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Temi di discussione

(Working Papers)

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ChaMP

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ChaMP is coordinated by a team chaired by Philipp Hartmann (ECB), and consisting of Diana Bonfim (Banco de Portugal), Margherita Bottero (Banca d'Italia), Emmanuel Dhyne (Nationale Bank van België/Banque Nationale de Belgique) and Maria T. Valderrama (Oesterreichische Nationalbank), who are supported by Gonzalo Paz-Pardo and Jean-David Sigaux (both ECB), 7 central bank advisers and 8 academic consultants.

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ISSN 2281-3950 (online)

Designed by the Printing and Publishing Division of the Bank of Italy

HEAT, COLD AND THE MACROECONOMY: TEMPERATURE SHOCKS ARE NOT ALL ALIKE

by Filippo Natoli*

Abstract

Hot temperatures are known to impair economic growth, but extreme cold also poses significant macroeconomic risks. Yet, despite the rising temperature volatility in a warming climate, the aggregate effects of cold shocks remain comparatively understudied, particularly regarding their transmission through the business cycle and their implications for inflation and monetary policy. I construct monthly unexpected heat and cold shocks for the United States using daily county-level temperatures. I find that heat shocks have negligible aggregate effects, whereas cold shocks significantly reduce industrial production, increase uncertainty, and are deflationary, triggering an endogenous monetary policy response. I show that identifying temperature surprises crucially depends on how expectations, extremes, and aggregation are defined. As climate instability increases the probability of cold air outbreaks in the US, adaptation policies should take account of unexpected cold spells, highlighting a dimension of climate risk that has received limited attention so far.

JEL Classification: C32, E32, E52, Q54.

Keywords: temperature shocks, cold shocks, climate change, monetary policy.

DOI: 10.32057/0.TD.2026.1541

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1. Introduction[1]

Hot temperatures are widely recognized as harmful to economic activity, but they are not the only extremes that matter. Extreme cold likewise poses first-order macroeconomic risks, for example disrupting agricultural production and depressing retail sales, with cascading effects on output and prices. The aggregate consequences of cold spells and related phenomena – of which the 2021 Texas ice storm is a prominent example – remain the subject of active debate. Yet, while a large literature documents the macroeconomic effects of heatwaves and rising average temperatures, the economic impact of extreme cold remains comparatively understudied.

This gap is increasingly problematic because climate change not only raises mean temperatures but also amplifies temperature volatility, increasing the likelihood of sharp swings and cold extremes even in a warming world. More generally, despite growing attention to long-run warming trends and rare climate disasters, evidence on the macroeconomic consequences of local, high-frequency temperature fluctuations remains scarce and inconclusive. In particular, most studies do not distinguish between extreme heat and extreme cold and provide mixed predictions regarding inflationary versus deflationary pressures, leaving unclear whether—and through which channels—heat and cold shocks propagate differently to the economy and may have distinct implications for monetary policy.

This paper quantifies the short-run macroeconomic effects of extreme hot and cold temperatures in the United States, emphasizing their unexpected component. Because temperature levels exhibit strong local trends and seasonality that agents anticipate and adapt to, economic effects should arise primarily from deviations from expected conditions. Using daily county-level data, I construct monthly nationwide heat and cold shocks

[1] I greatly thank James Cloyne, Simon Dietz, Òscar Jordà, Diego Känzig, Emi Nakamura, Brigitte Roth Tran, Jón Steinsson, Soroosh Soofi Siavash, Stephie Fried, Mauricio Ulate, Reed Walker, Piergiorgio Alessandri, Riccardo Degasperi, Valerio Ercolani, Fabrizio Ferriani, Andrea Gazzani, Valerio Nispi Landi, Fabrizio Venditti and seminar participants at UC Berkeley, San Francisco Fed, European Central Bank, Banca d'Italia, Banque de France, E-axes webinar series, 4th Behavioral Macro Workshop, the ESCB Research Cluster on Climate Change, WTSE 2022 and ChaMP Webinar Series for their helpful comments and suggestions. The views expressed in this paper are those of the author and do not necessarily reflect those of the Bank of Italy. All the remaining errors are mine.

in two steps. First, I measure county-level surprises as the excess number of extremely hot or cold days relative to what agents would expect in a given county and month, based on recent historical experience. Second, I aggregate these surprises using counties' economic weights. By construction, the resulting shocks purge seasonal, secular, and local temperature trends, isolating unexpected fluctuations in extreme temperatures at the monthly frequency. Overall, the shock construction rests on three key pillars—how unexpected shocks are defined, how expectations evolve, and how national-level aggregation is handled—which the paper tests by constructing alternative shocks under different assumptions.

I construct these shocks for 1975–2019 and estimate their effects using local projections. Three results stand out. First, heat and cold shocks have sharply asymmetric effects: only cold shocks affect economic activity in the short run. Second, cold shocks behave like demand disturbances, reducing industrial production, consumer prices, and short-term interest rates, with effects peaking about two years after the shock. Third, this asymmetry is not only aggregate: panel estimates using county GDP confirm that cold shocks have significant local effects, whereas heat shocks do not.

I then investigate the mechanisms behind this asymmetry. Winter cold shocks reduce both goods and services consumption, whereas summer heat shocks mainly reallocate spending from services to goods, leaving aggregate consumption largely unchanged. Cold shocks also disproportionately hit counties with higher per capita consumption, amplifying their aggregate impact. Moreover, cold—but not heat—shocks raise macroeconomic uncertainty. Using administrative data on federal disaster declarations, I show that cold shocks increase the frequency of winter disasters (e.g., snowstorms, ice storms, floods), plausibly heightening income risk. Consistent with this channel, private investment gradually contracts; moreover, firms increase discussion of climate adaptation and sustainability investment following cold shocks, based on textual analysis of earnings calls.

Contribution and literature review. My contribution to the literature is twofold. First, I provide new findings on the macroeconomic effects of high-frequency temperature fluctuations, which add to the existing evidence in the literature. By focusing on *frequent*, albeit surprising, weather events – very hot and cold daily temperatures in each month – I uncover relevant demand-side effects. This complements research in the climate economics field studying the effects of lower-frequency weather events (e.g., 1-in-50-years storms and 1-in-20-years heat waves as in Bilal and Rossi-Hansberg, 2023), the long-term effects of local temperatures (Leduc and Wilson, 2023), and the impact of higher levels of countries' and world's annual average temperatures (Nath et al., 2023 and Bilal and Känzig, 2024). These papers adopt a longer-run perspective and find temperatures having persisting supply-side effects over the years. Differently, investigating the long-run effects of climate change is out of the scope of this paper, showing instead that mostly disregarded cold shocks have important short-run economic consequences that align with the horizon of business cycle policies. The threat of severe cold spells for the US economy and, in particular, for the conduct of US monetary policy is not expected to disappear as climate change accelerates: at the opposite, scientists document that climate instability due to climate change makes cold air outbreaks more frequent in the Northern Hemisphere due to the polar jet stream moving southwards (Cohen et al., 2021). As adaptation to climate change usually translates into adaptation from heat, preparedness for cold spells can arguably be much lower, especially in usually hot places.

Second, this paper contributes to the empirical macro literature as the approach and the perspective adopted here link directly to the stream identifying temporary unexpected shocks at business cycle frequency (Ramey, 2016 and Nakamura and Steinsson, 2018 for a review). A similar perspective is adopted by other papers on the impact at the same frequency of a set of weather-related extreme events (Kim et al., 2021, among others). By proposing a way to measure the aggregate macroeconomic impact of local temperatures in isolation, this paper sheds light on their unique transmission mechanisms, which are different from that of other, more destructive weather events.

Other works exploring the impact of extreme weather have sometimes reached conflicting results, especially on inflation – extreme temperatures are found to be inflationary (Kim et al., 2021 and Makkonen et al., 2021) or deflationary (Faccia et al., 2021). Relative to the growing literature exploring macroeconomic effects of temperatures (e.g., Donadelli et al., 2017, Gallic and Vermandel, 2020, Billio et al., 2021, Lucidi et al., 2024, Ciccarelli et al., 2024, Colombo and Ferrara, 2024), I here propose a different approach to capture unexpected extreme 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 in Moscona and Sastry (2022), Leduc and Wilson (2023) and Bilal and Rossi-

Hansberg (2023)– and takes into account seasonal patterns as in Colacito et al. (2019) and Addoum et al. (2023). As my notion of temperature shocks is based on the evolution of the entire distribution of local temperatures, this paper also connects to those studying the economic implications of actual or expected temperature volatility.[2] Differently, my shock targets variations in the tails of the distribution, linking more closely to the *thickness* of the distribution. 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).

The findings on the prevailing demand-side effects of cold shocks are in line with others pointing to their detrimental effects on consumption – just temporary for Starr-McCluer (2000) and Bloesch and Gourio (2015), more persistent for Roth Tran (2023) – while evidence on their supply-side effects through labor are more mixed (negative in Boldin and Wright, 2015, not significant in Wilson, 2016). All in all, this paper suggests that an overall assessment of the economic effects of temperatures should also consider unexpected cold spells happening in local markets, emphasizing the importance of adaptation to both heat and cold over time (Fried, 2021).

The remainder of the paper is organized as follows. Section 2 describes the shock construction. Section 3 presents the data. Section 4 estimates the macroeconomic effects. Section 5 examines transmission mechanisms. Section 6 concludes.

