Inflation in the Face of Weather Shocks: Evidence from Germany, India, and Spain

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Abstract

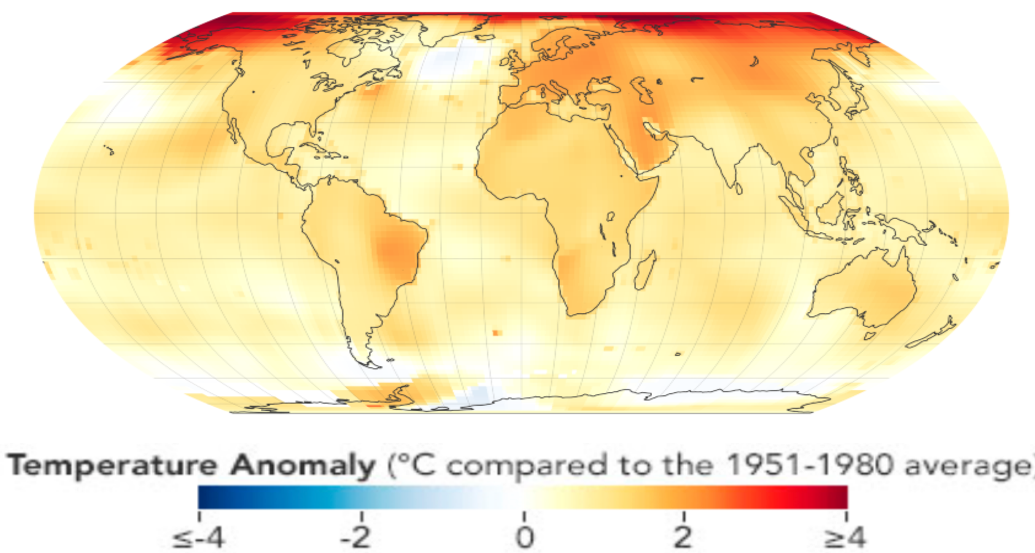
Climate change is universally recognised as the challenge of our generation, with the potential for material effects on all aspects of the economy. The incidence of more frequent and more severe weather shocks will pose significant challenges for Central Banks globally in maintaining price stability. Weather shocks, such as extreme short-term temperatures, could potentially lead to higher volatility in inflation, rendering it increasingly difficult for policymakers to calibrate the appropriate monetary stance. This paper explores this channel by relying on a granular, high-resolution weather database to quantify the effect of temperature shocks on inflation across three major economies. We estimate country-level local projections to quantify the effect of temperature shocks on a range of inflation sub-components. Our results suggest that temperature shocks transmit asymmetrically. In advanced economies, the effects are largely muted with mild downward price movements observed in the price of energy, indicative of lower demand for heating. For the emerging economy in our sample, temperature shocks have a short-run deflationary impact, but prices return to target quickly. Ultimately, our results suggest a weak transmission of weather shocks on prices, with the effects primarily driven by a negative demand adjustment following the shock.

Contents

1 Introduction

Climate change is recognised as the defining challenge of our generation. Over recent decades, the scientific consensus has largely coalesced around the view that climate change, and by extension climate shocks, pose a very real threat to human activity. Re-affirming this threat, the Intergovernmental Panel on Climate Change documented the increasing likelihood of the earth's surface-reaching 1.5°C above pre-industrial levels - a critical threshold above which the capacity to adapt is severely hindered (IPPC [2021]). As shown by figure 1, significant deviations from historical temperatures have become increasingly common, reflecting the accelerated threat of climate change on human activity. Beyond historical averages, projections of future climate scenarios point to the likelihood of more damaging climate shocks such as droughts, extreme temperatures, and extreme precipitation taking effect as global mean temperatures continue to rise (Cubasch et al. [2001]). With the intensification of climate shocks, both in their frequency and magnitude, the economic effects could potentially be severe.

Figure 1: Temperature deviations (°C) for the period 2015-2019 relative to 1951-1980



Source: Nasa Earth Observatory

As climate shocks have become more pronounced, climate change has become increasingly important for the conduct of monetary policy. Climate change can have both short-term and long-run implications for the optimal calibration of monetary policy. For example, short-term physical shocks (e.g., extreme temperatures), could conceivably have opposing effects depending on the transmission channel. On the demand side, previous evidence has documented that frequent temperature shocks result in reduced output and weaker consumption which could be reflected in downward price adjustments. However, on the supply side, extreme temperatures have been shown to reduce productivity

(Deryugina and Hsiang [2014]), lower agricultural yields (Vogel et al. [2019]), and lower labour supply (Graff Zivin and Neidell [2014]. These negative supply shocks serve to raise costs which could result in higher price levels. On a longer horizon, the transition towards a carbon-neutral will weigh heavily on the mandate of central banks. Specifically, carbon taxes will affect consumers directly through higher electricity and energy costs as well as indirectly through higher production costs for firms, particularly in carbon-intensive industries. Taken together, this adds renewed importance to the need to quantify how climate shocks propagate through the economy.

Despite the relevance of climate change for the conduct of monetary policy, the literature on the link between climate shocks and inflation remains relatively nascent. Exploring the effect of climate shocks and inflation across a panel of emerging and advanced economies Faccia et al. [2021] finds heterogeneity in the response to inflation between advanced and emerging economies. Specifically, the effect on inflation in advanced economies appears rather muted following a temperature shock while emerging economies experience price growth following the materialisation of a climate shock. In advanced economies, Ciccarelli and Marotta [2024] finds that temperature shocks primarily operate through the demand channel, resulting in lower prices.

We extend the literature along two main dimensions. Firstly, we rely on high-resolution temperature data to construct a novel temperature shock. In a departure from the previous literature, we compute the temperature shock as the difference between average temperatures in a month relative to the previous five-year average monthly temperature. As opposed to relying on a longer historical average to calculate a temperature anomaly (as is the case in the literature), the computation of our shock reflects the fact that agents update beliefs as to what constitutes a 'true' temperature anomaly over time and hence relying on historical averages as a baseline neglects the possibility of this adaption to hotter climates. Additionally, as opposed to relying on a simple aggregation technique, we take advantage of the granularity of our data by weighting the temperature shocks by population at the administrative level. Hence, our shock represents the weighted average temperature shock experienced by agents in a country. Secondly, we contribute to the literature by exploring the effect of weather shocks (since monthly analysis) on a range of inflation sub-components across three major economies - Germany, Spain, and India. The selection of these economies facilitates an analysis of the effect of temperature shocks across a range of different climates and levels of economic development.

