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THE MACROECONOMIC EFFECTS OF TEMPERATURE SURPRISE SHOCKS

by Filippo Natoli*

Abstract

The question of how climate change and weather fluctuations affect the economy is high on the economic research agenda, but the quantification of the effects of temperatures at infra-annual frequencies still remains an open issue. Using daily county-level data since 1970, I construct quarterly temperature shocks for the United States that capture the average surprise effect of very high and low temperatures in each county and quarter, isolating their unanticipated component. Unfavorable temperature shocks are found to reduce GDP, consumer prices and interest rates, pointing to a slowdown in aggregate demand.

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1. Introduction[1]

Understanding the multifaceted effects of climate change is of utmost importance for the design of appropriate climate policies. A long standing literature explores the different implications of rising temperatures for advanced and developing countries or in hot and cold regions, focusing on the low-frequency effects on GDP growth (see Dell et al., 2014 and Carleton and Hsiang, 2016 for a review). This evidence has two potential limitations. One is that high-frequency fluctuations in temperatures may be as important as low-frequency trends, if not more (Kotz et al., 2021). The other one is that observed temperature fluctuations have both a predictable and an unpredictable component, and it is not obvious a priori that these affect economic outcomes in the same way. While a nascent literature has started to investigate temperature impacts at business cycle frequency, it has shown conflicting evidence on key outcomes such as the inflationary or deflationary effects, impairing the still under-investigated evaluation of their monetary policy implications. This lack of consensus lies on the identification of the unexpected component of temperatures, a crucial element to capture the effects of within-year fluctuations due to the existence of local trends and seasonal patterns.

I take up these issues and propose a new way to construct unexpected temperature shocks using county-level data. For this purpose, I resort to a concept that is common in the empirical macro literature, which is that of surprise shocks (see Ramey, 2016 and Nakamura and Steinsson, 2018b). Using daily county-level temperatures, I obtain quarterly US-wide shocks in two steps. First, I compute quarterly temperature surprises in each county as the number of extremely hot and cold days – relatively to the county and

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quarter of the year – in excess those agents expect at the end of the previous quarter, based on past realized temperatures. Temperature beliefs are constructed over multi-year spans reflecting the documented learning behavior regarding climate-related phenomena (Kelly et al., 2005; Deryugina, 2013; Moore, 2017, among others), and updated yearly to reflect salience of the most recent temperature realizations. Second, I average county-level surprises based on counties' weight on the national economy. By construction, the obtained series of US-wide unanticipated shocks nets out any seasonal and secular variation in the temperature distribution, including local (and potentially highly heterogeneous) trends in temperature levels and volatility. Economically, such shock reflects the surprise, at quarterly frequency, of a higher/lower number of extremes than expected, and can be used as a way to quantify the effect of severe weather on the economy, above and beyond any adapting behavior of agents to expected temperatures.

I construct temperature shocks starting from the beginning of the most recent phase of the global warming era (the 1970s), up to the end of 2019.[2] I then use these shocks to explore their effects on the US economy in a local projection framework and I get three main results. First, unfavorable temperature surprises have a significant negative effect on economic activity Quantitatively, a one-standard deviation positive shock (i.e., about 4 severe weather days more than expected) causes real GDP to decrease in the same quarter, with a maximum contraction of 0.3% after 2 years. Second, temperature shocks act mainly on the demand side of the economy, as the consumer price index also decreases following the shock. Moreover, investments and durable consumption fall more than non-durable expenditures, which is consistent with unexpected weather events raising awareness over future climatic risks (as in Choi et al., 2020 and Hong et al., 2020, among others) and inducing adaptation measures and precautionary behavior. In line with those impacts, short- and long-term interest rates on government bonds decrease, pointing to an expansionary monetary policy reaction. Further evidence on the behavior of the Federal Reserve, obtained by looking at the response of Greenbook forecasts to the shocks and by analyzing discussions within the FOMC, suggests that temperatures impact the Fed's short-term economic projections and stimulate some debate during official meetings. Third, the influence of temperature shocks change depending on the

[2]The years 1970s mark the beginning of the acceleration of global warming trends in the 20th century.

season and the type of surprise, as the effects are largest in summer and, on average, when shocks originate in the left tail of the temperature distribution – surprises related to cold days.

My contribution to the literature is twofold. First, I bring into the climate debate key insights on identification developed in the macroeconomics literature. The temperature surprise shocks I construct share the economic and econometric characteristics of other popular shocks considered in the empirical macro field. Having a measure of unanticipated weather-related shock can help tackle a wider range of questions than those faced in this paper, and can be the basis of further climate research. The procedure I propose can be easily replicated for other countries, geographical aggregation levels and weather-related variables. Second, I quantify the aggregate short-term implications of unexpected temperature fluctuations in the United States, including the extent of monetary policy reaction. The comprehensive assessment of their economic impact made in this paper, revealing a slowdown in aggregate demand, a medium-run fall in consumer prices and a negative effect on interest rates, stands out in the literature. In this respect, looking at temperature shocks in isolation is key, as temperatures impact the economy through a set of transmission channels that can shape output, prices and interest rates differently than other weather-related extreme events.

The paper is organized as follows. Section 2 reviews the theoretical and empirical contributions related to our study. Section 3 illustrates the possible transmission mechanisms of temperature variations to the economy. Section 4 discusses the key issues surrounding the identification of an exogenous temperature shocks and describes how the shock is constructed. Section 5 presents the data used in the analysis and works out the shock series. Section 6 proposes an empirical application to estimate the domestic effect of temperatures on the US economy using the previously constructed shock. Section 7 and 8 provide robustness checks and additional findings, and Section 9 concludes.

2. Related literature

The effects of climate change on the economy are found to be multifaceted. Increasing temperatures substantially raise mortality rates (Carleton et al., 2022) and reduce activity and growth, especially in hot and poor countries (Dell et al., 2012; Burke et al., 2015;

Burke et al., 2018; Acevedo et al., 2020; Kiley, 2021; see Dell et al., 2014 and Carleton and Hsiang, 2016 for a review of the literature). Advanced economies appear not to be immune either, as more recent analysis points to a negative impact of temperatures even in most G7 countries (Berg et al., 2021) and OECD economies (Ciccarelli and Marotta, 2021). Evidence of an impact of temperatures in the United States, initially mixed, is also growing. Indeed, US output is negatively affected in a wide range of industries (Hsiang et al., 2017; Colacito et al., 2019), with income per capita losses being concentrated during business days (Deryugina and Hsiang, 2014).[3] From a wider perspective, extreme weather events are found to have increased their negative impact on the US economy in the most recent decades, according to Kim et al. (2021). However, the propagation of the effects of temperatures throughout the economy and their implications for consumer prices still remain an open issue, especially in the case of the United States. For example, severe weather (including extreme temperatures) are found to be, in the medium run, either inflationary (Kim et al., 2021 and Makkonen et al., 2021) or deflationary (Faccia et al., 2021), with radically different implications for the conduct of monetary policy. Moreover, challenges in isolating the economic effects of temperatures remain, also because their implications differ substantially in different seasons and sectors (Addoum et al., 2021).[4] I contribute to this literature by shedding light on the impact of temperatures shocks on the US economy, exploring their effects beyond aggregate output including consumption, investment, consumer prices and bond yields.

From a methodological point of view, this paper contributes to the recent strand of the literature that aims at quantifying the short-term impacts of climate change, notably using temperature fluctuations. A common empirical approach is to retrieve shocks in a recursively-identified structural VAR, with average temperatures included as the most exogenous variable (Donadelli et al., 2017); the same logic has been applied to extrapo-

[3]A significantly negative effect is also found on agriculture (Fisher et al., 2012; Burke et al., 2015), despite earlier evidence suggested no impact (Deschênes and Greenstone, 2007).

[4]While pointing to a detrimental effect on firm activity, micro evidence is still mixed. Some papers do not find any consequence of high temperatures on firm sales and labor productivity (Addoum et al., 2020), while others document negative effects on upstream firms in the supply chain (Custódio et al., 2021; Pankratz and Schiller, 2021) and a reduction in the number of employees and firm establishments in the medium run (Jin et al., 2021).

late shocks from other weather series.[5] Other studies employ the so-called temperature anomalies, constructed by re-scaling actual temperatures with averages of a pre-global-warming (or pre-1970) reference period, and use them as a direct measure of exogenous temperature variations (Makkonen et al., 2021, among others); finally, other works adopt a down-scaled version of the panel framework used in the multi-country literature to analyze the effect of average temperatures along the business cycle. I document potential identification issues that arise by applying standard methods to retrieve shocks from temperature variations, and propose a way to tackle them by using daily data and a granular geographic coverage.[6] In particular, I propose a method to compute shocks that capture, from a business cycle perspective, the unexpected component embedded in daily temperature realizations. To take into account the fact that temperature events in different areas and seasons can produce profoundly different aggregate effects, my application to the US case is based on county-level data – as it is done by Moscona and Sastry (2022) to study the technological response to climate change – and takes into account seasonal patterns as in Colacito et al. (2019) and Addoum et al. (2021).[7]

My notion of temperature shock is based on the variation over time in the shape of the distribution of local temperatures. In this respect, this paper connects to those studying the economic implications of actual or expected temperature volatility (Kotz et al., 2021; Donadelli et al., 2021; Alessandri and Mumtaz, 2021; Diebold and Rudebusch, 2022; Bortolan et al., 2022). While these papers isolate changes in the second moment of the temperature distribution, my shock is defined over the number of severe temperature days experienced by agents, linking more closely to the thickness of the distribution's tails.

The idea of constructing macroeconomic temperature surprises is inherited from the empirical macro literature, in which the identification of shocks typically rely on extrapolating an exogenous component from policy announcements or decisions (see Nakamura

[5] Gallic and Vermandel (2020) uses a de-trended version of the soil moisture index, a measure capturing the combined effect of temperatures and precipitations, in a VAR model; Cashin et al. (2017) includes deviation of the Southern Oscillation Index (SOI) from their historical averages in a Global VAR framework.

[6] Concerns regarding the commonly used methods to estimate temperature effects – particularly with panel data – are raised, for different reasons, by Berg et al. (2021).

[7] My analysis is focused on identifying economic impacts of weather variations. For a review of the literature investigating the link with longer run climatic effects, see Kolstad and Moore (2020).

and Steinsson, 2018b for a review of the literature). For example, the notion of surprise shocks related to monetary policy refers to the contemporaneous surprise component of monetary policy announcements (Gurkaynak et al., 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018a; Miranda-Agrippino and Ricco, 2021 among others); regarding fiscal policy, government spending surprises can reflect the unanticipated component of public spending decisions (Forni and Gambetti, 2016, among others). As in the case of policy surprises, what matters here is defining agents' ex-ante temperature expectations in the correct way: in a quarterly setting, what agents expect in a given year can be well proxied by temperatures directly experienced during the same period in the most recent years, i.e. those agents are used to. Defining expectations based on past temperatures connect to the literature on learning from climatic events (Kelly et al., 2005; Deryugina, 2013; Moore, 2017; Kala, 2019; Choi et al., 2020; Pankratz and Schiller, 2021) and, more generally, to learning from direct experience (Malmendier and Nagel, 2015).

Last, my paper links to those investigating the effects of climate change on consumer prices and the reaction of monetary policy. With respect to output effects, the implications for prices are less clear in the literature, sometimes providing opposite evidence (Mukherjee and Ouattara, 2021; Faccia et al., 2021). This can be due to the fact that temperatures might have relevant demand-side – other than supply-side – effects, which might offset the final impact on consumer prices at some particular horizons. I find that the effects of temperatures on prices are skewed towards a price fall in the medium run. This price response is broadly in line with that found in Faccia et al. (2021) for a panel of countries, for which the impact is initially positive and it becomes negative in the longer term. On monetary policy, the literature has mainly focused on how changes in the monetary stance might have implications for climate and how central banks might cooperate to stimulate the low-carbon transition (Hansen, 2021, among others), almost disregarding the effects of actual weather occurrences on its conduct. I fill this gap by documenting that monetary policy responds to the economic damage caused by temperature shocks by cutting short-term rates, with effects passing through the whole term structure of government bond yields.