2. Constructing the shock

The design of my heat and cold shocks is based on the following arguments. First, as science suggests, temperatures turning very hot or cold in a short time can be considered 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, while temperature highs and lows can have either positive or negative effects across industries, their *unexpected* coming may turn out to be bad for the economy. In this respect, the role of expectations is key. Third, and related, I argue that what matters is the *length* of an extreme temperature spell in a short period: while agents can be able to

[2] Kotz et al. (2021); Donadelli et al. (2021); Alessandri and Mumtaz (2021); Diebold and Rudebusch (2022); Bortolan et al. (2022).

find a workaround to isolated episodes, e.g., by rescheduling temperature-exposed working tasks, their consequences become unavoidable if extreme heat or cold are frequent or protracted enough, as there are limits to adaptation in the short run.[3][4]

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. A calendar month is ideal as it is short enough – daily temperatures within it are sufficiently homogeneous – but, at the same time, it can be a meaningful reference for agents forming their beliefs on the *distribution* of temperatures based on their memories and experience, in the form of a learning process.

2.1. US-wide cold and heat shocks

Country-level temperature shocks at time t can be thought of as the weighted average of local-level (e.g., county-level in the US) temperature expectation errors

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

where $\mathrm{f}(\mathrm{T}_t^i)$ is the value of a temperature statistics for county $i = 1, \ldots, k$ and month t; $E_{t-1}\mathrm{f}(\mathrm{T}_t^i)$ is the expectation about $\mathrm{f}(\mathrm{T}_t^i)$ made in the previous month; w_t^i are the weights to aggregate local errors to a country-level shock. Shocks as in Equation 1 can be constructed in two steps: first, by making monthly county-level surprises from daily temperatures; second, by aggregating them to monthly series of US-wide heat and cold shocks. For this purpose, I collect average temperatures in each county at a daily frequency. For each county, I group observations by month and compare the distribution of temperatures in each month to a reference set, which encompasses all daily temperatures recorded in the same months of the previous five years.[5] Then, I construct the expectations over

[3]Moreover, evidence also shows that the anticipatory behavior of households and firms regarding future temperatures – inducing protective actions – is limited at best (Morss et al., 2010; Graff Zivin and Neidell, 2014).

[4]A detailed description of the transmission channels of temperature shocks to the economy is reported in Appendix A.

[5]As five years is a sufficiently long period for agents to learn about the shape of the underlying temperature distribution (Moore et al., 2019), I construct the reference distribution based on that period length. 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

the number of very hot (or cold days) in the month, $E_{t-1}\mathrm{f}(\mathrm{T}_t^i)$, as the number of days in the reference distribution that lie beyond a specified threshold. As the distribution rolls over time, i.e. it is updated every year for each month of the year, the thresholds also change over time. The shock is computed as the difference between the actual and expected number of extremes: a larger number in the current month than in the recent past represents a positive surprise, while a lower number is a negative one. Economically, the reference distribution represents the information set of economic agents, who directly experienced temperatures in the same county: they are caught by surprise if the number of extreme days in current month, defined relative to the reference distribution, exceeds (or falls short of) what they expect according to their most recent experience. Relying on the most recent experience reflects the rapid declining remarkability of temperatures found in the literature (e.g., Moore et al., 2019, Choi et al., 2020, Pankratz and Schiller, 2021, among others). 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.

In formulas, let $T^i_{d,t,y}$ being average daily temperatures in county i, day d, month t and year y, for $i = 1, \ldots, z$ counties; $n^i_{t,y}$ is the number of days in county i, month t, and year y. Denote with $F^i_{t,y} = \{T^i_{d,t,y-j},\ \mathrm{d} = 1, \ldots, n^i_{t,y-j},\quad \mathrm{j} = 1, \ldots, 5\}$ the empirical cumulative distribution function of the reference temperature set for the month t and year y, based on the same month in the last 5 years. The 10th and 90th percentiles are

$$\mathrm{p90}^i_{t,y} = {F^i_{t,y}}^{-1}(0.9) \tag{2}$$

$$\mathrm{p10}^i_{t,y} = {F^i_{t,y}}^{-1}(0.1) \tag{3}$$

Thresholds are defined, for heat (cold) shocks, as the maximum (minimum) between the 90th (10th) percentile of the reference distribution and a fixed threshold, which reflects the lowest (highest) temperature value that can harm business because of excessive heat (cold), according to Addoum et al. (2023), i.e.

$$\mathrm{ut}^i_t = \max\ (\mathrm{p90}^i_{t,y}, 70\mathrm{F}) \qquad\qquad i\ \in\ k \tag{4}$$

Choi et al. (2020), see Section Appendix E.

$$\text{lt}_t^i = \min\ (\text{p10}_{t,y}^i, 50\text{F}) \qquad\qquad i\ \in\ k \tag{5}$$

where 70F and 50F are average daily temperatures expressed in degrees Fahrenheit. This way of defining thresholds allows to flexibly set extremes relative to each county and month but, at the same time, it imposes a floor (for heat) or a cap (for cold) to only count tail values that can be thought of as *true* extremes in each month.[6] County-level surprises are computed as the number of beyond-threshold days in the current month *in excess* of those in the reference distribution. County-level cold surprises (Csurprise) and heat surprises (Hsurprise) with respect to temperatures in the past five years (the limit of temperature memory found in Moore et al., 2019) can be expressed as

$$\text{Csurprise}_{t,y}^i = \underbrace{\sum_{d=1}^{n_{t,y}} \text{I}\left(T_{d,t,y}^i < \text{lt}_t^i\right)}_{\text{f}(\text{T}_t^i)} - \underbrace{\frac{1}{5}\sum_{k=1}^{5}\sum_{d=1}^{n_{t,y-k}} \text{I}\left(T_{d,t,y-k}^i < \text{lt}_t^i\right)}_{E_{t-1}\text{f}(\text{T}_t^i)} \qquad i\ \in\ k \tag{6}$$

$$\text{Hsurprise}_{t,y}^i = \underbrace{\sum_{d=1}^{n_{t,y}} \text{I}\left(T_{d,t,y}^i > \text{ut}_t^i\right)}_{\text{f}(\text{T}_t^i)} - \underbrace{\frac{1}{5}\sum_{k=1}^{5}\sum_{d=1}^{n_{t,y-k}} \text{I}\left(T_{d,t,y-k}^i > \text{ut}_t^i\right)}_{E_{t-1}\text{f}(\text{T}_t^i)} \qquad i\ \in\ k \tag{7}$$

where $I(x)$ is an indicator function that values 1 if x is true, 0 otherwise. To compute US-wide shocks, I make a weighted average of county-level surprises in the k counties:

$$\text{Cshock}_{t,y} = \sum_{i=1}^{k}\left(\underbrace{\frac{pop_{y-1}^i}{pop_{y-1}}}_{\text{w}_t^i} \times \text{Csurprise}_{t,y}^i\right) \tag{8}$$

$$\text{Hshock}_{t,y} = \sum_{i=1}^{k}\left(\underbrace{\frac{pop_{y-1}^i}{pop_{y-1}}}_{\text{w}_t^i} \times \text{Hsurprise}_{t,y}^i\right) \tag{9}$$

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

[6]This procedure is halfway between two commonly used ways to define thresholds: the variable-threshold approach and the fixed-threshold approach. Its benefits, particularly against the fixed-threshold approach, are described in Section 4.4.

3. Data

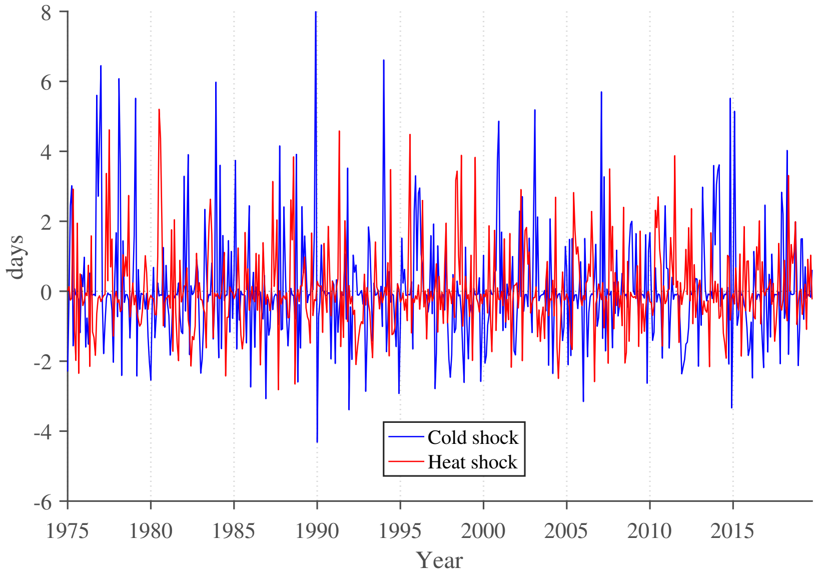
3.1. Temperature data

To construct the shocks, I rely on two data sources. Daily county-level temperatures, i.e. the mean value of temperatures recorded daily (during the 24 hours) and averaged at the county level, are computed from the gridded air temperature database for the continental US of the Northeast Regional Climate Center. 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 from the Census Bureau, from 1969 to 2018. In the baseline formulation of the shock, I consider county-level population, also used in Colacito et al. (2019) for the same purpose and construct weights as the county share over nationwide values. The rationale for this choice is that the higher the population, the higher the exposure to extreme temperatures, so the higher the potential impact on the economy. As a robustness, I also consider other weighting schemes such as the number of employed people, personal income, or county GDP proxying counties' weight in the US economy. 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.

3.2. The shock series

The time series of the US-wide shocks are displayed in Figure 1. The heat (cold) shock is expressed as the number of surprising hot (cold) days per month. From an economic point of view, they feature the three characteristics, explained in Ramey (2016), which make them suitable for macroeconomic applications: they are exogenous to current and lagged outcome variables, they can be considered as uncorrelated with other exogenous economic shocks and they represent unanticipated movements in an exogenous variable.

