighted by the time-varying cross-correlations. As a result, the FSSI places greater weight on periods in which more than one market is under stress simultaneously.

2.2 Design of the FSSI

Data

The choice of variables for inclusion is crucial since the final indicator should capture key features of financial stress. The choice is, to some extent, driven by ex ante requirements: (i) the FSSI should be comparable across a large set of countries, (ii) available at a monthly frequency, and (iii) for a sufficiently long time to account for as many crisis events as possible. A higher-frequency variable may be desirable to identify changes in financial conditions and for policy purposes. However, the inclusion of emerging countries in the sample presents certain data limitations and I have prioritised cross-country comparability at the cost of frequency.

Different aspects of financial stress are accounted for by including a set of variables that can be individually interpreted as a measure of financial instability in the stock, bond, and foreign exchange markets and the banking sector. Each variable captures specific observable stress symptoms and increases with the level of stress. Appendix 5.1 reports a version of the indicator that includes the real estate market.

Data on the stock market, bond market, and banking sector have a daily frequency and come from Thomson Reuters Datastream, Bloomberg, FRED, and the websites of national central banks. The real effective exchange rate is available on the Bank of International Settlements (BIS) website at a monthly frequency. [1]. I include two variables to consider different sources that capture the level of strain in the stock market and banking sector. Ideally, they should record complementary information, be almost perfectly correlated under severe stress and slightly divergent in normal times (Hollo, Kremer and Lo Duca, 2012).

The new FSSI is available for a sample of 20 countries: Australia, Austria, Brazil, Canada, Chile, China, France, Germany, India, Indonesia, Italy, Mexico, the Philippines, Portugal, South Africa, South Korea, Spain, Thailand, the United Kingdom, and US. The sample countries were chosen based on data availability, which is limited for emerging economies.

The sample period spans from the first quarter of 1995 to the second quarter of 2020 for most of the advanced countries. Some countries in the sample have more limited data available for the macroeconomic and financial time series (e.g. China, India, Indonesia, and South Korea), hence the sample period starts from the early 2000s.

In the remainder of this section, I describe the variables.

Stock market: Financial stress in the stock market is identified with two variables. The first variable reflects the volatility of daily stock market returns estimated with a GARCH$(1,1)$ model. The second, a stock market crash indicator, reflects where there has been an equity crisis, defined as a period of sharp decline in equity prices that may indicate greater-than-expected loss or increased uncertainty about returns (Illing and Liu,

[1] Cubic spline interpolation is applied to match the monthly frequency of the dataset and the final indicator.

2006). I identify significant and abrupt price declines by computing the cumulative maximum loss (*CMAX*) of stock market prices as the ratio of the index at time t to its maximum over the previous T periods. [2]

$$CMAX = 1 - \frac{x_t}{max\ \left[x \in \left(x_{t-j} | j = 0, 1, ..., T, \right)\right]}$$

where x_t represents stock market prices at time t. The rolling window is set to two years (522 days due to the working days in a business year).

Banking Sector: Stress in the banking sector is captured by two variables. First, the short-term interbank lending rate measures banking sector fragility: a substantial increase in the interbank lending rate signals a liquidity shortage in the banking sector. This choice contrasts with studies that employ balance sheet indicators or banking sector betas (e.g., Louzis and Vouldis, 2013). It is mainly driven by the limited availability of banking sector data such as total deposits and loans. Second, the volatility of daily bank equity returns is estimated with a GARCH(1,1) model, which may be indicative of market expectations regarding the banking sector or potential bubbles.

Sovereign Debt: I calculate the indicator of stress in the bond market by computing the spread between the 10-year bond yield of each country and the US 10-year Treasury Yield. The US is chosen as a benchmark for all except the EU countries, for which the German Bund is used. When the 10-year government bond yield is unavailable, I employ the JP Morgan Emerging Market Bond Index Global Spread.

Foreign exchange market: Currency risk is captured by the cumulative change over six months of the real effective exchange rate (*rEER*) as in Duprey, Klaus and Peltonen (2017): if $CUMUL > 0$, *rEER* is volatile around the period considered.

$$CUMUL_t = |rEER_t - rEER_{t-6}|$$

Transformation and aggregation of the sub-indices

The first step in constructing the indicator consists is to establish a common scale for the sub-indices. Since some indices would violate the assumption of normal distribution re-

[2] A crash in the equity market can be defined as a relative decline in the price index of more than 20% (Patel and Sarkar, 1998).

quired for standardisation, I follow the method proposed by Hollo, Kremer and Lo Duca (2012) to transform the indices based on their empirical CDF. This method projects the raw indices into variables measured on an ordinal scale with range $(0,1]$. The CDF transformation is applied recursively over an initial window of 10 years that expands progressively by adding one new observation at a time. I compute the CDF-standardised indices as follows:

$$\hat{x}_t = F_n(x_t) = \begin{cases} \frac{r}{n} & \text{for}\, x_{[r]} \leq x_t \leq x_{[r+1]}, \quad r = 1,2,\ldots,n-1 \\ 1 & \text{for}\, x_t \geq x_{[n]}, \end{cases} \tag{1.1}$$

for $t = 1,2,\ldots,n$. The function $F_n(x_t)$ transforms each variable x into percentiles. For each t, it computes the rank r of the observation x_t in the sample. Hence, the CDF-standardisation projects the indices into unit-free variables distributed over the interval $(0,1]$, allowing aggregation by taking the arithmetic average.

The choice of aggregation scheme should be driven by the main aim of the final indicator. The usual choices in the recent literature can be broadly summarised into three classes: variance-equal weighting of the sub-indices (e.g. Cardarelli, Elekdag and Lall, 2011), factor analysis (e.g. Dovern and van Roye, 2014), and portfolio-theory-based aggregation (e.g. Hollo, Kremer and Lo Duca, 2012).

The primary purpose of the final indicator here is to capture the *systemic dimension* of financial stress. Hence, it is crucial to consider the relationship between stress across market segments to account for the potential system-wide implications of instability arising in one market. Accordingly, following Hollo, Kremer and Lo Duca (2012), I aggregate the market indices into the final indicator based on a portfolio theory approach that allows consideration of time-varying correlations between market segments. The intuition here is that the stronger the co-movement across market segments, the more widespread is the state of financial instability.

Using this aggregation methodology, high levels of systemic financial stress reflect two conditions in the market: the sub-indices measuring financial instability show extremely high values, and the market segments' movements are strongly correlated (i.e., there is strong co-dependence between them). This is in line with Chavleishvili and Kremer (2021), which suggests that systemic financial stress can be characterised as a state of "co-extremeness", that is, co(-dependence) cum extremeness (referring to the extreme values in (i)).

The indicator is thus computed as follows:

$$FSSI_t = I_t C_t I_t',$$

where I_t is the 1×4 vector of market indices, and C_t is the 4×4 matrix of time-varying correlation coefficients $\rho_{ij,t}$.

$$C_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \rho_{24,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \rho_{34,t} \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} & 1 \end{bmatrix}$$

The time-varying cross-correlations are estimated recursively employing an exponentially weighted moving average with $\lambda = 0.85$, as in Duprey, Klaus and Peltonen (2017).

$$\sigma_{ij,t} = \lambda \sigma_{ij,t-1} + (1-\lambda)\bar{s}_{i,t}\bar{s}_{j,t}$$

$$\sigma_{i,t}^2 = \lambda \sigma_{i,t-1}^2 + (1-\lambda)\bar{s}_{i,t}^2$$

$$\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sigma_{i,t}\sigma_{j,t}},$$

where $i, j = \{1, \ldots, 4\}$, $i \neq j$, $t = 1, \ldots, T$; $\sigma_{ij,t}$ stands for the covariance, $\sigma_{i,t}^2$ for the volatility, and $\bar{s}_{i,t} = I_{i,t} - 0.5$ represents the demeaned market indices (since the sub-indices are distributed over the interval $(0, 1]$, the theoretical median is set to 0.5). The initial mean, covariance and volatility are determined as the average values over the pre-recursion period, meaning over the first five years for which the sub-indices are available.

2.3 FSSI

Figures 1 and 2 plot the FSSI for all countries in the sample. Despite the levels of stress differing significantly, most critical events are evident for most countries. Wherever possible, the FSSI signals an increase in financial stress during the Asian and Russian crisis of 1997 to 1998, assuming high values mainly for emerging countries (e.g. Brazil, Thailand and South Africa). Also, the dot-com crash at the end of 2000 resulted in a significant deterioration in financial markets. A prominent synchronised peak is observed during the GFC: starting from the third quarter of 2008, almost all countries in the sample show exceptionally high levels of financial stress, and the reaction of emerging countries does not seem to lag. An aggravation in financial conditions is seen during the third quarter of 2011, which corresponds with the European debt crisis and is mostly visible for European countries but also for some emerging economies. Also, there is a common increase in financial stress due to the COVID-19 outbreak in the first half of 2020.

Although the choice of raw indices for inclusion in the FSSI was made subject to data limitations, a comparison with existing measures of financial instability (see, e.g., Dovern and van Roye, 2014; Hollo, Kremer and Lo Duca, 2012; Miglietta and Venditti, 2019) reveals that the variables included do capture key aspects of financial stress as its peaks coincide with known financial crisis in sample countries.

Overall, the FSSI values show a high degree of commonality over the sample period. The first PC extracted for the entire sample accounts for 61% of the total explained variance. In the sub-sample of advanced countries, it accounts for 64% of the cumulative variance while, for the sub-sample of emerging countries the first PC explains 60%. Figure 3 shows the first PCs: the red line, computed on the sample as a whole, can be perceived as a global indicator of the levels of financial stress.

Figures 5.1 and 5.2 in the Appendix show the extended version of the FSSI, that is, including the real estate market. The decomposition of the two versions of the FSSI (as suggested by Miglietta and Venditti, 2019) allows an assessment of each segment's contribution to the stress in the financial market. The results confirm that, on average, the real estate market contributes more for emerging than for advanced economies (this is shown in Appendix 6.1). However, it is hard to disentangle the extent to which house prices are relatively more important for emerging markets: on the one hand, the diverse patterns may be due to concrete higher volatility of the variable for this sub-sample, on the other hand it may be (partly) the result of measurement issues. Indeed, it is plausible that the market prices for residential real estate in this heterogeneous sample are collected and aggregated employing vastly different methods. Accordingly, and given that this version is available for a shorter sample period, the empirical analysis in the remainder of the paper relies on the four-segment FSSI.

Figure 7.1 in Appendix 7 depicts the performance of the FSSI and the CISS for the US and China. There are two reasons for choosing these two countries. First, the aim is to explore how the FSSI's performance compares to similar indicators of systemic stress based on larger datasets. Second, there are very few measures of financial stress for emerging countries, and/or the data are unavailable.

Figure 1: Financial systemic stress indicators. The indicators are constructed using the methodology described in Section 3.3. The FSSI is based on four segments: stocks, foreign exchange, bond market and banking sector.

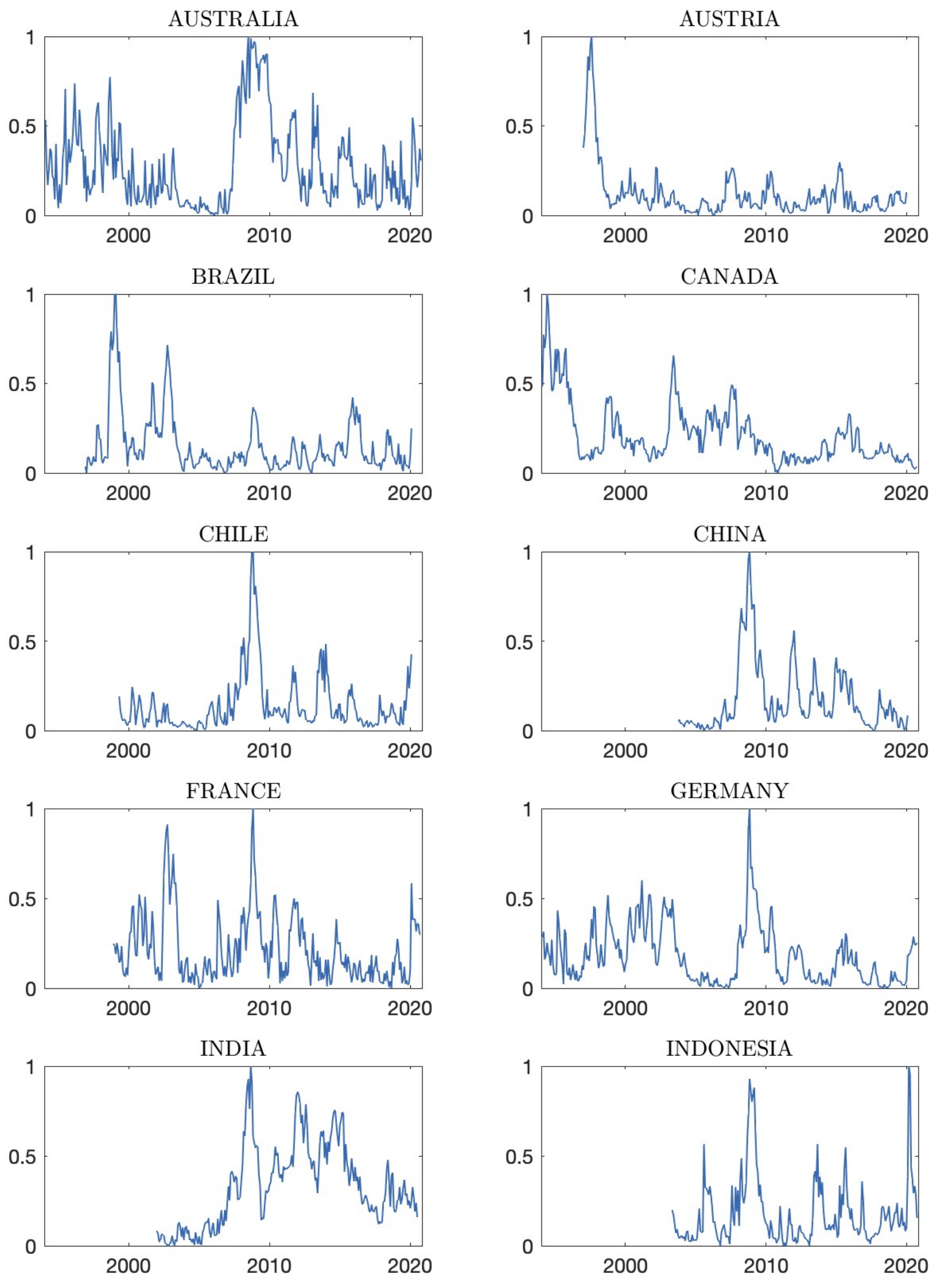


Figure 2: Continue

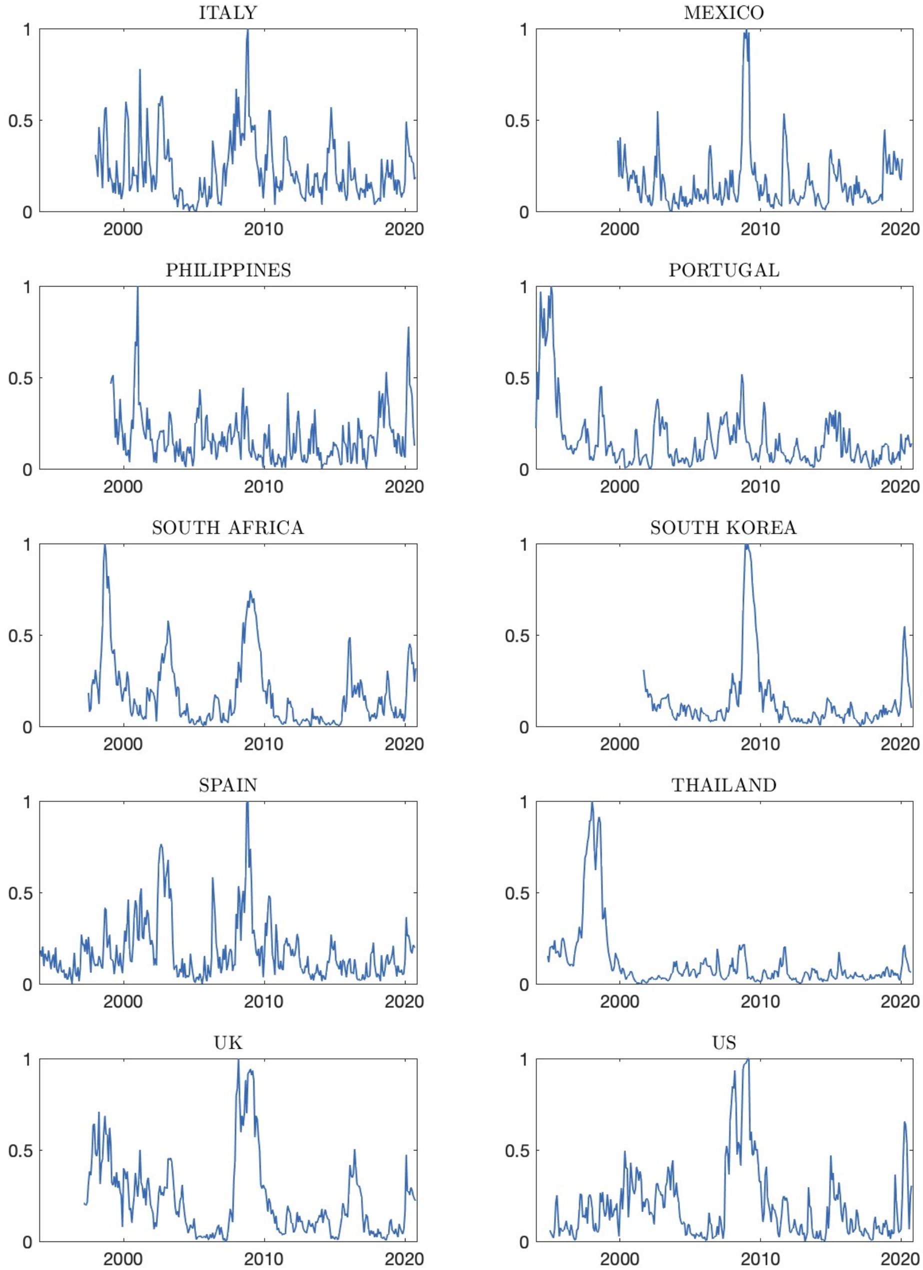
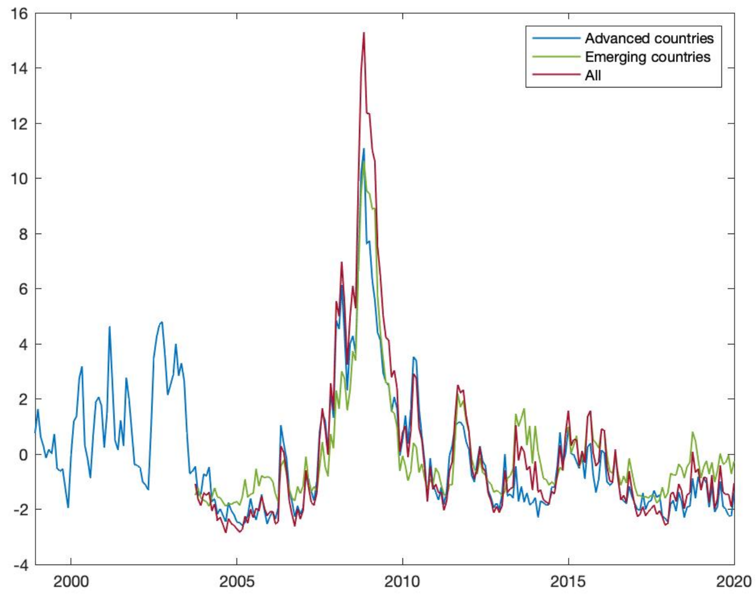


Figure 3: First principal component of the FSSIs considering all countries and the subsamples of advanced and emerging countries.



3 Transmission of Financial Shocks

This section outlines the econometric framework and describes the macroeconomic dataset.

3.1 Model Set-up

The transmission of the US financial shock is estimated in a two-stage procedure. First, I identify and estimate a shock to the US-FSSI in a model for the US. Second, I exploit the previously estimated shock to analyse the transmission of US financial stress to other countries.

Stage 1

Following Gilchrist and Zakrajšek (2012), I estimate the financial shock using a model for the US. I assume that the macroeconomic and financial variables in the vector Y_t are described by the following structural form equation.

$$A(L)Y_t = \varepsilon_t, \tag{1.2}$$

where $A(L)$ is a matrix of polynomials in the lag operator L, Y_t is an $n - dimentional$

vector, and e_t is an $n \times 1$ vector of structural disturbance. Equation 1.2 can be rewritten as follows:

$$A_0 Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{1.3}$$

The structural shocks can be recovered by estimating the following reduced-form equation:

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{t-p} + u_t = B(L) Y_{t-1} + u_t \tag{1.4}$$

where $B_i = A_0^{-1} A_i$ for $i = 1, \ldots, p$, and $var(u_t) = \Omega$.

3.2 Data

The monthly US dataset used in the first step runs from January 1989 to December 2019 and is taken from the Federal Reserve Bank of St. Louis (FRED) website. I include the following variables: the log-difference of industrial production (*INDPROD*), the log-difference of the GDP price deflator (*DEFL*), the unemployment rate (*UNRATE*), the FSSI for the US (*US-FSSI*), the Standard & Poors Composite Stock Index (*S&P*), and the Federal Funds Rate (*FFR*). Since the sample period includes a long period in which interest rates are at or very close to the zero lower bound, I create a composite interest rate indicator using the effective FFR before the Lehman Brother collapse and the shadow interest rate by Wu and Xia (2016) from the third quarter of 2008.

In the second step, the VAR model for each country is estimated at a quarterly frequency and including the following variables: log-difference of industrial production (*INDPROD*), Consumer Price Index (*CPI*), short-term policy rate (*INTRATE*), and *FSSI*. The baseline country sample consists of 19 countries: Australia, Austria, Brazil, Canada, Chile, China, France, Germany, India, Indonesia, Italy, Mexico, the Philippines, Portugal, South Africa, South Korea, Spain, Thailand, and the United Kingdom.

Due to data limitations, the time period differs for each country's VAR. The start date is dictated by the availability of the financial time series used to construct the FSSI, while the sample period ends in the fourth quarter of 2019 for all countries.

3.3 Empirical Methodology

I start by examining how a financial shock in the US affects real domestic conditions. Following Gilchrist and Zakrajšek (2012), I estimate a standard VAR model where slow-moving variables are placed first, and financial variables and the interest rate are last.
The variables enter the model in the following order: *INDPROD*, *DEFL*, *UNRATE*, *FSSI*, *S&P*, *FFR*. This allows macroeconomic variables to have contemporaneous effects on financial variables;, financial shocks can only have an impact on the real economy with a lag. However, S&P and the interest rate can respond contemporaneously to financial shocks.
The financial shock in the US, $\hat{u}_{ft}$, is identified and estimated by imposing a Choleski scheme on a VAR model. In other words, the recursive scheme implies that the financial shock is the fourth one with the above ordering of the variables. The lag length to be used in the VAR is determined using the Bayesian information criterion (BIC; $p = 2$) and Akaike information criterion (AIC; $p = 3$) criteria. Since the results do not change significantly, I opt for a parsimonious approach and set the number of lags to 2.
To analyse how financial shocks spread from the US to other countries, I use the previously estimated financial shock as a regressor in the country-specific VAR model based on the following variables for each country: $\hat{u}_{ft}$, *INDPROD*, *CPI*, *INTRATE*, *FSSI*. The identifying assumption is that the estimated financial shock is exogenous concerning the country-specific variables; that is, financial stress in the US may have an impact on macroeconomic variables in other countries. The lag length of the endogenous variables is determined with the usual BIC and set equal to 2.