3. Transmission channels

The economic effects of temperatures may unfold through different transmission mechanisms. The one that received most attention in the literature is the physical impact of extreme temperatures on human health, the so called heat stress channel. As extreme temperatures have the potential to cause several illnesses (e.g., heat strokes), they can hit labor supply by shrinking hours worked and inducing a fall in individual productivity in temperature-exposed working tasks (Cachon et al., 2012; Somanathan et al., 2021).

However, temperatures might also hit the economy from the demand side. Indeed, some papers have documented significant behavioral effects, according to which extreme temperatures would discourage open air activities: perception of waiting time worsens in hot days (Baker and Cameron, 1996) and social interactions with strangers are felt as more unpleasant (Griffit and Veitch, 1971), reducing time allocated to outdoor leisure (Graff Zivin and Neidell, 2014). These effects can put downward pressure on consumer spending, for example through a decrease in shop retail sales (Starr-McCluer, 2000; Roth Tran, 2022). Another demand-side effect works through an expenditure channel. Upward trending temperatures will raise electricity demand (McFarland, 2015), increasing energy expenditures for households and firms. For the latter, the need of cooling/heating down work spaces or production processes in times of exceptional highs and lows might entail unanticipated expenses, reducing the available liquidity and, possibly, eroding profits. A third channel of transmission, which also works through the demand side, is related to the uncertainty over future climatic developments. Temperature oscillations, if wide or frequent enough, can raise attention towards the future repercussions of climate change – wake-up call effect – thereby influencing decision making: this is documented in Choi et al. (2020), who link extreme temperature episodes to larger financial investments in green than brown assets. As in the case of financial investors, temperatures can induce preference shifts among households and firms, who can modify their attitude to hedge against the future consequences of climate change. For example, forward-looking entrepreneurs might undertake adaptation investments to make their business more resilient to temperatures, which can be detrimental for short-run firm performance if this crowds out other productive investments.[8]

[8] In the longer run, the overall effects of temperatures might be heterogeneous across firms depending

All in all, the economic effects of temperature oscillations can be diverse, potentially impacting both the consumption and investment components of output. In what follows, I explain how my shock is constructed, starting from methodological issues and insights, and test its effects on GDP, consumer prices and interest rates.

4. Constructing the shock

4.1. Key points

Using temperatures to quantify the economic effect of weather variations has some clear advantages with respect to other weather events: temperatures are continuously recorded and collected simultaneously across the country, allowing to compute high-frequency statistics with granular geographic detail. However, constructing shocks using temperaturespresents non-trivial challenges: temperatures are a very local phenomenon, they have strong seasonal components and are pretty unforecastable beyond very short time spans.

In order to quantify their economic impact at infra-annual frequencies, the literature has so far adopted one of the following empirical strategy: (1) estimating country-level shocks in a time-series framework, where shocks are retrieved within VAR models based on fluctuations in country-averaged temperatures levels (or temperature anomalies); (2) estimating local impacts using fixed-effect panels at sub-national level, where local shocks are identified as deviations of average temperatures – or the count of days with temperatures beyond certain thresholds – from their long-run means. Both of these methods rest on some problematic assumptions. For example, average temperatures are not suitable to construct "shocks" based only on their positive/negative time variations, as those can be either good or bad for the economy depending, for example, on temperature levels – passing from 50°F to 60°F and from 85°F to 95°F can have even opposite economic effects. As what can be labeled as severe weather varies across location and over time, using statistics based on the occurrence of temperatures beyond fixed thresholds (eg., 85°F in all locations and seasons) is also problematic. A different issue related to the use of anomalies or fixed effects is that deviations of temperatures vis-à-vis long-run averages

on whether adaptation measures spur innovation and technological progress, as explored in Cascarano et al. (2022).

may not be unexpected, as agents can adapt over time to higher and more volatile temperatures and update their beliefs accordingly. Last, when dealing with the country-level dimension, shocks built on country-averaged temperatures may not properly reflect the aggregation of local shocks, as the latter may depend non-linearly from local temperature variations.

To overcome these issues, macroeconomic shocks based on temperatures should be defined at the most granular geographic dimension as possible, to identify their economic impact on top of any expectations about the incidence of "good" and "bad" temperatures in each localities and periods. As stated in Ramey (2016), a shock should represent "either unanticipated movements in exogenous variables or some news about future movements in the exogenous variable". Finally, identified temporary local shocks need to be compounded to get an aggregated macro shock.

I use daily temperatures in each US county to construct a nation-wide shock at the quarterly frequency. The shock design is based on the following arguments. First, as science suggests, temperatures turning very hot or cold in a short period of time can be considered as exogenous to current and recent past economic activity, as feedback effects to local temperatures from human-generated CO2 emissions unravel only in the longer term. Second, very high ad low temperatures are intrinsically undesirable and, as documented in the literature, generate mostly detrimental effects on the economy. Indeed, while the direction of the impact can be different by season and depend on the type of business exposed, studies recognize that, overall, both extremes are bad for the economy. At the hearth of this outcome lies, for example, the U-shaped relationship between temperatures and mortality documented for the United States by Deschenes (2014) and Barreca et al. (2016), among others.[9] Third, I argue that while agents can be able to find a workaround to isolated extreme temperature episodes, e.g., by rescheduling working tasks or outdoor activities, exposure to very hot or cold temperatures could become impossible to avoid if these events are frequent enough within a short time span, with negative effects on human and firm activity accumulating over time. This might be so because there are limits to adaptation in the short run, and time constraints (notably

[9]A similar U-shaped relationship is found with respect to the impact on crop yields, see Schlenker and Roberts (2009).

in business) that impede to postpone any important activity.[10]

All these arguments suggest that a shock to temperatures can be inferred by looking at the incidence of multiple extreme temperature episodes within a specific period of time. I choose to work at quarterly frequency for different reasons. One reason is that quarterly performance matters in firm's business – e.g., publicly-traded companies file reports quarterly – so substitution of work activities over time, for example due to unfavorable temperatures, might be less feasible across quarters. Another reason, from an empirical point of view, is that quarterly frequency is convenient to explore the effects of temperature shocks on official GDP figures. Last, and most important, quarters roughly coincide with calendar seasons, which are quite homogeneous in terms of temperatures. In this respect, it is important to note that temperature highs or lows in each seasons can be damaging even if they do not reach extreme levels in absolute terms. For example, the impact of an exceptionally cold summer, while not reaching winter lows, can be nonetheless material for tourism. If this is so, to be surprising extreme realizations need to be evaluated with respect to what the distribution of temperatures is expected to be for that period.

In this perspective, as the shape of the entire temperature distribution changes over time, a proxy of agents' beliefs on current temperatures must be based on past realizations that cannot go too far back in time. One reason for that, from an economic viewpoint, is that agents have memories and learn from their past experience: this form of experience-based Bayesian learning, which takes multiple years, has been documented to drive the dynamics of beliefs also related to global warming (Kelly et al., 2005; Deryugina, 2013; Moore, 2017; Kala, 2019; Choi et al., 2020; Pankratz and Schiller, 2021). In my shock computation, I assume that the reference distribution for each quarter rolls over time, in order to compare current values with updated temperature beliefs. This identification procedure marks a stark difference with all past approaches based on temperature anomalies or on deviations from historical averages, which implicitly assume that agents anchor their beliefs to some average values and do not update them over time. According

[10]For households, although available at very short horizons, daily weather forecasts may in principle help to cope with undesirable temperatures: however, evidence shows that an anticipatory behavior of future temperatures – inducing protective actions – is limited at best (Morss et al., 2010; Graff Zivin and Neidell, 2014).

to those metrics, observing a larger number of extreme realizations than in the pre-1970 period would always imply a positive shock, even though agents can be, in fact, used to them: therefore, outdated beliefs may lead to overestimate the size of the most recent shock. In the following section I provide the formula to recover my shock at local level, as well as the procedure to aggregate it to country level.

4.2. A US-wide temperature shock

According to a very general framework, country-level shocks at time t can be thought as the weighted average of county-level temperature expectation errors

$$\sum_{i=1}^{k} w_t^i \quad \underbrace{\left[\mathrm{f}(\mathrm{T}_t^i) - E_{t-1}\mathrm{f}(\mathrm{T}_t^i)\right]}_{\text{expectation error in county } i} \tag{1}$$

where $\mathrm{f}(\mathrm{T}_t^i)$ is the value of a temperature statistics for county $i = 1, \ldots, k$ and quarter t; $E_{t-1}\mathrm{f}(\mathrm{T}_t^i)$ is the expectation about $\mathrm{f}(\mathrm{T}_t^i)$ made at the end of the previous quarter; w_t^i are the weights to aggregate local errors to a country-level shock. In order to define $\mathrm{f}(\mathrm{T}_t^i)$ in the case of the United States, I first collect average temperatures in each county at daily frequency. For each series, I group observations by quarter and compare the within-quarter distribution of temperatures to a reference distribution, which is made by pooling daily observations recorded in the same quarter of the past years: this reference distribution is the one over which $E_{t-1}\mathrm{f}(\mathrm{T}_t^i)$ are constructed. As five years is a sufficiently long period for agents to learn about the shape of the underlying temperature distribution, I construct the reference distribution based on that time span.[11] The reference distribution rolls over time, i.e. it is updated every year for each quarter. In each period, I compute the 10th and 90th percentiles, which are taken as upper and lower thresholds for current temperatures, i.e. the values beyond which actual observations are labeled as very high or low. In order to be perfectly aligned with expectations, I posit that the share of extreme days in current quarter must be the same of that distribution: differently, a larger number of extremes represent a positive surprise, while a lower number makes a negative one.

[11] Pankratz and Schiller (2021) test learning periods of five, ten, and fifteen years length. As a robustness check, I construct an alternative version of the shock using a 10-year learning window as in Choi et al. (2020), see Section 8.

In formulas, let $T^i_{d,q,y}$ being average daily temperatures in day d, quarter q and year y, recorded in county i, for $i = 1,\dots,K$ counties. Denote with $F^i_{q,y} = \{T^i_{d,q,y-j},\ \text{j} = 1,\dots,5\}$ the empirical cumulative distribution function of the reference temperature distribution for quarter q and year y, totalling $N_{q,y}$ days. The reference temperature values are

$$\text{ut}(q)^i_y = F^{-1}_{q,y}(0.9) \qquad \forall \quad q = \{\text{q1},\text{q2},\text{q3},\text{q4}\} \tag{2}$$

$$\text{lt}(q)^i_y = F^{-1}_{q,y}(0.1) \qquad \forall \quad q = \{\text{q1},\text{q2},\text{q3},\text{q4}\} \tag{3}$$

where $\text{ut}(q)^i_y$ and $\text{lt}(q)^i_y$ are yearly series for upper (lower) thresholds for county i, quarter q and year y. By combining threshold values together by quarter, I get quarterly series of upper and lower thresholds for each county, i.e.

$$\text{ut}^i_t = \{\text{ut}(\text{q})^i_y,\ q = \text{q1},\dots,\text{q4}\}$$

$$\text{lt}^i_t = \{\text{lt}(\text{q})^i_y,\ q = \text{q1},\dots,\text{q4}\}$$

The same can be done with the size of the reference distribution, yielding $\text{N}_t = \{\text{N}(\text{q})_y,\ q = \text{q1},\dots,\text{q4}\}$. Note that I change notation for the quarter (from q to t) as q denotes quarters in yearly series, while t indicates quarterly frequency. Denoting with n_t the number of days in quarter t, county surprises are then evaluated as the number of beyond-threshold days in the current quarter in excess of those in the reference distribution. Provided that, by construction, the share of extreme days in the reference distribution is 20 percent, and that this number must be rescaled to a single quarter dimension, county surprises can be expressed as

$$\text{county\_surprise}^i_t = \underbrace{\sum_{d=1}^{n_t} \left[\text{I}(T^i_{d,t} < \text{lt}^i_t) + \text{I}(T^i_{d,t} > \text{ut}^i_t)\right]}_{\text{f}(\text{T}^i_t)} - \underbrace{N_t \times 0.2 \times 0.2}_{E_{t-1}\text{f}(\text{T}^i_t)} \qquad i \in k \tag{4}$$

where $I(x)$ is an indicator function that values 1 if x is true, 0 otherwise. County surprises are the difference between the number of hot and cold days in quarter t and the number of “extremes” in the reference distribution for that quarter. The underlying idea is that the reference distribution, which updates quarterly, represents the information set of economic agents, who directly experienced a range of temperatures for that season in the past. As they have no reason to foresee any significant change in the distribution with respect to the very recent past, agents expect that the same number of hot and cold days also occur in current quarter. In this setting, temperatures go beyond expectations if the number of extreme days exceed (or is below) what agents expect.