Adopting a local projection approach, our results show limited effects of a temperature shock in both Spain and Germany. In the case of India, although headline inflation remains well-anchored, temperature shocks transmit through the demand channel for core and producer prices, with downward price adjustments following a temperature shock. Our results also document a fall in energy prices following a temperature shock in Spain and Germany, providing further evidence that the reduction in heat demand is stronger than the increased demand for cooling technologies from higher temperature shocks. Ultimately, our results support the view that temperature shocks transmit primarily through the demand side, although this link is weaker in advanced economies.

The rest of the paper is structured as follows. Section 2 provides a brief overview of the literature. Section 3 outlines issues identifying exogenous temperature shocks and provides an overview of our identification strategy. Section 4 presents the methodology. Section 5 provides an overview of the main results. Section 6 presents robustness checks and section 7 concludes.

2 Literature Review

As the threat posed by climate shocks has accelerated and garnered greater attention, a large body of literature has emerged seeking to explore the transmission of climate shocks through the economy. Previously, studies focusing on climate variables faced a basic identification challenge. Namely, since the prevailing climatic conditions are a fixed, immutable characteristic of a country, disentangling the *ceteris paribus* effect of the climate on the economy is empirically challenging. Overcoming this identification problem, a new strand of literature has emerged that harnesses high-frequency deviations in climate conditions to quantify the economic effect of climate change. Adopting this approach, Acevedo et al. [2020] explores the impact of temperature shocks on output using local projections. Their results suggest a non-linear effect of temperature on GDP. Namely, mild temperature increases raise GDP while extreme fluctuations induce a negative effect. The presence of a non-linear response is further corroborated by Burke et al. [2015], who find that economic growth is non-linear in temperature. Specifically, they find economic production peaks at an annual average temperature of 13°C with sharp declines thereafter. These findings suggest that, as climate shocks increase in magnitude and frequency, the ability of Central Banks to 'see through' these shocks is severely hindered, given the potential for large output losses.

Beyond aggregate effects, the sectoral transmission of climate shocks is also a pertinent consideration for the formulation of monetary policy. Exploring the channels through which temperature fluctuations influence the economy, Dell et al. [2012] find that higher temperature shocks depress agricultural output in developing countries. However, developing countries are not entirely insulated from weather shocks. Using within-country variations in weather Deryugina and Hsiang [2014], explore the effect of daily temperature fluctuations on U.S. productivity and income sub-components. Their results further affirm the presence of non-linearities in the response of these components to temperature shocks. For example, agricultural income begins to fall sharply as average temperatures rise above 27°C while non-farm income declines systematically at temperatures rise above 15°C. These non-linearities uncovered are particularly relevant for the conduct of monetary policy. Namely, temperature shocks appear to transmit analogously to a negative supply shock by dampening productivity and output. Therefore, understanding how climate shocks influence the price level gains further importance, given the possibility of a negative output shock coupled with higher inflation following a climate shock - i.e., a breakdown of the 'divine coincidence'.

Despite the rich literature exploring the effect of climate shocks on output, the literature on the interaction between climate shocks and inflation remains relatively nascent.

Adopting a similar identification to the one proposed here, Faccia et al. [2021] study the effect of temperature shocks on inflation and sub-components across a panel of 48 advanced and emerging economies using a local projection method. The overall impact depends on the timing of the shock. Specifically, cold winters do not affect inflation while hot summers have the most durable effect on inflation. Building on this, they consider the possibility of non-linearities through the introduction of a dummy variable denoting a shock greater than 2°C above the historical average. These non-linear shocks reduce medium-term headline inflation in advanced economies, a finding they attribute to lower demand from extreme climate shocks dampening the price level. As opposed to the methodology proposed here, they retrieve temperature data from the FAOSTAT Agri-Environmental Indicators dataset, which constructs an average temperature based on a simple aggregation from the station level. A key concern espoused in the literature is that these shocks may not necessarily be representative. For example, this simple aggregation ignores the possibility that a temperature shock may be restricted to urban areas, which could have a more pronounced effect and ultimately induce a higher inflationary response. We overcome this problem by relying on granular temperature data and aggregating based on a population-weighted average based on administrative population weights.

Relying on higher frequency data, Ciccarelli et al. [2023] consider the effect of seasonally dependent temperature shocks on four Eurozone Economies using a Bayesian Vector Autoregression (BVAR). In terms of the computation of the shock, the analysis relies on the ERA5 reanalysis dataset to compute a monthly temperature deviation relative to a long-term historical average (the monthly mean temperature during the period 1980-2011). Their results suggest significant heterogeneity in response to temperature shocks. For example, euro area inflation decreases in non-summer months while persistent inflation follows a shock in summer in Spain and Italy.

In terms of the construction of our shock, the approach adopted here is similar to that of Natoli [2023] who identify temperature 'surprise shocks' to estimate the effect of climate change on the US economy. Specifically, their identification of the shocks is based on the fact that comparisons with long-run averages neglect the possibility that agents begin to adapt to the changing climate which inevitably assuages the impact of climate shocks on the economy. To address this identification problem, they consider temperature shocks as the difference between the number of hot and cold days per quarter and those observed in the same county during the same quarter of the past five years. Assessing the impact on the U.S economy using local projections, they find considerable demand side channels. Namely, output falls immediately after a surprise temperature shock. Tracing out the impact, the burden of adjustment largely falls on investment which falls by 1.5%. The rationale behind these results is relatively straightforward; temperature shocks transmit through the economy analogously to a negative demand shock, which triggers falling consumption, lower investment, and ultimately an expansionary response by the Central Bank.

3 Data

3.1 Key points

A common strategy to derive exogenous weather shocks is to compute average monthly deviations from the long historical average. This corresponds to the following for each month (m) of each year (y) for each reference point (i) - for example, this reference point could be at the country level or a more granular level (i.e., one temperature station).

$$Temp_{\text{diff},i,my} = Temp_{i,my} - \overline{Temp}_{i,m} \tag{1}$$

Additionally, much of the previous literature has relied on relatively simple aggregation techniques when constructing the shock. For example, the UN Food and Agriculture Organisation statistics (FAOSTAT) on temperature anomalies have been frequently used to estimate the economic effect of temperature shocks (see Faccia et al. [2021] and Cevik and Jalles [2022]). This approach assumes that climate shocks transmit symmetrically across all geographical areas.