3.4 Results

US Domestic Response

I start the empirical exploration by looking at the macroeconomic consequences of a shock to the FSSI in the US. The estimated financial shock time series is plotted in Figure 4. This shows some peaks and greater volatility corresponding with most important recent crisis events, such as the 1990 US recession, the Asian Crisis in 1999, the 2000 dot-com bubble and the September 2001 terrorist attacks in the US, and increased volatility during the GFC with a major peak in 2008. On average, the period between 2000 and

2010 is characterised by higher volatility than in the rest of the sample. Overall, the peaks captured by the shock are in line with major financial events of recent decades and with the newly constructed FSSI.

Figure 5a shows the impulse response functions (IRFs) of the endogenous variables to an orthogonalised shock to the FSSI, along with the 68 per cent confidence bands computed with standard bootstrapping (500 replications). An unexpected one-unit increase in *FSSI* depresses prices and real economic activity, causing a substantial reduction of output and a sizeable increase in the unemployment rate approximately three quarters after the shock. Also, *FFR* declines after several months. Expectations of lower economic activity are quickly reflected in the stock market, leading to a sudden and pronounced drop in prices. The reactions of US domestic macroeconomic variables to a financial shock are not immediate and build up over time.

I assess the robustness of the results obtained with the FSSI and in Panel B of Figure 5a shows the IRFs for a shock to the excess bond premium developed by Gilchrist and Zakrajšek (2012). The responses are very similar to the main findings of Gilchrist and Zakrajšek (2012), confirming that the new broad-based FSSI captures instabilities arising in the US financial market.

Figure 4: Financial shock estimated in the US VAR.

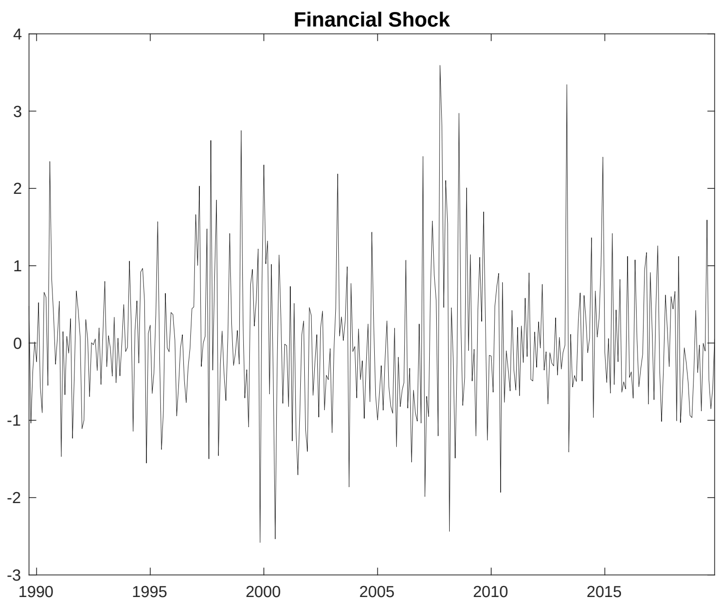
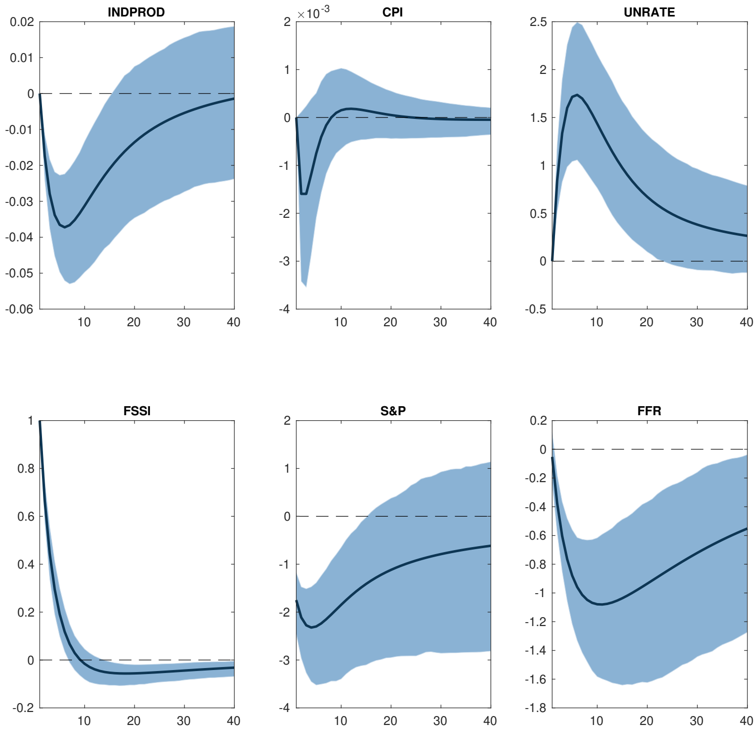
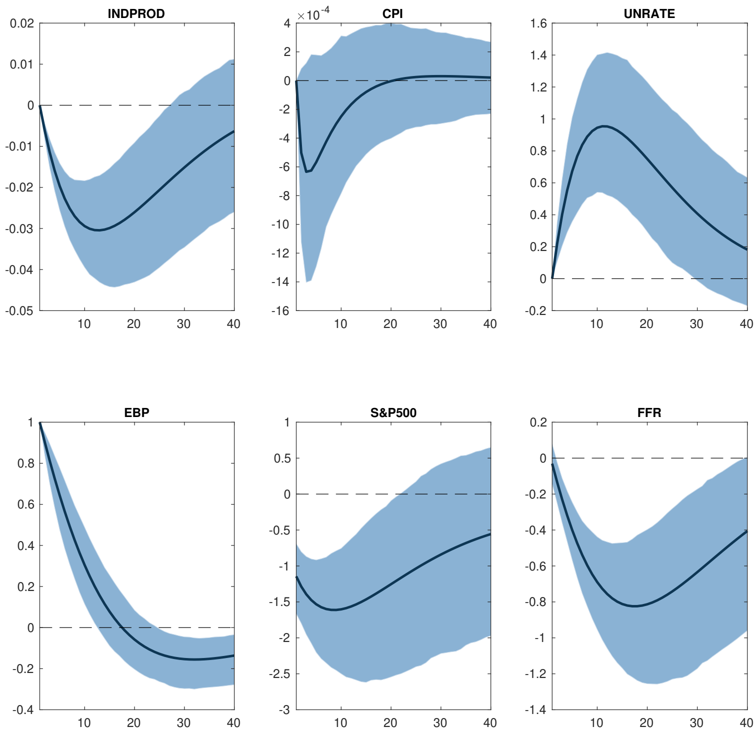


Figure 5: Macroeconomic implications of a financial shock in the US
The figure depicts IRFs for a one-unit shock to the FSSI (Panel A) and for the excess bond premium by Gilchrist and Zakrajšek (2012) (Panel B). Solid lines are point estimates; blue areas represent 68% confidence bands obtained with 500 bootstrap replications.



(a) IRFs to a shock to the FSSI



(b) IRFs to a shock to the EBP

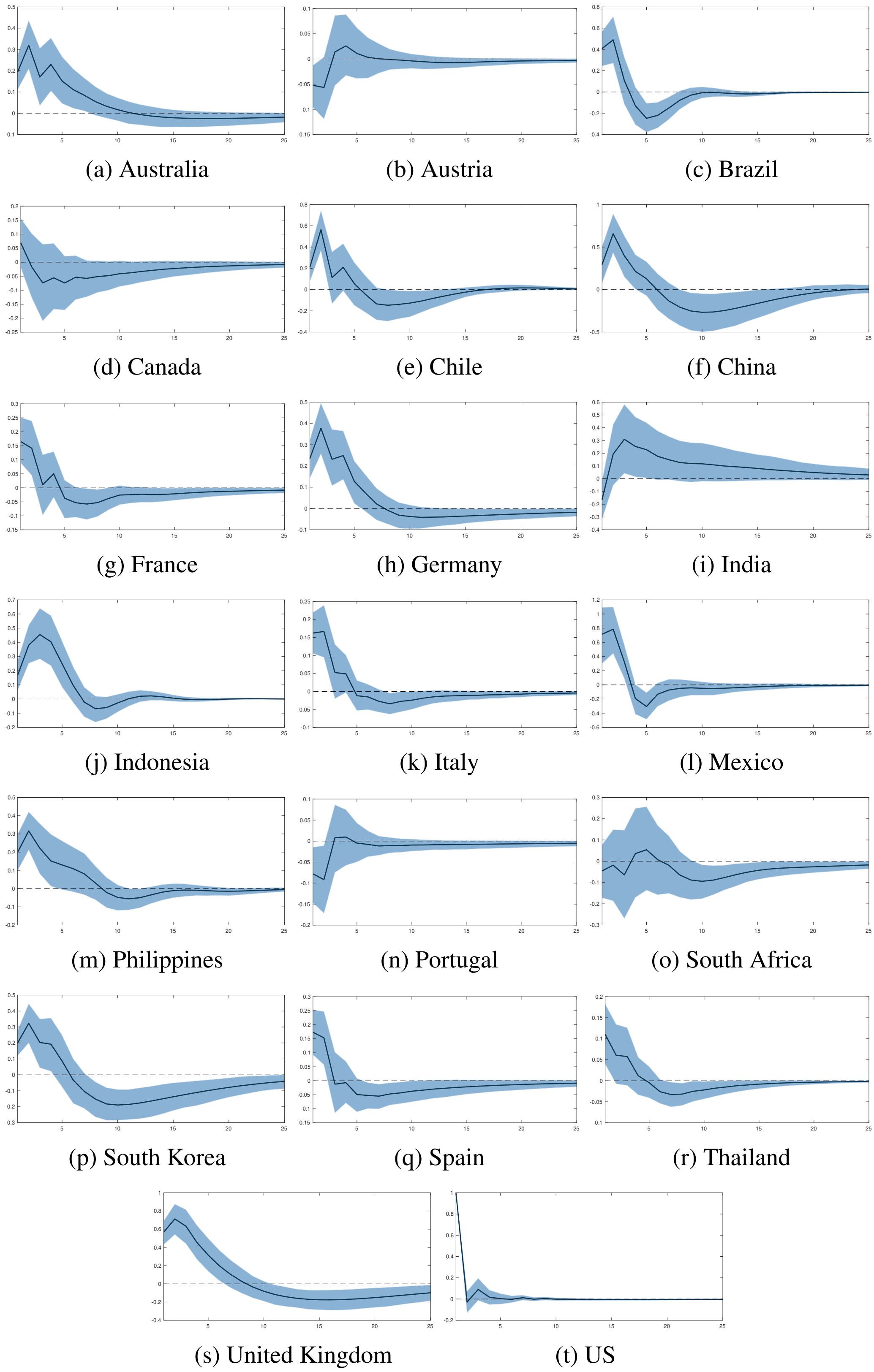
International Responses

I present the results in the form of dynamic responses of each country's FSSI to a financial shock in the US. Figure 6 compares, for each country in the sample, the IRFs for a 1% rise of the FSSI in the US. The black solid lines are point estimates, while the blue bands denote 68 per cent confidence intervals based on 500 bootstrap replications.

The impact of an unexpected rise of financial stress in the US is unambiguous in all countries, except Austria, Canada and Portugal. An exogenous US financial shock increases financial stress in almost all countries in the sample, although this is not significant in all cases. On average, the spread of financial stress takes some time since the greatest impact is reached one or two quarters after the shock. The financial shock seems to have persistent effects on the financial conditions of advanced and emerging economies; nevertheless, after an average of six quarters, financial stress returns to pre-shock levels.

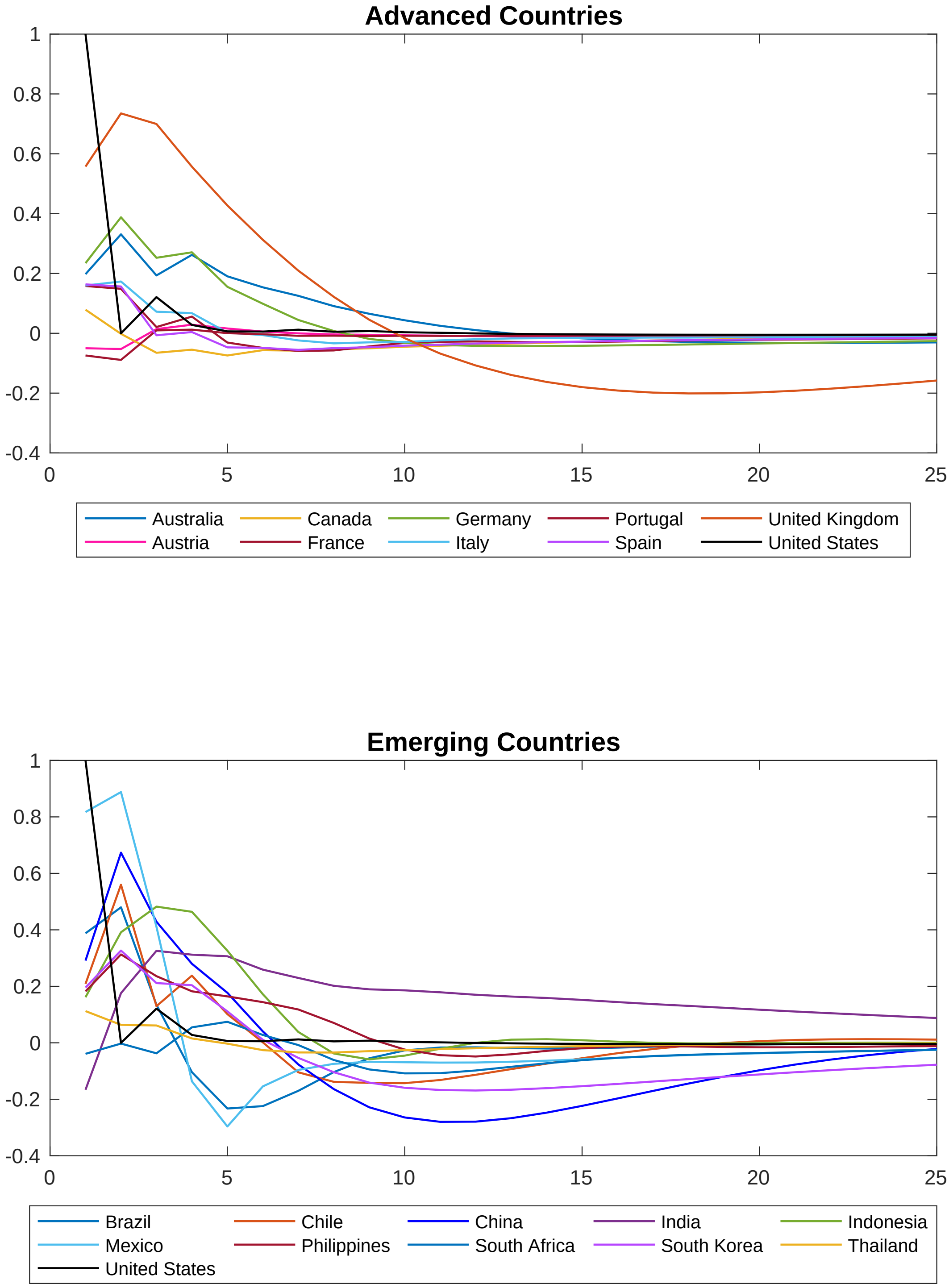
Figure 7 plots the IRFs of the FSSI to the US financial shock grouped by advanced and emerging countries. The black line represents the US shock. Almost all the IRFs show a hump-shaped pattern, but the figure shows that advanced countries seem to have more homogeneous responses. After a one-unit shock in the US, the average increase in financial stress for the sub-sample of advanced economies is approximately equal to 0.2 and this is around 0.35 for emerging economies. Accordingly, the increase in financial stress in other countries is much lower than the initial shock in the US. The IRFs for China, Mexico, and the United Kingdom diverge significantly from the responses for other countries, with an average increase after two quarters of 0.75.

Figure 6: International transmission of a financial shock in the US
Impulse response functions of FSSI to a financial shock in the US. Solid lines are point estimates; blue areas represent 68% confidence bands obtained with 500 bootstrap replications. The VAR specification includes the following variables for each country: US financial shock, industrial production, CPI, interest rate, and FSSI.



(a) Australia (b) Austria (c) Brazil
(d) Canada (e) Chile (f) China
(g) France (h) Germany (i) India
(j) Indonesia (k) Italy (l) Mexico
(m) Philippines (n) Portugal (o) South Africa
(p) South Korea (q) Spain (r) Thailand
(s) United Kingdom (t) US

Figure 7: Impulse response functions of the FSSI for each country to the US financial shock. The top panel represents the responses of advanced countries, and the panel below shows the IRFs for emerging countries.

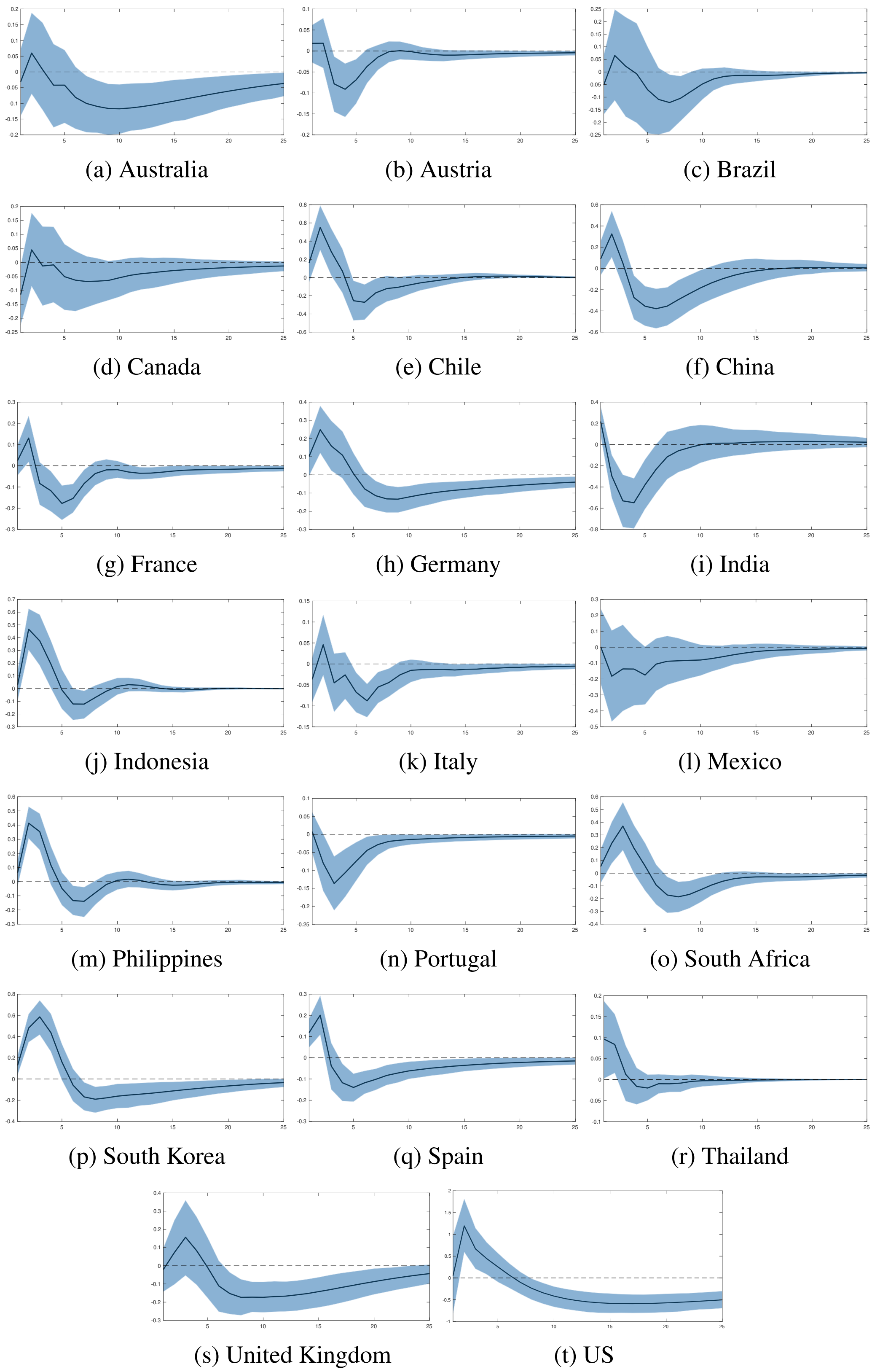


Extensions and alternative specifications

In this section, I estimate different specifications of the country-specific VAR models. I empirically investigate whether a slowdown in US economic activity triggers higher levels of financial stress elsewhere by including an estimate of a negative real shock in the US in the country-specific VAR models. The real shock, $\hat{u}_{rt}$, is identified as an innovation to the industrial production in the US baseline specification, as in 3.3.

Figure 8 shows the IRFs of FSSI for all economies in the sample. Panel 8t of the figure plots the response of FSSI in the US to the real shock, estimated in the US VAR model (first step). In the US, the negative real shock triggers considerable financial stress. The response of the FSSI in other countries in the sample is much smaller: on average, country FSSIs jump on impact by roughly 0.2 percentage points after the shock. Surprisingly, in some countries, the US economic slowdown has a negative or no impact on stress levels. Overall, the results suggest that there are differences in the transmission of US real shocks to the financial markets of other countries. However, emerging economies seem slightly more vulnerable than advanced ones.

Figure 8: International transmission of a negative real shock in the US
Impulse response functions of FSSI to a negative real shock ($\hat{u}_{rt}$) in the US. Black lines are point estimates; blue areas represent 68% confidence bands. The VAR specification includes the following variables for each country: $\hat{u}_{rt}$,$\hat{u}_{ft}$, industrial production, CPI, interest rate, and FSSI. Panel 8t shows the response of the FSSI in the US to the real shock estimated in the US VAR.



(a) Australia (b) Austria (c) Brazil

(d) Canada (e) Chile (f) China

(g) France (h) Germany (i) India

(j) Indonesia (k) Italy (l) Mexico

(m) Philippines (n) Portugal (o) South Africa

(p) South Korea (q) Spain (r) Thailand

(s) United Kingdom (t) US

4 CONCLUSION

The 2008 financial crisis emphasised the importance of financial stress and its implications for the real economy. There is considerable research devoted to the impact of financial stress on different dimensions of the economy, but the extent to which financial shocks propagate across borders is less understood.

In this paper, I try to bridge this gap in the literature. First, I construct a new FSSI that is available and comparable for a large set of advanced and emerging countries. The FSSI captures the broad and systemic dimension of financial stress by incorporating instabilities arising in the stock, foreign exchange, and bond markets, as well as banking sector fragility. I then use the new indicator to investigate the impact of a deterioration in US financial conditions on the levels of financial stress elsewhere. Employing a VAR based on monthly US macroeconomic and financial data, I estimate the financial shock in the US and infer its impact on domestic economic activity.

Next, I use the shock as the regressor in country VARs to analyse the global transmission of financial stress. Finally, I extend the baseline specification to include a negative real shock in the US to empirically assess whether an economic slowdown in the United States may increase financial stress in other countries. The analysis suggests that financial shocks in the US rapidly spill over globally, causing a sizeable and significant increase of financial stress in most of the countries in the sample. On average, the maximum effect is reached two quarters after the shock and seems to be stronger for emerging than advanced economies. Extending the baseline specification with the real shock, I show that a temporary economic slowdown in the US causes greater financial stress in a subsample of countries.

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5 APPENDIX

5.1 APPENDIX A: FSSI WITH REAL ESTATE MARKET

Although only a few studies use real estate vulnerabilities for constructing measures of financial instability, the importance of real estate prices for macro-prudential regulation is widely recognised (Hartmann et al., 2015). Furthermore, Cesa-Bianchi, Cespedes and Rebucci (2015) find that house prices in emerging countries tend to be highly volatile and are more associated with capital flows than in advanced economies.

The fragility of the residential real estate market is captured by calculating the inverted natural log of the BIS property prices. Since the shrinkage in real estate prices may have repercussions for financial stability, taking the inverse makes it possible to interpret an increase in the property prices as an increase of instability in the financial market. The residential property prices have quarterly frequency and are taken from the BIS.