In order to make a US-wide surprise shock, I make a weighted average of county-level surprises occurred in the k counties by quarter:

$$\text{US\_shock}_{t,y} = \sum_{i=1}^{K} \left(\text{county\_surprise}_t^i \times \text{w}_{y-1}^i\right) \tag{5}$$

where w are county-level weights, proxying counties' vulnerability to temperatures, which vary at annual frequency. Weights are lagged to capture the ex-ante exposure to temperatures.

4.3. Insights

The constructed shock presents the following characteristics. First, it is designed to have an unambiguous economic effect: a positive shock, meaning an unexpected increase in the occurrence of severe daily temperatures, should impact the economy in one direction (eg., weigh negative on output), while a negative one – milder temperatures than expected – in the opposite way. Second, it is season-specific, as surprises are measured within the same season. Therefore, the largest economic effects during the year do not necessarily come in winter and summer when temperatures show record lows and highs, as what matters is how temperatures deviate from their seasonal norm. Third, as the shock is measured with respect to updated expectations, it nets out longer-run phenomena such as the intensification of climatic trends – upward-drifting and increasing volatile temperatures – and adaptation to extreme temperatures: agents learning about the evolution of temperatures can continuously adjust their resilience to them. Last, the shock is two-sided and surprises coming from extremely hot and cold days are treated as equivalent. This can be considered as a neutral assumption, as taking a stance on which tails matter more in each season is not straightforward (Addoum et al., 2021).[12]

Overall, the shock measures the size of the variation in the distribution of temperatures in the short run. Being an aggregation of county-level surprises, it will depend more on counties that have a higher weight in the US economy. As explained in Section

[12]In a robustness exercise, I decompose the US-wide shock into heat and cold shocks and explore their effects separately by season using local projections, see Section 8.

5.1, I follow the literature and propose alternative methods to rank counties based on the potential economic damage due to unfavorable temperatures, and use them to weight county-level surprises to get the US-wide shock.

5. Data

5.1. Temperature data

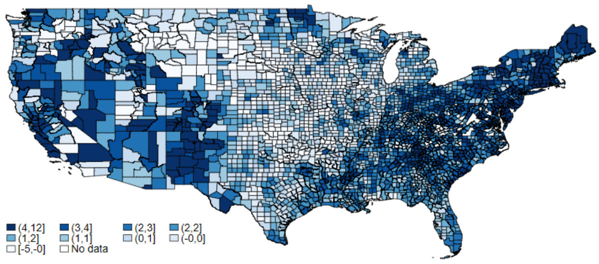
To construct my shock, I rely on two data sources. The first one is the gridded air temperature database for continental US taken from the Northeast Regional Climate Center. From that source I extract daily temperatures, i.e. the mean value of temperatures recorded during the 24 hours, averaged at county level. I consider data starting from Jan 1, 1970, i.e. when the human-induced global warming trend started to reinforce, and ending on Dec 31, 2019. To construct the weights to aggregate county-level surprises, I take annual data on US counties' economies from the Census Bureau, from 1969 to 2018. In the baseline formulation of the shock, I consider county-level population and construct weights as the county share over nation-wide values. The rationale for this choice is that the higher the population, the higher the incidence of agents that are exposed to extreme temperatures, so the higher the potential impact on human health and the economy. As a robustness, I also consider land extension – used as an alternative to population in Colacito et al. (2019) – and other weighting schemes such as the number of employed people, personal income or county GDP to weight temperature surprises: while population, employed people and land extension also reflect temperature exposure, personal income and county-level GDP proxy counties' economic weight in the US economy, independently from their exposure. Merging the two datasets yields time series of temperatures and weights for 3053 counties. This sample is highly representative of the US economy, covering more than 98% of the country's population, jobs and personal income as of 2019.

5.2. County-level statistics

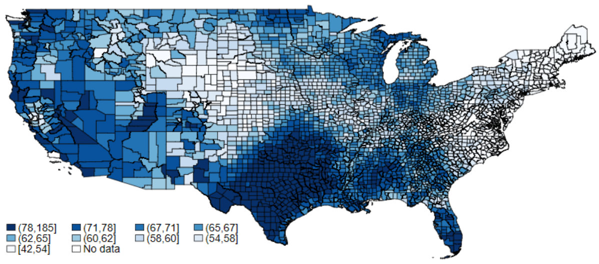
Figure 1 represents county-level statistics over geographic maps of the United States. Panel 1 shows the growth rate of temperatures in the years 2010s with respect to the 1960s. On average, temperature grew by 1.7%, but climatic trends have been quite diverse, with some counties experiencing temperatures rising by more than 8%, while

Figure 1: Within country comparison

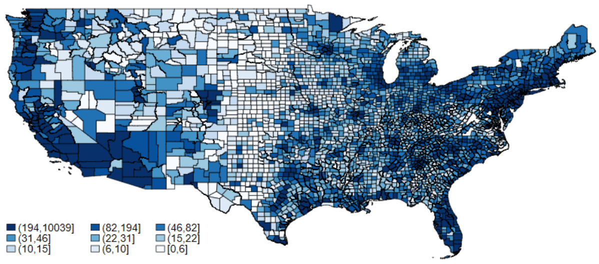
Panel (1): Growth rate of temperatures, 2010s vs 1960s averages (percent)



Panel (2): Time series variance of surprises



Panel (3): Population, 2019 (thousand units)



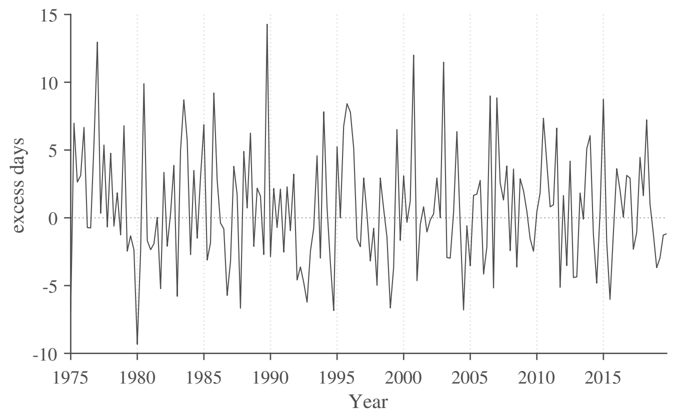
Notes: The figure shows county-level statistics of temperatures, surprises and population. Panel (1) shows the historical growth rate of temperatures in the most recent phase of the global warming era (post-1970), computed by comparing average temperatures in the years 2010s with average temperatures in the 1960 decade. Panel (2) shows the time series variance of county-level surprises, a measure of their average historical size, computed for the period 1975q1–2019q4. Panel (3) displays population levels in 2019.

others in which temperatures decreased by 5%. Overall, northeastern counties and the west coast experienced the steepest temperature increase. The picture looks different when evaluating the size of county-level surprises occurred over time, which depend on the evolution of the entire temperature distribution: surprise shocks in northeastern counties have been small on average, while they have been very large in the south (Panel 2). Overall, what matters is the combination of shocks and weights: even small surprises can be important if occurred in highly exposed (or rich) counties. Panel 3 shows counties' population in 2019. At that time, the 20 most populated counties, covering about 20 percent of US population, were mostly in California, Texas, New York and Florida.

5.3. The shock series

The time series of the US-wide shock is displayed in Figure 2. The shock is expressed as the total number of surprisingly hot and cold days per quarter, and reaches a minimum at -9 and a maximum at 14. The shock embeds the basic econometric requirements to be used in empirical analysis: it is zero-mean and serially uncorrelated (see Appendix Appendix A). From an economic point of view, it features the three characteristics, explained in Ramey (2016), which make it suitable for macroeconomic applications: it is exogenous with respect to current and lagged outcome variables, it can be considered as uncorrelated with other exogenous economic shocks and it represents unanticipated movements in an exogenous variable.

Figure 2: US-wide temperature shock



Looking at the plotted series, one thing that catches the eye is that temperature shocks have not been particularly large in the last 15 years with respect to the earlier period. Indeed, the volatility of the shock series computed on a rolling 10-year window slightly decreases throughout the sample, from a peak of 5 to about 3.5 days. It suggests that adjustments in the shape of the temperature distribution have been largest – inducing greater surprises – in the early part of the sample than in recent times. This evidence reverses the common wisdom that climate change is generating shocks of increasing size. In fact, my shock dynamics is not in contrast with the intensification of climate-related weather events (including temperatures extremes), as climate indicators such as the Actuaries Climate Index show.[13] As I take out predictable climatic trends to capture the unexpected component of temperature fluctuations, it is well possible that large weather episodes with respect to the pre-1970 period have become increasingly frequent, but also less surprising than in the past.[14]

As explained, shocks are computed with respect to temperature expectations that are backward-looking and based on the closest, past temperature data. These features are tested in two separate robustness exercises (see Appendix Appendix B and Section 7.1). Regarding the first one, results suggest that publicly available temperature forecasts cannot be of help in forming expectations for the quarter because days that are labeled as surprisingly hot or cold under this procedure are also more difficult to predict at one- and two-day horizons, as an exercise using Washington DC data shows. The second exercise reveals that, if expectations are modeled as anchored at some pre-sample level (eg., the average of temperatures in 1970-1974 in the same quarter), the incidence of positive shocks – and the role of heat over cold surprises – are increasingly overestimated over time.

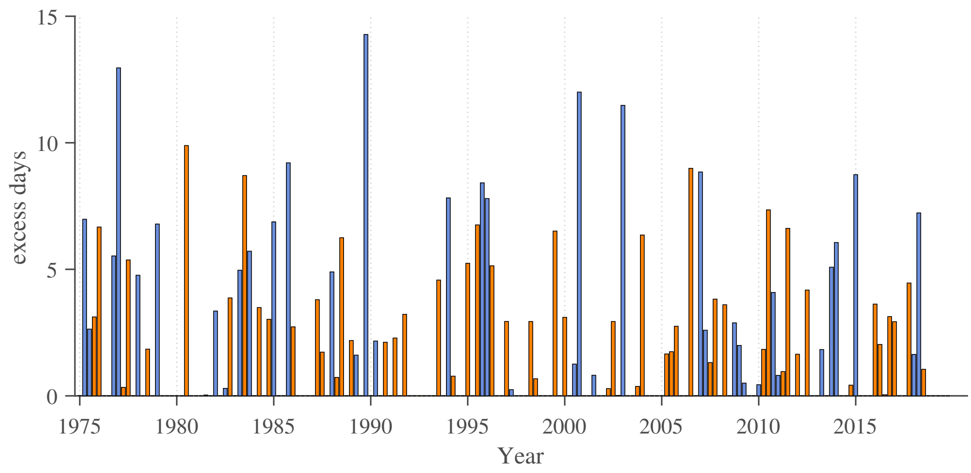
The peaks in Figure 2, i.e. largest positive values of the shock, are recorded in 1977q1, 1989q4, 2000q4 and 2003q1. For a description of the main events surrounding those dates, see Appendix Appendix C. All of them were mainly due to abnormally cold periods. However, heat-related surprises have also been frequent in the history of US temperatures. To have a flavor on how both extremes contribute in shaping US-wide shocks, I inspect the incidence of surprisingly hot and cold days in the shock series within

[13]The Actuaries Climate Index is a composite indicator of the frequency of a set of climate-related natural events including extreme temperatures, precipitation, wind, drought and sea level rise (American Academy of Actuaries, Canadian Institute of Actuaries, Casualty Actuarial Society and Society of Actuaries, 2020). The components are constructed as anomalies, i.e. in difference with respect to a fixed reference period in the past (1961-1990).