Several limitations are associated with these approaches. Firstly, historical averages are inappropriate for constructing an exogenous temperature shock. Namely, climate change is an ongoing and well-documented phenomenon. To some extent, these changes have been internalised by agents whose expectations of what constitutes a temperature anomaly or shock have changed significantly over time. Hence, reaching far into the past and using historical averages as a baseline to construct a shock neglects the fact that agents have adapted to warmer conditions. We assuage this issue by constructing the shock concerning the previous five-year average. Secondly, failing to weigh by population neglects the fact that temperature shocks can transmit asymmetrically within a country. For example, a temperature shock in a densely populated urban area would have a larger economic effect relative to more isolated geographical areas. The construction of our shock accounts for these dynamics by weighting by population at the administrative level. Therefore, our shock can be seen as "representative" in the sense it captures the weighted average shock experienced by an agent in a given country.

Finally, a large body of research has utilised annual data when estimating the impact of temperature shocks. A clear drawback of this approach is that climate shocks can have opposite effects depending on the time of the year. For example, higher temperatures could plausibly boost economic activity in winter, while it could reduce activity in summer, which would inevitably be reflected in the price level. Therefore, the net effect of a temperature shock is closely related to the season during which they manifest, rendering annual data inappropriate for exploring this heterogeneity. We overcome this by utilising data at the monthly frequency for our analysis, which permits a full exploration of the temporal heterogeneity inherent in the manifestation of temperature shocks.

3.2 Macroeconomic data

Table ?? in Appendix gives an overview of the macroeconomic data used in our analysis. We compiled the country-level dataset from multiple official sources. The inflation data was sourced from the World Bank's extensive global database on inflation, as documented by Ha, Jongrim, M. Ayhan Kose, and Franziska Ohnsorge in their 2023 study (Ha et al. [2023]). For the industrial production data, we combined information from Eurostat with official data from individual countries.

To ensure consistency and comparability, all variables in their original levels were seasonally adjusted using the Seasonal Extraction in ARIMA Time Series (SEATS) method. Following Ciccarelli et al. [2023], the data was transformed into annual growth rates,

$$y_{it} = 100 * \frac{Y_{it} - Y_{it-12}}{Y_{it-12}}$$

where Y_{it} stands for seasonally adjusted data in levels. This transformation allows for a clearer analysis of year-over-year changes, providing a robust basis for analysing price growth in response to both macroeconomic factors and weather shocks.

3.3 Temperature data

To construct our weather shock variable, we relied on two data sources. The first one is the ERA5 reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset provides high-resolution gridded data and has been made available monthly since 1940, updated with a three-month lag. We elect to use the ERA5 reanalysis dataset for the following reasons.

- **Comprehensive coverage:** ERA5 offers global, uniform coverage with a high spatial resolution of 0.25 degrees (approximately 30 km). This extensive coverage addresses the significant limitations of traditional weather stations, which are often unevenly distributed and sparse, especially in less developed or less populated regions. This disparity in station distribution can lead to gaps in data and unreliable coverage in critical areas.

- **Physical Consistency:** Traditional weather stations, while valuable, often suffer from measurement biases and inaccuracies. For instance, rain gauges typically underestimate peak rainfall, and temperature sensors can become less accurate under extreme conditions. In contrast, ERA5 combines historical observations with sophisticated atmospheric models to produce a physically consistent dataset that is reliable across both time and space. This ensures a higher level of data integrity suitable for detailed economic and policy analysis.

Complementing the weather data, we utilized the Gridded Population of the World (GPW), v4 dataset from NASA's Socioeconomic Data and Applications Center (SEDAC) to obtain detailed population counts for each administrative unit in our sample countries.

The GPW, v4 dataset provides population data at a high resolution of 0.25 degrees, which matches the resolution of our ERA5 weather data, allowing for seamless integration of demographic and weather variables. However, because GPW, v4 population data is available starting from 2000, we limited our analysis to the period from 2000 onwards. This limitation was imposed to ensure the accuracy of population-weighted estimates of monthly mean temperature for each country, a critical component of our research methodology. 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.

Besides, the integration of weather data with the population estimates involves excluding weather observations in those grid cells where population estimates are unavailable. Table 1 provides a detailed breakdown of weather data observations across the countries used in our analysis. Each country's dataset is characterized by a distinct number of latitudes and longitudes, reflecting the geographical diversity of their regions. Merging the two datasets results in varying numbers of observations, influenced by the spatial coverage of cities in Spain, Germany, and India, our sample countries. In total, the integration yields a time series dataset comprising approximately 7.3 million observations. [1]

Table 1: **Spatial observations**

Country	Latitudes & Longitudes	Months	Observations
Spain	8,020	288	2,309,760
Germany	11,292	288	3,252,096
India	5,967	288	1,718,496
Total	**25,279**	-	**7,280,252**

3.4 State-level statistics

The state-level statistics depicted in figure 2, 3, and 4 unveil the growth rate of temperature between the 1960s and 2010s in Germany, India, and Spain, respectively. These countries were chosen for our analysis due to their diverse climatic, economic, and regional characteristics.

[1] The global gridded dataset was processed to obtain a time series using the computing power of Kaggle.