Figure 5.1: FSSI based on five market segments: stock, bond, foreign exchange, real estate markets and the banking sector.

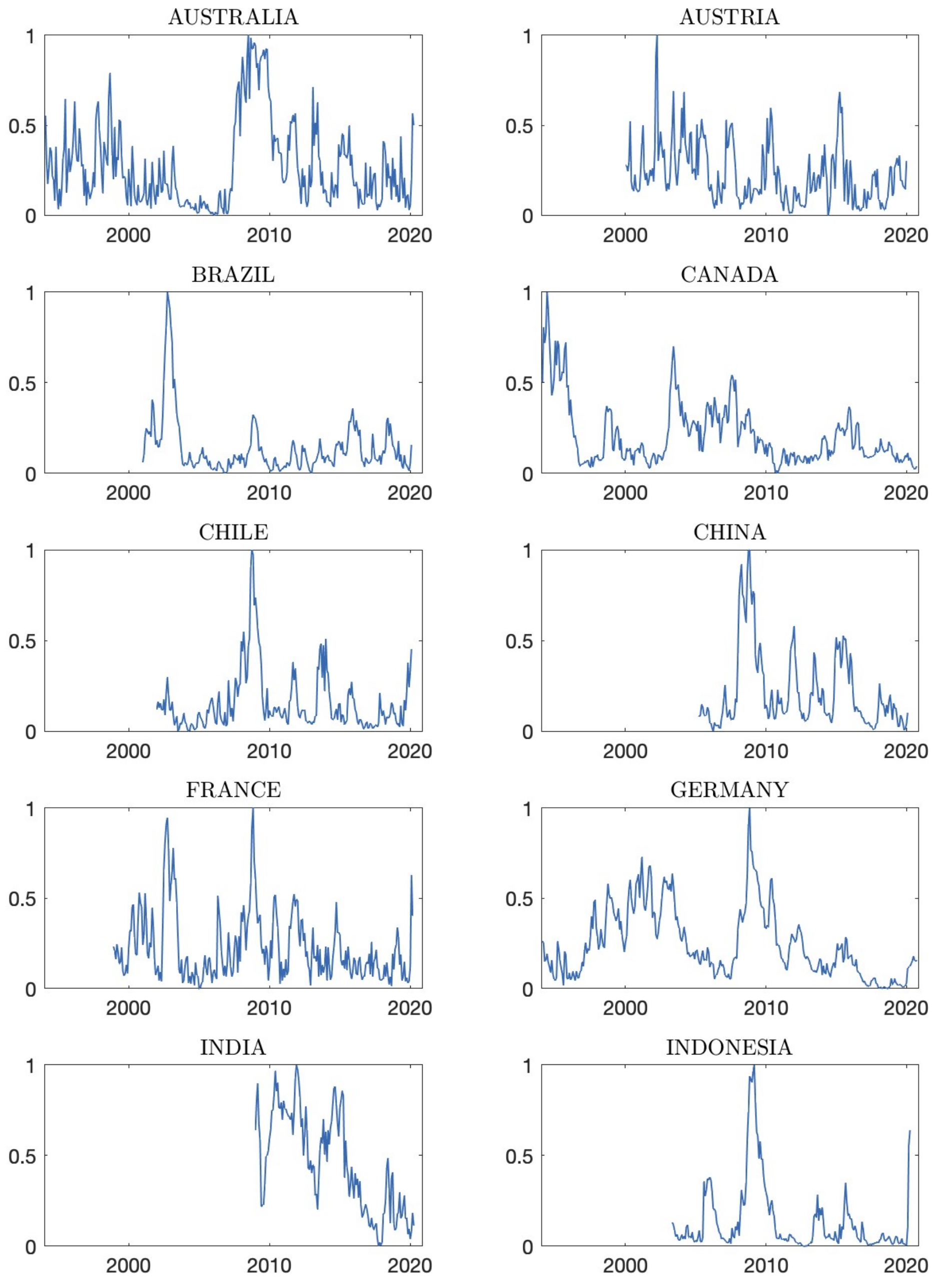
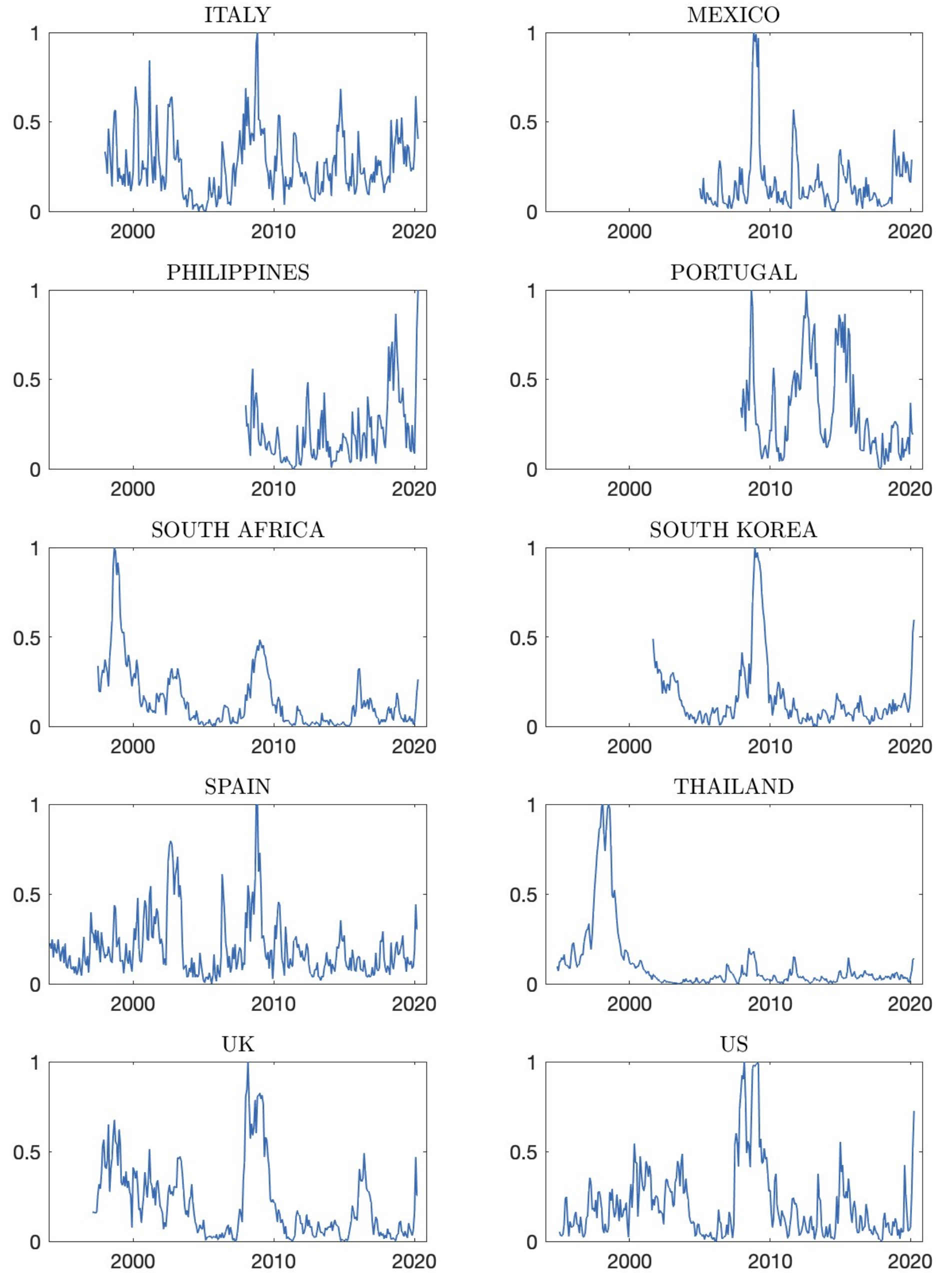


Figure 5.2: Continue



6 DECOMPOSITION OF THE FSSI

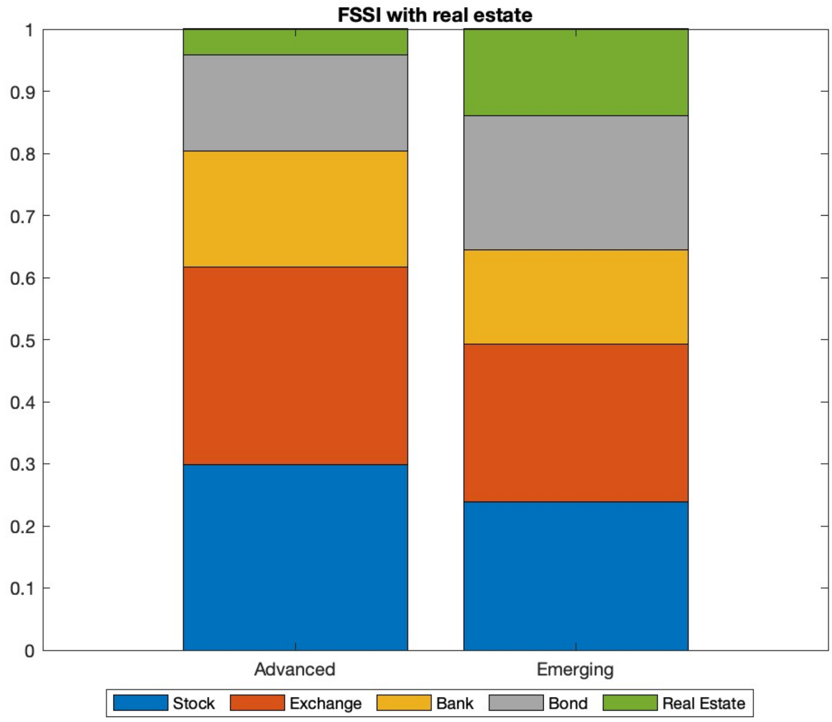
The contribution of each market segment to the final indicator is obtained following the procedure proposed by Miglietta and Venditti (2019):

1. Squaring the four market sub-indices $s_{i,t}^2$ for $i = 1, \dots, 5$ and $T = 1, \dots, T$
2. Computing for each t, $\frac{s_{i,t}^2}{\Sigma s_{i,t}^2}$
3. Multiplying, for each t, the matrix obtained in step 2 with the indicator under the assumption of perfect correlation.

The main assumption underlying this procedure is that all the sub-indices are always perfectly correlated. The indicator under the assumption of perfect correlation (FSSI-PC henceforth) can be computed as the square of the arithmetic average of the sub-indices since, in that case, the cross-correlations are all equal to 1 (all the market segments are either at very high or very low levels of stress). Furthermore, the FSSI-PC emerges as a special case of the FSSI: during a crisis, when all market segments are experiencing very high levels of stress, the FSSI converges towards the FSSI-PC, while during tranquil times, the FSSI signals lower values.

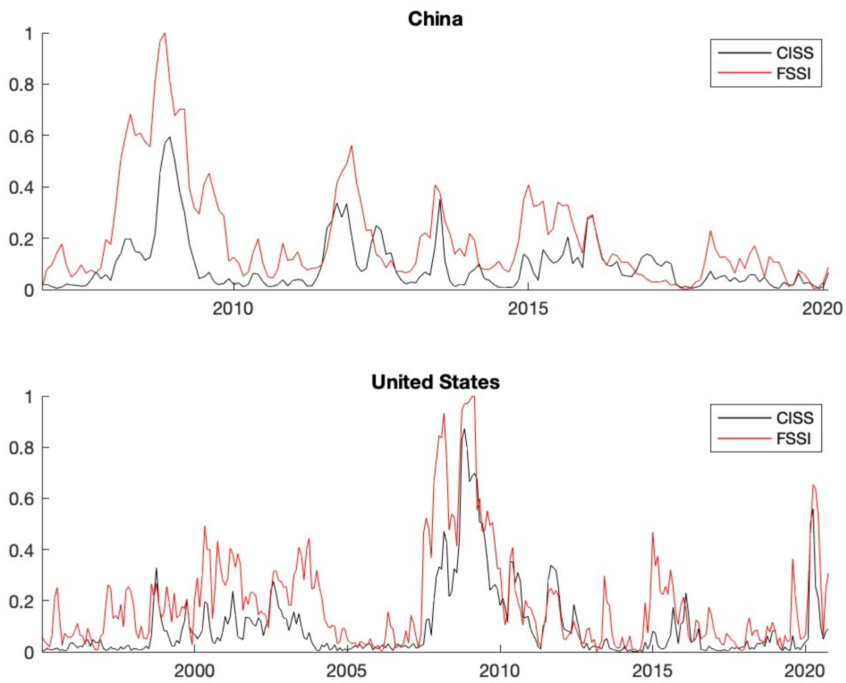
I compute the decomposition of each country FSSI for the two versions of the indicator to investigate the contribution of the real estate market for the advanced- and emerging-economy sub-samples. The right panel of Figure 6.1 shows that house prices contribute more to financial stress in emerging than in advanced countries, although the difference in the average contributions is not large.

Figure 6.1: Average contribution of each segment of the financial market for the sub-samples of advanced and emerging countries.



7 PERFORMANCE OF THE FSSI

Figure 7.1: FSSI vs CISS for the United States and China.



Chapter 2

WHAT GOES AROUND COMES AROUND: THE US CLIMATE-ECONOMIC CYCLE

Konstantin Boss, Alessandra Testa

Abstract: We use a spatial data set of US temperatures in a factor-augmented VAR to quantify the contribution of the US economy to fluctuations in temperatures over the past 70 years. Disentangling natural from anthropogenic effects, we find that economic expansions do not only lead to warming: technology improvements initially decrease temperatures, whereas investment and labor supply shocks increase them rapidly and persistently. Taken together, these economic shocks explain around 25% of long-term temperature variation in the US. In turn, temperature shocks induce small contractions in aggregate GDP, but can even be beneficial for the economy, when they predominantly hit the western states.

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

JEL classification: C32, C38, Q54.

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 known to be important 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 and Greenstone, 2007), more premature deaths (Barreca et al., 2015), and diminished productivity (Burke, Hsiang and Miguel, 2015), resulting in potentially severe losses in welfare (Bilal and Känzig, 2024).

In this paper we develop an empirical framework for the United States (US) to study how economic activity has affected temperatures and vice versa. We use a factor - augmented vector autoregression (FAVAR, Bernanke, Boivin and Eliasz (2005)) to model the dynamics of US temperatures on a $0.5^\circ \times 0.5^\circ$ spatial grid together with key macroeconomic 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 use partial identification techniques to pin down 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 DiCecio and Owyang (2010) and Dieppe, Francis and Kindberg-Hanlon (2021). Second, conditional on the technology shock, we identify an investment shock in the spirit of Justiniano, Primiceri and Tambalotti (2010,0) and Auclert, Rognlie and Straub (2020) as the main driver of business-cycle fluctuations in investment. Third, similar to Shapiro and 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. On the other hand, we rely on statistical arguments to identify temperature shocks. As Angeletos, Collard and Dellas (2020) identify an economic "main business-cycle shock", we apply a similar reasoning to capture 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, as well as in specific frequency bands, for example at the El Niño-La Niña periodicities. We then compute the impulse responses of US real GDP to these shocks.

Based on our analysis, we report the following qualitative results: first, it is insufficient to rely on a single measure of national temperatures such as (weighted) averages, as is frequently done in the literature (Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015; Acevedo et al., 2020). This is because there is a lower bound of five large shocks driving US temperatures. Average temperatures alone only reflect variation in the Midwest region and neglect temperature changes in the economically important coastal areas. This happens because the American Midwest is affected by strong cold air flows from the North and warm air flows from the South leading to very high temperature variability (Kunkel et al., 2013). Geographic heterogeneity also matters for the effect of temperatures on aggregate GDP, a crucial relationship for environmental policy-making: if warming affects only the west of the country, this can be net positive for the economy, whereas temperature increases generally diminish output slightly. Second, we provide evidence for a relationship between temperatures and socio-economic activity mostly through changes in TFP. A loss in productivity is thought to be one of the main channels for the negative effects of temperature warming (Burke, Hsiang and Miguel, 2015). We argue along the lines of Pretis (2021) that it is important to properly distinguish if temperature fluctuations cause productivity changes or vice versa. In the case of the US, we find that the majority of the negative co-movement between temperatures and TFP is caused by economic shocks.

In addition, we contribute the following 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 10%, investment shocks for 11%, and labor supply shocks for 4%. 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 anthropological shocks. The economic shocks have small, yet persistent effects on temperatures. While technology shocks initially decrease temperatures in the industrial part of the country, this effect recedes in the long-run in spite of the permanent effect on economic activity and emissions. Investment shocks and labor supply shocks lead to geographically homogeneous warming, in the area of 0.01°C, even though the economic expansion is mostly transitory. We argue that decreases in temperatures can be explained by a stronger effect of aerosol emissions than GHG emissions, whereas warming is observed when aerosols are removed and GHGs emitted. Second, central US and east coast centered increases of 1°C lead to mild losses of aggregate GDP around $0.1\% - 0.13\%$. This is in line with the view that the US for the most part has been close to a bliss-point where temperature warming has so far had essentially zero aggregate effects (see e.g. Dell, Jones and Olken (2012), Nath, Ramey and Klenow (2023) or 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.

Comprehensive overviews of the climate-econometric literature are provided by Newell, Prest and Sexton (2021) and de Juan et al. (2022). The authors show that especially the estimates of economic damages from climate change vary substantially across methodologies. We relate to and expand the literature that quantifies the effect of temperatures on the US economy. Important contributions over the existing empirical literature are as follows: we identify the direct effect on temperatures of economic shocks that explain the bulk of macroeconomic fluctuations. This is necessary because policy oriented models such as Cai and Lontzek (2019) focus on damages from temperature changes induced by such economic shocks on the economy, although usually relying on TFP shocks alone. In addition, we allow the data to determine the timing of the effects of emissions on temperatures rather than assuming that economic activity translates into temperature changes with a delay of a year, as is customary in the literature (e.g.Donadelli et al. (2017) or Goulet Coulombe and Göbel (2021), since this is not supported by climate research (e.g. Joos et al. (2013) or Forster et al. (2020)). Instead, we propose an identification based on statistical arguments with no implied timing restrictions.

Other studies in this area use mostly panel regressions without dynamic causal response estimates (e.g. Deryugina and Hsiang (2014), Colacito, Hoffmann and Phan (2019), Gourio and Fries (2020)), which are less focused on the transmission mechanism of temperature fluctuations to the real economy. Kaufmann et al. (2013), Montamat and Stock (2020), and Stock (2020) 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), Fosten (2019) and Bennedsen, Hillebrand and Koopman (2021), however, no explicit connection to temperature changes is made. Since the effect of economic activity on temperatures is not exclusively driven by GHG emissions, but also other gases such as aerosols, Magnus, Melenberg and Muris (2011), Storelvmo et al. (2016), Phillips, Leirvik and Storelvmo (2020) provide a breakdown of the respective warming and cooling effects. We show that the aerosol cooling effect prevails for technology shocks, whereas other business cycle shocks lead to warming through a dominant impulse of GHGs. From a methodological view our paper is closely related to Mumtaz and Marotta (2023), Berg, Curtis and Mark (2023) and Bastien-Olvera, Granella and Moore (2022). The first two for the authors' use of a factor structure for temperature dynamics and the third one for the frequency domain decomposition of temperatures. While Mumtaz and 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. Berg, Curtis and Mark (2023) consider only a single factor for their global data set, whereas we show that this captures a very localized temperature phenomenon. Bastien-Olvera, Granella and Moore (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 3 describes the temperature and economic data we use in the empirical model, section 3 introduces the model and explains the identification methodology, section 5 presents the findings, which are discussed in section 5. Finally, section 7 concludes.

2 Data

Temperature data are obtained from the *Terrestrial Air Temperature and Precipitation* $1900-2017$ *Gridded Monthly* data set (Matsuura and 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, Jolliffe and Stephenson, 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, Barigozzi and Capasso (2010), which suggests using between 8 and 17 factors. For parsimony, we set the number of principal components to $r = 8$ and study the effect of choosing $r = 17$ 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. Expanding the information to $r = 8$ yields much higher explained variation, in the area of 80% almost everywhere in the US. Similar results appear in other large countries of the world, but are not reported here. 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 only nationwide averages will likely miss important spatial temperature information.

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

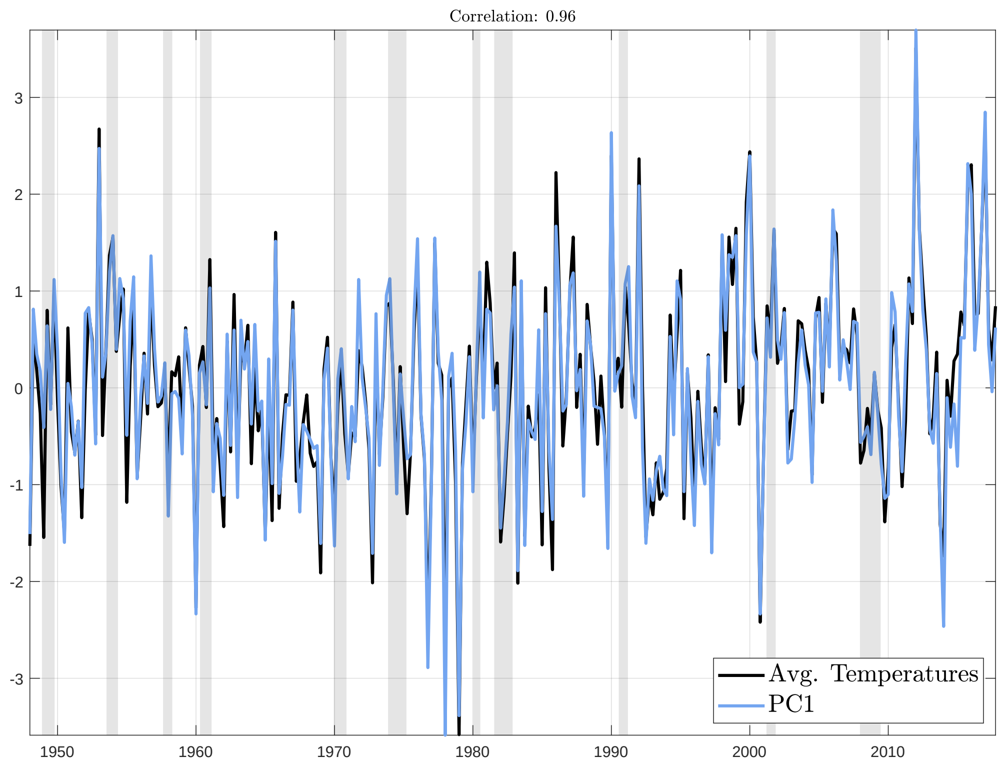
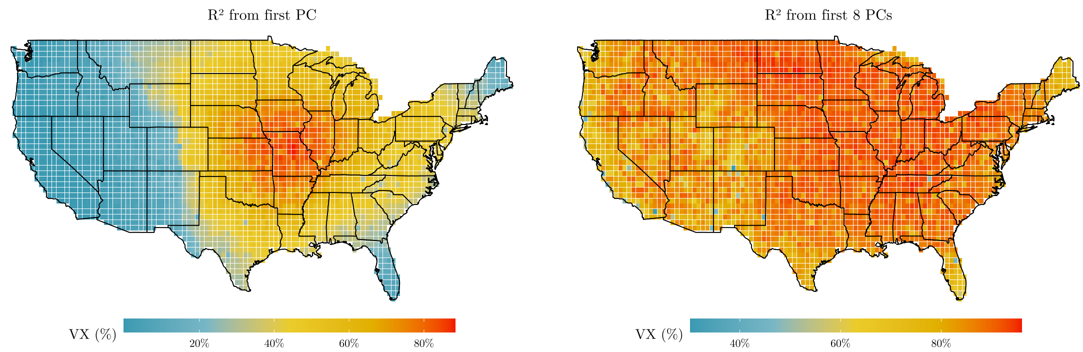


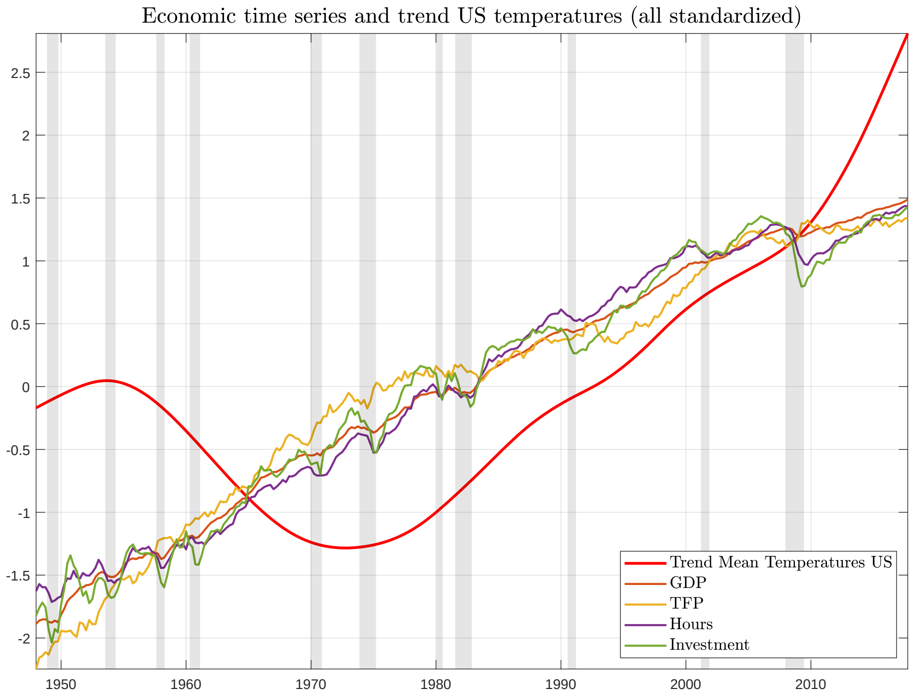
Figure 2: R^2 from regression of grid cell temperatures on principal components.