[14]This higher predictability speaks to the evidence of an upward trend in annual temperature volatility found for a panel of countries in Alessandri and Mumtaz (2021), over which the US economy may have adapted over time.

each quarter. Figure 3 displays positive US shocks in a bar plot where observations are labeled as orange or blue depending on whether surprisingly hot or cold days prevailed at each point in time. Abnormally hot and cold quarters have been almost equally frequent, with the former being slightly more (55% of times). Moreover, their incidence has been mostly balanced throughout the sample, with no apparent clusters in the most recent period. This finding also dispels the myth that, in a global warming era, abnormally hot days largely predominate over cold ones. In Section 8, I break down the US-wide shock into heat and cold shocks and estimate the economic effect of each component separately, finding comparable albeit not equal effects.

Figure 3: Hot vs. cold quarters



Notes: Positive shocks only. Orange (blue) bars: quarters in which surprisingly hot (cold) days predominate.

6. The impact of temperature shocks on the US economy

In this section I use the constructed shock to evaluate the effect of temperature surprises on the US economy. In the following, I describe my approach and comment on the main findings.

6.1. Impulse-response analysis

I estimate the response of US domestic variables to the previously constructed shock using the local projections framework of Jorda (2005). Impulse response functions (IRFs) are obtained from the following linear regressions:

$$y_{t+s} = \alpha_s + \beta_s \text{ US\_shock}_t + \psi_s(L)\mathbf{X}_{t-1} + u_{t+s} \qquad s = 0,1,2,\ldots,H \tag{6}$$

where t are quarters, y is the target variable and $\mathbf{X}_t$ is a vector of controls.[15] Estimates are made separately for each time horizon s and for each dependent variable. IRFs are defined by the sequence $\{\beta_s\}_{s=0}^{H}$, and inference is performed with Newey-West standard errors.

6.2. Target variables

In my baseline estimates, I test the effects of temperature shocks on the following set of domestic dependent variables: GDP, private consumption and investment (all in real terms); the CPI index, 3-month interest rate and the 10-year Treasury yield.[16] On the right hand side of Equation 6, I include a tight set of controls: linear, quadratic and cubic time trends, seasonal dummies, eight lags (up to 2 years) of the shock and of the aforementioned variables, and the 1-year less 3-month yield to control for the impact on the short-term portion of the yield curve.[17] A summary of all data used in this paper is reported in Appendix Appendix D. Impulse responses are estimated on a 16-quarter horizon, and displayed with 68% and 90% confidence bands. The baseline estimates are carried out on the full sample, going from 1975 Q1 to 2019 Q4.

6.3. Results

Impulse response functions from a one-standard deviation shock are displayed in Figure 4. In response to a positive (unfavorable) temperature surprise, real GDP in the United States significantly declines on impact, with the effect becoming larger over time reaching a trough between 1 and 2 years after the shock. Both private consumption and investment shrink, with investment being much more impacted – response is five times larger at the trough.[18] With some lag, the CPI index also decreases after the shock,

[15] Note that, with respect to previous notation, I here suppress subscript y to indicate years.

[16] All variables except the 3-month rate and the 10-year yield are expressed in natural logarithm.

[17] In the set of controls, variable lags are reduced to 4 in estimates made on shorter samples.

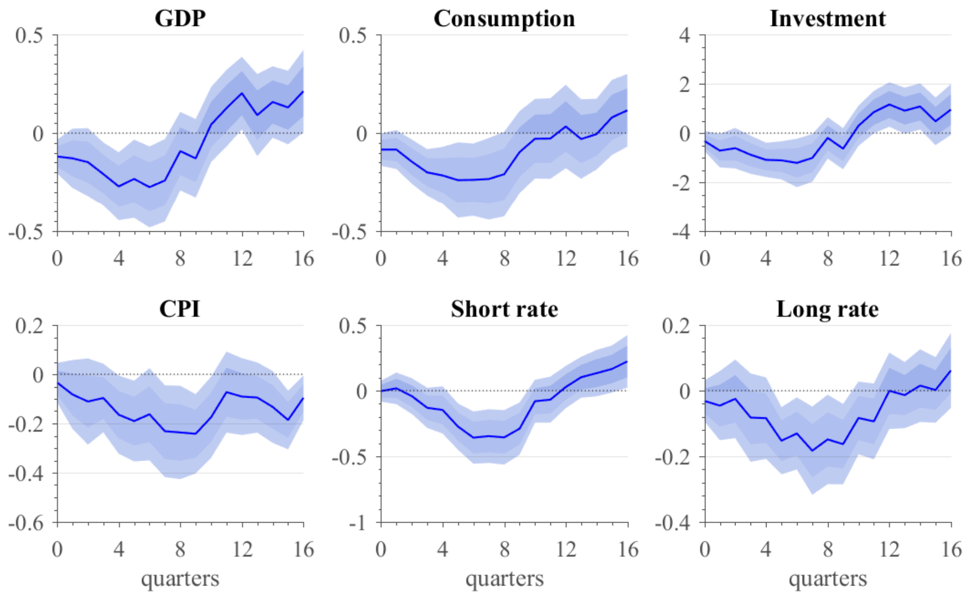
[18] The latter also sees some rebound, possibly due to an increase in climate adaptation investments, which is not enough to significantly raise output in the longer term.

suggesting that demand-side effects dominate over supply-side ones. Coherently with the slowdown in both output and prices, short-term interest rates also decline, suggesting an expansionary monetary policy response. This effect passes through the long end of the government yield curve, as the 10-year yield also falls significantly.

In terms of size, the economic effects can be quantified as follows: a positive shock in a single quarter by one standard deviation, which is equal to 4.3 days (5% of the days in the quarter), entails a decrease in real GDP by 0.1% on impact, which increases up to -0.3% in about two years, when also lagged effects come into play.[19] Temperature effects growing over time speak to the findings in Lemoine (2021), showing that weather shocks induce different forms of adaptation adding up dynamically to the direct effects of the shocks. However, as temperatures are found to eventually reduce consumer prices, there should also be other explanations for such persistent effect, pointing to a drag on aggregate demand. Looking beyond GDP effects, the shock also implies an overall decrease in real private consumption by 0.2%, in real investment by 1.2% and in the CPI index by 0.2%. Regarding interest rates, it generates a fall in the 3-month rate by 35 basis points, and in the 10-year yield by 18 bps. Taken together, the effects of GDP, CPI and interest rates stand out in the literature. In particular, this is the first evidence, as far as I know, of a significant response of US interest rates to temperature fluctuations.

[19] A negative impact of temperature shocks on GDP is in line with the negative effects of an increase in average temperatures found in Deryugina and Hsiang (2014), Hsiang et al. (2017) and Colacito et al. (2019).

Figure 4: Baseline estimates



Notes: 68% and 90% confidence bands.

6.4. Shock transmission

In this section I explore the impact of the shock to a number of additional macroeconomic variables to help figure out how temperature surprises propagate throughout the economy, with a focus on demand components. Figures 5 and 6 display the breakdown of the response of private consumption and investment. Figure 5, on consumption, shows that the effect of the shocks are stronger on the consumption of durables than on that of non-durables or services. Together with the evidence of investment being more impacted than consumption (Figure 4), this suggests that temperature shocks can weight on long-term economic beliefs, maybe inducing a heightened risk aversion or higher economic uncertainty due to weather- and climate-related risks. On the other hand, the impact on non-durables expenditures can also be associated to the effect of weather on retail sales, as in Roth Tran (2022). Among non-durables, the figure also singles out the effects on energy consumption, which increases on impact (driven by a rise in the amount of electricity consumed for air conditioning or heating purposes) and becomes negative in the medium run, indicating that low aggregate demand may also end up depressing that for energy. Figure 6, on investment, shows that investment in equipment, both residential and non-residential, are the first to be cut to cope with the surprising temperature events, while other components, including R&D investment, are reduced with some lag.[20]

Figure 5: Consumption breakdown

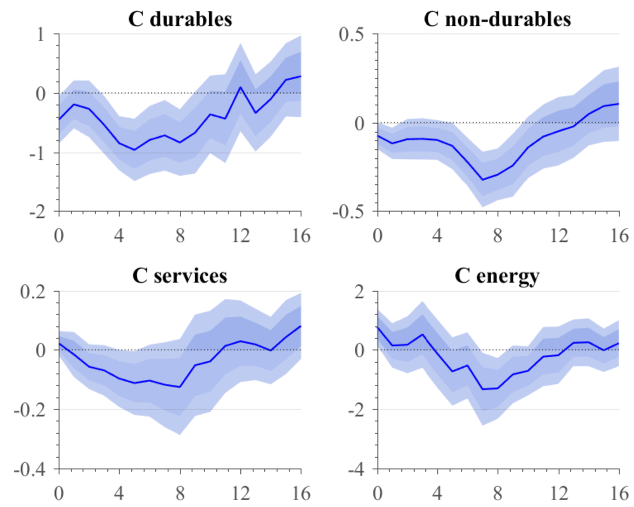


Figure 6: Investment breakdown

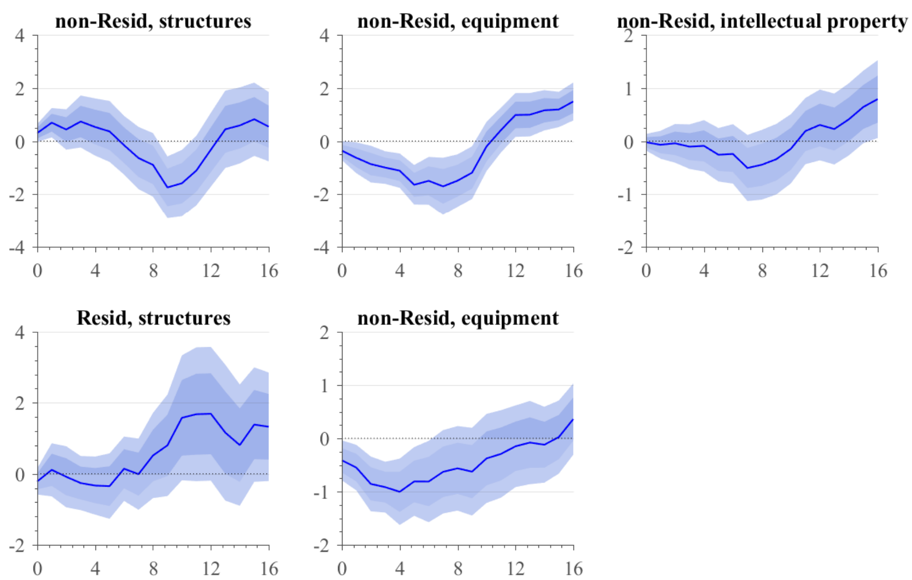


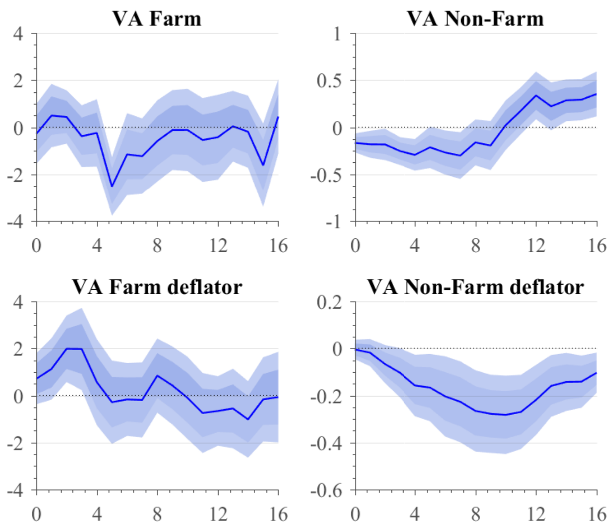
Figure 7 investigates possible differences in the shock transmission across sectors. As official figures on quarterly output by economic industry are only available since 2005, I

[20]On the contrary, investments in non-residential structures increase on impact, possibly because of some short-term relocation as in Castro-Vincenzi (2022).