Figure 1: **US-wide heat and cold shocks**



Looking at the plotted series, two things catch the eye. First, there are no trend nor volatility clusters – big and small shocks are spread out throughout the sample; peaks have been reached in the 80s and 90s, suggesting that some of the largest adjustments in the shape of the temperature distribution, inducing greater surprises, have occurred in the early part of the sample. Second, cold and heat shocks are only mildly correlated with each other (-7%), reflecting highly heterogeneous temperatures in different parts of the country. This entails that in the same month, there can be cold shocks in some counties and heat shocks in others, whose loads on the macro shock series depend on the weights of the hit counties.

4. The impact of temperature shocks on the US economy

4.1. Impulse-response analysis

I estimate the response of US domestic variables to the previously constructed shocks using local projections in a time series framework (Jorda, 2005). As a preliminary analysis, I sum heat and cold US shocks within each month to estimate the overall effects of temperature extremes on the economy; then, for the rest of the analysis, I estimate the impact of heat and cold shocks separately to highlight their potentially heterogeneous transmission. Impulse response functions (IRFs) for extreme temperature shocks are obtained from the following linear regression

$$y_{t+s} = \alpha_s + \beta_s \text{ Tshock}_t + \psi_s(L)\mathbf{X}_{t-1} + u_{t+s} \qquad s = 0, \ldots, H \tag{10}$$

where y is the target variable, $\text{Tshock}_t = \text{Cshock}_t + \text{Hshock}_t$, Cshock and Hshock are US-wide cold shocks and heat shocks, and $\mathbf{X}_t$ is a vector of controls.[7] Separate IRFs for heat and cold shocks are instead obtained from the following regression

$$y_{t+s} = \alpha_s + \beta_s \text{ Cshock}_t + \delta_s \text{ Hshock}_t + \psi_s(L)\mathbf{X}_{t-1} + u_{t+s} \qquad s = 0, \ldots, H \tag{11}$$

For both Equation 10 and 11, estimates are made separately for each time horizon s and for each dependent variable y, and IRFs are defined by the sequence $\{\beta_s\}_{s=0}^{H}$ and $\{\delta_s\}_{s=0}^{H}$. Inference is performed with Newey-West standard errors.

4.2. Target variables

In the baseline estimates, the effects of temperature shocks are tested on three macro variables: industrial production, the CPI index, and the 3-month interest rate, where the first two variables are expressed in natural logarithm. On the right-hand side of Equation 11, I include a tight set of controls: linear and quadratic time trends, seasonal dummies, and 12 lags of all the aforementioned variables in each estimate (including those of the dependent variables).[8] A summary of all data used in this paper is reported in Appendix B. Impulse responses are estimated on a 40-month horizon, and displayed with 68% and 90% confidence bands. The estimation sample goes from January 1975 to December 2019.

4.3. Results

Impulse response functions from a one-standard deviation extreme temperature shocks, and a one-standard deviation cold and heat shocks, are displayed in Figure 2 and 3. As it is visible from Figure 2, an extreme temperature shock has an overall negative effect on industrial production and interest rates while a more muted impact on consumer

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

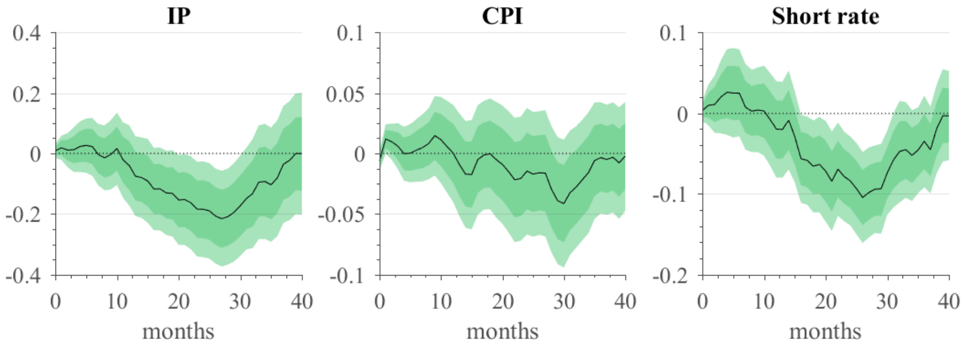
[8]Including also 12 lags of the two shocks as controls, or including 24 instead of 12 lags of the dependent variable do not change the results.

prices. Figure 3 sheds light on this result by uncovering a substantial heterogeneity in the effects of heat and cold shocks: indeed, following a positive cold surprise, industrial production declines gradually, reaching a trough 20–30 months after the shock. CPI and short-term interest rates display similar dynamics. The joint decline in output and prices indicates that cold shocks propagate primarily as aggregate demand shocks, with demand-side effects dominating supply-side channels and eliciting an expansionary monetary policy response. On the contrary, heat shocks do not have significant economic effects: if anything, industrial production and consumer prices slightly increase in the short run, driving the short rate up. In terms of size, the economic effects of cold shocks can be easily quantified by rescaling the shock to a one-day shock (one standard deviation is 1.6 days).[9] A positive, one-day cold shock in a single month reduces industrial production by 0.27% after 28 months, the consumer price index by 0.12% and the short rate by 13 basis points.

The evidence of a negative and significant effect of cold shocks on economic activity, consumer prices, and interest rates, in conjunction with no effect of heat shocks, is new in the literature. Such a finding is not an artifact of the aggregation of local shocks to the national level, as the different output effects of the two shocks clearly show up also at the granular level. In Section 5, I restrict the sample to the post-1990 period (due to data availability) and test the effect of county-level shocks on county-level GDP in a yearly panel: results are confirmed even in such a different setting. Appendix E presents additional robustness checks based on: (1) defining temperature surprises using more or less extreme percentiles of the temperature distribution; (2) alternative aggregation weights for county-level surprises, using employment, personal income, or GDP instead of population; and (3) a longer learning period (10 years rather than 5). The results remain consistent with the baseline findings.

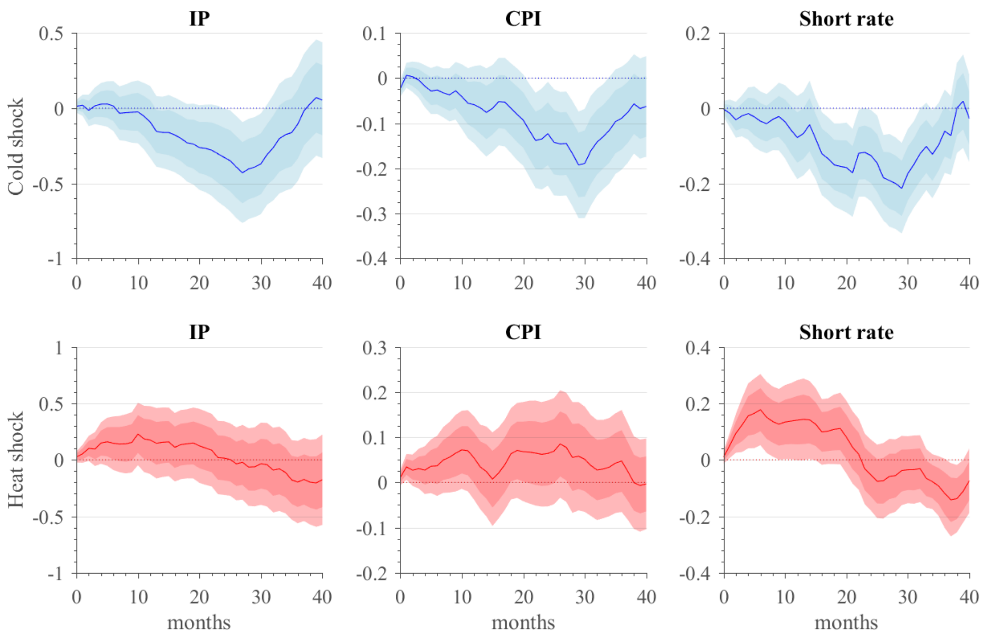
[9] Figure 3 reports impulse responses to a one-standard-deviation shock, where the standard deviation is 1.6 days for cold shocks and 1.2 for heat shocks.

Figure 2: **Extreme temperatures shocks**



Notes: Impulse response functions to a one-standard-deviation extreme temperature shock. 68% and 90% confidence bands.

Figure 3: **Baseline estimates: Cold vs Heat shocks**



Notes: Impulse response functions to a one-standard-deviation cold shock (blue IRF) and heat shocks (red IRF). Shock standard deviation is 1.6 days (cold shock) and 1.2 (heat shock). 68% and 90% confidence bands.

4.4. Comparison with the literature

My results differ from most findings in the literature on weather shocks. In that strand, papers disagree on whether and how high-frequency temperature shocks affect the economy, propagating as demand shocks in some papers or as supply shocks in others. Appendix D shows that these differences largely stem from how temperature shocks are constructed. In particular, results are highly sensitive to (i) how temperature extremes are defined, (ii) whether temperature expectations are allowed to evolve over time, and (iii) whether shocks are built from local surprises or from pre-aggregated temperatures. Using fixed health-based temperature thresholds, time-invariant expectations (temperature anomalies), or country-level aggregated temperatures fails to net out local trends and seasonality, biases the incidence of heat relative to cold shocks, and obscures the aggregate effects of cold extremes. This comparison clarifies why cold shocks play a central macroeconomic role in this paper but are largely absent from the existing literature.

5. Inspecting the mechanism

The baseline results in Section 4 show that cold shocks are detrimental to economic activity and deflationary, while heat shocks do not have significant effects in the short run. To gain insights into the economic propagation of heat and cold shocks, I conduct a deeper investigation along several dimensions, examining in particular their potentially heterogeneous effects across seasons and sectors, as well as their repercussions on macroeconomic uncertainty and the likelihood of natural disasters.