(a) First PC. (b) First 8 PCs.

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, Boivin and Eliasz (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

$$T_{it} = \lambda_i Y_t + \eta_{it} \tag{2.1}$$

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. This is a simple version of the model in Phillips, Leirvik and Storelvmo (2020), where we accommodate spatial dependence of temperatures on common factors. The reduced form model for Y_t is a VAR of lag order p:

$$A(L)Y_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim WN(0, \Sigma) \tag{2.2}$$

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 (2.2) is efficiently estimated using OLS for each equation. The lag order is determined using the Akaike information criterion, which yields $p = 2$. Higher lag orders do not change our results substantially. The reduced form VAR in (2.2) is assumed to admit a moving average (MA) representation given by

$$Y_t = C(L)\varepsilon_t \tag{2.3}$$

where $C(L)$ is obtained by inverting $A(L)$ and we have dropped the constant as it is immaterial for our identification strategy and the model dynamics.

3.2 Identification

To identify economic and temperature shocks we rely on techniques that have been proposed for the study of business cycles fluctuations. Most environmental models focus on aggregate productivity shocks as drivers of emissions (Annicchiarico et al., 2021). However, the recent contributions in Angeletos, Collard and Dellas (2020) and Forni et al. (2023) have shown that the economy, and by extension also emissions, fluctuates largely because of sources that are not purely related to movements in TFP. Therefore, our analysis is set up to provide evidence on alternative channels for the effect of socio-economic activity on temperatures, beyond RBC-style technology shocks alone. It is most common to distinguish fluctuations of high frequency, business cycle frequency and low frequency.

Table 1 shows the definitions of frequency bands we adopt for our purposes:

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, Collard and Dellas, 2020). This definition roughly coincides with medium cycles that are observable in climatic data as well. For example, ENSO (El Niño-Southern Oscillation) influences global weather and occurs every 3-5 years and lasts for roughly 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 low frequency band is where we expect the strongest influence of socio-economic activity to show up, as it contains the slight upward trend in the data that is believed to be caused by human beings. Allowing the medium-cycle band to include a few more years (e.g. to include the 11-year solar cycles) does not affect our results.

The structural MA representation of (2.3) is given by

$$Y_t = C(L)SHu_t = D(L)Hu_t = K(L)u_t, \quad u_t \sim WN(0, I) \tag{2.4}$$

where $SS' = \Sigma$, $HH' = I$, and $u_t = H'S^{-1}\varepsilon_t$. 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

$$IRF_E = D_E(L)H \tag{2.5}$$

$$IRF_T = \Lambda D(L)H \tag{2.6}$$

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.

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, Primiceri and Tambalotti (2010,0). 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 (2.4). The cyclical variance-covariance matrix of all variables in Y_t in the frequency band between $[\underline{\theta}, \bar{\theta}]$ is given by

$$V(\underline{\theta}, \bar{\theta}) = \int_{\underline{\theta}}^{\bar{\theta}} D(e^{-i\omega}) D(e^{i\omega})' d\omega \tag{2.7}$$

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 (2.7)). 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

$$\Psi(\underline{\theta}, \bar{\theta}) = \int_{\underline{\theta}}^{\bar{\theta}} D(e^{-i\omega}) hh' D(e^{i\omega})' d\omega \tag{2.8}$$

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:

$$h = \arg\max \quad h' \left(\int_{\underline{\theta}}^{\bar{\theta}} D_m(e^{-i\omega})' D_m(e^{i\omega}) d\omega \right) h, \quad \text{s.t} \quad h'h = 1 \tag{2.9}$$

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 (2.9) (as shown for the time domain in (Uhlig, 2003)).

We first identify the technology shock as the main driver of low frequency variation in TFP as in Dieppe, Francis and Kindberg-Hanlon (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. Dieppe, Francis and Kindberg-Hanlon (2021) show this method to be more robust to interference from other shocks that typically occurs in variance maximization approaches such as Barsky and Sims (2011). Conditional on the identified technology shock, we then proceed to identifying the investment shock as the main driver of aggregate investment over the business cycle. Justiniano, Primiceri and Tambalotti (2010,0) 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 shock typically induces positive co-movement between investment and consumption in both representative and heterogeneous agent models (Auclert, Rognlie and Straub, 2020). The conditional shock is identified by finding another column of H, call it h_j:

$$\begin{aligned} h_j = \arg\max \quad & h_j' \left(\int_{\underline{\theta}}^{\bar{\theta}} D_m(e^{-i\omega})' D_m(e^{i\omega}) d\omega \right) h_j \\ \text{s.t} \quad & h_{tech}' h_j = 0 \quad \text{and} \quad h_j' h_j = 1 \end{aligned} \tag{2.10}$$

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 and Watson (1988) with an analogy to the relationship between Dieppe, Francis and Kindberg-Hanlon (2021) and Gali (1999). It is easy to extend the maximization constraints in (2.10) to pin down this labor supply shock.

To check whether our approach delivers valid identification, we study it in a controlled experiment, using the model of Justiniano, Primiceri and Tambalotti (2011). The approach correctly recovers the true IRFs to the economic shocks in the majority of cases as reported in the Appendix. Moreover, we check if the sequence of conditional identifications matters for the results in a robustness exercise.

Identification of temperature shocks

We use a similar method as for the economic shocks to identify temperature shocks. Conditional on the three economic drivers, we extract 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, 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.[1] 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 $\Omega(L) = \Lambda C(L) S$ 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:

$$\begin{aligned} h_{Tj} &= \arg\max \quad h'_{Tj}\left(\int_{\underline{\theta}}^{\bar{\theta}} \Omega_m(e^{-i\omega})' W \Omega_m(e^{i\omega}) d\omega\right) h_{Tj} \\ &\text{s.t} \quad h'_{Tj} H_E = [0,0,0]' \quad \text{and} \quad h'_{Tj} h_{Tj} = 1 \end{aligned} \tag{2.11}$$

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 (2.11). W is a diagonal weighting matrix which contains the reciprocals of the square roots of the variances 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

[1] We also found imposing sign restrictions on the impact IRF of all temperatures or on the long run response of all temperatures to be computationally unfeasible in our application.

concern, but is done for completeness.

We do not require the temperature shocks to be orthogonal to each other, only to the economic shocks and inspect the resulting IRFs case by case. This is because the main identifying property these shocks have come from geography, which are hardly exclusive. Temperature fluctuations on the US west coast, for example, may be driven by additional impulses elsewhere in the country. Requiring these impulses to be orthogonal appears too restrictive. 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
7. Maximize the business-cycle spectrum temperature variation everywhere to capture the ENSO pattern
8. Maximize the high-frequency temperature variation everywhere to capture the weather shock predominantly used in the literature

The choice is motivated by the geographical patterns we observe in the data, 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 is 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.

It is important to point out two properties of the shocks that are identified in our FAVAR framework. First, the shocks induce deviations of temperatures at many geographical locations in the US from their deterministic components. If the deterministic component of temperatures contains any trending behavior, a temperature shock constitutes a deviation from this trend. In that sense, explicitly computing the deviation of temperatures from some long-term trend and then using these deviations as a shock, as is done in Kahn et al. (2021), for example, is very similar, but skips the identification step that tries to pin point if the deviation comes from human sources or is of natural causes. Second, some climate econometric research stresses the importance of extreme weather events as more suitable measures of temperature shocks (Natoli, 2023). The shocks that we construct are precisely this: they are not predictable from past information about temperatures anywhere in the contiguous US and neither from information about GDP, TFP, investment or hours worked. Whether this information set is sufficient is a difficult question to answer. Moreover, non-linearities or state-dependence may play an important role for the transmission of such shocks, all of which we consider to be important avenues for future research.

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 (2.1) and (2.2). 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 (2.7) 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.	0.3	0.48	0.58	0.78	0.83	0.87	0.42	0.63	0.78	0.81	0.87	0.92	0.42	0.65	0.77	0.8	0.86	0.92
GDP	0	0.01	0.01	0.07	0.08	0.12	0	0.01	0.01	0.19	0.22	0.27	0.01	0.02	0.02	0.08	0.09	0.12
TFP	0	0.04	0.06	0.23	0.27	0.28	0	0.03	0.07	0.52	0.59	0.6	0.01	0.02	0.04	0.29	0.3	0.31
Hours	0	0.01	0.01	0.08	0.1	0.14	0	0.01	0.02	0.25	0.31	0.36	0.02	0.03	0.05	0.18	0.2	0.22
Investment	0	0.02	0.02	0.04	0.06	0.08	0.01	0.01	0.02	0.13	0.16	0.2	0	0.01	0.03	0.06	0.07	0.09

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.	0.03	0.22	0.31	0.33	0.4	0.47	0.01	0.02	0.05	0.06	0.14	0.24	0.01	0.02	0.03	0.04	0.1	0.2
GDP	0.93	0.96	1	1	1	1	0.71	0.84	0.91	0.99	0.99	0.99	0.78	0.83	0.87	0.93	0.93	0.97
TFP	0.57	0.96	1	1	1	1	0.17	0.83	0.92	0.98	1	1	0.42	0.78	0.84	0.91	0.95	0.97
Hours	0.78	0.98	0.99	1	1	1	0.43	0.96	0.96	0.99	1	1	0.34	0.85	0.88	0.94	0.96	0.98
Investment	0.88	0.94	0.97	1	1	1	0.53	0.75	0.76	0.99	1	1	0.44	0.54	0.55	0.9	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 fourth temperature variance maximizer is responsible for a sizable share of TFP variation at all frequencies, particularly at the medium part of the spectrum. This seems intuitive: the low and medium 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, Collard and Dellas (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.

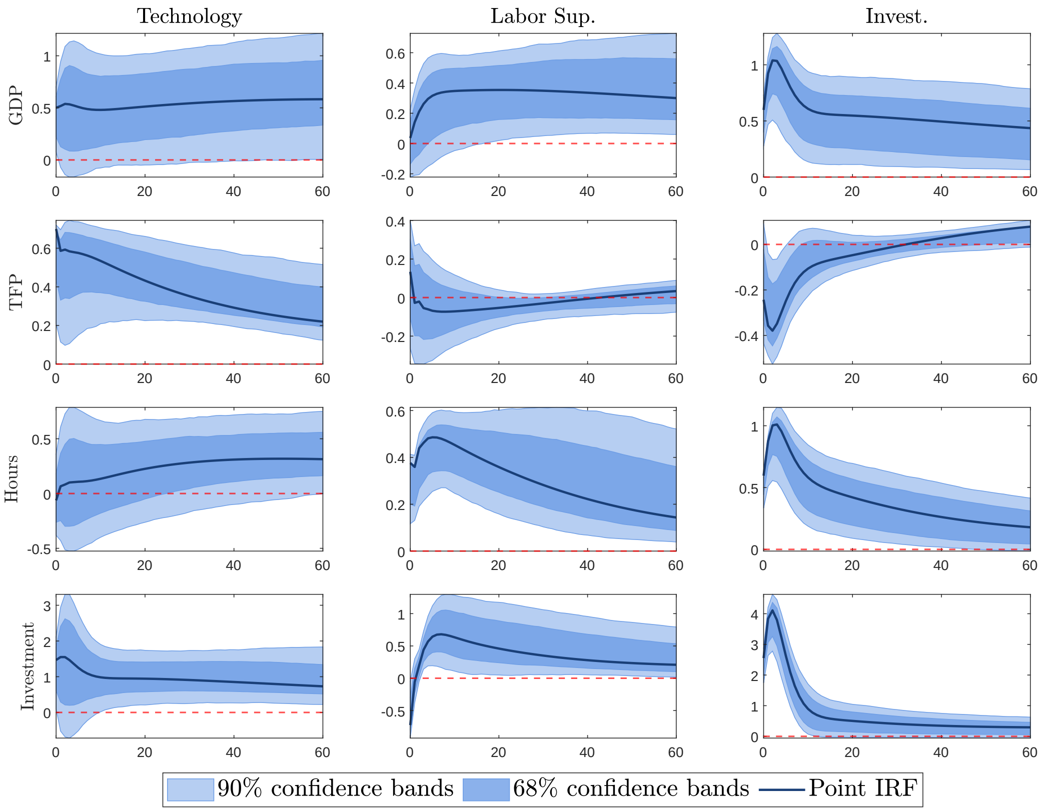
The descriptive exercise does not allow us to tell apart the respective source of the fluctuation. Is the variation in temperatures due to climatic or economic shocks? What part of GDP variation is truly due to climatic shocks and which part just masquerades interference from economic shocks? These questions 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.

4.2 Semi-structural results

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 4.

Figure 4: Impulse response functions for the three structural economic shocks. Shaded areas are bootstrapped 68% and 90% confidence bands.

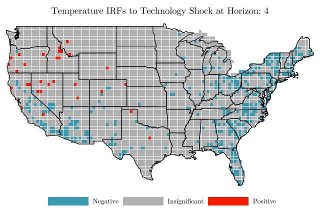


First, the technology shock leads to an immediate increase in TFP which is accompanied by an expansion of real GDP of around 0.4%. Hours initially decline (although this is statistically insignificant) and investment increases. These results are very similar to those found in Dieppe, Francis and Kindberg-Hanlon (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, Furlanetto and Lepetit (2018) (for the US) and Peersman and Straub (2009) (for the euro area). The responses of hours and GDP are in line with the paper of Shapiro and 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, Primiceri and Tambalotti (2011). The decrease in TFP is also observed in Ben Zeev and Khan (2015) (although in their paper the response is insignificantly different from zero) for investment-specific technology shocks. More inputs are used to produce only slightly more output, thus productivity must fall. 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.

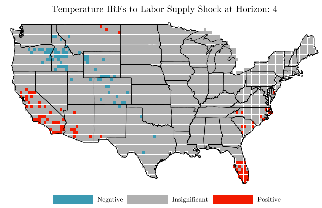
Next, we describe the responses of US temperatures to the three expansionary economic shocks, a key result of this paper. It is important to note that the impact reactions (near impulse response horizon $h = 0$) of temperatures across the US to the shocks are difficult to measure accurately due to the 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 5 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).[2]

[2]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.

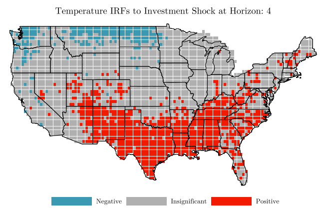
Figure 5: Grid cell temperature IRFs at given horizons in response to the three economic shocks.



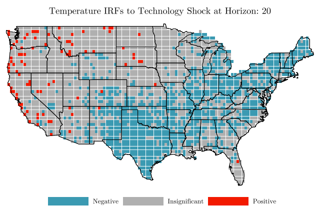
(a) Tech. shock after 1 year



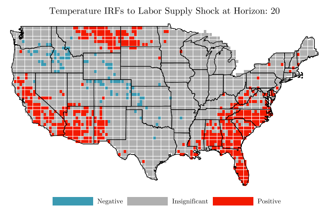
(b) Lab. sup. shock after 1 year



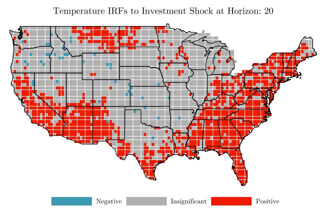
(c) Inv. shock after 1 year



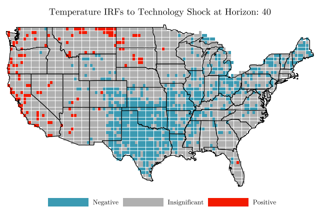
(d) Tech. shock after 5 years



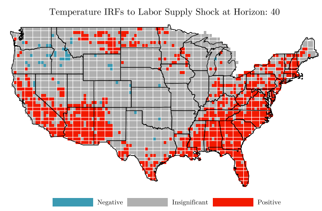
(e) Lab. sup. shock after 5 years



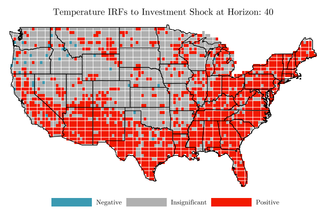
(f) Inv. shock after 5 years



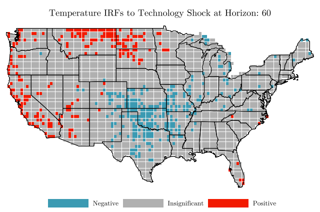
(g) Tech. shock after 10 years



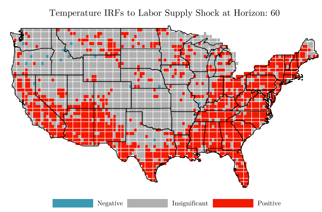
(h) Lab. sup. shock after 10 years



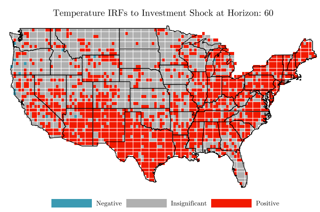
(i) Inv. shock after 10 years



(j) Tech. shock after 15 years



(k) Lab. sup. shock after 15 years



(l) Inv. shock after 15 years

Next, in Table 4 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.

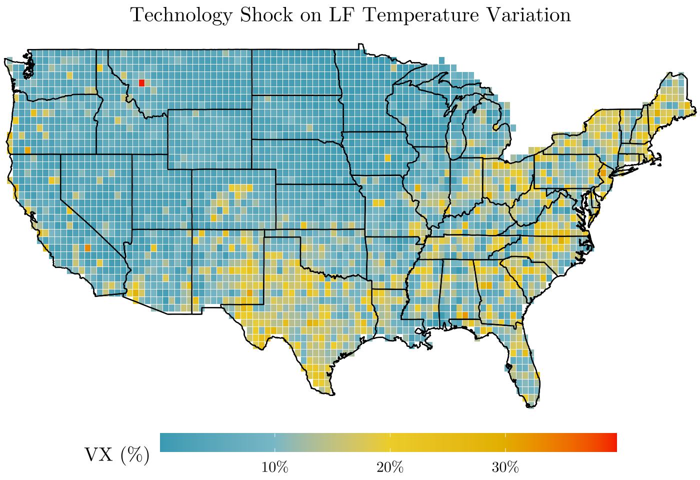
Table 4: Individual cyclical variances explained by the three identified economic shocks over the three frequency bands. Numbers in parentheses are the 90% confidence bands associated with the percentage above. Rounded to two decimals.

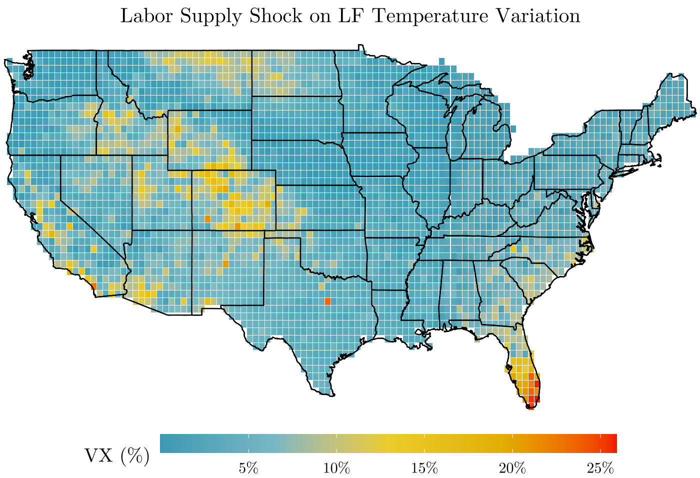
	Low Frequencies			Business Cycles			High Frequencies		
	Tech.	Lab. Sup.	Invest.	Tech.	Lab. Sup.	Invest.	Tech.	Lab. Sup.	Invest.
Avg. Temp.	0.1	0.04	0.11	0.01	0.01	0.01	0.01	0.01	0
	(0.04,0.36)	(0.04,0.19)	(0.05,0.22)	(0.01,0.06)	(0.01,0.06)	(0.02,0.07)	(0.01,0.05)	(0.01,0.05)	(0,0.03)
GDP	0.46	0.13	0.34	0.24	0.05	0.58	0.46	0.04	0.36
	(0.04,0.93)	(0.01,0.47)	(0.02,0.58)	(0.04,0.75)	(0.01,0.21)	(0.13,0.73)	(0.11,0.79)	(0.01,0.26)	(0.06,0.54)
TFP	0.84	0.02	0.08	0.57	0.02	0.28	0.7	0.07	0.09
	(0.62,0.99)	(0,0.16)	(0,0.15)	(0.14,0.83)	(0.01,0.27)	(0.04,0.46)	(0.19,0.72)	(0.01,0.29)	(0.02,0.21)
Hours	0.32	0.24	0.44	0.04	0.14	0.79	0.13	0.24	0.54
	(0.06,0.83)	(0.07,0.5)	(0.04,0.65)	(0.02,0.53)	(0.03,0.21)	(0.26,0.82)	(0.07,0.59)	(0.04,0.29)	(0.14,0.56)
Investment	0.52	0.08	0.39	0.1	0.03	0.85	0.21	0.11	0.56
	(0.11,0.89)	(0.01,0.33)	(0.06,0.64)	(0.02,0.51)	(0.01,0.07)	(0.42,0.92)	(0.06,0.42)	(0.01,0.16)	(0.26,0.66)

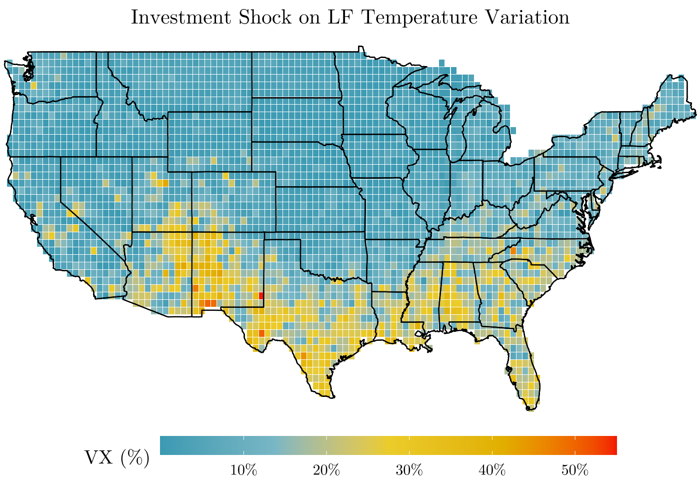
Taken together the three economic shocks explain around 25% of the low frequency movement of temperatures. Technology and investment shocks contribute the most (10% and 11% respectively), labor supply shocks contribute less (4%). We conclude from this that a non-negligible share of the trend- and long-cycle 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 87% of the BC variation in GDP, 87% of the variation in TFP, 97% of the variation in hours, and 89% of the variation in investment.