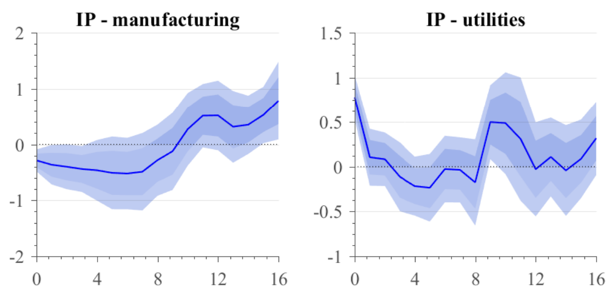
here display the impact on the real value added of the business sector for the farm and non-farm sub-sectors (Panel a), and on GDP-deflated industrial production of manufacturing and utility (Panel b). As expected, while the effect on the farm sector is way larger – confirming that agriculture is the most exposed activity to climate change – value added in the non-farm sector also significantly declines, suggesting that temperature effects are widespread across the US economy. Within the industrial sectors, the negative effects come from a slowdown in manufacturing while utility production goes up on impact, in line with the finding on energy consumption in Figure 5. Regarding prices, the negative effects on CPI are clearly driven by non-farm sectors only, as the price index on farm value added goes up following a temperature shock, as expected.

Figure 7: Sector breakdown

Panel a: Farm vs non-farm



Panel b: Industrial production



Price effects are investigated in greater detail in Figure 8, where the response of the CPI is decomposed into its core (left) and volatile components: food and beverages (center picture) and energy (right picture). The price response appears overall muted on impact, with food prices responding positively – albeit non-significantly. However, after four quarters the response of both core and energy components become negative, suggesting once more that temperatures act mainly by lowering aggregate demand.

Finally, figure 9 displays labor market effects, focusing on employment per capita (employment/population), hours worked per worker of the business sector (total hours/employment), and labor productivity of the business sector. Following a temperature shock, employment per capita falls, remaining below the baseline for eight quarters; together with that, the number of hours worked per worker also decreases, suggesting that the effects on total labor supply come from both the extensive and the intensive margin. In addition, labor productivity falls significantly. Taken together, results for labor market variables confirm the relevance of the heat stress channel found in previous contributions.

Figure 8: Price effects

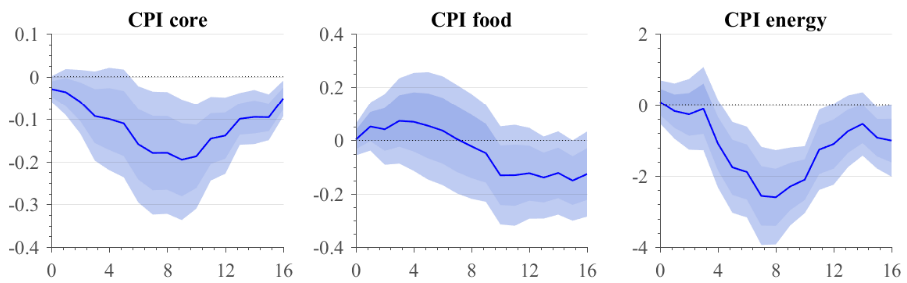
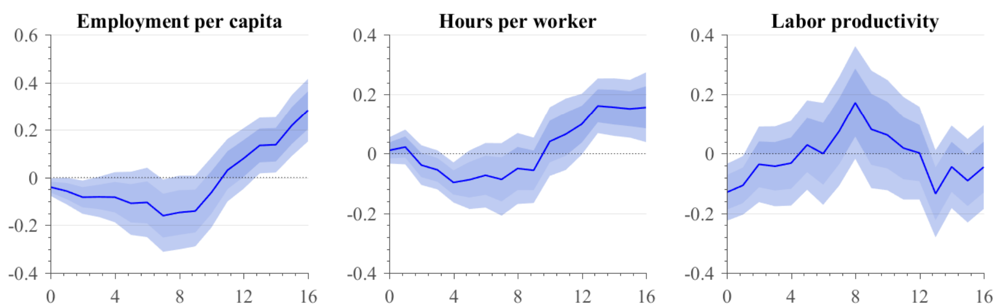


Figure 9: Labor market



7. Robustness exercises

In this Section I test a number of alternative assumptions to construct my temperature shock and perform robustness exercises to confirm my baseline findings.

7.1. Fixed pre-sample temperature expectations

As pointed out in Section 4, it is well documented by the literature that agents learn about temperatures over time and update their temperature beliefs accordingly. This feature is embedded in the constructed shock by making the thresholds for county-level surprises (*lt* and *ut* in Equation 4) vary over time. We here evaluate how results change whether these thresholds are instead made time-invariant, i.e. anchoring expectations of the temperature distribution to some pre-sample level without updating them over time.[21] In formula, this alternative version of county-level surprises looks as follows

$$\text{county\_surprise}_t^i = \sum_{j=1}^{n_t} \left[\mathrm{I}(T_{d,t}^i < \bar{\mathrm{lt}}^i) + \mathrm{I}(T_{d,t}^i > \bar{\mathrm{ut}}^i) \right] - N_t \times 0.2 \times 0.2 \qquad i \in k \quad (7)$$

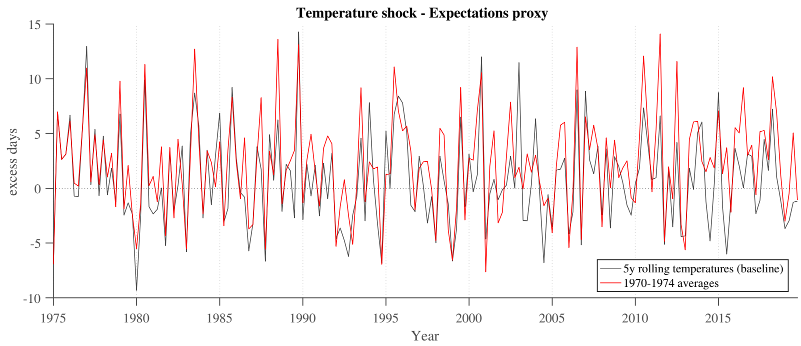
where $\bar{\mathrm{lt}}^i$ and $\bar{\mathrm{ut}}^i$ are 10th and 90th percentiles computed by quarter over the years 1970-1974. County-level surprises constructed in this way are then used to made an alternative version of the US shock according to Equation 5. Figure 10 displays this alternative version together with the baseline shock series. Anchoring expectations at pre-sample level yields a distorted picture of agents beliefs, as the shock constructed in this way increasingly overestimates the incidence and size of positive shocks over time. A closer look at the composition of hot and cold surprises within positive shocks, shown in Figure 11, also reveals that the incidence of hot surprising days is increasingly overestimated, reflecting the upward temperature trend that time-invariant expectations are unable to net out.

7.2. Surprise thresholds

The temperature surprise shock is constructed in each quarter with respect to some threshold values, which are the 10th and 90th percentiles of the reference distribution. I propose alternative specifications of the shock in which I modify the definition of surprising days by setting threshold values at the 5h and 95th percentiles, or at the 25th and 75th percentiles of the reference distribution. Figure 12 shows the median responses for my 6 variables of interest in these two cases, together with the baseline IRFs. Impulse responses of the two alternative specifications look very similar to the baseline, with shocks

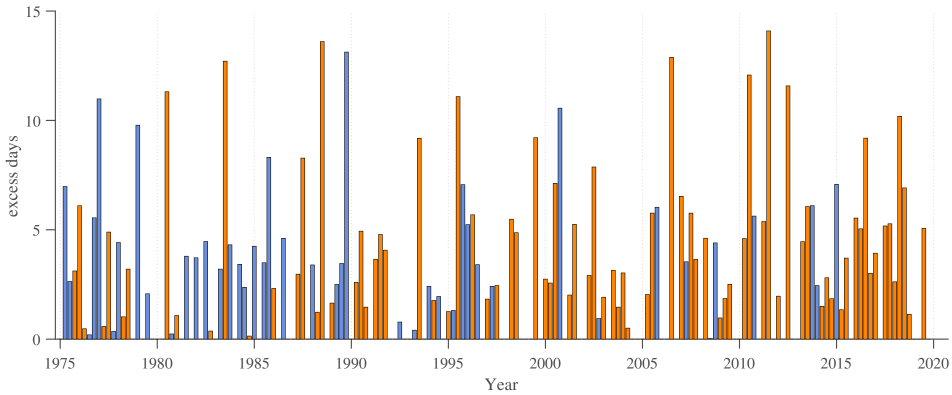
[21] Such alternative formulation is in the spirit of using temperature anomalies to evaluate the economic effects of current temperatures.

Figure 10: Shock with fixed pre-sample temperature expectations



Notes: Red: shock based on fixed 1970-1974 thresholds. Black: baseline shock

Figure 11: Heat vs cold surprises in the shock with fixed pre-sample temperature expectations



Notes: Positive shocks only. Orange (blue) bars: hot >(<) cold surprises.

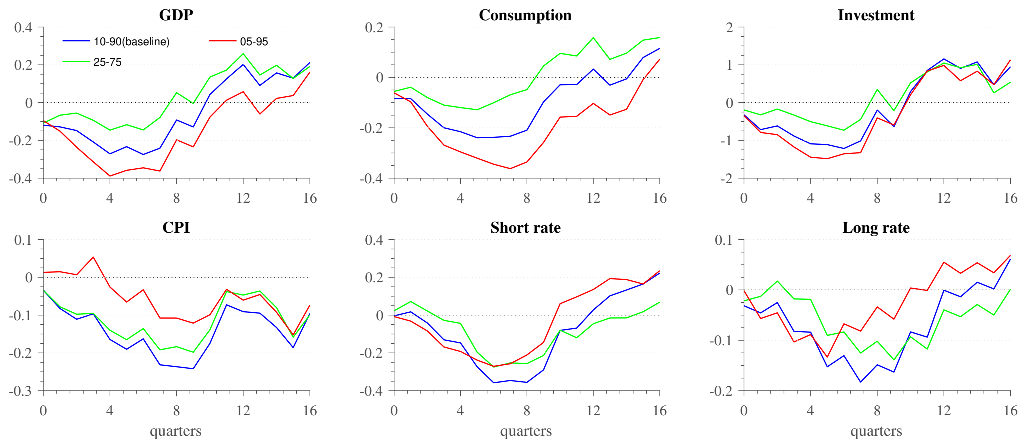
based on temperatures in the farthest part of the tails (5th-95th perentiles thresholds) having a slightly stronger impact on GDP. Correlations between baseline US shock and the two alternatives are about 96%.

7.3. Weighting scheme

I here compute alternative formulation of the US-wide shock using different weights to aggregate county-level surprises. In particular, instead of counties' population shares, I use the counties' share of the following variables: (1) land extension; (2) employment; (3) personal income; (4) real GDP in 2001.[22] The median impulse responses obtained

[22]As county-level real GDP is only available since 2001, I made time-invariant GDP weights based on that first observation. Differently, variables (1) to (3) are used to compute annual time-varying weights as in the baseline computation.