5.1. Effects by season and expenditure components

Each calendar season can be impacted by heat and cold shocks differently, for example because human activities that are vulnerable to heat and cold can be more concentrated in some periods of the year than in others. To study how the baseline effects vary across seasons, I estimate the following variant of Equation 11:

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

where $s = 0, 1, 2, \ldots, H$. D_t^j with $j = \{1, \ldots, 4\}$ are four dummies that equal 1 if month

t belongs to season j of the year, 0 otherwise.[10] γ_s^j and δ_s^j represent impulse response functions to cold and heat shocks in winter, spring, summer and fall.

Figure Appendix C.1 displays impulse responses for heat and cold shocks by season. The negative effects of cold shocks mainly depend on their impact in winter, and, to a lesser extent, fall. In these two seasons, consumer prices decrease together with industrial production following the shock. Differently, the effects of heat shocks on output are mostly insignificant in all seasons, with slightly positive short-run effects in summer driving aggregate results in the baseline estimate.

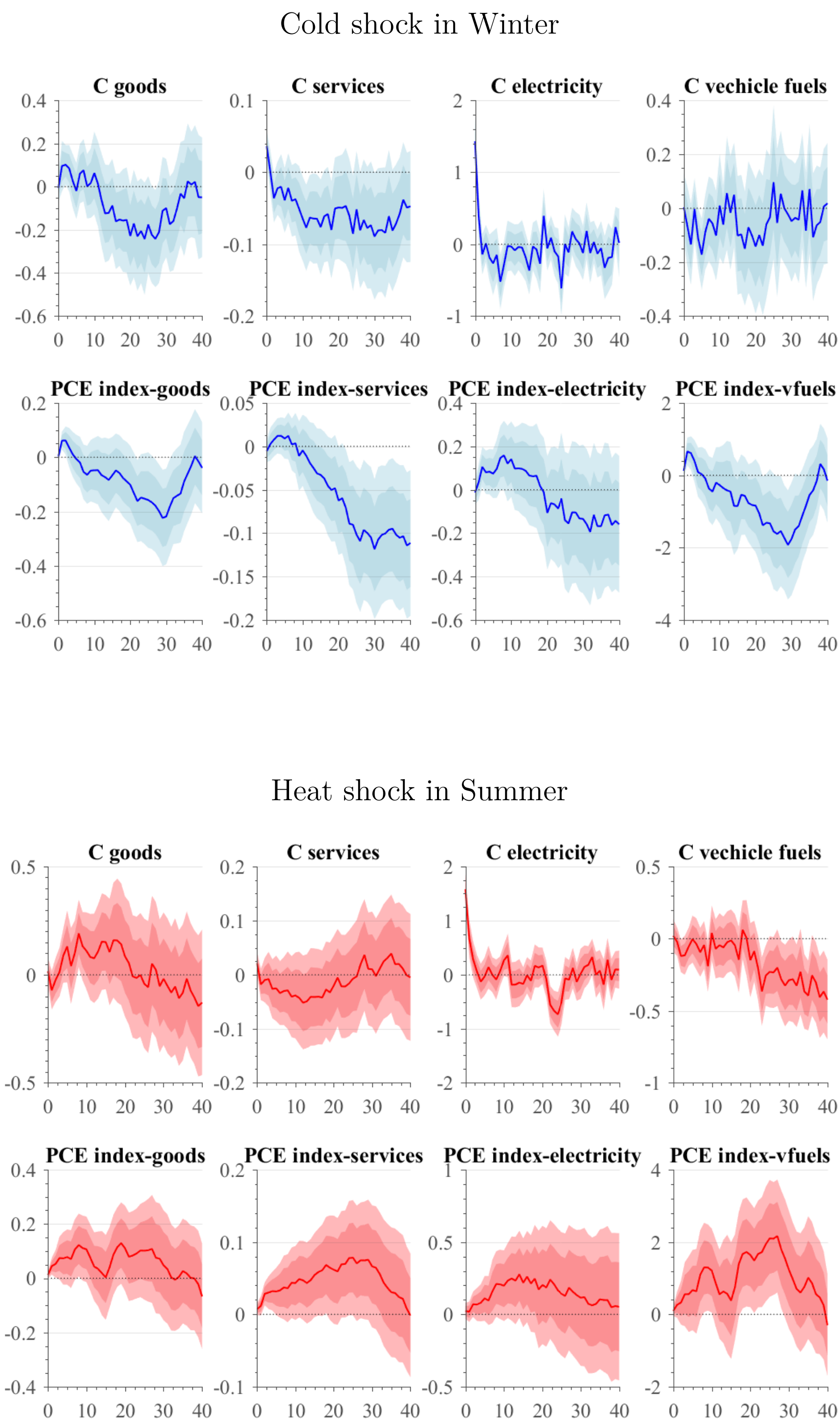
Are different components of aggregate demand equally affected? I exploit the monthly breakdown of Personal Consumption Expenditures data to investigate the responses of some specific items in the consumption basket, looking at both consumption quantities and consumer prices. I estimate impulse responses on goods vs services consumption – where the latter may not always be purchased from remote, so they are possibly more exposed to temperatures – and on two goods whose consumption strongly depends on the weather: electricity and vehicle fuels. I here only consider cold shocks in winter and heat shocks in summer, the seasons in which the economic effects are largest.

Figure 4 reports the impulse responses of the four aforementioned items to cold and heat shocks. Cold shocks in winter have three main effects. They depress both goods and services consumption (with the latter effect being more persistent), reduce consumption of vehicle fuels, and raise electricity consumption. Consistently, consumer prices (measured by the deflator of personal consumption expenditures) decrease – with services prices contracting more persistently – while electricity prices increase on impact, in line with higher demand. Heat shocks in summer also increase electricity consumption (consistent with higher demand for air conditioning) and decreases that of vehicle fuels.[11] However, the overall effects on personal consumption expenditures appear different in the case of cold and heat shocks: while cold shocks reduce consumption of both goods and services, heat shocks induce just a recomposition from services to goods, leaving aggregate consumption barely affected.

[10] Months are imputed to calendar seasons as follows: winter (December to February), spring (March to May), summer (June to August), fall (September to November).

[11] On the price side, the effect on the prices of goods, electricity, and vehicle fuels in summer contributes to the upside.

Figure 4: **By season and expenditure components**



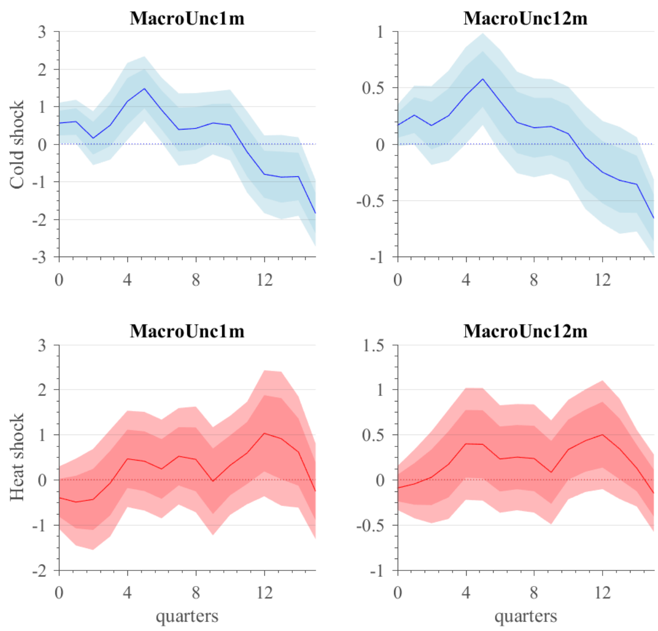
Notes: 68% and 90% confidence bands.

5.2. Uncertainty and natural disasters

To dig more into the asymmetric effect of heat and cold shocks, I explore the possibility of other demand-side channels being at work, on top of the expenditure channel analyzed above. In particular, as described in Section Appendix A, one important aspect to be investigated is whether unexpected temperature shocks affect macroeconomic uncertainty. A priori, the sign of the effect is ambiguous, as extreme climate events may either reduce uncertainty if they act as a wake-up-call information device or increase it if agents revise their expectation on temperature volatility upwards (Donadelli et al., 2021; Alessandri and Mumtaz, 2021), as empirically shown in Baker et al. (2020). I here test the effects of cold shocks in winter and of heat shocks in summer on macroeconomic uncertainty at 1-, 3- and 12-month horizons using the indicators constructed in Jurado et al. (2015), which have the advantages of covering different horizons and of being available since the beginning of our sample.

Figure 5 shows the response of macroeconomic uncertainty to heat and cold shock at 1-month and 12-month horizons. Following a heat shock, uncertainty doesn't change significantly, while it rises immediately in case of cold shocks.

Figure 5: **Macroeconomic Uncertainty**

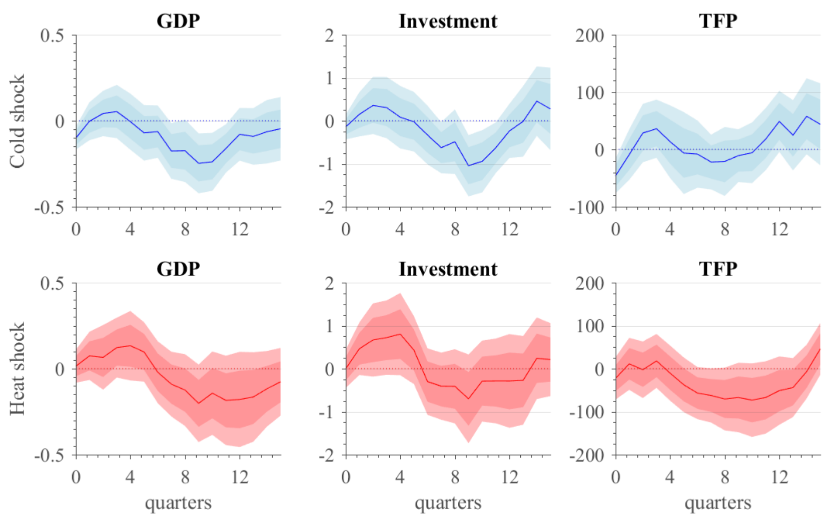


Notes: 68% and 90% confidence bands.