The spatial distribution of explained variances of the three shocks is presented in Figure 6. 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 6: Grid cell level cyclical variation explained at low low frequencies from the three economic shocks.



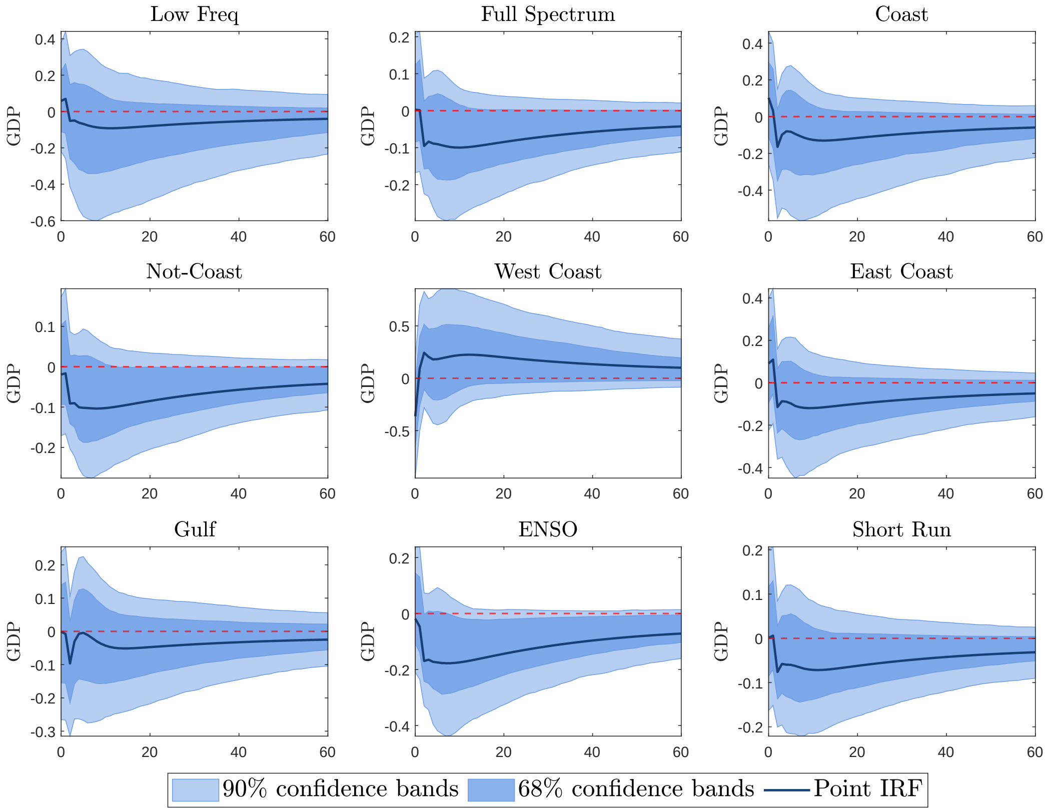




Temperature shocks

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 7 summarizes the resulting IRFs.

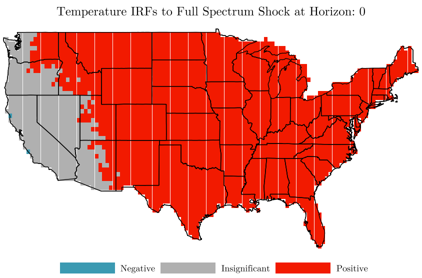
Figure 7: Impulse response functions for the different temperature shocks. Shaded areas are bootstrapped 68% and 90% confidence bands.



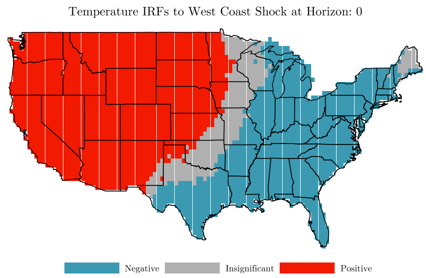
All of the identified shocks lead to small and persistent GDP contractions between 0.1% and 0.2% except for the shock that hits primarily the West coast of the US. The confidence bands are always very close to the zero line. This result is consistent with the majority of the literature, which finds substantial uncertainty involved in the estimates of temperature shocks in the US, see for example Newell, Prest and Sexton (2021) and Nath, Ramey and Klenow (2023), who find nearly zero effect for countries with an average temperature around 13 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, Hoffmann and Phan (2019), while Dell, Jones and Olken (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 8 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.

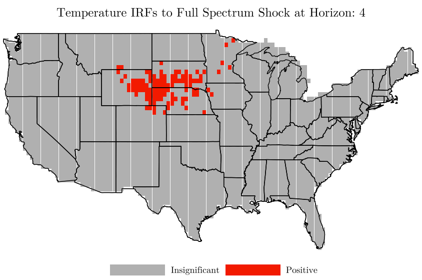
Figure 8: Grid cell temperature IRFs at given horizons in response to the full spectrum and the west coast temperature shocks.



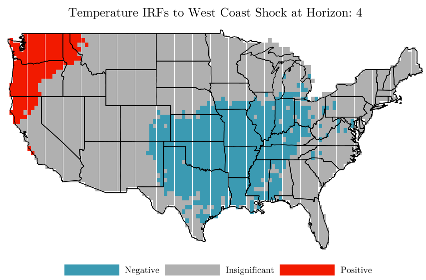
(a) Full spectrum shock on impact



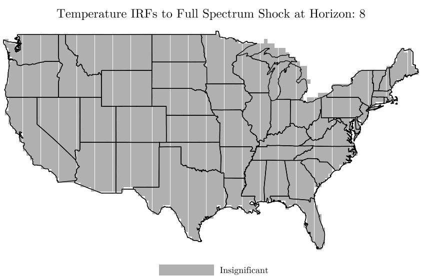
(b) West coast shock on impact



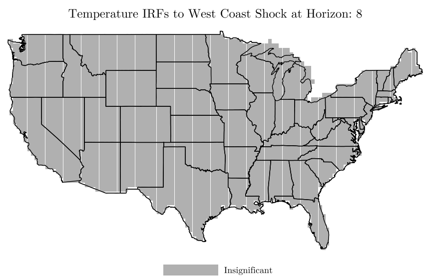
(c) Full spectrum shock after 1 year



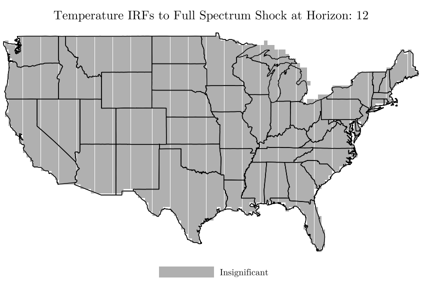
(d) West coast shock after 1 year



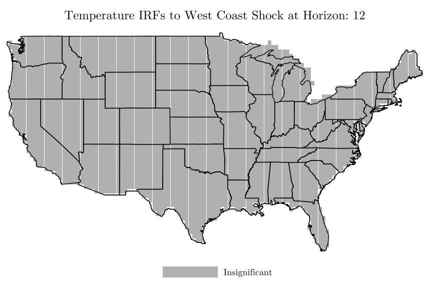
(e) Full spectrum shock after 2 years



(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 temperature warming which are fed into models used for policy decisions.

5 Discussion

5.1 The effects of economic shocks on temperatures

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, Melenberg and Muris (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 long-lived, well-mixing gas, which spreads through the Earth's atmosphere over time, while SO2 produces quick, but more short-lived localized cooling by reflecting incoming solar radiation. There is increasing evidence from the natural sciences literature which suggests that emission impulses can lead to temperature effects within a short time span. Notably, Ricke and Caldeira (2014) and Zickfeld and Herrington (2015) suggest that CO2 emission impulses can lead to significant warming relatively quickly – 93% of the peak warming effects materialize after 10-15 years following an emission impulse in their experiments, even taking potential non-linearities into account. Such horizons are well within the customary projection range for FAVAR models. Complementary to this, Joos et al. (2013) calculate average surface-temperature responses to CO2 emission impulses and find positive reactions contemporary with the initial impulse. Methane is another powerful GHGs that develops much of its effects over a short horizon (Mar et al., 2022). Therefore, our finding of quick temperature changes in the US after economic shocks is in line with results found in climatology research. Nevertheless, we want to emphasize that the very long run where GHG effects are still active may be less precisely estimated in our model.

Technology shocks induce cooling in parts of the US east and south. This suggests that the solar radiation effect from aerosol emissions outweighs the heating effect from GHG emissions at these locations, especially in the short run. We investigate this hypothesis further by running the following analysis: to the VAR consisting of GDP, TFP, investment and hours worked we add time series for GHGs and SO2 emissions in the US for the same sample we have used in our previous analysis. The emissions data are available at yearly frequency. The data for GHGs are retrieved from `https://ourworldindata.org/greenhouse-gas-emissions` and are based on Jones et al. (2023), 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`). We estimate the VAR with a single lag and identify a technology shock and an investment shock in exactly the same fashion as before, using frequency domain techniques.

Figure 9: Impulse response functions of log emissions to technology and investment shocks in the yearly VAR(1) for only economic variables. Identification in the frequency domain adapted to yearly measurements.

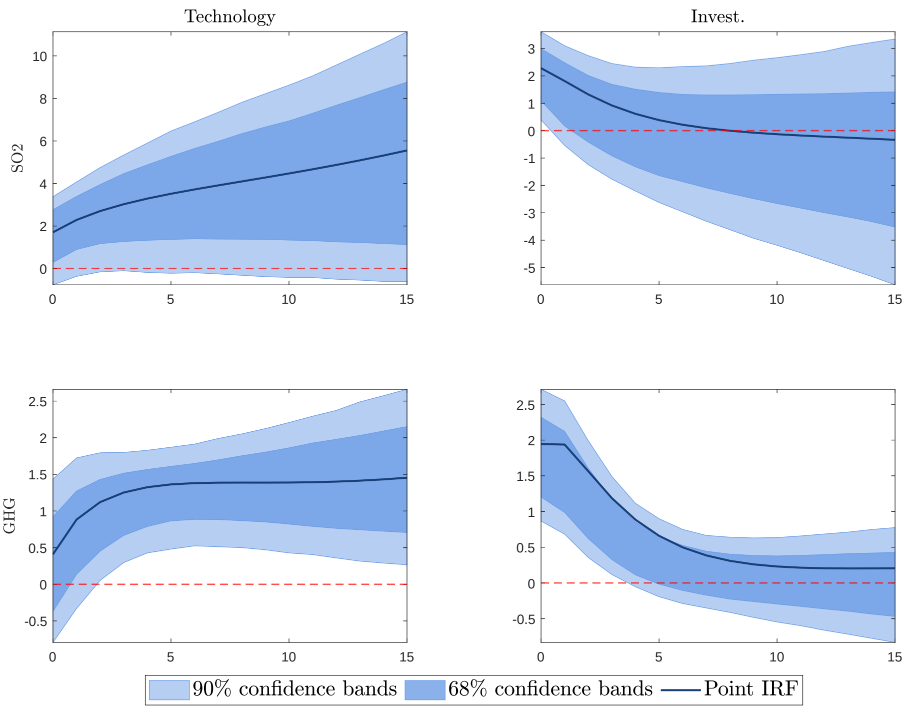
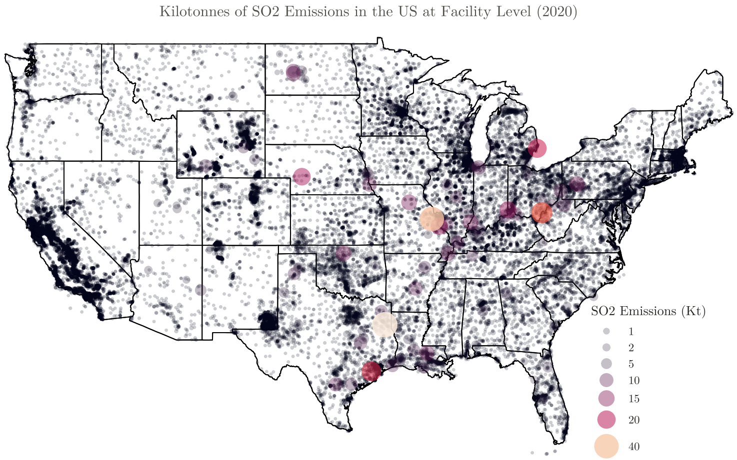


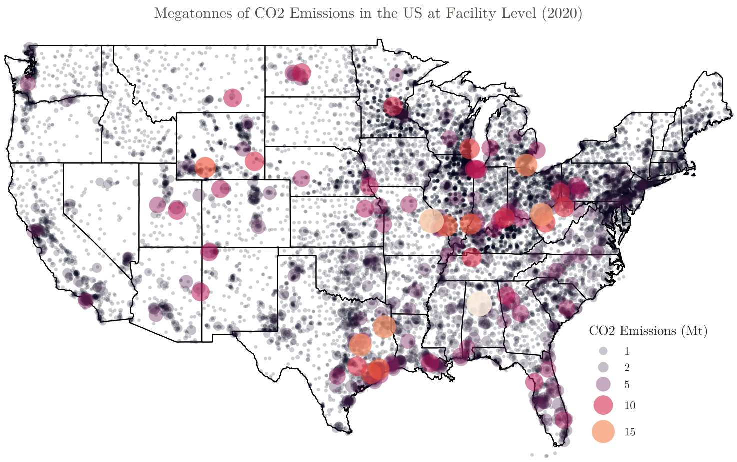
Figure 9 shows the responses of SO2 and GHG emissions to the two main expansionary shocks (technology and investment). The IRFs for the other economic variables are in line with the quarterly exercise and are therefore not reported again. The permanent shock to TFP also leads to permanent increases in both SO2 and GHG emissions, but the increase in SO2 emissions is in the area of 2% initially and up to 6% after 15 years, while GHG emissions increase only between 0.5% on impact and slightly below 1.5% in the long run. We take this as evidence that what we pick up in the quarterly FAVAR is cooling from increased aerosol emissions. This also speaks to the localized effects in the south-east of the country which we comment on more below. Importantly, as suggested in Magnus, Melenberg and Muris (2011), SO2 is itself short-lived and so in spite of the sustained increase in SO2 emissions, the cumulative warming effect from GHGs eventually neutralizes the cooling from aerosols in our quarterly FAVAR, which is why as the IRF horizon increases, the cooling effects disappear or even turn to warming. For the investment shock, on the other hand, we see impulses in both SO2 and GHGs of equal magnitude, but the SO2 impulse is only mildly significant for about one year before emissions (insignificantly) reduce. GHG emissions are strongly increased and persist for a longer period, which is why the cooling effect here dissipates fast and is dominated by the warming effect from GHGs throughout the horizon in the quarterly FAVAR. This also explains, why the temperature changes after the investment shock are observed across almost the entire country and remain significant even after 15 years – there is no sustained counteracting cooling effect.

Curiously, the geographical pattern of temperature changes after a technology shock in Figure 6 roughly coincides with the location of important parts of the American energy producing, manufacturing and natural resource processing industries. Figure 10 shows that these areas are also centres of CO2 and SO2 emissions. Conley et al. (2018) study the responses of temperatures to the hypothetical removal of all US based SO2 emissions and document a very similar geographical pattern (evidently with inverted signs as they consider SO2 removal, instead of emission). Based on this observation, we are confident that our economic shocks lead to temperature-altering emissions in the parts of the country where these should be expected to occur. Moreover, given the localized nature of aerosol-related cooling, we take this spatial pattern as evidence that the channel we pick up for our technology shock is indeed dominated by SO2 emissions.

Figure 10: SO2 and CO2 emissions are computed from EPA's NEI 2020 data set for site-specific emissions (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) Sulfur dioxide emissions 2020



(b) Carbon dioxide emissions 2020

5.2 The effects of temperature shocks on GDP

Next, we turn to the discussion of the different effects of west coast centered temperature shocks and the other temperature shocks we have identified. We focus on the full spectrum maximizer as a representative of the other shocks and recall that both shocks lead to a one centigrade increase in average US temperatures, but the GDP responses present opposite signs. Our reasoning for this finding is based on previous results in the literature. First, consider sector level responses. Increases in temperatures have been shown to reduce output in almost every industry, especially in agriculture and construction (Colacito, Hoffmann and Phan, 2019). The temperature increase that follows the full spectrum shock affects almost the entire US and thus essentially all industries (a notable exception being California), thus depressing also aggregate GDP. Conversely, the west coast shock leads to increased temperatures on the west coast, but is accompanied in the data by lower temperatures in the east. In our linear model, decreasing temperatures should be beneficial for output in those states. The heating in the west does not appear to offset this positive effect.

Second, we turn to geographical differences. Hsiang et al. (2017) provide estimates of the projected spatial 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 country, whereas the north-western states experience positive effects from warming. The largest damages from temperature increases go through excess mortality in the densely-populated east and the already warmer south of the US in their study, also reported by Carleton et al. (2022). Therefore, the warming in the west and cooling in the east we document after the west coast shock should benefit the western industries and lead to fewer deaths in the east, which sums to a net positive effect for aggregate GDP. The full spectrum shock, on the other hand, does not produce the warming gains in the north-west but leads to warming in the areas where excess mortality has been shown to be of high importance in the transmission of temperatures to GDP.

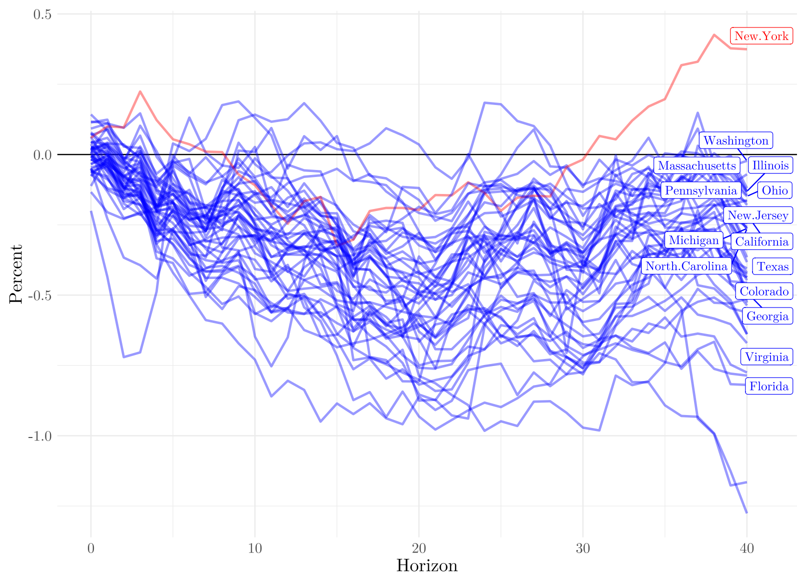
In light of these arguments, we carry out the following exercise to better understand how the shocks impact state-level income. We expect the full spectrum shock to be damaging almost everywhere and the west coast shock to be expansionary, at least in the eastern states, but potentially also in the west. To do this, we run the following local projections (Jordà, 2005) for each state in the contiguous US individually:

$$y_{t+h} = \mu_h + \beta_h \hat{s}_t + \gamma_h(L) y_{t-1} + \varepsilon_{t+h}, \quad \text{for } h = 1, 2, \ldots, 40 \tag{2.12}$$

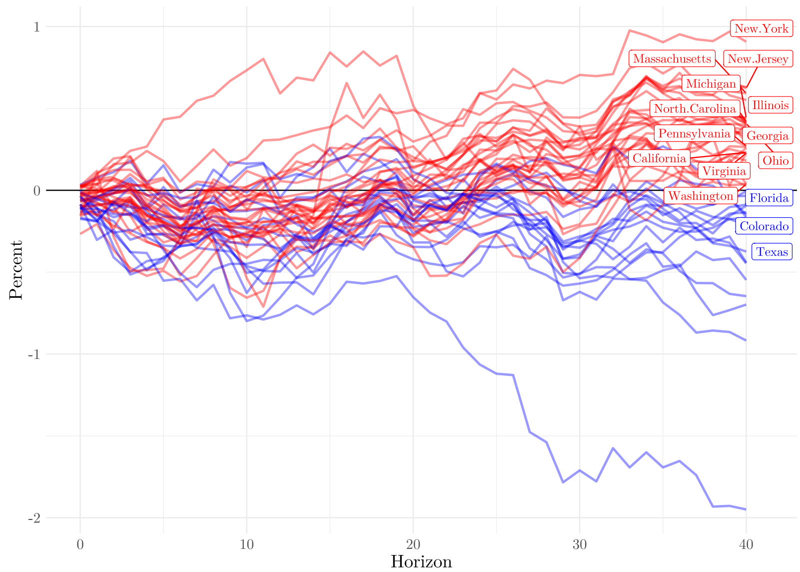
where y_{t+h} is the log of quarterly real personal income,[3] μ_h is a constant, $\hat{s}_t$ is alternatively the unit variance full spectrum or west coast shock estimated in the FAVAR, $\gamma_h(L)$ is a lag-polynomial of order two as in the FAVAR and ε_{t+h} is a forecast error. The coefficient β_h measures the response to the shock of interest at each horizon h.

[3]Personal income data at the state level at quarterly frequency is collected from BEA table SQINC4 and deflated using the GDP deflator and alternatively the CPI. The sample spans Q1:1948 - Q4:2017.

Figure 11: Impulse responses to the full spectrum and the west coast temperature shocks identified in the FAVAR. IRFs are obtained by means of a local projection of real personal income at the state level onto its own lags and the identified unit variance shock. The states with name tags are the largest 15 states by GDP. Blue lines indicate negative responses after 40 quarters. Red lines indicate positive responses after 40 quarters.



(a) Full spectrum shock on real personal income



(b) West coast shock on real personal income

Figure 11 shows that the full spectrum temperature shock indeed decreases income in nearly all states, except for New York, which nonetheless experiences reductions in income for most of the horizon. The west coast shock, on the other hand, produces mixed IRFs. The majority of economically large states (by share of national GDP) experience income increases, except for Colorado, Florida and Texas, where the losses are relatively small. Big west coast economies such as California and Washington see long-run benefits from the shock, although these are small in magnitude. We take the evidence from this auxiliary model as supportive of the idea that temperature increases, in general, are detrimental for output, possibly by increasing mortality or lowering productivity. However, we caution that a measured increase of average US temperatures of one degree Celsius can come in different shapes, that produce different dynamics at the state level which then translate into different aggregate responses. We believe that our two example shocks are good representations of actual co-movement in temperatures experienced in the US. Any exercise focusing on the simple average temperature, which is similar to the full spectrum maximizer, will likely miss the effects induced by the west coast shock and may lead to incomplete conclusions for damage functions and policy implications.

6 Conclusion

We model an empirical 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 at least five shocks are necessary to accurately reflect temperature variations of different frequencies everywhere in the contiguous US, calling into question papers that use a single “climate shock" or focus on cross-sectional averages to reflect temperature warming. 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 the 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. There is clear evidence that economic activity has affected US temperatures. Together the three shocks account for around 25% of the low frequency component of US temperatures. Investment shocks increase temperatures on average, technology shocks decrease them, and we explore the reasons for this by showing a significant role for aerosol emissions that induce local, short-lived cooling and GHG emissions that lead to slow-paced, encompassing warming.