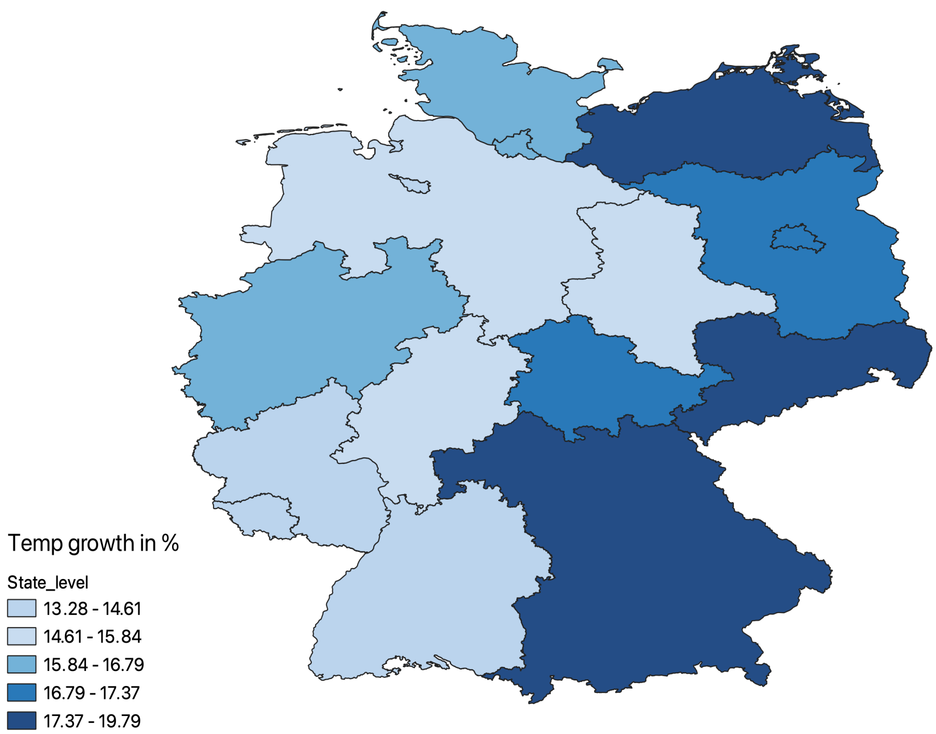


Figure 2: Growth rate of temperatures, 2010s vs 1960s averages - Germany

Germany, a leading industrial economy in Europe, has witnessed significant temperature growth, averaging 16.7% across its states. This substantial increase highlights the country's exposure to climate change, despite its advanced infrastructure and adaptive capacity. Particularly, eastern states like Saxony and Brandenburg have experienced rises surpassing the national average. This pattern suggests that eastern Germany, with its historically agrarian economy and more recent industrial development, might be more susceptible to the impacts of temperature changes.

Spain has experienced an average temperature growth of 11.3%. However, the regional disparities are stark, with northern provinces such as Galicia and Castilla y Leon seeing increases above 16%, while central and southern regions like Andalusia and Castilla-La Mancha show milder growth. The pronounced temperature rise in the northern provinces may be linked to changing Atlantic weather patterns and urbanization. Conversely, the traditionally hotter southern regions might already be close to their temperature thresholds, showing less dramatic increases.

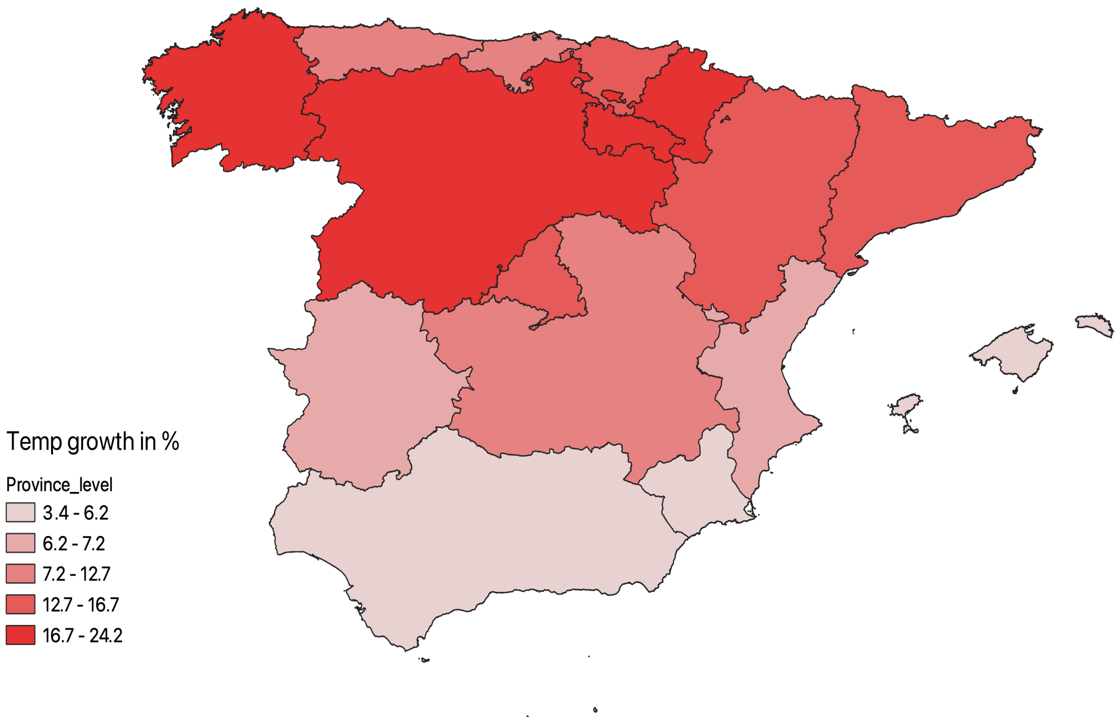


Figure 3: Growth rate of temperatures, 2010s vs 1960s averages - Spain

India, characterized by its tropical climate, has experienced an average temperature growth of 3.5%. However, northern and southern states like Jammu & Kashmir (7.9%) and Ladakh have experienced substantial growth, raising concerns for these ecologically sensitive areas. Agrarian economies in the southern states, such as Kerala (4.91%), and Tamil Nadu (4.41%), have also shown higher increases. These varying regional impacts across Germany, Spain, and India underscore the complexity of climate change effects and highlight the need for region-specific strategies to mitigate and adapt to the evolving climate realities. This is why our analysis, which weights temperature changes at the city level, can provide granular insights that are essential for precise policy guidance.