As macroeconomic uncertainty is known to weigh negatively on economic growth

(Baker et al., 2023), it can potentially reduce investment making the macroeconomic effects of cold shocks persistent as the baseline impulse responses indicate. To investigate this further, we re-run our local projections on quarterly national accounts variables (GDP and investment) and on the utilization-adjusted total factor productivity constructed by Fernald (2012). The results, reported in Figure 6, show that following cold shocks, GDP declines on impact and falls further as investment gradually contracts. This pattern confirms the presence of multiple transmission channels, generating both immediate and lagged negative effects on the economy.

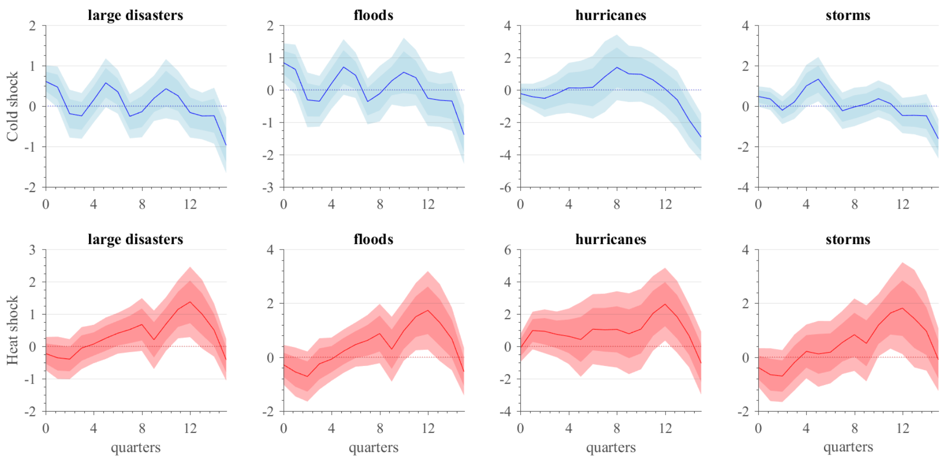
Figure 6: **GDP, investments and TFP**



Notes: 68% and 90% confidence bands.

Why do cold shocks (and not heat shocks) induce higher macroeconomic uncertainty? One reason might be related to the different associations of those shocks with other damaging natural events – natural disasters. Disasters can destroy wealth and workplaces, reduce disposable income and the value of collateral for loans; moreover, if larger temperature swings can also make them more *frequent* over time, a greater disaster risk might be a driver of macroeconomic uncertainty. To test the link between cold and heat shock with natural disasters, I use the real-time administrative Disaster Declarations Summary dataset of the Federal Emergency Management Agency (FEMA), which has already been employed in other analyses in the literature (e.g., Tran and Wilson, 2020). The dataset contains all disasters for which state governments have requested assistance by FEMA (i.e. federal aid). Among them, I focused only on the disaster types that can be more closely related to climate change: coastal storm, drought, fire, flood, freezing, hurricane, mud/landslide, severe ice storm, severe storm, snowstorm, straight-line winds, tornado, tropical storm, tsunami, typhoon, winter storm.[12] I group those disasters by month and, in line with the previous analysis, test the effect of cold shocks in winter and heat shocks in summer on the number of disasters that occurred in the same month and up to 40 months after the shock. Figure 7 shows the impulse response of the cumulative effect on the number of all declared disasters, and on the number of large disasters only – those that received a *Major Disaster* Presidential declaration – of heat and cold shocks. Results show that the association of temperature shocks with natural disasters is not symmetric. While cold shocks in winter are associated with a higher number of disasters (by about 10% on impact following one-standard deviation cold shock), heat shocks in summer do not significantly affect them. In particular, positive winter cold shocks correlate with a higher incidence of storms and floods, which jointly account for more than 50 percent of all FEMA disasters in our sample. All in all, the association of cold shocks with a higher frequency of damaging natural disasters can be a key factor contributing to the increase in macroeconomic uncertainty perceived by consumers and investors.

Figure 7: **Number of FEMA-declared natural disasters**



Notes: Cumulated effect on the number of disasters, where disasters are those that are present in the Federal Emergency Management Agency (FEMA) dataset. Large disasters received a *Major Disaster* Presidential declaration according to the FEMA data. 68% and 90% confidence bands.

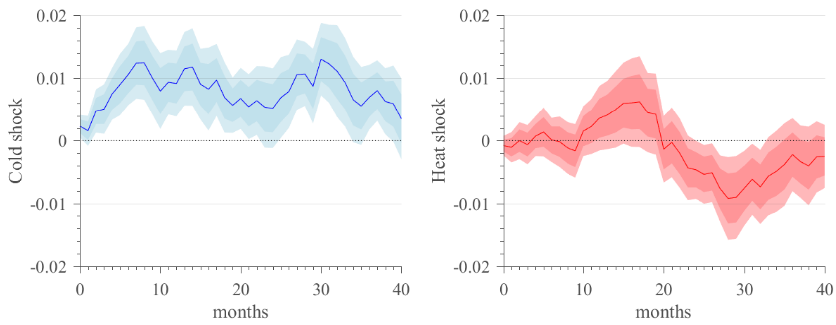
[12] I also included few cases labeled as Dam/Levee break that can be related to floods.

How do firms assess the risks coming from heat and cold shocks? As timely indicators of firms' perception of climate risks or adaptation expenditures are not available, I construct an aggregate measure of agents' willingness to adapt by reading into the earnings calls of US-listed firms. More precisely, I use NL analytics, a platform to interact with text-based corporate disclosures, to count the number of times each US-listed firm mentions weather-related adaptation expenditures and sustainability investment during the calls. I then construct an index for the entire US market and investigate whether its fluctuations over time are affected by heat and cold shocks, i.e. whether those shocks induce firms to talk more (or less) about what they should do to hedge from weather-related risks.[13] Earnings calls are only available through NL Analytics since January 2002, so the impulse-response analysis is carried out in this shorter sample. As Figure 8 shows, cold shocks induce firms to talk more about their potential strategy and actions to be more climate resilient or to make their business more sustainable. On the contrary, no substantial increase in such wording is found in the case of heat shocks, where the impulse response hovers over time around zero.

Overall, the results are consistent with the view that heat shocks do not introduce additional uncertainty beyond the already expected trajectory of global warming; consistently, they do not induce additional stimulus for firms to adapt on top of the trend adaptation process already underway. Conversely, cold shocks increase the likelihood of natural disasters and overall macroeconomic uncertainty, causing firms to increase discussion about adaptation. Spending to hedge against cold might divert money away from firms' core businesses, so contributing to the negative demand effect observed in the baseline estimate.

[13]For each earning call, I compute the ratio of the number of climate expense-related words over the total number of words in the call, and then average across all earnings calls in the sample at the monthly frequency. The 12-month moving average of such series is then used as response variables. The set of words is the following: *climate resilience, environmental initiatives, climate action, sustainability framework, sustainability programs, water conservation, sustainability initiatives, environmental strategy, sustainability efforts, ESG activities, emissions reductions, ESG efforts, environmental goals, environmental responsibility, ESG strategy, ESG initiatives, ESG commitments.*

Figure 8: **Firms' willingness to adapt**



Notes: 68% and 90% confidence bands.

5.3. *Geographic dimension*

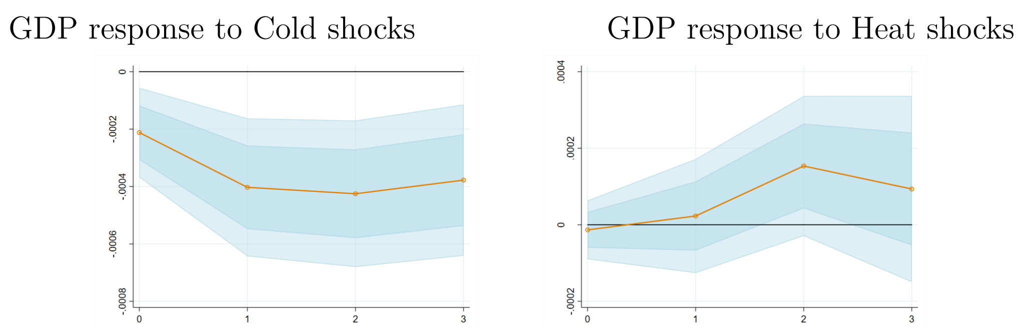
The other interesting angle to be analyzed is the geographic dimension. Indeed, the aggregate macro effects of cold shocks might hide a potentially heterogeneous sensitivity to the shock in different areas of the country, or a different incidence of the shock itself across counties, which can give some insights into the mechanisms behind the obtained results. I here explore the *local effects* of heat and cold shocks, i.e. at the *county* level. For this purpose, I collect county-level GDP data, available at yearly frequency from 2001 onwards, and test the impact of heat and cold surprises (summed within the year) on local GDP using panel local projections. In formula

$$y^{i,z}_{y+s} = \alpha_s + \beta_s \text{ Csurprise}^{i,z}_y + \delta_s \text{ Hsurprise}^{i,z}_s + \psi_s(L)\mathbf{X}_{y-1} + \phi^{i,z} + \gamma zy + \epsilon^{i,z}_{y+s} \qquad s = 0, \dots, H \tag{13}$$

where z indicates the state county i belongs to; $y^{i,z}_{y+s}$ is county-level GDP for county i in state z, in year $y+s$. Controls are two lags of Csurprise and Hsurprises, and two lags of the dependent variable; $\phi^{i,z}$ are county fixed effects; γ is the coefficient of a state×year dummy. Figure 9 reports the impulse response of county-level GDP. Even in such a different framework, which only covers a subperiod of the previous analysis, the effects of heat and cold shocks are qualitatively similar to the baseline, with cold shocks reducing local GDP (with a trough around 2 years after the shock) while heat shocks having no significant effects.