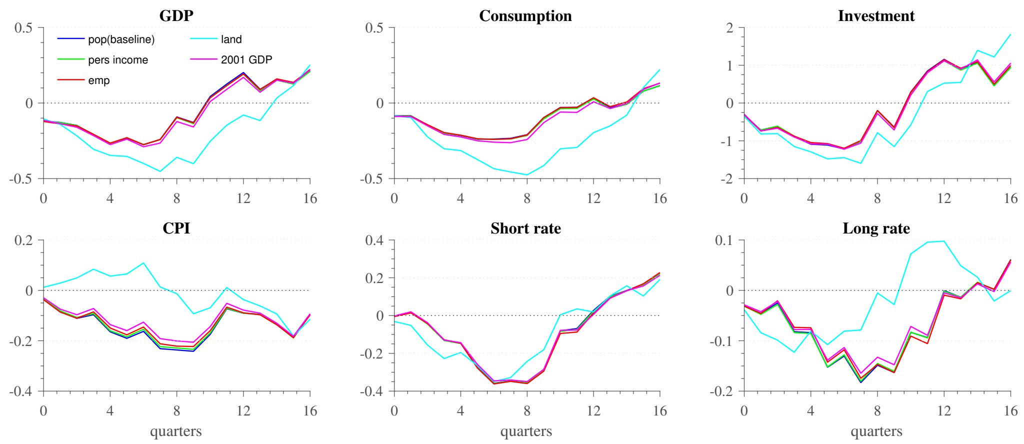
Figure 12: IRFs to shock computed with different thresholds



Notes: 68% and 90% confidence bands.

from these alternative shocks are displayed in Figure 13. Using employment shares, personal income shares and GDP shares leave results mostly unchanged with respect to the baseline. Using land instead of population weights change responses a bit more, although remaining broadly in line with baseline results.

Figure 13: IRFs to shock computed under different weighting schemes

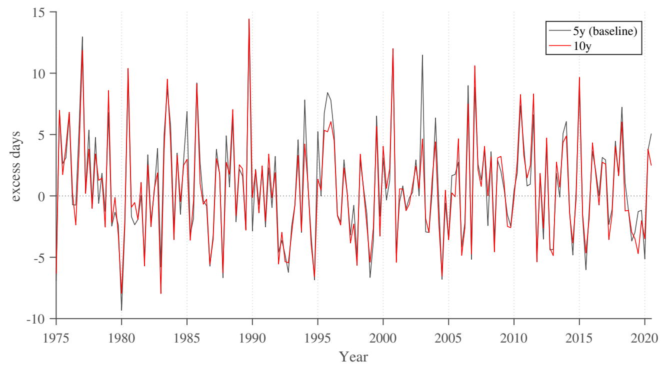


Notes: 68% and 90% confidence bands.

7.4. Learning period

In the baseline specification I construct reference distributions by aggregating temperatures observed in the five years prior to the shock. Here, I assume that learning takes longer and construct those distributions over 10-year rolling windows. The shock, plotted in Figure 14, is very similar to the baseline version (95% correlation).

Figure 14: Shock computed with 10-year reference distribution



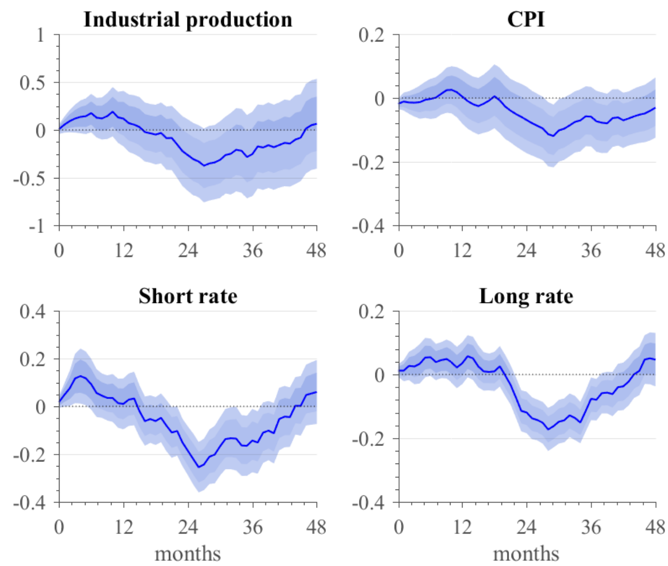
7.5. Monthly temperature shocks

Throughout the paper, temperature shocks have been constructed at quarterly frequency. I here propose a monthly version of the shock that, following the same logic of the baseline, starts from computing monthly surprises at county level. Surprising hot and cold days within each month are assessed with respect to a rolling, reference distribution computed by pooling daily average temperatures recorded for the same month of the year during the past 5 years; county-level surprises are then aggregated using annual population weights to get a US-wide monthly time series. To estimate the economic effect of temperatures at the higher, monthly frequency, a local projection estimate is carried out using this monthly version of the shock. Regarding the response variables, given the unavailability of GDP at such frequency, an indicator of industrial production is used to evaluate the output effect on the industry sector; monthly Consumer Price Index, 3-month rate and 10-year yield are employed as additional response variables. Results, show in Figure 15, suggest that the direction, size and timing of the response is in line with the baseline. The response of industrial production is negative as that of GDP but somewhat lagged, maybe due to the positive impact on the utility sector found in Figure 7.

8. Other estimates

In this Section I explore the economic effects of temperature shocks along other dimensions, including impacts at local level, a focus on the central bank reaction, the different

Figure 15: IRFs to shock computed at monthly frequency



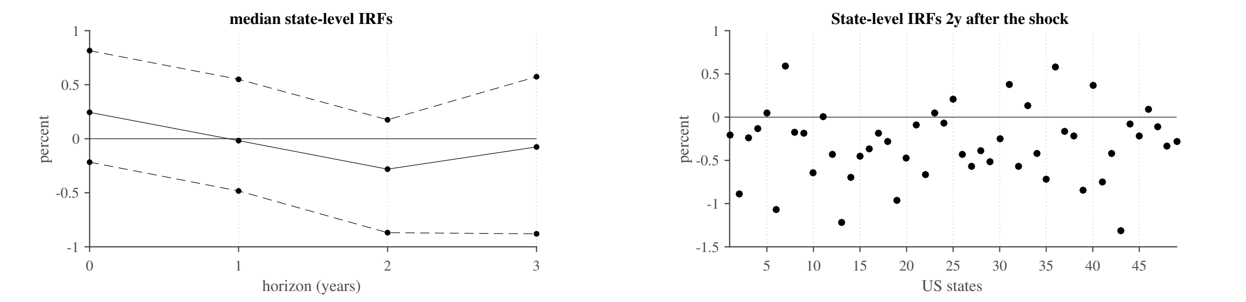
Notes: 68% and 90% confidence bands.

implications of heat vs cold shocks and of temperature shocks over time.

8.1. Local effects of temperatures

According to the shock formulation in Section 4.2, county-level temperature data are used to estimate US-wide economic effects. One interesting question that arises is how this aggregate effect is made up, i.e. how temperatures are able to affect the economy at local level. I take up this question by estimating the impacts of temperatures on local output. As county-level GDP is only available since 2001, I resort to an estimate of the effects of temperatures at state level and annual frequency, as it is also done in Colacito et al. (2019). For this purpose, I first sum the quarterly county-level surprises within each year to obtain yearly county-level series; then, I compute annual state-level shocks by weighting county-level surprises with population shares within the state[23] As the series of real Gross State Product (GSP) is consistently available for each state only since 1998, the estimation sample is here restricted to the 1998-2019 period.[24] Figure 16 shows the response to a one-standard deviation annual state-level shock obtained with local projections. In the left panel, pointwise median responses are shown together with 10-90 percentiles for horizons up to 3 years ahead. While the response of GSP is quite heterogeneous on impact in this sample, it becomes predominantly negative between one and two years after the shock, in line with what is found in the baseline exercise at national level. Indeed, the right panel shows that the vast majority of the US states experience a slowdown in real GSP two years after the shock; the size of the response is in line with the baseline, albeit on average smaller (if scaled by a factor of four), as expected for the most recent period.

Figure 16: Annual state-level IRFs (1998-2019): real GSP



Notes: Left panel: pointwise median state-level IRFs (solid line) and 10-90 percentiles (dashed lines) from a one-std deviation yearly state-level shock. Right panel: IRFs at 2y horizon, by US states.

[23]In formula, annual county surprises and state-level temperature shocks are

$$\text{county\_surprise}^i_y = \sum_{j=1}^{4} \left[\text{county\_surprise}^i_{j,y}\right] \qquad i \in k \tag{8}$$

$$\text{state\_shock}^p_y = \sum_{i=1}^{S_p} \left(\text{county\_surprise}^i_y \times \text{w\_state}^i_{y-1}\right) \tag{9}$$

where j=q1,...,q4, w_state is the state-level population weight of county i and S_p is the number counties in state p.

[24]See the Cautionary Note About Annual GDP by State Discontinuity on the Bureau of Economic Analysis's website.

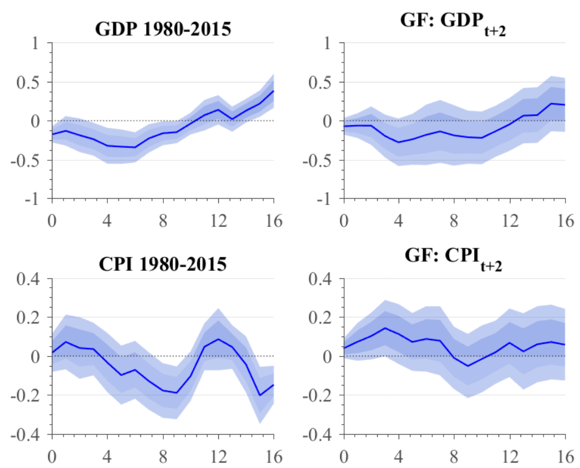
8.2. Central bank reaction

The impact of temperature shocks on the short-term rate observed in Figure 4 suggests that the Fed does react by lowering policy rates. A natural question that arises is whether temperature shocks are also able to affect the central bank's view on the economy, and whether shocks stimulate some specific discussion within the Federal Open Market Committee (FOMC).

To have insights on on the former, I re-run local projections on Greenbook Forecasts for GDP and CPI for quarter t+2, to see whether the Fed is able to foresee a persistent effect of temperatures beyond impact effects embedded in economic nowcasts. Greenbook forecasts for GDP and CPI are produced for the FOMC prior to each meeting and, at the time of the estimates, were jointly available to the public between 1980 and 2015. Figure 17 compares the response of GDP and CPI in the same sample period (first column) with the effect on GDP and CPI forecasts for quarter t+2 (GF:GDP$_{t+2}$ and GF:CPI$_{t+2}$). While output effects are not expected to persist when the shock hits – at time 0, confidence bands of the t+2 GDP forecast cross the zero line – GDP forecasts are then adjusted to include some, still persisting temperature effect. Differently, the predicted response of the CPI goes to the opposite direction with respect to where it eventually goes. All in all, while the central bank displays a timely reaction by lowering short rates, the identification of the current shock as a persisting drag to aggregate demand seems to be a much harder task.

Do temperature shocks raise the attention of the FOMC regarding weather variations? I analyze the transcripts of all FOMC meetings historically available (i.e., from 1976 to 2015) and define three sets of weather-related terms: a wording related to the climate change phenomenon (Climate change wording); a wording related to temperatures and strictly related phenomena (Temperatures wording); a wording related to climate-related non-temperature events (Natural disasters wording).[25] Figure 18 displays the word count over time for each set of words. The first panel reveals that the FOMC has explicitely mentioned the climate change phenomenon very rarely (only 7 times since 1976), but temperatures and, to a lesser extent, natural disasters, quite frequently. Overall, evidence suggests that during the most recent phase of the global warming era, climate change has rarely been a hot topic in official central bank's conversations, at least before 2016 (temperatures had mentioned, on average, just 4 times per quarter).[26] Using the temperature and natural disaster word counts as dependent variables in local projections, it turns out that the FOMC slightly increases mention of temperatures after shocks, suggesting some moderate attention devoted to weather variations by the Committee (Figure 19).

Figure 17: Effects on Fed's Greenbook Forecasts



Notes: GF:X_t is Greenbook Forecast for time t, variable X.