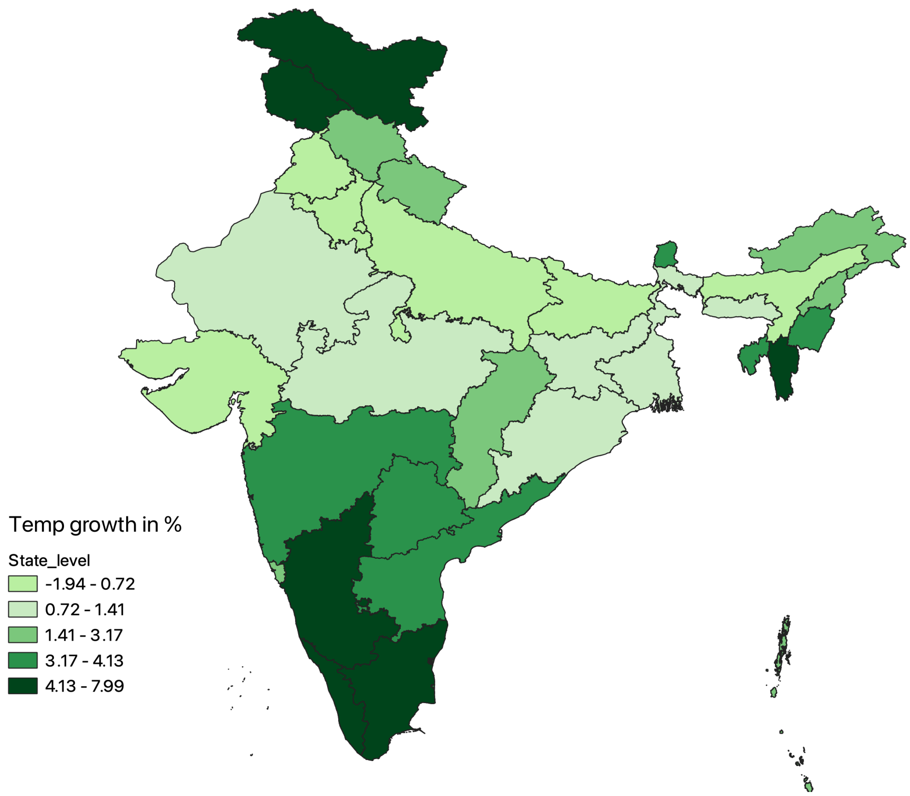


Figure 4: Growth rate of temperatures, 2010s vs 1960s averages - India

3.5 The shock series

The temperature shock time series for each country is depicted in Figure 5. This shock quantifies the deviation of the monthly mean temperature from its average over the past five years for the corresponding month. They are computed based on backward-looking temperature expectations derived from the closest past temperature data.

Adhering to fundamental econometric principles, the shock exhibits essential characteristics for empirical analysis: they maintain a zero-mean and display stationarity, as verified by the Augmented Dickey-Fuller Test (see Table 5 in appendix). From an economic standpoint, it embodies three key attributes, elucidated by Ramey [2016], rendering it suitable for macroeconomic applications. Namely, it is exogenous to current and lagged outcome variables, demonstrates independence from other exogenous economic shocks, and signifies unforeseen fluctuations in an exogenous variable.

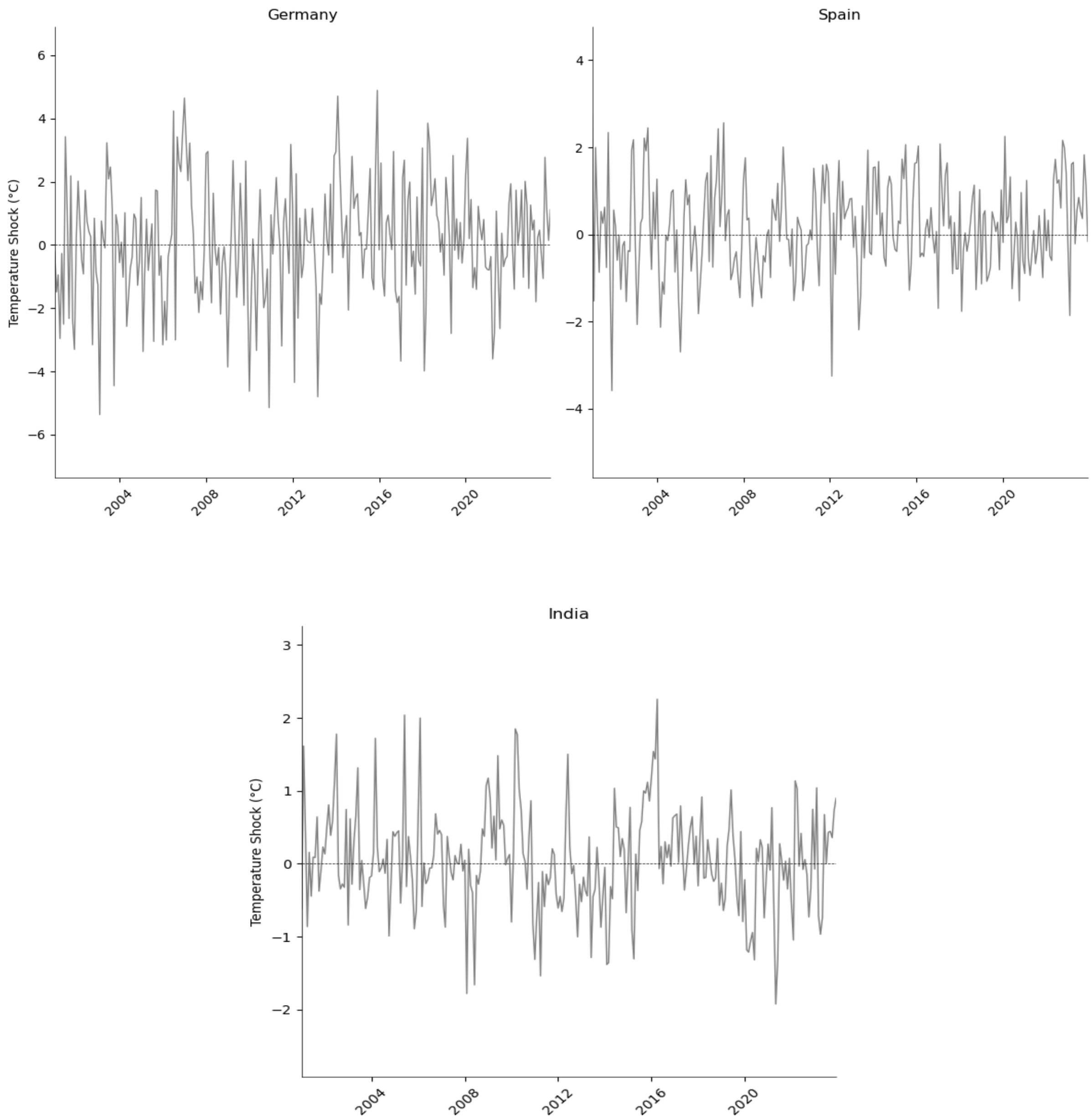


Figure 5: Deviation of monthly average temperature from its past five-year average

Observing the plotted data series, it becomes apparent that temperature fluctuations were notably significant in the earlier years of the sample compared to recent years. While Germany exhibited the highest degree of variability throughout the observation period, India demonstrated the lowest variability. This challenges the conventional notion that climate change is leading to increasingly severe shocks. By filtering out predictable climate patterns to focus on the unexpected component of temperature variations, it is plausible that large-scale weather events occurring post-1970 have become more frequent but also less surprising than in earlier times.