But how are shocks spatially distributed? Figure 10 displays three maps of the US, where the first two report the geographic distribution of the historical severity of cold and heat shocks across countries, and the third one the distribution of real per capita consumption across US states.[14] A stark split shows up, where cold shocks have been strongest in the northern part of the country (plus California and parts of the East Coast) while heat shocks are mostly in the Sun Belt. Moreover, a visual comparison with the map in panel (c) suggests that historically, severe cold shocks hit higher per capita consumption states than heat shocks. This adds another element to document the larger economic impact of cold than heat shocks, passing through a negative demand-side propagation of weather shocks to the economy.

Figure 9: **County-level panel**



Notes: Panel local projections, 2001-2019. Estimates are weighted by share of real GDP. 68% and 90% confidence bands.

6. Conclusions

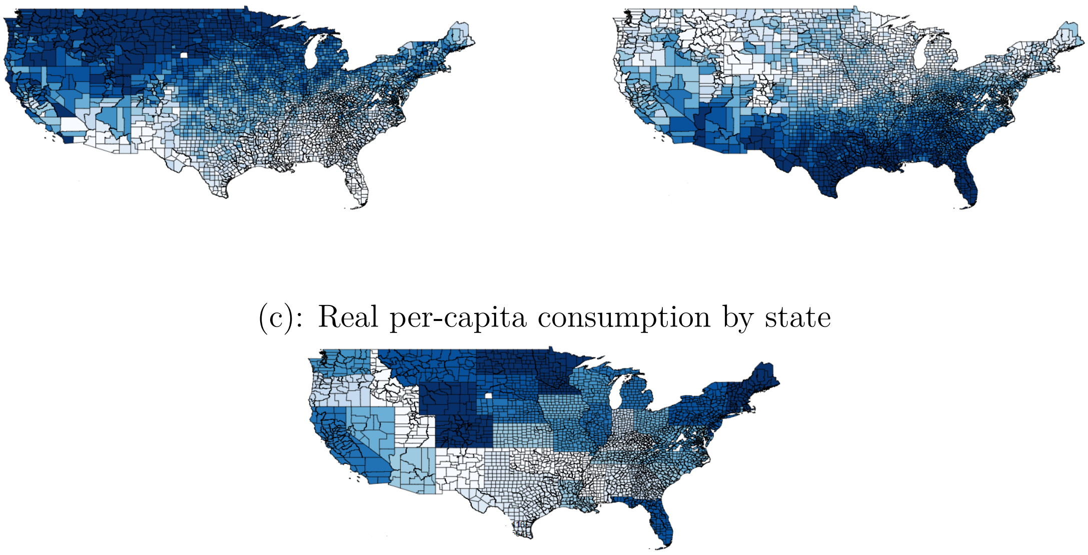
Understanding the short-run macroeconomic effects of weather fluctuations is of utmost importance for the conduct of business cycle policies in a climate change era. Leveraging on the insights of the empirical macroeconomic literature, I identify the unexpected

[14]The index of heat and cold severity is constructed, for each shock, as the average size of the shocks over time considering only months in which shocks have been positive (i.e., economically harmful). A similar picture shows up for both heat and cold shocks by displaying the standard deviation of shocks over time by county. For state-level consumption, the ranking is based on the 2019 levels but remains fairly stable over time.

Figure 10: **Geography of weather shocks and private consumption**

(a) Severity of cold shocks

(b) Severity of heat shocks



(c): Real per-capita consumption by state

Notes: Panel (a) and (b) report an index of the severity of cold and heat shocks, measured as the average size of cold (or heat) shocks in all months when they have been positive. Panel (c) displays real per capita consumption by state as of 2019 – state ranking did not change substantially with respect to 2008, first year of state-level data available.

component in the occurrence of very hot or cold days, obtained from high-frequency, granular data for the USA. Estimates made with local projections show that temperature shocks in the United States significantly affected the economy in the most recent phase of the global warming era, but this has occurred because of cold and not heat shocks. One interpretation is that cold shocks, which bring uncertainty over the future consequences of climate change, occur in high-consumption areas and are difficult to manage as preparedness for extreme cold is lower than adaptation to heat. Indeed, my result shows up in the context of longer-run global warming trends, which are damaging to the economy and to which households and firms gradually adapt. What happened in other countries? How large is the heterogeneity of temperature shocks within them? Identifying the key local markets worldwide where temperature shocks have the largest economic impact (and pose higher risks going forward) can help target adaptation investment and understand the spillover effects of local temperatures (and of climate change more generally).

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Appendix A. 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 or worsen 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).[15]

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, 2023).

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, also working through the demand side, is related to the uncertainty over future climatic developments. On one side, 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 empirically in Choi et al. (2020) for extreme temperatures and in Ferriani et al. (2023) for climate-related disasters, and modeled in Hong et al. (2023). On the other side, *unexpected* weather fluctuations can increase macroeconomic uncertainty because agents' adjust their beliefs about the volatility of future temperatures (Donadelli et al., 2021; Alessandri and

[15]Studies document a U-shaped relationship between temperatures and mortality in the United States (Deschenes, 2014 and Barreca et al., 2016).

Mumtaz, 2021) or because uncertainty on the future economic policies to be implemented increases (Zhang et al., 2024). In both cases, uncertainty acts as an additional driver weighting negatively on aggregate demand. As for financial investors, temperatures can induce an adapting behavior by households and firms, who may want to hedge against the future consequences of climate change: for example, forward-looking entrepreneurs might undertake targeted expenditures to make their business more resilient to temperatures, which can be detrimental for short-run performance if this crowds out other productive investments.[16]

[16] In the longer run, the overall effects of temperatures might be heterogeneous across firms depending on whether adaptation measures spur innovation and technological progress, as explored in Cascarano et al. (2025).

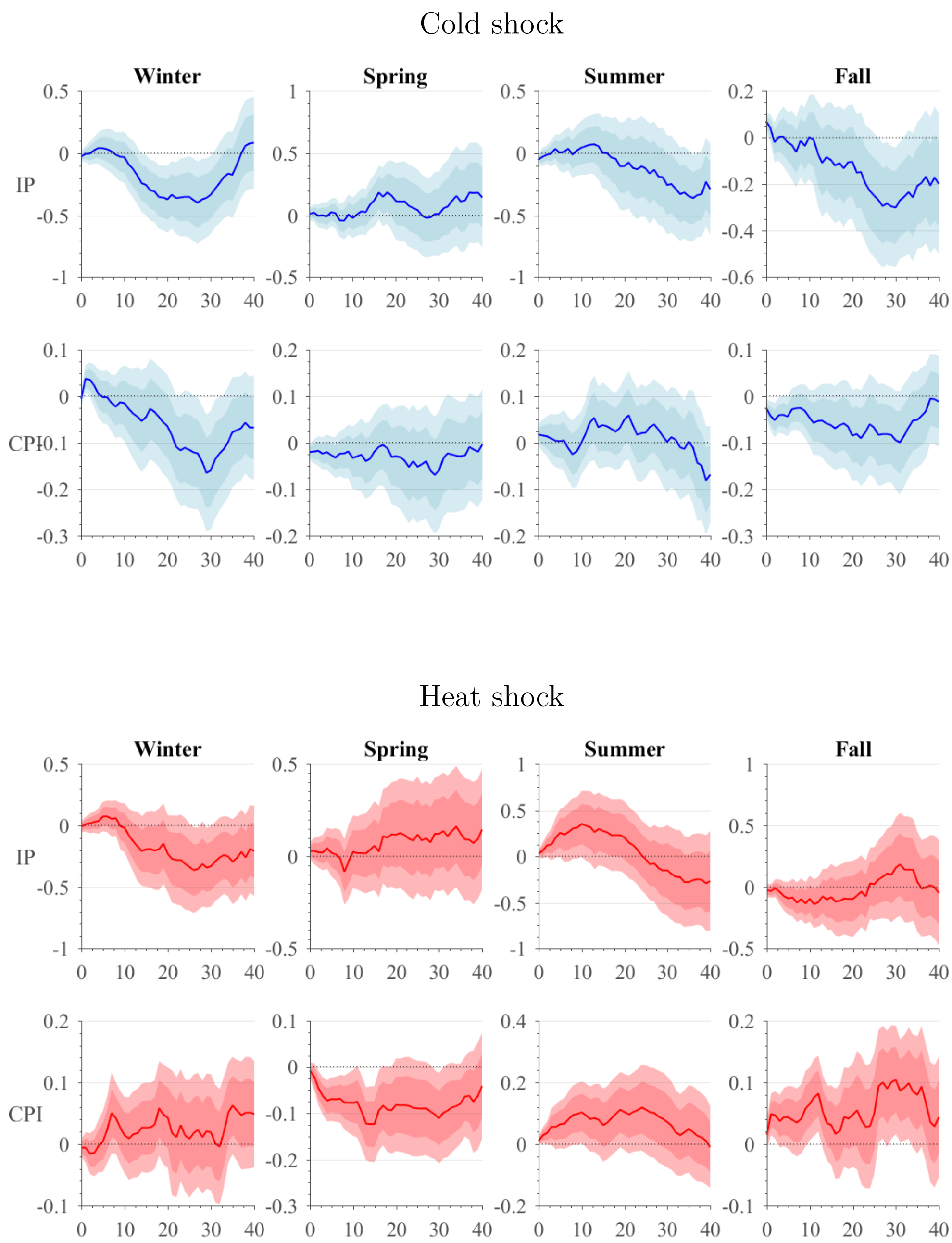
Appendix B. Data sources

Table Appendix B.1: Data summary

Variable	Source	Frequency	Sample
Temperature shock			
gridded average daily temperatures	Northeast Regional Climate Center	daily	01-01-1970 - 31-12-2019
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
Real GDP (by county) (CAGDP9)	Bureau of Economic Analysis	yearly	2001
Response variables			
Industrial production (INDPRO)	Fred	monthly	1975m1-2019m12
3-month rate (TB3MS)	Fred	monthly	1975q1-2019q4
CPI (CPIAUSCL)	Fred	monthly	1975m1-2019m12
Real PCE: Goods (DGDSRA)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Real PCE: Services (DSERRA)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Real PCE: Electricity (DELCRA)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Real PCE: Vehicle fuel (DMFLRA)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Price index of PCE: Goods (DGDSRG)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Price index of PCE: Services (DSERRG)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Price index of PCE: Electricity (DELCRG)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Price index of PCE: Vehicle fuel (DMFLRG)	Bureau of Economic Analysis	monthly	1975m1-2019m12
Indexes of macroeconomic uncertainty	Jurado et al. (2015)	monthly	1975m1-2019m12
N. of natural disasters	FEMA	daily	1975-2019
Mentions of adaptation expenditures	NL Analytics (earnings calls)	daily	2002-2019
Real PCE by state	Bureau of Economic Analysis	yearly	2019

Appendix C. Impulse responses by season

Figure Appendix C.1: **By season**



Notes: 68% and 90% confidence bands.