On the other hand, the economic damages from changing temperatures are small and come with substantial uncertainty. We show that temperature changes that affect primarily the US west coast lead to small economic expansions, as they are accompanied by decreasing temperatures in the east and south. Shocks raising temperatures elsewhere are mildly recessionary, suggesting that the US has been well adapted to temperature change in the past.

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APPENDICES

A DATA CONSTRUCTION

We follow Angeletos, Collard and Dellas (2020) in constructing the economic variables.

Table A.1: 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

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:** $GDPC1/A939RX0Q048SBEA$

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.

B BOOTSTRAP PROCEDURE

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

1. Use (2.2) 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 (2.2) 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.

C 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 1970:
We have used data between 1948 and 2017. The trend in temperatures that is usually attributed to human influence becomes very pronounced in our data as of around 1970.

Moreover, as of the 1970s, SO2 emissions in the US start to decline. We repeat our exercise by excluding the first 22 years from the sample.

4. Potential interference from outside shocks:
There may be non-US shocks driving BC and LF variation in US aggregates that then affect temperatures. While the US is usually treated as having frontier technology (Nath, Ramey and Klenow, 2023). It may be that shocks in China spill over to the US and then show up as US shocks affecting temperatures when really the origin in elsewhere. Long quarterly time series for China are difficult to obtain, but annual series for CO2 emissions show an impressive uptick as of the year 2000. We therefore cut the sample at Q4:1999 to check if our results obscure external influences from China.

5. 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, Gambetti and Sala (2014). Since the connection between the economy and temperatures appears to run largely through TFP, correct identification of the technology shock is crucial.

6. Variables in per capita terms:
Long-run economic dynamics may be affected by demographic sources (Francis and 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.

Robustness results:
The results are insensitive to the selection of the lag order, number of factors or specification of variables in per-capita terms. Minor changes obtain for sub samples and when altering the long-run identification assumption as in robustness check 5. Figure C.12 shows the IRFs for average US temperatures to the economic shocks. The most significant differences arise when we change the sub-samples to post 1970 and pre-2000, as then the technology shock leads to positive temperature responses. This is because the role of SO2 emissions and other aerosols in depressing temperatures is diminished after 1970. Similarly, excluding the more recent period from the sample attributes some cooling to the investment shock as the reduction on SO2 emissions has not yet materialized. While these changes are interesting, we rather see them as further evidence for the importance of this additional channel for the transmission of economic activity to temperature changes.

Figure C.12: Impulse response functions of US average temperatures to economic shocks for robustness checks 1-6.

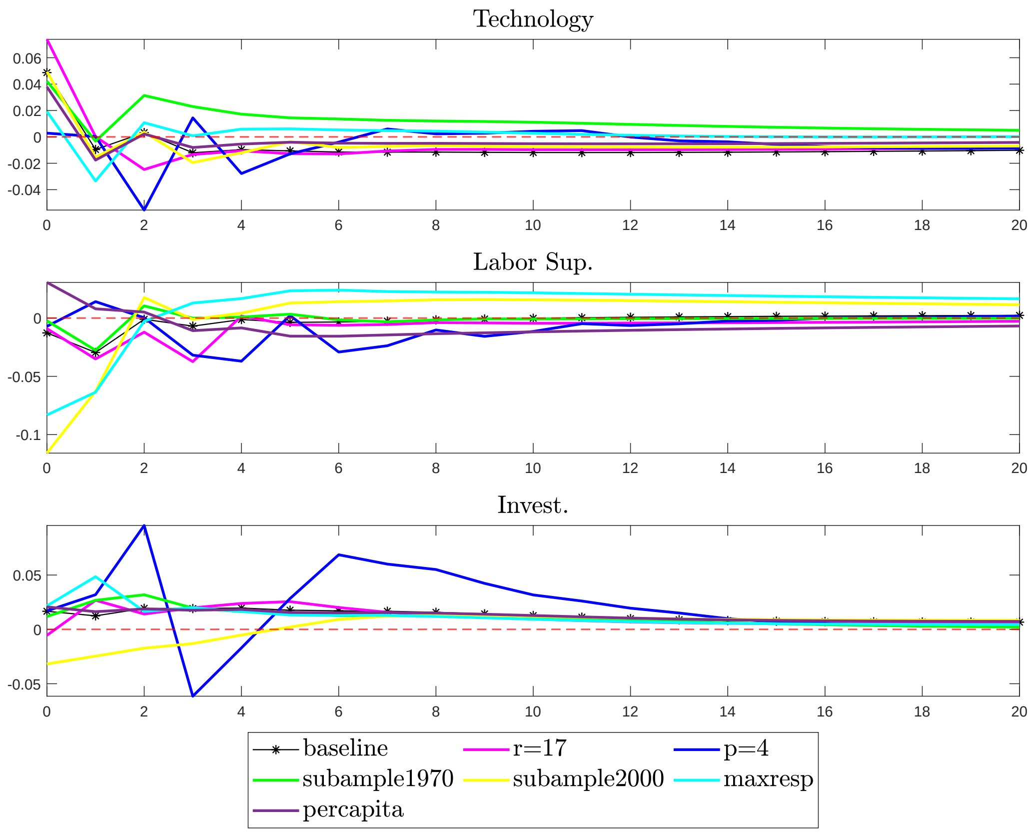


Figure C.13, on the other hand, reports the IRFs of real GDP to the different temperature shocks for all robustness checks. We observe that changing the number of temperature principal components or the number of lags has negligible effects on the IRFs compared to our baseline specification. The same 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 C.13: Impulse response functions of GDP to temperature shocks for robustness checks 1-6.

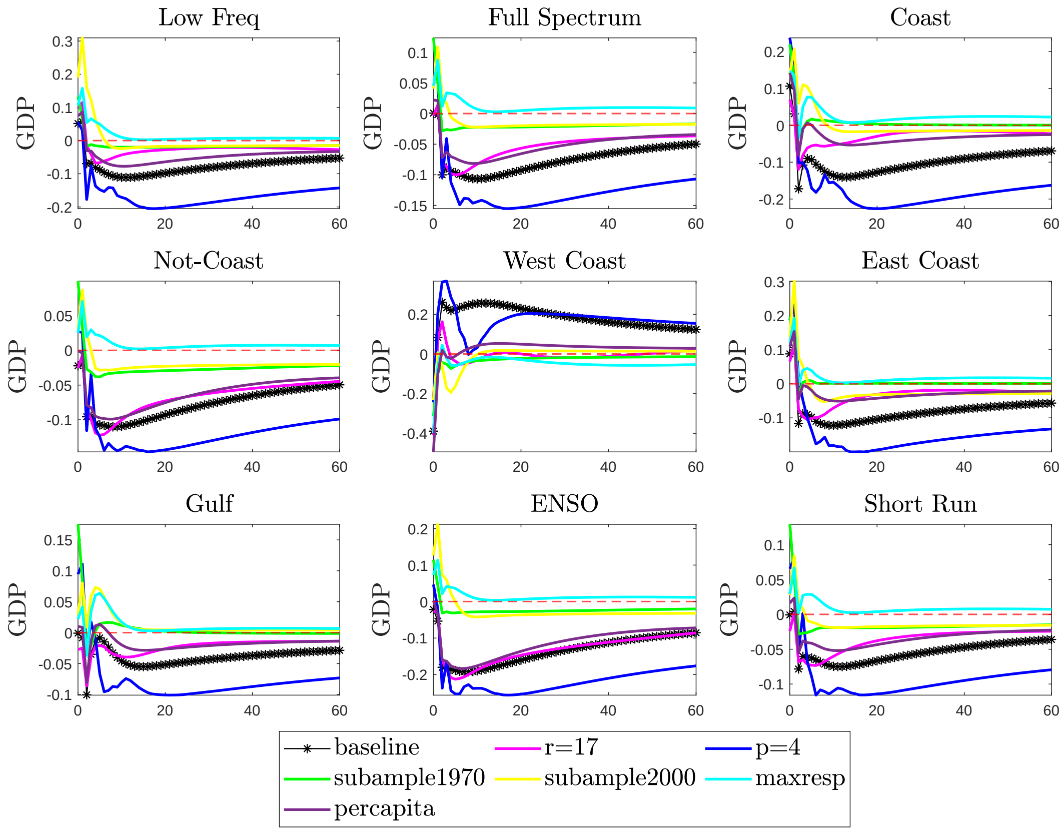
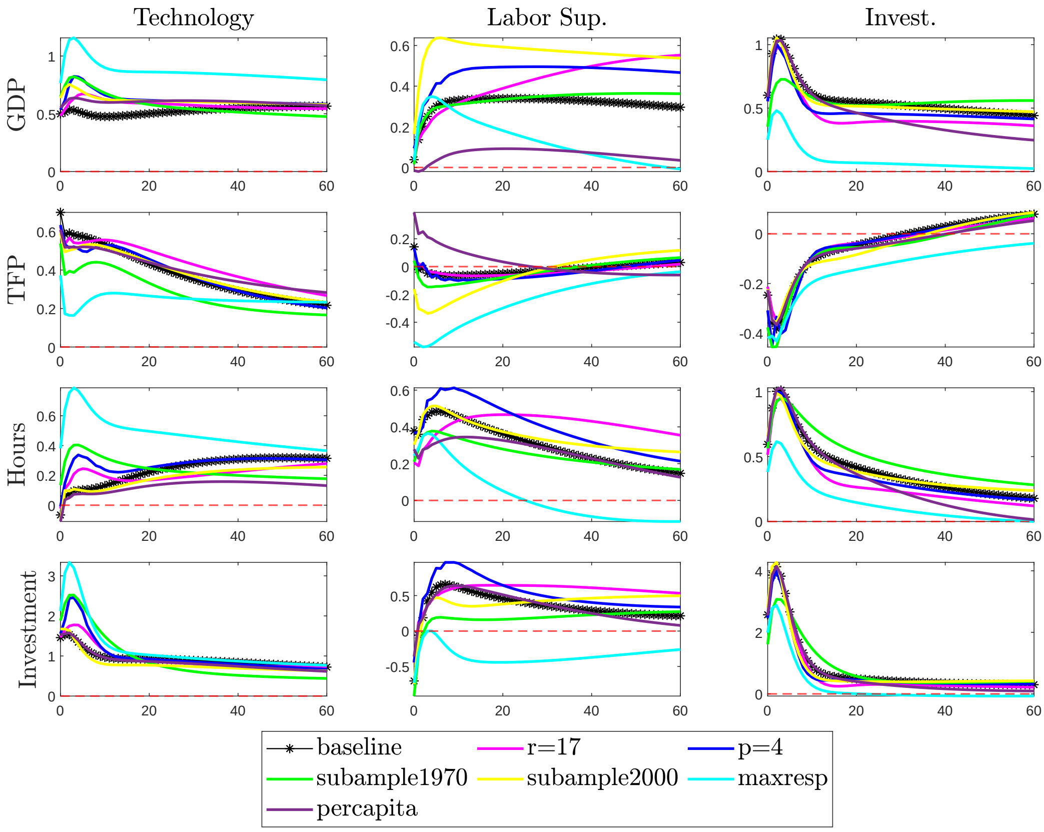


Figure C.14: Impulse response functions of economic variables to economic shocks for robustness checks 1-6.



Lastly, we check if the sequence of conditional identifications matters for our results. We therefore permute the identification order of the three economic shocks – technology (T), investment (I) and labor supply (H) – to allow for all possible orderings and report the economic and temperature IRFs.

Figure C.15: Impulse response functions of economic variables for different orderings of identification.

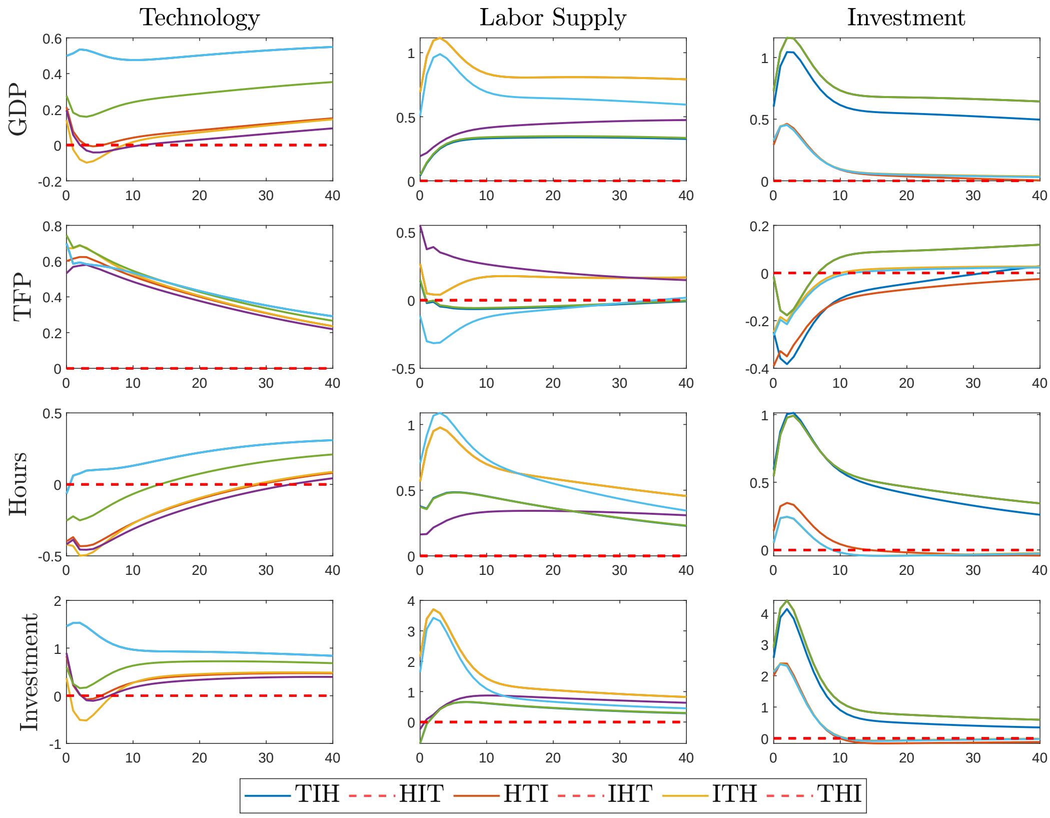
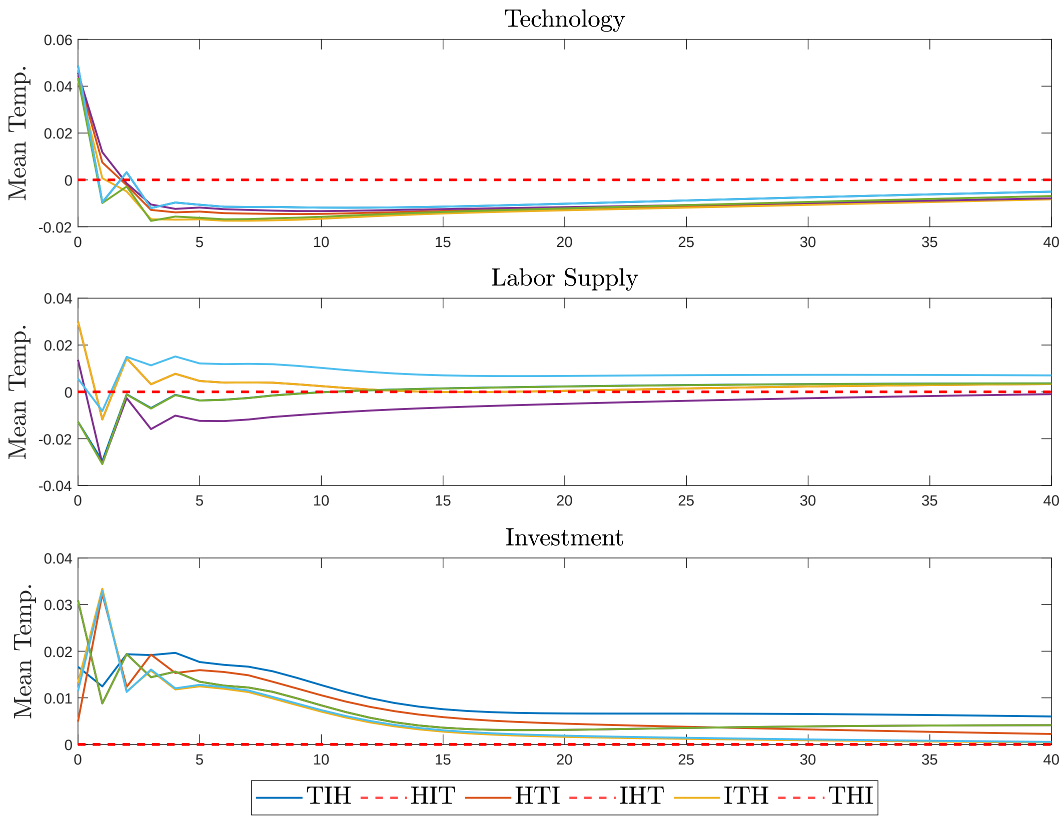


Figure C.16: Impulse response functions of average temperatures for different orderings of identification.



Figures C.15 and C.16 show that while there are some differences in the responses of the economic variables if the investment shock is identified first, these do not translate to changes in the more important results for temperature changes following the economic expansions.

D Simulation exercise

We simulate 1,000 instances of the model of Justiniano, Primiceri and Tambalotti (2011) using the *Macroeconomic Model Data Base* in Dynare (Wieland et al., 2012,0), without changing the standard settings. Each instance contains data for GDP, TFP, hours worked and investment (plus other series which we disregard for this exercise). We also extract the true IRFs to neutral technology, investment and wage markup shocks (having a similar interpretation to our labor supply shocks). For all 1,000 simulations we then use our sequential identification strategy to identify the three structural shocks in the frequency domain for a VAR(4) with the four economic time series of interest. In the model of Justiniano, Primiceri and Tambalotti (2011) the neutral technology shock is the only driver of TFP growth, the wage markup shock is the dominant force of low frequency changes in hours worked and the investment shock is the main influence on investment variation in the business cycle band. Therefore, our identification approach is theoretically justified to work for this case.

Figure D.17: Impulse response functions of economic variables to economic shocks from simulated data as per Justiniano, Primiceri and Tambalotti (2011).

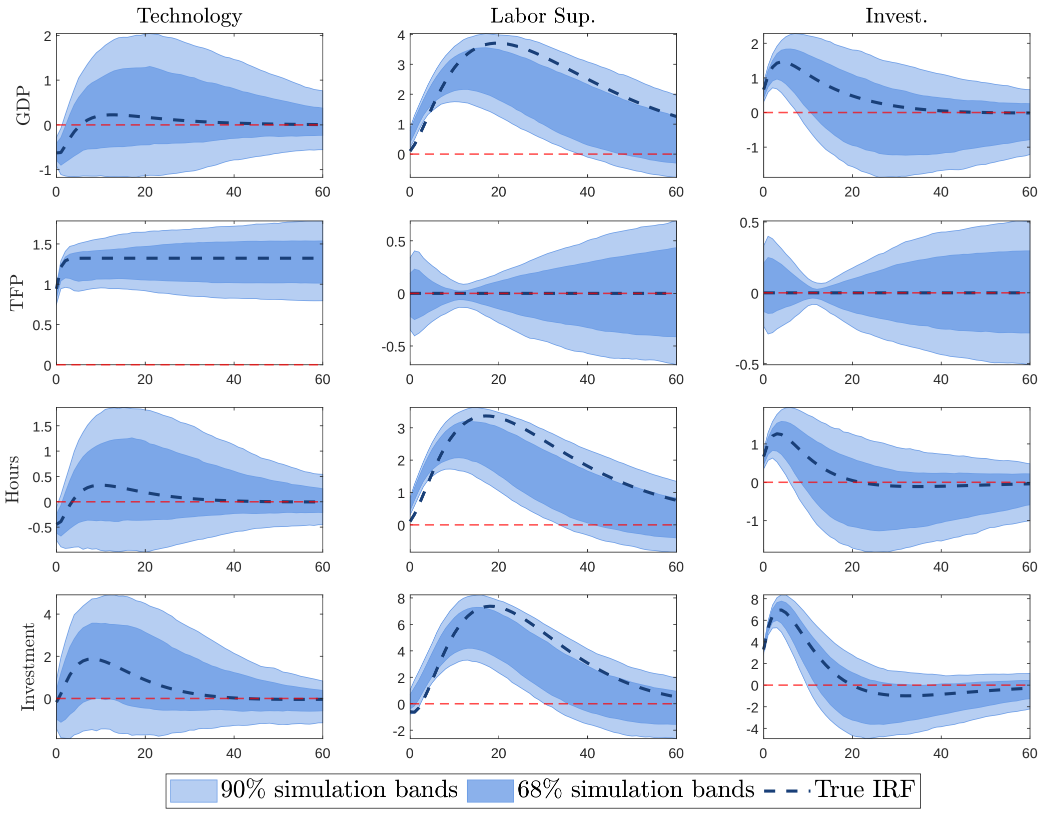


Figure D.17 shows the bands resulting from the 1,000 identification exercises on simulated data as well as the theoretically true IRFs. Our VAR-based approach is very successful in capturing the correct dynamics in the vast majority of the simulation runs. This gives us confidence that it may also be useful in a purely applied setting.

Chapter 3

Time-varying effects of temperature shocks

Konstantin Boss, Alessandra Testa

Abstract: We explore how the macroeconomic effects of temperature shocks in the United States have evolved over time. Using a time-varying coefficient vector autoregressive (TVC-VAR) model, we show that industrial production and consumption in the US have decreased especially in the period since 2010. Prices always decrease after temperature shocks and hours worked mildly increase. These findings suggest a limited role for adaptation to climate change in the US and a higher importance for consumption channels rather than the labor market for economic damages of climate change.

Keywords: Temperature shocks, Adaptation, TVC-VAR.
JEL classification: Q54, C32

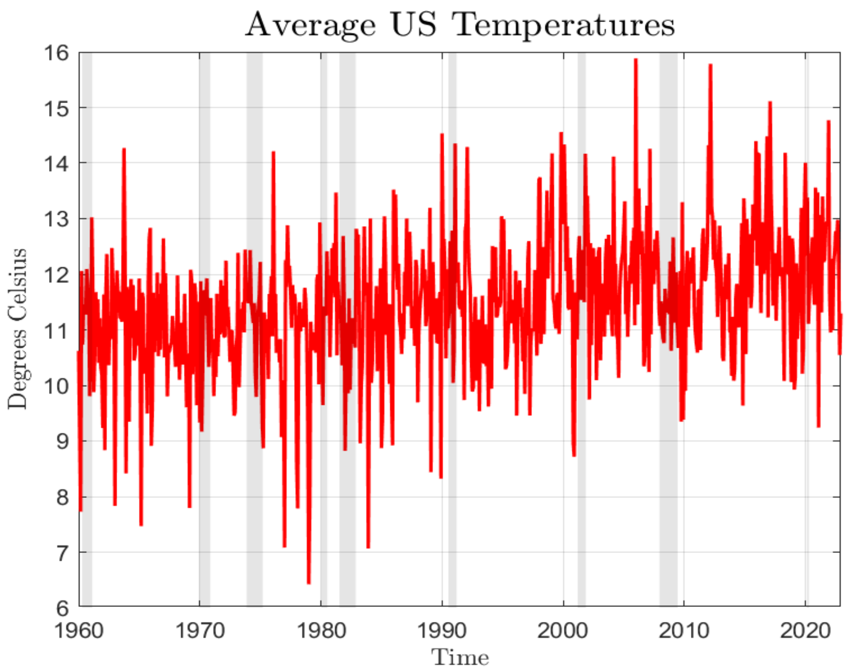
1 INTRODUCTION

Have the effects of temperature shocks in the United States changed over time? In this paper we provide new evidence on the time-varying response of economic activity to unexpected temperature increases over the period 1960-2022 using a dataset on the US macro economy and a time-varying coefficient vector autoregressive (TVC-VAR) model. Allowing for time-varying endogenous dynamics in a climate-economic model may be important for at least two reasons, as suggested in Berg et al. (2024): first, if tipping points, such as the melting of the Greenland ice sheet or imbalances in the salinity of the oceans are triggered, the data-generating process shifts drastically and second, if people adapt to the new climate conditions, for example, through new technologies or behavioral changes, some active transmission channels between the economy and the climate are shut off or newly activated. Given that critical tipping points such as the full melting of the polar ice caps have not yet occurred in our data sample, the evidence in this paper speaks primarily to the process of climate adaptation. Moreover, adaptive behavior represents a key challenge in the analysis of the economic costs of climate change. If economic agents successfully adapt to the new climatic conditions, the projected damages caused by climate change will be lower than if no adaptation at all takes place. Thus, not accounting for it can severely bias estimates and forecasts of the economic costs of climate change.