4 Methodology

To estimate the impact of temperature shocks on inflation we estimate local projections à la Jordà [2005] seperately for each country. Formally, we estimate the following equation for each country (i):

$$y_{i,t+h} = \alpha_{i,h} + \beta_{i,h}\text{TempShock}_{i,t} + \psi_{i,h}(L)X_{i,t-1} + u_{i,t+h}, \quad s = 0, 1, 2, \ldots, H \tag{2}$$

Where $y_{i,t}$ is the year-on-year change in inflation, $TempShock$ is the temperature shock, and X contains a vector of lagged controls. In terms of controls, we include lagged headline inflation, lags of the inflation sub-indexes, lags of industrial production, and two lags of the temperature shock. The lengths are determined by Akaike's Information Criterion (AIC), which suggests a lag length of 5 for the endogenous variables. The rationale behind the reliance on AIC to determine lag length is that AIC tends to lead to an over-parameterization of the lags. Hence, we adopt the AIC to guard against the introduction of omitted variable bias within our model specification. The model is estimated up to horizon 12, while inference is performed with Newey-West errors. The estimates are conducted with the sample from 2001M1 until 2023M12.

As opposed to Vector Autoregressions (VARs), local projections estimate the model at each horizon rather than extrapolating from an initial model specification (Jordà [2005]). This multi-step process presents numerous benefits, particularly in the context of estimating the impact of temperature shocks. Firstly, since local projections are not constrained by an initial model, they are less prone to mis-specification bias. Secondly, local projections are less prone to the curse of dimensionality often associated with VARs (Barnichon and Brownlees [2019]). Finally, relative to VAR models, local projections can more easily incorporate non-linearities. In addition to these attractive properties of local projections, they are frequently used in the climate literature (see Natoli [2023], Burke et al. [2015], and Akyapi et al. [2022]) which provides a further rationale to adopt this method.

5 Results

5.1 Results for Headline Inflation

The first target variable of interest is headline inflation. Impulse responses from a one-degree temperature shock are shown in Figure 6 with the 90% confidence bands shown in shaded. The results indicate that headline inflation remains well anchored following the incidence of a temperature shock across all three economies of interest. Although all impulse responses fall below zero, reflecting a mild negative demand shock, the shaded band indicates the response remains statistically insignificant across all horizons. For example, for India, the change in annual inflation falls by 0.2 percentage points 5 months after the shock, although this remains insignificant at the 90% confidence level. These results appear consistent with Natoli [2023] who documents a very mild deflationary effect in the U.S following a temperature shock.

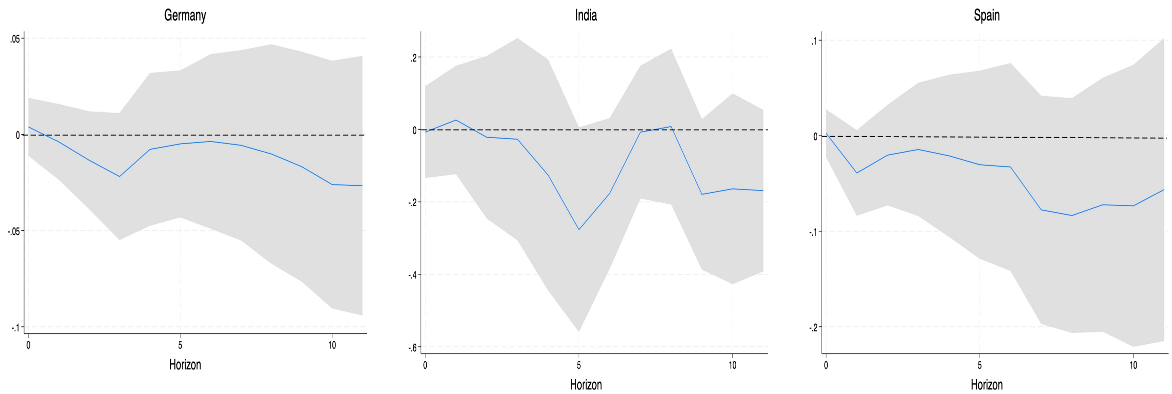


Figure 6: Response of headline inflation to a (1°C) temperature shock

5.2 Results for Producer Prices

Although headline inflation remains well-anchored following a temperature shock, the response of headline figures may mask significant heterogeneity in the response of sub-components, which are an important consideration for the formulation of monetary policy. To further explore whether temperature shocks propagate through the economy through a demand or supply channel, we investigate the impact on producer prices. Examining the impulse responses shown in Figure 7, temperature shocks induce a negative effect on producer prices. For the case of India, producer prices fall by 0.6 percentage points after 5 quarters but rebound thereafter. For both Spain and Germany, the results appear similar. Namely, the results are insignificant at short horizons following the shock but dip below zero at longer horizons. These results again appear consistent with the presence of a negative demand channel. Specifically, these results share similarities Roth Tran [2023], whose results showed the presence of a negative demand-side impact from climate shock. This result goes against previous evidence which, relying on a long-term historical average, documents an upward response for producer prices (Ciccarelli et al. [2023]). Specifically, they rationalise an increase in the price of industrial goods as evidence of a positive demand response in milder countries (where temperature shocks could plausibly be a positive economic outcome). Our results indicate that, when we compute the shock relative to a more recent base period, this upward movement in producer prices fails to materialise - a result which is consistent with Natoli [2023] who adopts a similar shock identification strategy for the U.S.