Appendix D. Details on the shock construction and comparison with alternative assumptions

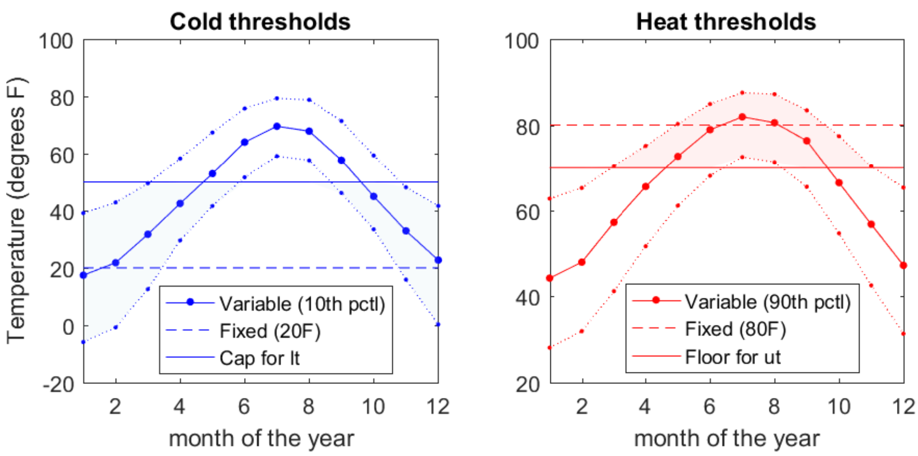
Appendix D.1. Temperature extremes

In the climate literature, temperature extremes have been defined in two alternative ways: by means of *fixed thresholds*, that are not relative to the temperature distribution under study, or by means of *variable thresholds*, which can vary over time or by geographic area depending on realized temperatures. Figure Appendix D.2 displays fixed and variable thresholds by months using US data, where the former are set on the values (20F for cold and 80F for heat) beyond which temperatures are known to be bad for human health, as it is done in many papers, and the latter as the median of the 10th and 90th monthly percentiles across all counties and years. Health-related fixed thresholds are very restrictive: according to them, extremely cold days appear only in winter and extremely hot days mostly in summer.

When it comes to estimating the macro effects of temperature extremes, selecting them this way ignores days in other seasons or in specific geographic areas in which temperatures might not be as severe but still economically harmful: as shown in Addoum et al. (2023), for example, in the software industry earnings decrease when temperatures in summer fall below 7°C (44F), and the sector of personal products makes losses in winter when they go above 22°C (71F). As fixed thresholds cannot capture the strong seasonal variability of temperatures, their upward trend and geographic heterogeneity, they should not be used to compute aggregate economic effects properly. On the other hand, computing thresholds based on the temperatures that occurred in the same month and county in the past accommodates all dimensions of temperature variability mentioned above. In particular, the way described in Section 2 to improve the variable threshold approach works nicely to exploit the advantage of re-computing thresholds over time (which takes into account temperature dynamics) and, at the same time, avoids unrealistically high (low) values for cold (heat) thresholds in milder seasons.[17]

[17] Results using uncensored variable thresholds, available upon request, delivers similar results.

Figure Appendix D.2: **Fixed vs variable thresholds**



Notes: In the two subplots, the solid lines with round markers are the medians of the thresholds by month of the year, while dotted lines are their 5th and 9th percentiles; the dashed lines are fixed thresholds (20F for cold shocks and 80F for heat shocks); solid lines with no markers are caps (floors) for cold (heat) shocks used in Equation 4 and 5. Shaded areas (and their cap or floor) represent threshold values set according to Equation 4 and 5.

Appendix D.2. Temperature expectations

As pointed out in Section 2, it is well documented in the literature that agents learn about temperatures over time and update their temperature beliefs accordingly. This feature is embedded in the shock constructed in this paper by making the thresholds for county-level surprises vary over time based on the rolling, past temperature data. However, most empirical contributions define unexpected shocks based on the concept of temperature *anomalies*, i.e. deviations of actual temperatures from long-run, pre-sample averages (the so-called climate normals). In economic terms, this implies setting expectations of the temperature distribution as fixed over time and anchored to pre-sample data.

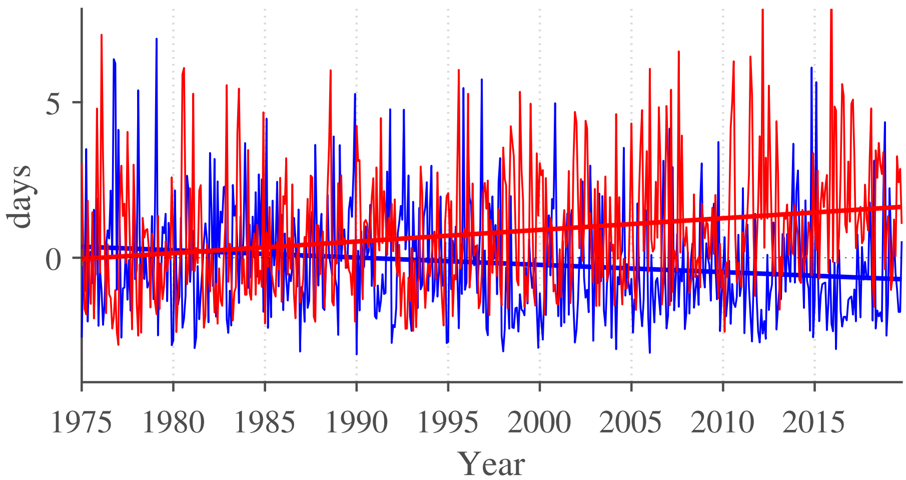
To show how this formulation can impact shock identification (and so the estimated effects), I make a toy example in which I reconstruct county-level surprises using thresholds computed as in Section 2, but kept fixed to the levels obtained using the 1970-1974 (pre-sample) period. In formula, Equation 4 and 5 are substituted with the following time-invariant versions

$$\text{ut}_t^i = \max\ (\text{p}90_{t,1975}^i, 80\text{F}) \qquad i \in k \tag{D.1}$$

$$\text{lt}_t^i = \min\ (\text{p}10_{t,1975}^i, 20\text{F}) \qquad i \in k \tag{D.2}$$

where percentiles for county surprises in 1975 (computed with 1970-1974 data) are set as threshold values throughout the entire sample. These thresholds are used to compute an alternative version of US-wide heat and cold shocks based on Equations 6, 7, 8, 9. Figure Appendix D.3 displays the new shock series. As the figure clearly shows, anchoring expectations at pre-sample levels yields shock measures that diverge over time: the incidence of heat over cold shocks is increasingly overestimated and, within heat shocks, positive surprises appear as more and more frequently than negative ones. These results reflect the climate-related temperature trend that time-invariant expectations are unable to net out. The evidence that the two shock series have trends (positive for heat shocks, negative for cold ones) suggest that a distorted picture of agents' beliefs can seriously bias shock estimates. All in all, the results of such toy example indicate that temperature anomalies are not suitable to construct unexpected shocks for econometric analyses.