[25]The three sets of words are the following:

- Climate change: climate change, climate crisis, climate emergency, climate breakdown, global warming, global heating, carbon emissions, greenhouse gas emissions
- Temperatures: extreme heat, heat wave, temperature, hot days, weather, cold days, drought, wildfires, heat stroke, sunstroke
- Climate-related non-temperature events: flood, landslide, tornado, hurricane, dustnado, snowfall, snow, rainfall, precipitation

[26]Nonetheless, this attitude could have changed since then, as climate change debate increased strongly in popularity.

Figure 18: Climate mentions by FOMC members

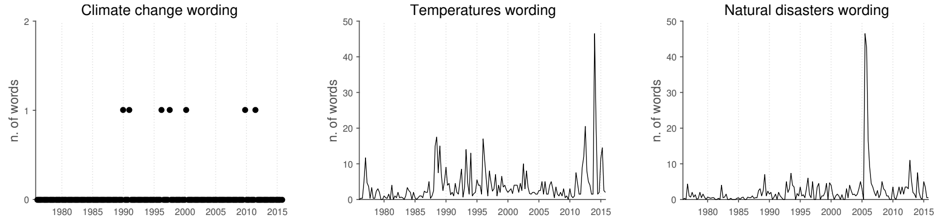
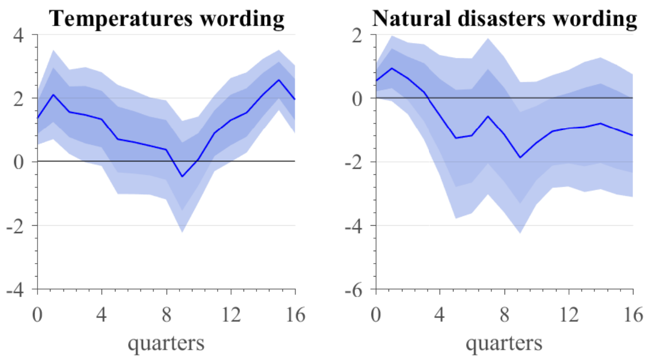


Figure 19: Effect on Fed's climate-related wording



Notes: 68% and 90% confidence bands.

8.3. Heat vs cold shocks

The baseline temperature surprise shock is constructed by summing left and right tail surprises in each quarter. In this section I dissect the economic effects of these two components by including them separately in local projection estimates. According to Equations 4 and 5, left- and right-tail shocks, which I call cold and heat surprise shocks, can be retrieved as

$$\text{US\_shock}^{b}_{t,y} = \sum_{i=1}^{K} \left(\text{county\_surprise}^{i,b}_{t,y} \times \text{w}^{i}_{y-1}\right) \qquad b = \{\text{cold}, \text{heat}\} \tag{10}$$

where

$$\text{county\_surprise}^{i,\text{cold}}_{t,y} = \sum_{j=1}^{n^i_t} \text{I}(T^i_{d,t,y} < \text{lt}^i_{t,y}) - N_{t,y} \times 0.1 \times 0.2$$

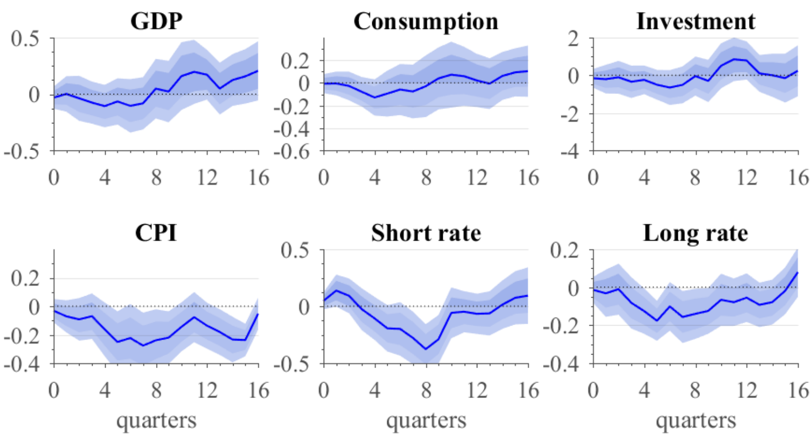
$$\text{county\_surprise}^{i,\text{heat}}_{t,y} = \sum_{j=1}^{n^i_t} \text{I}(T^i_{d,t,y} > \text{ut}^i_{t,y}) - N_{t,y} \times 0.1 \times 0.2$$

I then employ those variables into linear local projections as

$$y_{t+s} = \alpha_s + \gamma_s \text{ US\_shock}_t^{\text{cold}} + \delta_s \text{ US\_shock}_t^{\text{heat}} + \psi_s(L)\mathbf{X}_{t-1} + u_{t+s} \qquad s = 0, 1, 2, \dots, H \tag{11}$$

where γ_s and δ_s are impulse response functions to cold and heat shocks, respectively, and $\mathbf{X}$ is the set of control variables. Figures 20 and 21 show the response to the two shocks of all the variables considered in the baseline estimates. The economic impact of heat and cold shocks looks overall quite similar, although the response to cold shocks is somewhat larger (especially for GDP, consumption and investment) and more significant.

Figure 20: IRFs to heat shock



Notes: 68% and 90% confidence bands.

8.4. Impacts by season

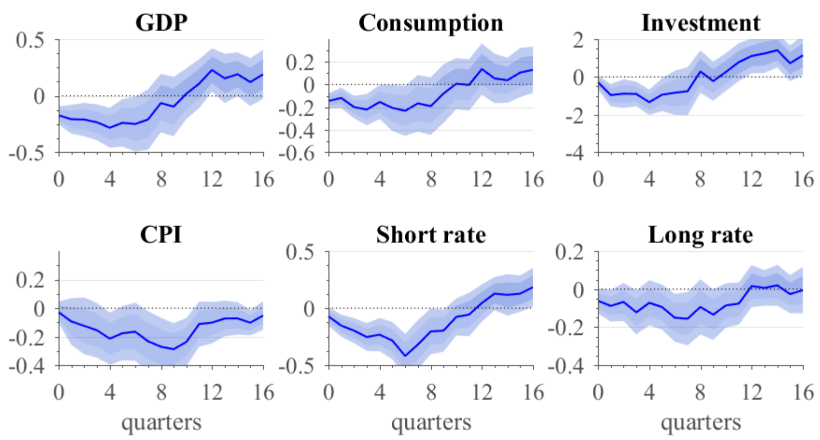
How does the impact of heat and cold shocks vary by season? For this purpose, I estimate the following variant of Equation 11 :

$$y_{t+s} = \alpha_s + \sum_{j=1}^{4} \left(\gamma_s^j \text{ US\_shock}_t^{\text{cold}} \times D_t^j + \delta_s^j \text{ US\_shock}_t^{\text{heat}} \times D_t^j \right) + \psi_s(L)\mathbf{X}_{t-1} + u_{t+s} \tag{12}$$

where $s = 0, 1, 2, \dots, H$. D_t^j with $j = \{1, \dots, 4\}$ are four dummies that equal 1 if current quarter is quarter j of the year, 0 otherwise. As I interpret quarters as calendar seasons,

[26]The set of controls is the same I employed in the baseline estimate. Four lags of the shocks are substituted here with four lags of both heat and cold shocks.

Figure 21: IRFs to cold shocks



Notes: 68% and 90% confidence bands.

γ_s^j and δ_s^j represent impulse response functions to cold and heat shocks in winter (q1), spring (q2), summer (q3) and fall (q4). Figure 22 and Figure 23 represent IRFs for heat and cold shocks by season, which are displayed for GDP, CPI and short rate only to save space.[27] Overall, the two figures show that the impact of heat and cold shocks are generally more pronounced in summer than in other seasons. Regarding heat shocks, summer shocks have a stronger impact on GDP and the short rate than shocks in other seasons; the sign of the response of CPI vary substantially across seasons, appearing to be positive in winter and fall. Instead, cold temperature shocks have a detrimental economic effect not only in summer, but also in winter, while cold shocks in spring and fall seem to play a minor role.

[27]IRFs to heat and cold shocks by season of all the other variables in the baseline are available upon request.

Figure 22: IRFs to heat shocks by season

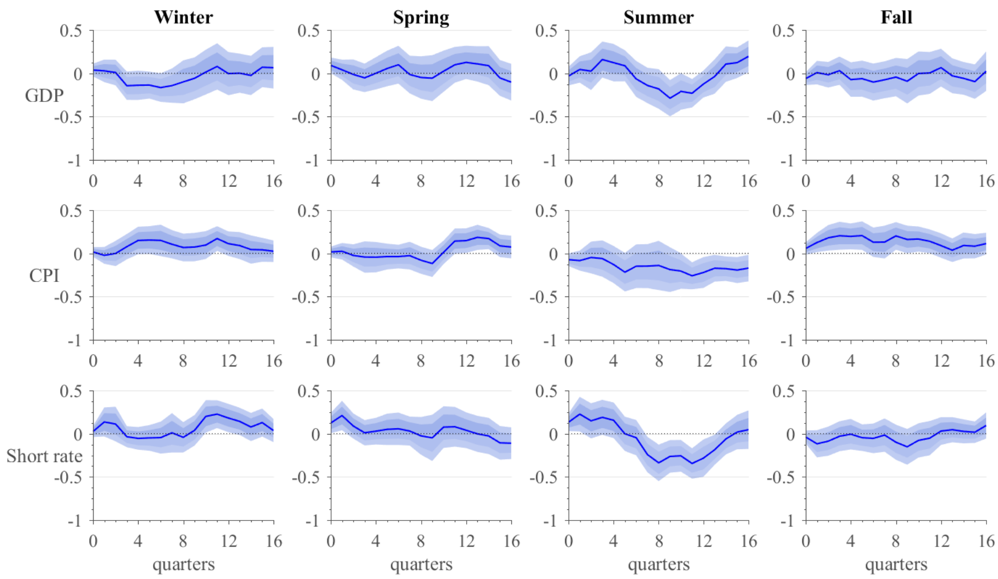
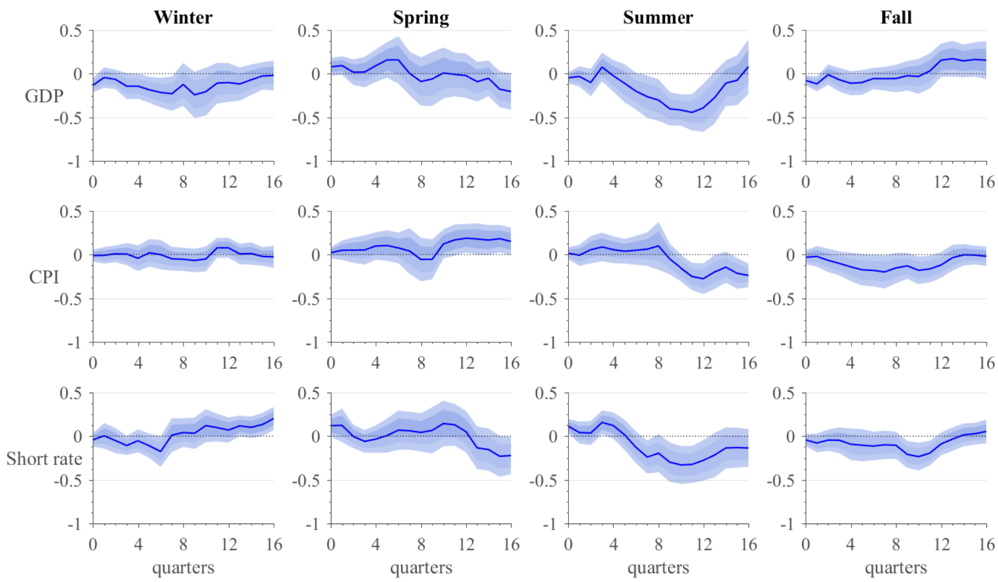


Figure 23: IRFs to cold shocks by season



8.5. Impact over time

The impacts found in the baseline estimates are the average effects of the shock throughout the sample period. However, as climate manifestations are the more and more visible and knowledge about them has become more widespread over time, the size of the economic impacts may have also changed. To gauge such potential time variation, I repeat local projections on sub-periods, focusing on the effects on GDP, CPI and the 3-month rate only. I set a trailing sample of 144 quarters (36 years) and perform new estimates by rolling it by one quarter at a time. In this way, I get 37 sets of estimates, which begin from the sample period 1975q1-2010q4 and end with the sample 1984q1-2019q4. To summarize the impulse responses obtained at each iteration, I display for both variables the IRFs at the horizon displaying the largest negative impact (trough) at each iteration.