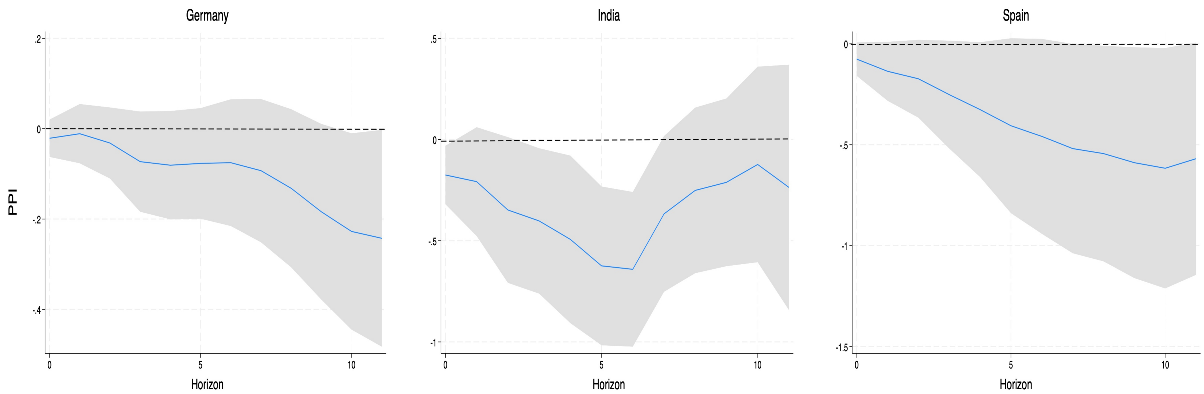


Figure 7: Response of producer price inflation to a (1°C) temperature shock

5.3 Results for Core Inflation

Examining the impact of temperature shocks through the lens of core inflation offers arguably the clearest indication as to how temperature shocks transmit through the economy. As evidenced by Figure 8, the response of all three IRFs remains consistent with the evidence from producer prices. Namely, the IRF for India provides further evidence of a weak demand channel, with core prices falling 5 months after the temperature shock. In a similar spirit to the first set of results, prices for both Spain and Germany remain stable following the realisation of a temperature shock, providing further evidence of a muted effect for advanced economies. These results further underline the key mechanism at play. Namely, the link between advanced economies and temperature shocks appears largely tenuous, while in the emerging economy, temperature shocks are transmitted through the demand channel. Further, the presence of a negative demand channel is consistent with previous literature. In particular, Ciccarelli and Marotta [2024] find that physical risks (which is the focus of this analysis) act as negative demand shocks, dampening output, and lowering prices.

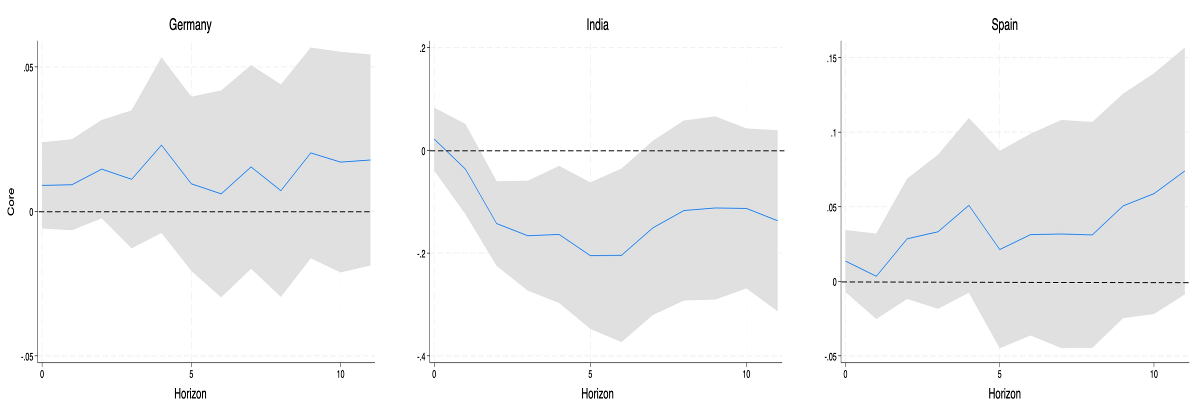


Figure 8: Response of core inflation to a (1°C) temperature shock

5.4 Results for Energy Inflation

The energy sector acts as one of the key propagating mechanisms in terms of how climate shocks permeate the economy. On a longer horizon, the transition to a carbon-neutral economy will weigh heavily on the functioning of energy markets. For example, as the cost of carbon rises, energy from non-renewable sources will rise, potentially imputing upward pressure on the price level. However, at shorter horizons, physical climate shocks can have a downward effect on the price level. For example, Lucidi et al. [2024] find that temperature anomalies induce downward pressure on European energy prices as demand for energy falls. They provide further evidence that the decline in energy prices is driven by a higher "turn-of-heating" which outweighs the "turn-on-cooling" effect (Lucidi et al. [2024]). Our results as shown in Figure 9 document a similar mechanism for European energy prices.

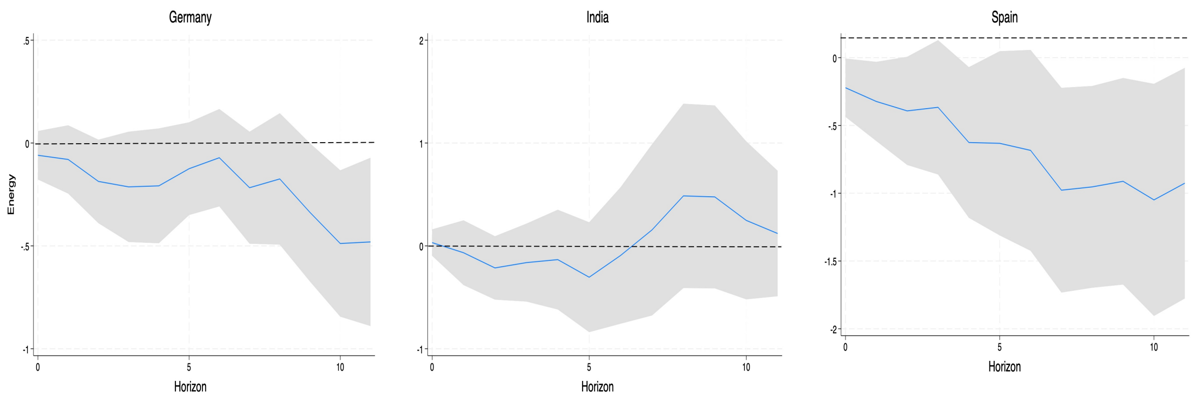


Figure 9: Response of energy inflation to a (1°C) temperature shock

Namely, the negative response of German and Spanish inflation is substantively quite large at longer horizons, indicative of the same mechanism documented by Lucidi et al. [2024]. In the case of India, energy prices show no statistically significant movement following the temperature shock. One possibility is that there are offsetting effects. Namely, weaker industrial demand would lead to downward pressure on the price level while a stronger "turn-on-cooling" effect would have the opposite effect.