Since the beginning of the last century, global temperatures have started to rise at an unprecedented speed, with the majority of warming occurring in the period after 1975. Figure 1 shows mean temperatures in degrees Celsius in the United States for the years 1960-2022. Over this period, many significant changes – both in the US and internationally – that affect how economic activity and temperatures interact have occurred. Some examples that have been studied in the literature are the widespread use of air conditioning, which has reduced temperature mortality Barreca et al. (2016) – a key component of the economic costs of climate change (Carleton et al., 2022), amendments in the Clean Air Act around 1970, which have significantly reduced the emission of air pollutants (Pretis, 2021), as well as growing awareness of climate change has shaped the political agenda (Venghaus et al., 2022). Given the variety of ways to adapt to climate change, the focus of our study is on documenting whether the same temperature shocks have led to different economic responses in different years, netting all possible forms of adaptation together, while being silent on the particular channels of adaptation at work.
Our analysis begins with estimating temperature shocks and impulse response functions (IRFs) using a structural VAR model. We then conduct a sub-sample analysis to explore potential changes in the effects over time. Finally, motivated by the significant differences

observed between the two sub-samples, we further investigate the time-varying impact of temperature shocks through a time-varying coefficient VAR (TVC-VAR) model.

Figure 1: Average temperature in the United States measured in degrees Celsius. Source: ERA5 re-analysis data from ECMWF.



We document the following key insights: the macroeconomic effects of temperature shocks in the United States fluctuate significantly over time. While the size of the reaction in average temperatures to one standard deviation shocks remains fairly constant, the persistence of the reaction in temperatures has increased. This suggests that heat periods are prolonged in more recent times. Moreover, on aggregate, temperature increases can be both positive in terms of industrial production, consumption and hours worked (during the 1970s and mid 1980s to mid 2000s) and negative (particularly in the 1980s and 2010s). Remarkably, we find that prices are almost always decreased when unexpectedly warm months occur, possibly due to lower energy demand during heating months. Overall, these results show little clear evidence of climate adaptation. Finally, the common finding of hardly any damages from climate change in the US (Dell et al., 2012) may be a result of averaging over the relatively regular changes in the IRFs over time.

The remainder of the paper is organised as follows. Section 2 summarizes the related literature. Section 3 describes the dataset. Section 4 presents the empirical model, and Section 5 shows the results. Section 6 provides some robustness checks. Section 7 concludes.

2 Related Literature

Our work lies at the intersection of two strands of research in the climate literature. The first one investigates adaptation to climate shocks. There is now a large literature including adaptation in the studies of the economic effects of climate change. Gourio & Fries (2020) introduce a new economic model for adaptation to predict income losses from climate change. Comparing the "adaptation" and "no adaptation" scenarios, they show that output losses are lower in the first case. Kahn et al. (2021) use the different speeds with which the historical temperature and precipitation norms change as a measure of how fast countries adapt to the new climate conditions, and show that adaptation can dampen the negative long-run growth effects of climate change. Some recent studies argue that climate shocks have larger effects on the economic activity and inequality of poor countries, that have limited adaptation capabilities and mostly rely on the agricultural sector (Alessandri & Mumtaz, 2021; Mumtaz & Theophilopoulou, 2024).

The second line of research employs time series methodologies to investigate the effects of climate-related shocks on economic activity. In the estimation of the time-varying effects of temperature shocks, our paper especially relates to Kim et al. (2022). Using the Actuaries Climate Index (ACI, *Actuaries Climate Index* (2023)), they estimate an extreme weather shock in the US using a smooth transition VAR to provide evidence of limited adaptation. The estimated extreme weather effects seem to be negligible at the beginning of the sample, and become significantly negative for industrial production at the end. Instead, Sheng et al. (2023) provide evidence of adaptation in the US by estimating an extreme weather shock imposing sign restrictions in a TVC-VAR. They show that the adverse effects of climate shocks diminish over time, which they interpret as arising from adaptive behavior of economic agents.

We contribute to the literature by estimating the time-varying responses of economic variables to temperature shocks using a version of the non-parametric methodology recently introduced by Giraitis et al. (2018), which imposes fewer assumptions on the data generating process than popular Bayesian counterparts as in Sheng et al. (2023). By allowing for time-varying variances, we are also able to investigate whether the size of the shock has changed over time. Indeed, most previous studies focus only on the larger/smaller economic responses to climate-related shocks to draw conclusions about adaptation. Though, lower responses in the most recent period do not necessarily imply higher adaptation. It might be the case that climate shocks are smaller.

3 DATA

3.1 TEMPERATURE DATA

In the empirical application we rely on monthly temperature data for the United States. The data source is ERA5 monthly averaged reanalysis data which are produced by the European Centre for Medium-Range Weather Forecasts within the Copernicus Climate Change Service (Hersbach et al., 2020). Climate reanalysis combines past observations with today's weather models to deliver a complete picture of past weather. This is necessary because, while past weather observations are sparse and unevenly distributed, modern observations are much more comprehensive. Reanalyses are among the most widely used datasets in in the geophysical sciences. ERA5 provides hourly estimates for a large number of atmospheric, ocean-wave and land-surface quantities. We use *2m temperature*, that is the temperature of air at two meters above the surface of land. The data are gridded with an horizontal resolution of $0.25^\circ \times 0.25^\circ$ and are available from 1940 to the present. For robustness, we check the results using another commonly used monthly temperature dataset: CRU TS (Climatic Research Unit gridded Time Series, Harris et al. (2020)). These data are derived through the interpolation of monthly climate anomalies from extensive networks of weather station observation. The final grid has $0.5^\circ \times 0.5^\circ$ resolution. We compute average temperatures by averaging over all grid cells in the contiguous US without population weighting.

A short comment on temperatures magnitudes is useful to understand the proposed methodology below and its interpretation. The typical way to present temperature shock results is to scale the shock so that it produces a 1°C increase in average temperatures (Dell et al., 2012; Bilal & Känzig, 2024). This goes for time series as well as panel data studies. It is important to note that a 1°increase in annual mean temperature is much more severe than a 1°C increase in monthly data, given that it has taken nearly the entire post-industrial period for temperatures to increase by (by now somehwat more than) 1°C. Moreover, 1°C increases in the 1980s may be much more common shock sizes than in the latter part of the sample given our finding that the standard deviation of the temperature innovation declines over time. Due to these reasons, we opt for reporting IRFs to one standard deviation shocks. While the standard deviation of monthly mean temperatures in the data set is 2.12°C, this does not mean that a one standard deviation shock increases temperatures by that number. The standard deviation refers to the size of the shock, not the reaction in temperatures.

3.2 Macroeconomic Data

All macroeconomic time series are sourced from FRED and Thomson Reuters Datastream. The key economic variables are (log) Industrial Production, (log) Real Consumption Expenditures for non-durable goods, (log) Consumer Price Index, (log) Hours worked in the manufacturing sector. The dataset has monthly frequency and the sample period spans from 1960-1 to 2022-12. All logged variables are multiplied by 100 to facilitate the interpretation of the IRFs in percent.

4 Methodology

Our final objective is to study the effect of temperature changes on the US economy. The baseline model that we estimate is a Structural VAR (SVAR) to investigate the relationship between temperature and macroeconomic variables in the US, similarly to many of the existent studies in the literature. The SVAR model has the following form:

$$B_0 y_t = \mu + B(L) y_{t-1} + u_t \quad u_t \sim (0, I) \tag{3.1}$$

The coefficients in $B(L) = A(L)SH$, where H is an orthonormal matrix, can be obtained from estimating the reduced form model

$$y_t = c + A(L) y_{t-1} + \varepsilon_t \quad \varepsilon_t \sim (0, \Sigma) \tag{3.2}$$

using least squares plus an identification step which pins down S and H. We use a Cholesky decomposition to obtain S as the lower triangular factor of the variance-covariance matrix Σ from the reduced form model and impose $H = I$, so that $u_t = H' S^{-1} \varepsilon_t$. The Cholesky identification implies that the order of the variables in the VAR matters. In particular, we order the temperature variable first, as the most exogenous component of the model, which implies that it is unaffected by any other contemporaneous shocks except for its own, but can drive economic variables on impact. This ordering is motivated by the following observations: First, while we do want to allow for feedback between the economy and our climate variable, this feedback is not instantaneous. The strongest link between economic activity and climate change is through greenhouse gas emissions, especially CO_2 and air pollutants, for example, SO_2. However, climate systems are subject to inertia which delays the translation of changes in emissions to temperature changes substantially (Samset et al., 2020). Given that our data is sampled at monthly frequency, this identifying assumption seems very mild.

We introduce adaptation into the model by allowing the parameters and variance-covariance matrix of the model to vary with time. This is a technique usually used to model economies with structural breaks as in Cogley & Sargent (2005) and Primiceri (2005), often in the context of studying monetary policy. The idea is to allow the structural parameters of the model to change (gradually) over time to accommodate, for example, interest rate policy rule changes and resulting changes in the behavior of the private sector. Moreover, such models admit estimation of time-varying shock intensities through the variance-covariance matrix. Given that climate change is a slow moving process, this choice of time variation is more appropriate than alternatives such as regime-switching models such as Markov Switching or Threshold models, which are more suitable for abrupt changes in the governing parameters. The reduced form model then becomes:

$$y_t = c_t + A_t(L)y_{t-1} + \varepsilon_t \quad \sim (0, \Sigma_t) \tag{3.3}$$

The time-varying parameter VAR (TVC-VAR) framework is well-suited for studying adaptation to temperature shocks for the following reasons: As documented above temperatures have been rising and may have become more volatile in recent years compared to the middle of the 20th century. Allowing for time-varying covariance matrices in the VAR can accommodate changing shock sizes over time. Moreover, agents have changed their behavior towards climate realizations over time, for instance, through equipping office spaces with air conditioning, developing heat resistant crops or spreading awareness of the health effects of continued exposure to heat. All of these factors can influence how exceptional temperatures affect the aggregate economy. If adaptation takes place, the same size shocks should produce reactions to temperature shocks today that are substantially different from those in the past. However, it may also be the case that adaptation has not proliferated enough to shield the economy from temperature events, especially when considering large temperature shocks. Evidence on time-varying effects of temperatures is relatively sparse until now. Burke et al. (2015) suggest that the negative effect of (large) temperature changes is unchanged since the 1960 on a global scale. However, they use a sub-sample analysis only and do not consider time varying parameters and adaptation technology explicitly. Lastly, Burke et al. (2015) suggest that non-linearities are crucial for the study of temperature shocks, as large shocks induce disproportionately larger reactions than small shocks. Granger (2008) shows that TVC models can approximate any form of non-linearity, which further motivates our choice of model.

The TVC-VAR is often estimated in a Bayesian framework (Primiceri, 2005). However, these methods tend to be computationally intensive and are usually not used for systems with many variables. A notable exception is the work developed in Koop & Korobilis (2013) who introduce forgetting factors to shrink the size of the VAR at different points in time and achieve significantly faster performance. We opt for the non-parametric approach using kernel weights advocated, for example, in Giraitis et al. (2014), Giraitis et al. (2018) and Kapetanios et al. (2019). This method is related to rolling-window estimation by placing a kernel weight on the observations in the full sample. The kernel weights are updated every period such that high weight is given to the periods near the current observation and low weights are given to further away points in time. Writing the TVC-VAR compactly we obtain:

$$Y_t = X_t \beta_t + \varepsilon_t \tag{3.4}$$

where X_t contains the deterministic regressors (constant, trends etc.) as well as the lags of the dependent variables. Kapetanios et al. (2019) show that the closed form weighted least-squares estimator of β_t is given by:

$$\hat{\beta}_t = (X'_{w,t} X_{w,t})^{-1} X'_{ww,t} Y_t \tag{3.5}$$

where

$$X_{w,t} = W_{H,t} X_t \tag{3.6}$$

$$W_{H,t} = diag(w_{1t}^{1/2}(H), ..., w_{Tt}^{1/2}(H)) \tag{3.7}$$

$$X_{ww,t} = W_{H,t} X_{w,t} \tag{3.8}$$

The weights $w_{1t}(H), ..., w_{Tt}$ are obtained from a Gaussian kernel $K(H)$ subject to a bandwidth H:

$$w_{j,t} = \frac{K_{j,t}(H)}{\sum_{j=1}^{T} K_{j,t}(H)} \tag{3.9}$$

The model is easy to estimate, does not impose a particular law of motion on the time-varying coefficients and can be expanded to large sets of variables by introducing shrinkage methods (Kapetanios et al., 2019). However, consistency of the estimator requires that β_t is a bounded sequence and changes only slowly over time, conditions which are fulfilled, for example, by a bounded *random walk* that is commonly found in the literature (Primiceri, 2005). The authors suggest checking for each period if the implied companion form matrix of the VAR coefficients has its largest eigenvalue smaller than one to fulfill the conditions.

The time varying variance-covariance matrix Σ_t can then be obtained as:

$$\Sigma_t = \hat{\varepsilon}_t W_{H_v,t} \hat{\varepsilon}_t \tag{3.10}$$

where $\hat{\varepsilon}_t$ are the estimated residuals from the regression of the reduced form VAR and H_{vt} is a bandwidth that is not necessarily the same as in the VAR estimation (Giraitis et al., 2014).

We use this approach to obtain estimates of β_t and Σ_t which allows us to model the time-varying impulse response functions (IRFs) as follows:

$$IRF_t = [I - A_t(L)]^{-1} S_t = C_t(L) S_t \tag{3.11}$$

where S_t is the lower triangular Cholesky factor of Σ_t.

Throughout the paper we set $H = H_v = (T-p)^{0.62}$. Setting the exponent higher introduces more smoothing and less-time-variation. The model is estimated including a constant and setting the number of lags equal to the recommendation by the Hannan-Quinn criterion estimated on the linear model as is common practice for non-linear VARs. We test robustness of these two assumption below, by varying the bandwidth and the lag order on a discrete grid of parameter pairs. For the calculation of the IRFs we make the common assumption that the parameters remain constant throughout the forecast horizon of 48 months. Given the relative smoothness of parametric changes this assumption is mild.

5 Results

The first part of this section presents a set of results based on the structural VAR introduced in Section 4, considering the dataset for the entire sample period (5.1), and for two sub-samples (5.2. The last part reports the results of the time-varying framework (5.3.

5.1 Baseline results

In the baseline model, we estimate the effects of a temperature shock, identified with a short-run recursive scheme, on the following set of macroeconomic variables: (log) Industrial Production (IP), (log) Real Consumption (CONS), (log) Consumer Price Index (CPI), and (log) Hours worked in the manufacturing sector. In all models the we set $p = 3$ as suggested by the HQ criterion for the full sample static coefficient model.

Figure 2: IRFs of economic variables to a one standard deviation temperature shock estimated with the SVAR on the entire sample period. Shaded areas are bootstrapped 68% confidence bands.

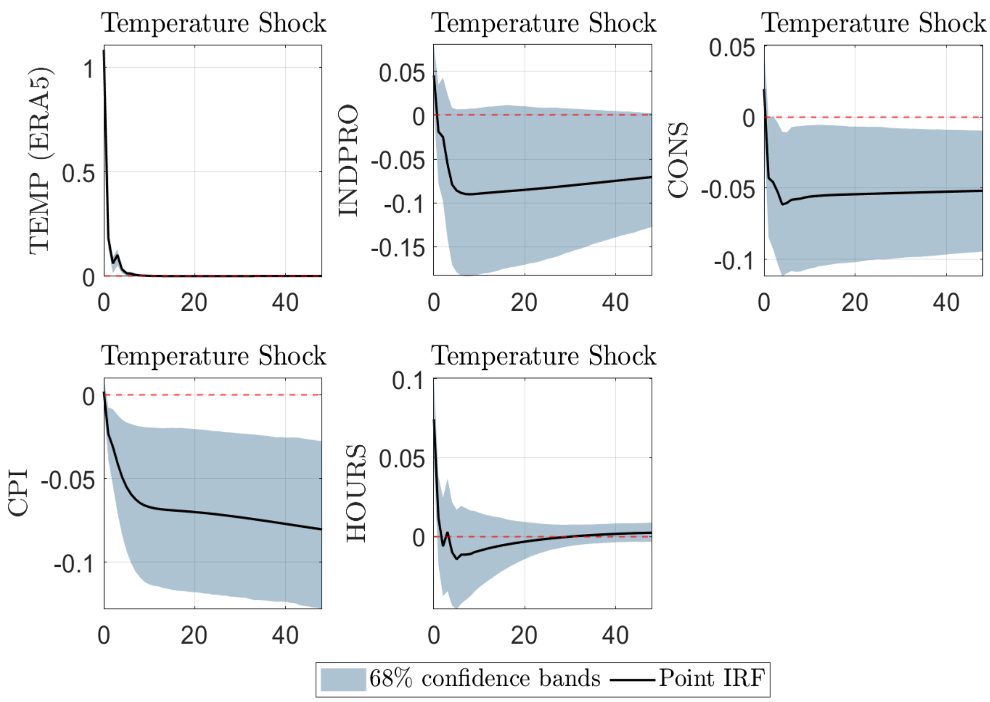


Figure 2 shows the impulse response functions of all variables to a one-standard-deviation increase in temperature. The results are in line with the climate literature, which generally finds negligible effects on output (Nath et al., 2024). The responses of the increase in mean temperatures is also insignificant for hours worked, while consumption and prices fall significantly, by 0.05% and 0.07% respectively, which are economically small magnitudes.

5.2 Subsample results

In order to start exploring the variation of the impulse response functions in the course of the last decades, we divide our sample period in two parts: the first spans from 1960 to 1989 (Figure 3), and the second from 1990 to 2022 (Figure 4). This is done as the sample reaches roughly half its observations around 1990. Different splits (e.g. starting the first sample in 1970 or splitting in 2000) produce very similar results.

Figure 3: IRFs of economic variables to a one standard deviation temperature shock estimated with the SVAR. Sample period 1960 – 1989. Shaded areas are bootstrapped 68% confidence bands.

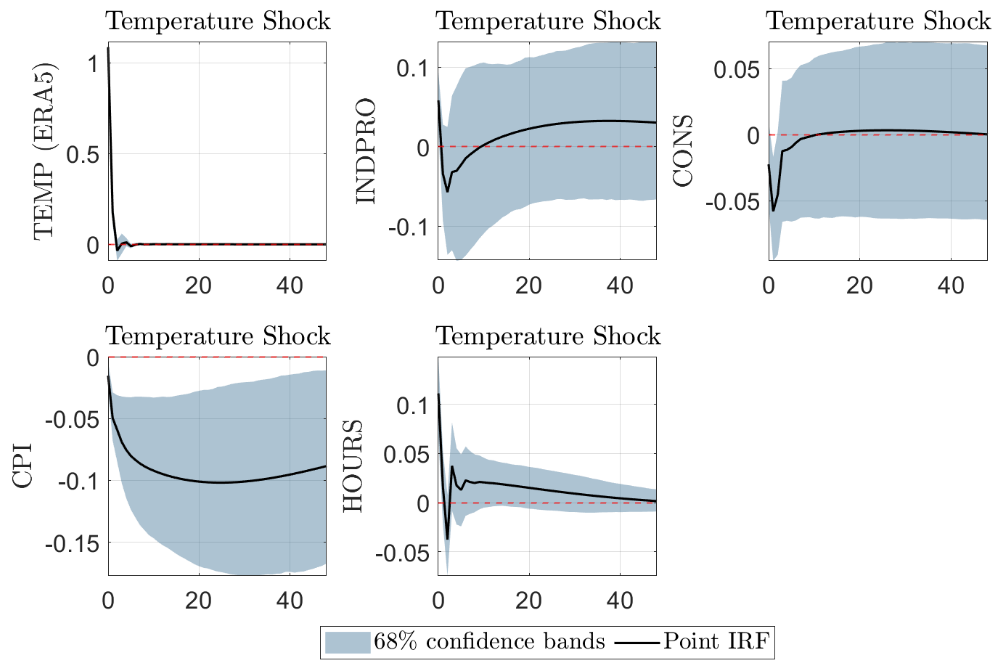
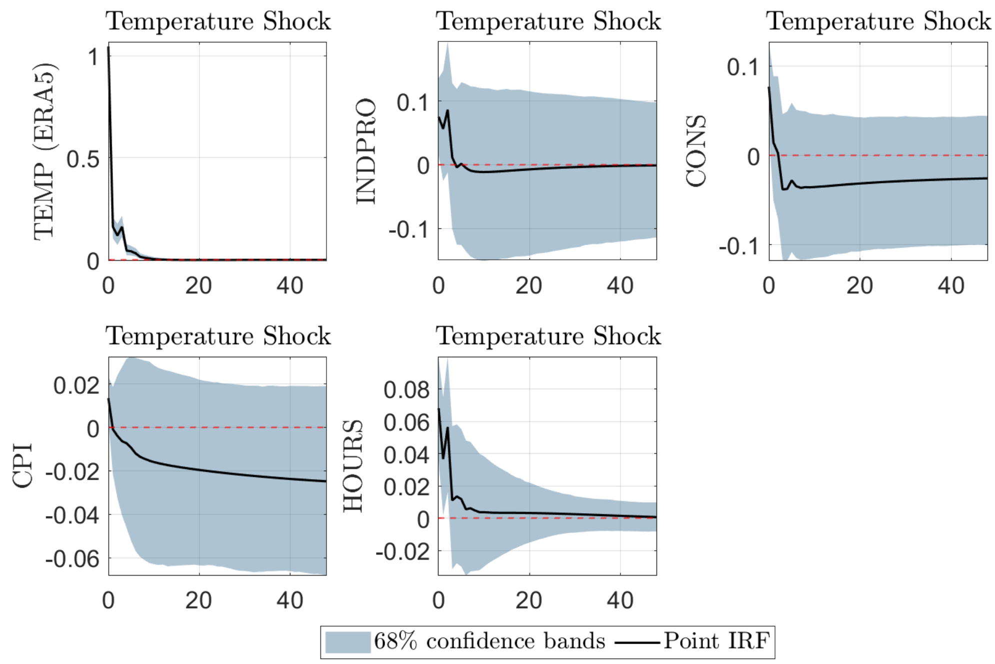


Figure 4: IRFs of economic variables to a one standard deviation temperature shock estimated with the SVAR. Sample period 1990 – 2022. Shaded areas are bootstrapped 68% confidence bands.



Comparing across horizons, the sub-sample analysis reveals intereting differences in the responses over the last decades. The macroeconomy, in general, seems to be more negatively affected by the temperature shock in the second part of the sample, although the reaction in industrial production is still insignificant. Indeed Figure 4 displays a negative path of industrial production and consumption whereas these were positive in Figure 3. Hours increase on impact in both sub-samples. The negative full sample response of prices seems to be driven primarily by effects in the first half of the sample. The differences observed between the sub-samples motivate a deeper exploration into the time-varying effects of temperature shocks.

5.3 Time-Varying Coefficient VAR results

Given the smoothing implied by our non-parametric estimation procedure, all IRF plots have been adjusted and the first and last 36 months of the sample are removed (only in the graphical representations, not in the estimation). This is because we are using a two-sided Gaussian kernel for the weighted least-squares estimates which cannot obtain information from pre-sample or post-sample values, so the earliest and latest results here may be affected. We check the relevance of including or omitting the COVID period in a robustness exercise.