Figure 24: Impact at the trough, rolling estimates

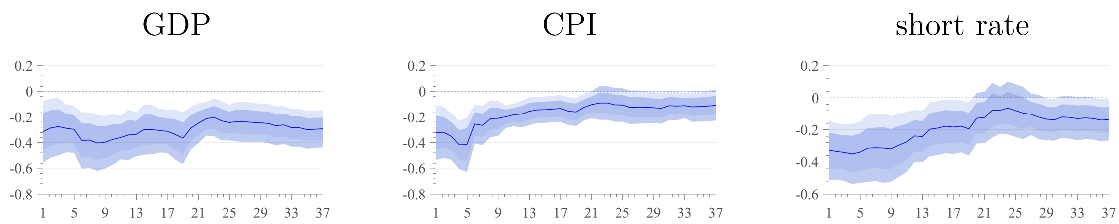


Figure 24 shows the results for GDP, CPI and the short rate, where pointwise median responses are displayed together with their 68% and 90% (pointwise) confidence bands. The estimates suggest two interesting facts. First, the elasticities of GDP, CPI and the short rate to the shock have slightly reduced in size over time: for example, the CPI passed from around -0.4% to about -0.10% This reduced impact may reflect the fact that the increasing adoption of heating and cooling systems in houses and firm establishments and, more generally, the adaptation measures put in place to safeguard from temperature oscillations have made agents more resilient to shocks than they were 50 years ago. However, temperature shocks continue to have a significantly negative impact on the US economy, inducing a concomitant fall in GDP, CPI and the short-term interest rate also in the most recent part of the sample.

9. Conclusions

The relation between climate and the economy is typically studied relating realized temperature changes to GDP. Leveraging on the insights of the empirical macroeconomic literature, I focus instead on the economic impact of temperature surprises, i.e. unexpected fluctuations in the occurrence of exceptionally hot or cold days obtained from high-frequency, granular data for the USA. I isolate unexpected temperature shocks based on the incidence of relatively high and low temperatures in excess what agents expect in each location and season, and then aggregate local shocks to the country level using population weights. Estimates made with local projections show that temperature surprise shocks in the United States have significantly damaged the economy in the most recent phase of the global warming era, and that the Federal Reserve has been reacting to the deteriorating environment by lowering short-term rates. All in all, results show that temperatures are an autonomous source of macroeconomic variation, adding another piece of evidence in the debate on the needed policy response to climate change. The shock constructed in this paper can be replicated for other countries and at wider or narrower geographic dimension, and can serve as reference to build other weather-related shocks.

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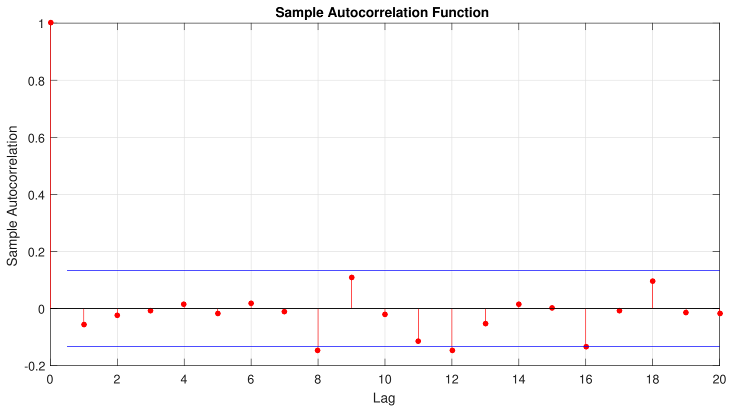
Appendix A. Diagnostics on the shocks

In order to check that my US-wide shock series has desirable properties to be used in macroeconomic analysis, I perform the Ljung-Box Q-test for serial correlation. I repeat the test 6 times including a different number of lags each time: 1,4,8,12,16 and 20 quarters. All tests fail to reject the null hypothesis of no residual autocorrelation. The autocorrelation function is displayed in Figure Appendix A.1, showing that evidence for serial correlation is limited at best.

Figure Appendix A.1: Autocorrelation function of the US-wide shock



Appendix B. Forecasting surprisingly hot and cold days

Expectations on the temperature distribution at quarterly frequency are fundamentally backward-looking. Assuming agents being able to quickly adjust their plans in exceptionally hot or cold days, can publicly available weather forecasts really help? To have some insights on this question, I here conduct an illustrative exercise to investigate whether days that are labelled as surprisingly hot or cold according to my technique are also more difficult to predict. I use data from the Model Output Statistics (MOS) database of the National Weather Service, collected from the Iowa State Mesonet archive and available since year 2000. I focus on Washington DC county and construct predictions of one- and two-day ahead average daily temperatures at daily frequency.[28] Using

[28]DC county is chosen because temperatures are recorded through one weather station only, simplifying the calculations. From that station, forecasts are made six times per day and relate to temperatures for the same day and up to 3 days ahead, at the 3-hour frequency. To construct predictions, I retain the

realized county temperatures, I construct daily ex-post forecast errors as

$$\mathrm{fe}_t{}^j = f_{t-j}^{\,j} - \mathrm{temp}_t$$

where $f_{t-j}^{\,j}$ are forecasts made at time $t-j$ with horizon j, with $j = 1,2$ days and $\boldsymbol{temp_t}$ are the realized average daily temperatures used to construct my temperature shock. To compare forecasts with surprises, I compute a dummy variable that equals one if the day is labeled as surprisingly hot or cold under my procedure, and 0 otherwise. I then estimate a probit regression model to test if high forecast errors (in absolute values) are correlated with a higher probability of a day being labeled as surprising. In formulas

$$\mathrm{Prob}_t\ (\text{surprising day}_t = 1) = F\ \left[\alpha + \beta_j\ |\mathrm{fe}_t{}^j|\right] \qquad j = 1,2$$

The estimates are carried out in the sample going from Jul 1, 2000 to December 31, 2019. Results, available upon request, show that the probability of a day being surprising is positively and significantly correlated with the size of forecasts errors, confirming that days with temperatures going beyond expectations are also more difficult to predict than those with milder temperatures.

Appendix C. Narrative on the shock

1977q1: As the New York Times described, 1977 was "a year of weather extremes", which spurred new climate research in the United States and worldwide (Sterba, 1977). Analyses made at that time by the National Weather Service reported that winter in 1977, especially in the eastern part of the country, was one of the coldest in the 20th century, with temperatures close to the record lows of 1917-18.

1989q4: The fourth quarter of 1989 also stood apart for its exceptionally low temperatures. Surges of Arctic air in December was, according to the National Weather Service, "a historic event, with many locations establishing monthly or all-time record lows" (National Weather Service, 1989). While the fall in temperatures was strongest in the northwest, the southeastern coast was also particularly damaged, with losses caused by damaged crops in Florida and broken water pipes in Texas causing failures at manufacturing plants. In that area, the 1989 cold wave also generated the largest snowstorm in

last forecasts made during the day (8 pm DC time).

recent history.

2000q4: The fourth quarter of year 2000 saw temperatures passing from one extreme to the other. The late summer period was characterized by a prolonged heat wave which, particularly, in southern states, resulted in record high temperatures. Then, after a warm October, temperatures plunged in November – the second coldest since records began in 1895, according to NOAA's National Climate Report. This turnaround in temperatures caused power outages and triggered other weather-related extreme events, such as tornadoes.

2003q1: The fourth peak in the series is that of winter of 2003. That period will be mainly remembered in northern states such as Minnesota and Michigan. While it was not among the coldest on record, it stood out for its persisting cold, which started in December and went through mid-March. In particular, Michigan recorded the second longest continuous streak of very cold temperatures (76% of days in January and February) on record, just one notch below the exceptionally cold winter of 1977.

Appendix D. Data sources

Table Appendix D.1: Data summary

Variable	Source	Frequency	Sample
Temperature shock			
gridded average daily temperatures	Northeast Regional Climate Center	daily	Jan 1,1970 - Dec 31,2019
population (by county)	Census Bureau	yearly	1969 - 2018
employment (by county)	Census Bureau	yearly	1969 - 2018
personal income (by county)	Census Bureau	yearly	1969 - 2018
land extension (by county)	Census Bureau	yearly	1969 - 2018
Real GDP (by county) (CAGDP9)	Bureau of Economic Aalysis (BEA)	yearly	2001
Response variables			
Real GDP (USGDP...D)	Refinitiv	quarterly	1975q1-2019q4
Real Personal Consumption Expenditures (USCNPER.D)	Refinitiv	quarterly	1975q1-2019q4
Real gross private domestic investment (USGDPRIND)	Refinitiv	quarterly	1975q1-2019q4
Consumer Price Index (USCONPRCE)	Refinitiv	quarterly	1975q1-2019q4
Population (USPOPTOTP)	Refinitiv	quarterly	1975q1-2019q4
Unemployment level (USUNPTOTO)	Refinitiv	quarterly	1975q1-2019q4
Unemployment rate (USUN%TOTQ)	Refinitiv	quarterly	1975q1-2019q4
3-month rate (TB3MS)	Fred	quarterly	1975q1-2019q4
1-year Treasury yield (GS2)	Fred	quarterly	1975q1-2019q4
10-year Treasury yield (GS10)	Fred	quarterly	1975q1-2019q4
PCE: Energy goods and services (DNRGRC1Q027SBEA)	Fred	quarterly	1975q1-2019q4
CPI: Energy (CPIENGSL)	Fred	quarterly	1975q1-2019q4
CPI: Food and Beverages (CPIFABSL)	Fred	quarterly	1975q1-2019q4
CPI: All Items Less Food and Energy (CPILFESL)	Fred	quarterly	1975q1-2019q4
GDP deflator (GDPDEF)	Fred	quarterly	1975q1-2019q4
Real Gross Value Added - Business - Farm	BEA NIPA Table 1.3.3	quarterly	1975q1-2019q4
Real Gross Value Added - Business - Non-Farm	BEA NIPA Table 1.3.3	quarterly	1975q1-2019q4
Real Personal Consumption Expenditures by Type of Product	BEA NIPA Table 2.3.3	quarterly	1975q1-2019q4
Real Private Fixed Investment by Type	BEA NIPA Table 5.3.3	quarterly	1975q1-2019q4
Real Gross State Product	BEA Regional Data	yearly	1998-2019
Employment level	Bureau of Labor Statistics	quarterly	1975q1-2019q4
Hours worked, business sector	Bureau of Labor Statistics	quarterly	1975q1-2019q4
Labor productivity, business sector	Bureau of Labor Statistics	quarterly	1975q1-2019q4
Industrial production - manufacturing	Federal Reserve Board G.17	quarterly	1975q1-2019q4
Industrial production - utility	Federal Reserve Board G.17	quarterly	1975q1-2019q4
GDP forecasts (t+2)	Greenbook Forecasts	quarterly	1980q1-2015q4
CPI forecasts (t+2)	Greenbook Forecasts	quarterly	1980q1-2015q4
FOMC word count			
Transcripts of FOMC meetings	federalserve.gov	meeting calendar	1976 - 2015
Weather forecasts			
1-day ahead temperature forecasts (at 8 pm DC time)	Iowa State Mesonet archive	daily	Jul 1,2000 - Dec 31,2019
2-day ahead temperature forecasts (at 8 pm DC time)	Iowa State Mesonet archive	daily	Jul 1,2000 - Dec 31,2019

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