Figure Appendix D.3: **Shock with fixed pre-sample temperature expectations**



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

Appendix D.3. Aggregated shocks vs aggregated temperatures

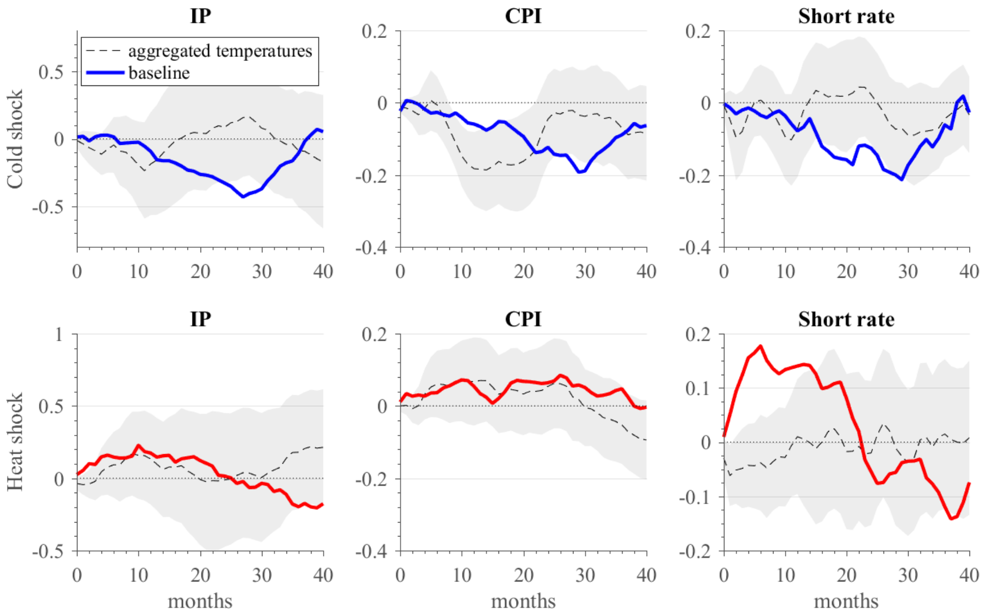
Many papers that estimate the effects of weather shocks proceed by aggregating granular temperature data at the country level first, then constructing shocks directly on those aggregated data. In formula, and going back to notation at the beginning of Section 2, this means defining shocks as

$$\text{TShockAgg}_t = \text{f}\Big(\sum_{i=1}^{n} w_t^i \text{T}_t^i\Big) - E_{t-1}\text{f}\Big(\sum_{i=1}^{n} w_t^i \text{T}_t^i\Big) \tag{D.3}$$

i.e., computing temperature statistics and their expectations over previously averaged local temperatures. It follows that the shock defined in Equation D.3 is equivalent to that in Equation 1 if and only if the statistics to compute shocks, $\text{f}(\text{T}_t^i)$ is linear in temperatures. In this framework, this doesn't hold, as $\text{f}(\text{T}_t^i)$ is an indicator function that takes value 1 if the temperature is above a threshold. As economically harmful temperatures are those at the extremes of the distribution, it's hard to figure out viable estimation strategies in which temperature aggregation can work the same way as aggregating local shocks, where the latter is the most intuitive and correct way.

To show how this alternative procedure can bias results, Figure Appendix D.4 reports impulse responses from heat and cold shocks constructed using Equation D.3, together with baseline median responses: as the first panel shows, such wrong procedure fails to display a key result of this paper, i.e. the significant negative effects of cold shocks on industrial production.

Figure Appendix D.4: **IRFs to shocks based on aggregated temperatures**



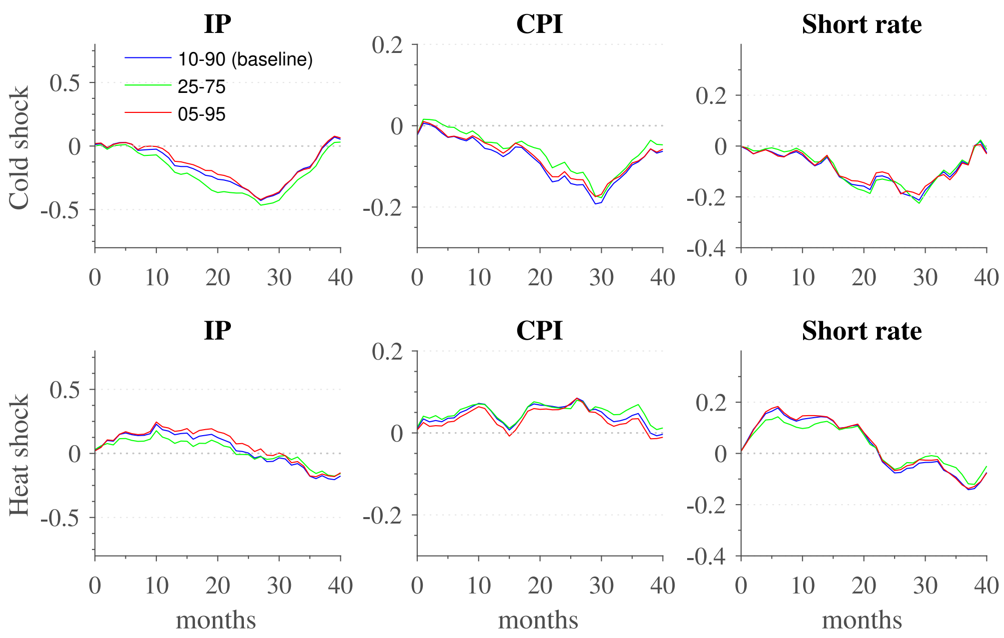
Notes: 68% and 90% confidence bands.

Appendix E. Robustness

Appendix E.1. Surprise thresholds

Threshold values to construct local heat and cold surprises in Equation 4 and 5 are based the 10th and 90th percentiles of the reference distribution. I propose alternative shock specifications by using 5-95 percentiles or 25-75 percentiles. Figure Appendix E.5 shows the median responses for the three variables of interest in these two cases, together with the baseline IRFs. Impulse responses of the two alternative specifications look almost identical to the baseline.

Figure Appendix E.5: **IRFs to shocks constructed using different temperature percentiles**



Notes: 68% and 90% confidence bands.

Appendix E.2. Weighting scheme

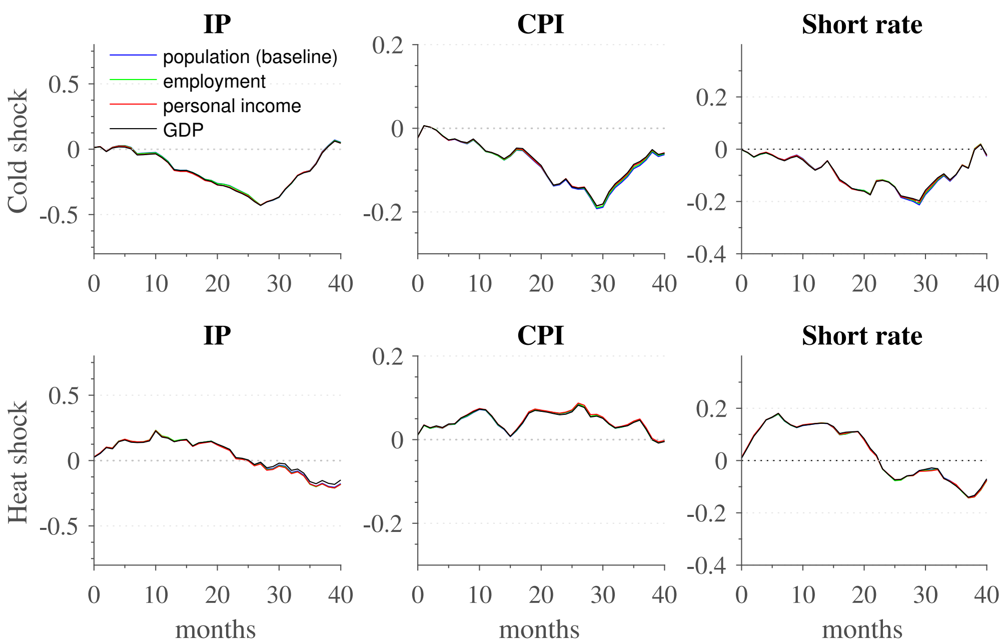
I here compute an alternative formulation of the US-wide shocks using different weights to aggregate county-level surprises. In particular, instead of counties' population shares, I use the counties' share of the following variables: (1) employment; (2) personal income; (3) real GDP in 2001.[18] The median impulse responses obtained from these alternative shocks are displayed in Figure Appendix E.6. Using employment shares, personal income shares and GDP shares leave results mostly unchanged with respect to the baseline.

Appendix E.3. 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 obtained shock

[18] 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.

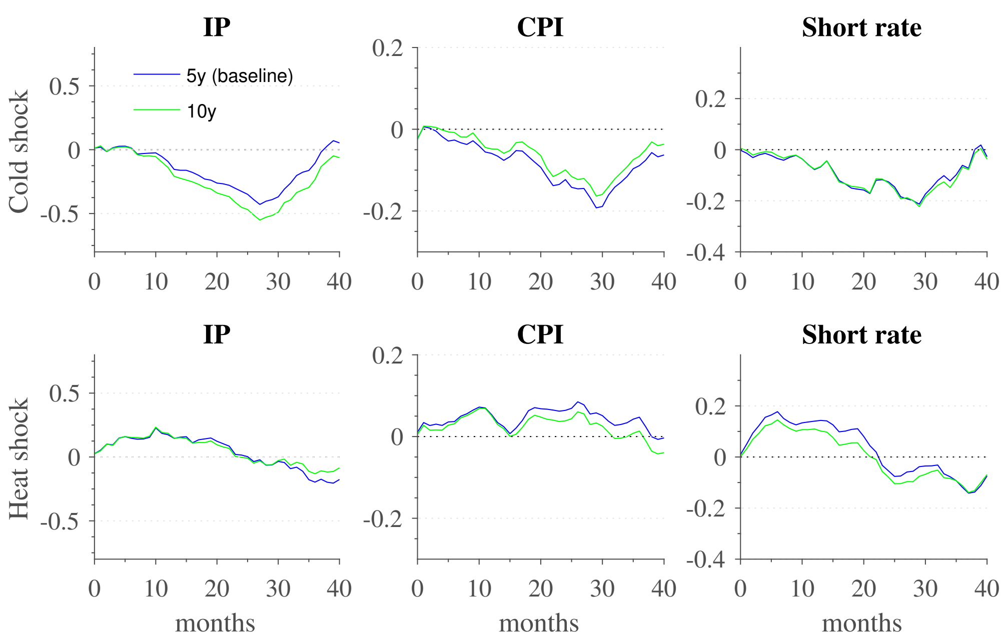
Figure Appendix E.6: **IRFs to shock computed under different weighting schemes**



Notes: 68% and 90% confidence bands.

is very similar to the baseline version (95% correlation), and so are the obtained impulse repsonses displayed in Figure Appendix E.7.

Figure Appendix E.7: **IRFs to shock computed under different weighting schemes**



Notes: 68% and 90% confidence bands.