Figure 5 displays the impulse response functions on impact to the temperature shock. The initial reactions to the shock are of particular interest for us. This is because in the VAR automatic stabilizers are allowed to endogenously mitigate effects of shocks after they occur, for example through an adjustment of the monetary policy rate. On impact, the reactions of the macro variables reflect mostly the response to the exogenous shock rather than the adjustment procedure that follows thereafter. Hence, if the initial reaction of industrial production changes from positive to essentially zero over time, this must come either from the size of the shock having changed or the structural model parameters having changed such that this occurs. We see that hours worked always increase after the shock and apprantly more inflationary initial reactions towards the end of the sample.

Figure 6 shows the TVC-VAR results for different horizons across all time periods for ease of visualization. Since the aim here is to investigate whether the responses of economic variables to the temperature shock vary over the sample period, we report in this section only point estimates. The responses of temperature on impact are not normalized to have a picture on the variation of the size of the main shock we are interested in. Actually, the temperature shock on impact slightly changes over time. It shows the biggest increase during the 80s, that apparently corresponds to the period in which average temperature started to rise significantly, as stated by scientists and climatologists. During our sample period, the magnitude of the shock on impact remained nearly constant.

Figure 5: Impulse response functions to the temperature shock on impact ($h = 0$)

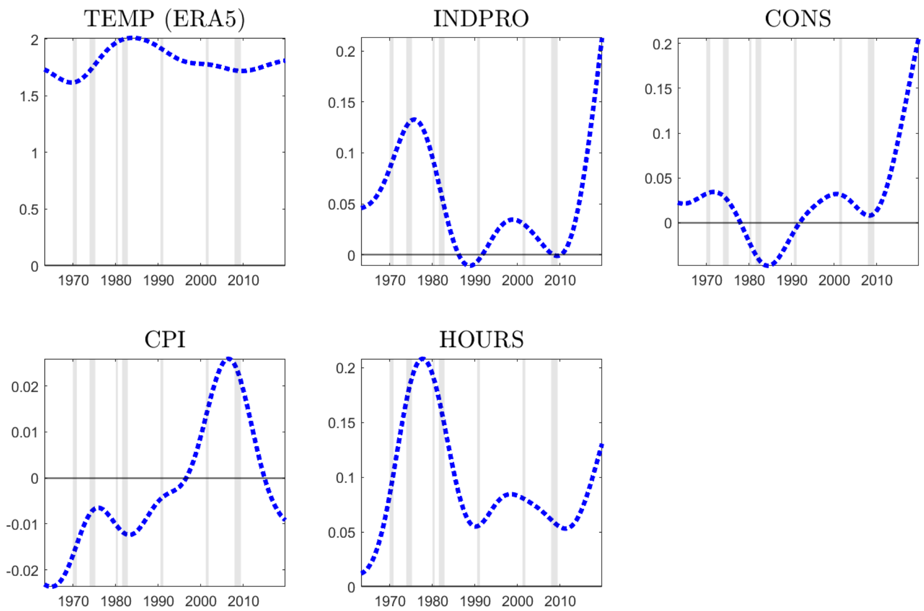
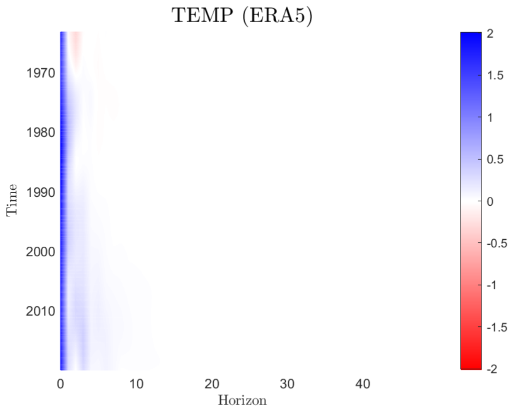


Figure 6a displays the reaction of average temperatures to the temperature shock. Interestingly, while the size of the initial shock has remained the same over time, recent decades are characterized by more persistent temperature shocks.

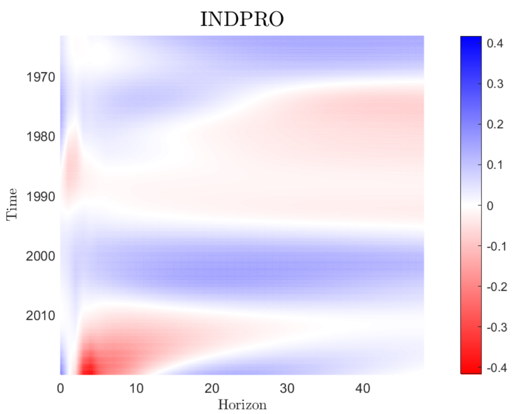
A few remarkable results emerge. First, on impact the response of industrial production was negative only briefly in the 80s and positive elsewhere. However, we see that particularly the medium horizon responses in industrial production and consumption have turned negative in the latest part of our sample. The contraction is mirrored by a small decrease in hours worked in the same periods. Overall the results seem to suggest that adaptation has not been sufficiently strong to offset the detrimental effects of higher temperatures on production and consumption. For hours worked, no clear pattern emerges. The direction of the effects on consumer prices is negative throughout the entire sample. The fall in consumer prices in the medium term, more pronounced in the 1970s and 2010s, is in line with the findings in Faccia et al. (2021).

Figure 7 suggests that shocks in the early sample were larger in magnitude than in the latter part. While this result may appear counter to common perceptions of climate change, we are by no means the first to document it (see e.g. Natoli (2022)). However, a decrease in the shock variance in itself does not convey any information about the severity

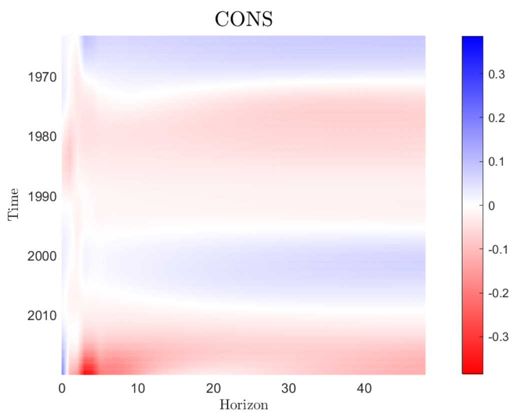
Figure 6: Impulse response functions over time and horizons to the temperature shock in the US.



(a)



(b)



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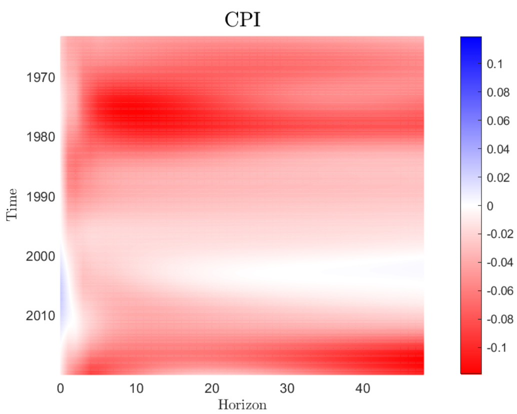

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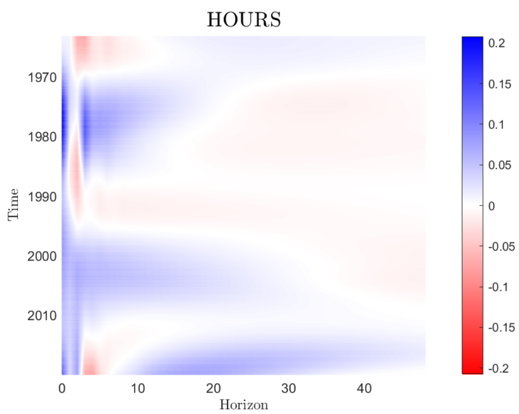
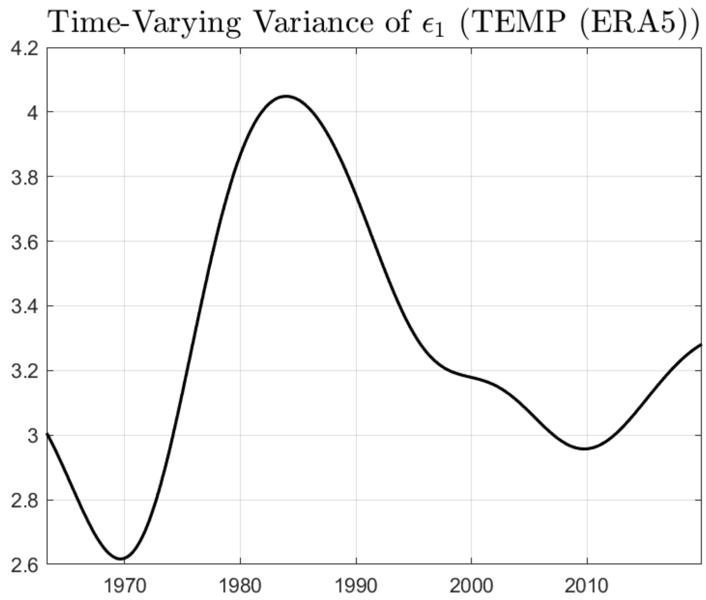


(e)

of economic damages that they induce. Indeed, higher levels of temperatures with fewer fluctuations away from the level could imply more sustained periods of high temperatures. Models which, for instance, condition on the state of climate conditions or on the current duration of an onset drought period may be more suitable to provide information about such circumstances. We consider this important territory for future research.

Figure 7: Time-varying variance of the reduced form shock to the temperature equation in the TVC-VAR.



6 ROBUSTNESS CHECK

In this section we perform a number of robustness checks to challenge our results.

Specification. The results presented in Section 5 are robust to the inclusion of more lags and to the selection of a different bandwidth, that represents always a crucial issue in kernel based estimation. Figure 8 shows the IRFs on impact to the temperature shock computed with different lags and bandwidth equal to $0.5, 0.6, 0.7, 0.8$.

Data. Our benchmark results are based on the Era5 Reanalyses Temperature Dataset. We perform the same exercise using CRU TS dataset, as well as the Actuaries Climate Index (ACI), and report them in Figure 9 and Figure 10 respectively. The IRFs are computed again with different lags and bandwidth. The heatmaps with the results for all time periods and horizons are presented in the appendix. We obtain results similar to the benchmark using both another temperature measure, and a more comprehensive climate index (ACI).

Figure 8: Robustness analysis. IRFs (for $h = 0$) to the Era5 temperature shock, computed with different specifications changing the number of lags and bandwidth.

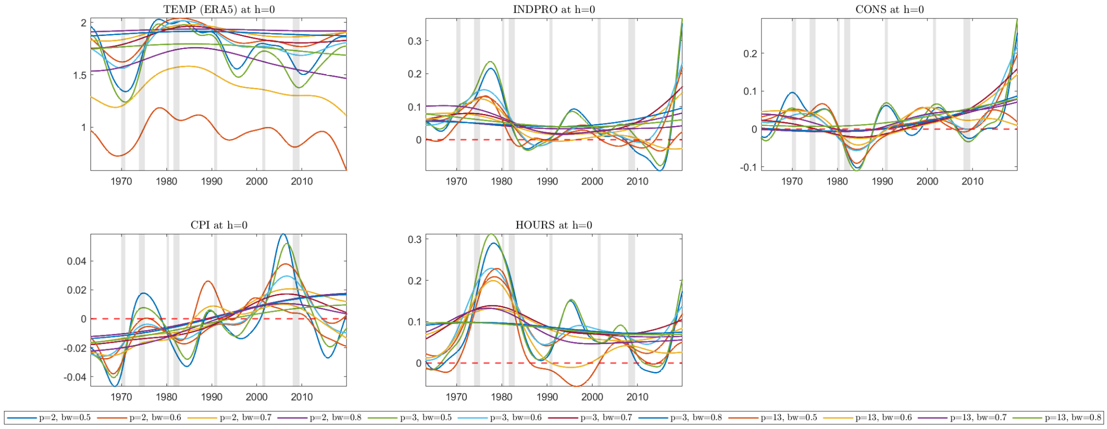


Figure 9: Robustness analysis. IRFs (for $h = 0$) to the CRU TS temperature shock, computed with different specifications changing the number of lags and bandwidth.

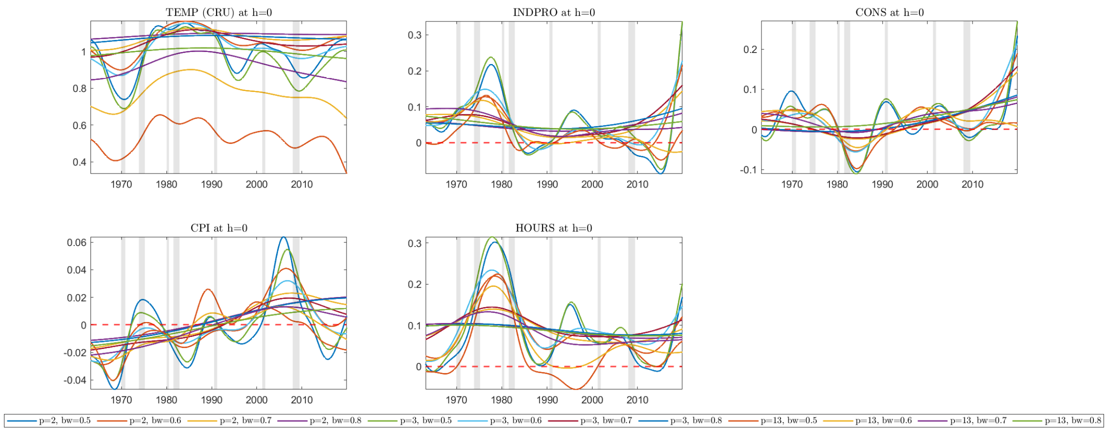
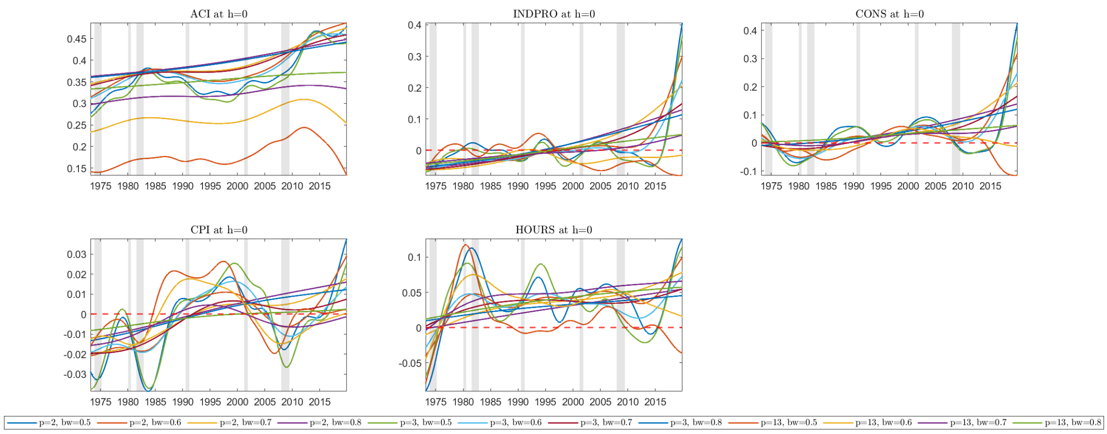


Figure 10: Robustness analysis. IRFs (for $h = 0$) to the ACI shock, computed with different specifications changing the number of lags and bandwidth.



7 Conclusions

This paper provides new evidence on the time-varying macroeconomic effects of temperature shocks in the United States from 1970 to 2021. Using a TVC-VAR model, we show that the negative impact of temperature shocks has diminished over time, suggesting that economic agents have increasingly adapted to rising temperatures. Our results indicate that, while the size of temperature shocks has remained constant, their persistence has increased, especially after the 2000s, yet with less severe economic consequences. These findings underline the importance of considering adaptation mechanisms when assessing and quantifying the effects of climate change on economic activity.
Further research is needed to identify the specific channels of adaptation, such as technological innovations or behavioral changes, that drive our results.

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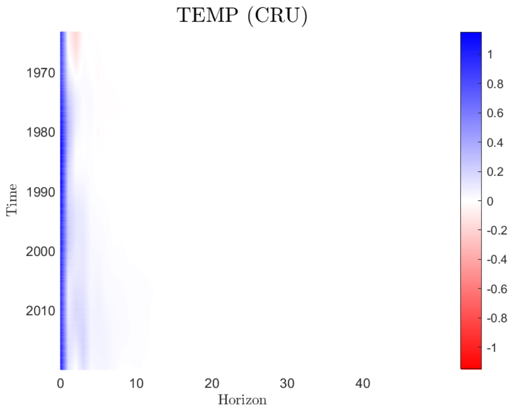
8 Appendix

8.1 Robustness

Figure 8.1 shows the IRFs to the temperature shock estimated using average temperature computed from the CRU TS dataset described in Section 3. As expected looking at the correlation between mean Era5 temperature and mean CRU TS temperature data (98%), the results are very much in line with the benchmark.

We also substitute mean temperature with a more comprehensive climate index, that is the ACI. The ACI is intended as an indicator of the frequency of extreme weather events and the extent of sea level change. Its construction is based on six components: high temperatures, low temperatures, heavy rainfall, drought, wind speed, and sea level. The IRFs are presented in Figure 8.2.

Figure 8.1: Impulse response functions over time and horizons to the (CRU TS) temperature shock in the US.



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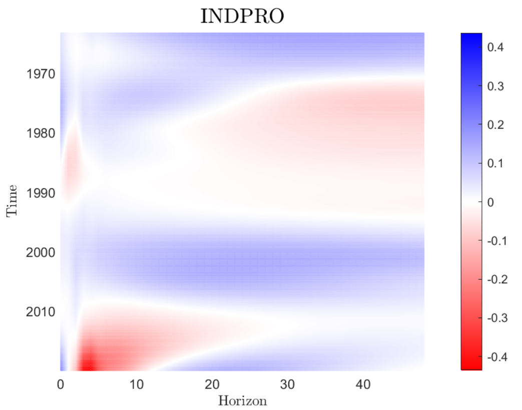

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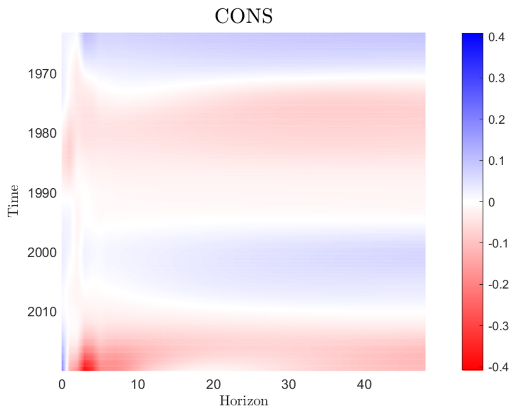

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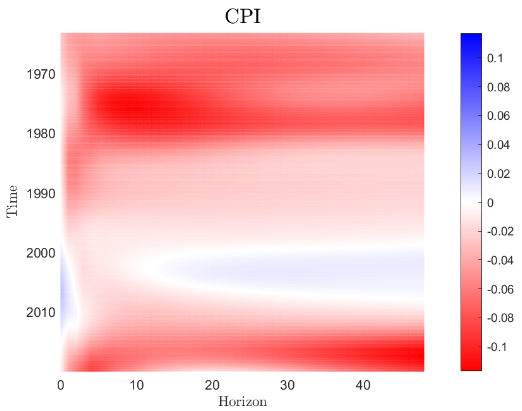

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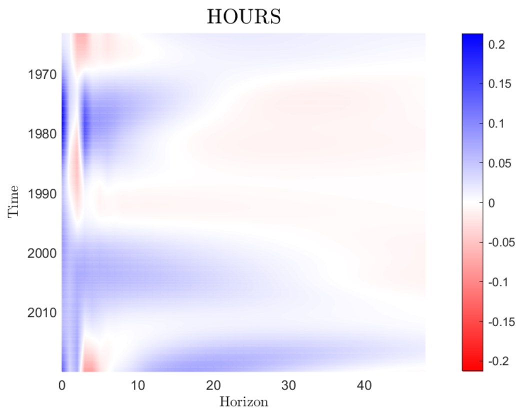

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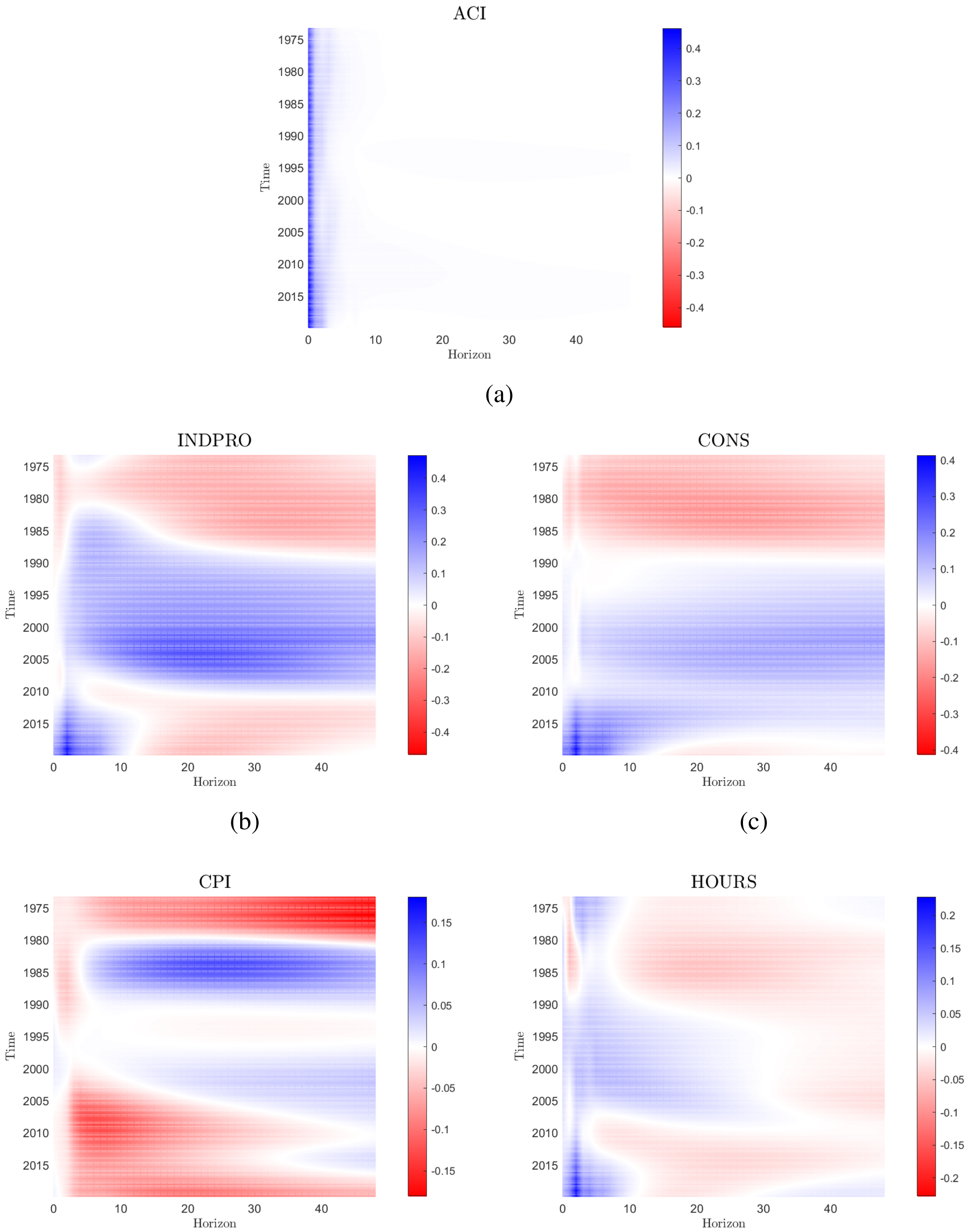
Figure 8.2: Impulse response functions over time and horizons to the ACI shock in the US.



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