6 Robustness

6.1 Exogeneity Tests

To provide further evidence that the temperature shock is exogenous from economic activity we run the following regression for each country:

$$TempertureShock_{i,t} = \alpha_{t,i} + \sum_{h=0}^{6} \gamma_{t,i} IPgrowth_{i,t-h}, \tag{3}$$

In all specifications, across all three countries, the coefficients associated with industrial production growth are statistically insignificant, as shown in the appendix. Although somewhat ad hoc, this test provides further confidence regarding the strength of the identification strategy adopted. Namely, this rules out the possibility of reverse causality - a result to be expected given temperature shocks are unresponsive to recent production.

6.2 Seasonal Dependence

A key point espoused in the literature is that there is significant heterogeneity in the response of inflation to temperature shocks depending on the time of the year when the shock materialises (Ciccarelli et al. [2023]). Considering the infra-annual frequency of our data, we explore this heterogeneity by estimating the following model:

$$y_{i,t+h} = \alpha_{i,h} + \sum_{j=1}^{4} \beta_{i,h}^{j} \text{TempShock}_{i,t} \times D_t^j + \psi_{i,h}(L) X_{i,t-1} + u_{i,t+h}, \quad s = 0, 1, 2, \ldots, H \quad (4)$$

Where D^j corresponds to 1 if the month falls in $j = \{\text{autumn}, \text{winter}, \text{spring}, \text{summer}\}$. The only exception is the case of India where we match the months to the Indian calendar, which includes monsoon season. These results highlight the source of some of the results discussed previously. In particular, these results provide insights into the response of seasonally dependent inflation sub-components, such as energy. Figure 10 underlines the strength of the "turn-off-heating" channel for Spain. Specifically, energy prices fall immediately after a temperature shock in winter, while no changes in energy prices are observed during the summer months. In the case of India, we see the opposite effect, with energy prices rising significantly (by approximately one percentage point) following a temperature shock during the summer period - evidence of a strong "turn-on-cooling" channel. Beyond seasonally volatile components such as energy, our results show limited evidence of significant heterogeneity by season. Further, a richer exploration of the seasonal variation using non-linear state-dependent local projections (for example, the method proposed by Akyapi et al. [2022]) is beyond the scope of this paper and left for future research.

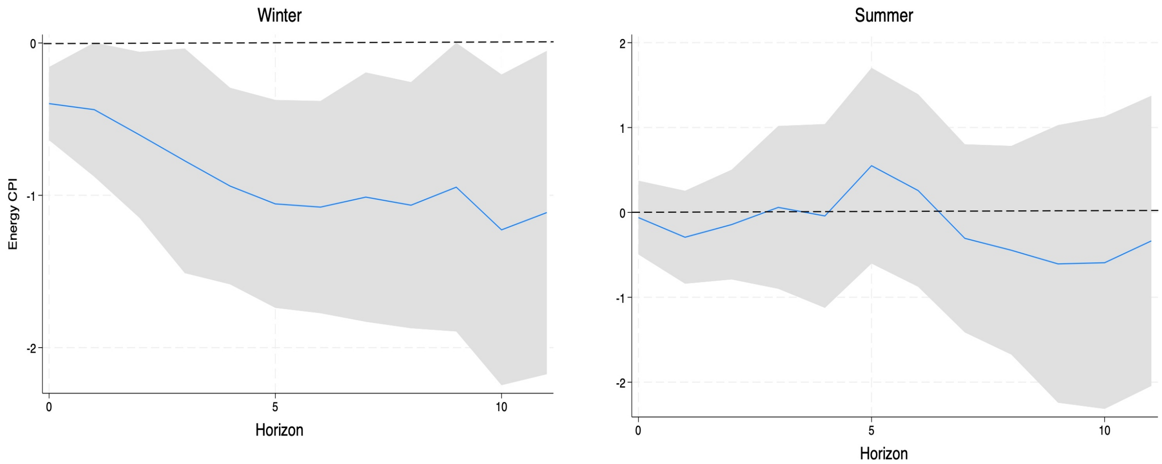


Figure 10: Energy inflation - Spain

7 Conclusion

This paper explores the impact of temperature shocks on inflation in three major economies - Spain, Germany, and India. The main contribution of the paper is twofold. Firstly, we harness high-resolution temperature data to construct a temperature shock that accounts for the possibility of agents adapting to changes in the prevailing climate while also weighting the shock by population to account for within-country variation in temperatures. Secondly, we estimate the effect of temperature shocks on headline inflation and a range of pertinent sub-components using local projections. Our results suggest a muted effect on headline inflation across all countries. However, this result masks significant heterogeneity in the response of the sub-indexes. In India, both core inflation and producer prices fall, providing evidence of a negative demand response following a temperature shock. In both Germany and Spain, temperature shocks are primarily transmitted through the energy sector, with energy prices falling after a temperature shock. This result provides further evidence that the fall in heating demand offsets the increasing demand for cooling in European economies, leading to lower energy prices. Ultimately, our results suggest that temperature shocks primarily transmit through the demand channel, leading to lower prices, although this effect is muted for advanced economies.

This paper opens up the possibility of several potentially fruitful avenues for further research. Firstly, this paper has not considered the possibility of multiple climate shocks. In reality, climate shocks tend to cluster and materialise simultaneously. Therefore, one interesting avenue to build on this study would be to incorporate precipitation shocks, droughts, and wildfires to gain a holistic understanding of how climate shocks impact price levels. Lastly, there is a need to complement studies on physical risks (such as this paper) with evidence on the cost of the climate transition. Indeed, it is entirely possible that the inflationary effect from transition costs could offset the negative demand channel documented here.

References

Sebastian Acevedo, Mico Mrkaic, Natalija Novta, Evgenia Pugacheva, and Petia Topalova. The effects of weather shocks on economic activity: what are the channels of impact? *Journal of Macroeconomics*, 65:103207, 2020.

Berkay Akyapi, Mr Matthieu Bellon, and Emanuele Massetti. *Estimating macro-fiscal effects of climate shocks from billions of geospatial weather observations*. International Monetary Fund, 2022.

Regis Barnichon and Christian Brownlees. Impulse response estimation by smooth local projections. *Review of Economics and Statistics*, 101(3):522–530, 2019.

Marshall Burke, Solomon M Hsiang, and Edward Miguel. Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239, 2015.

Serhan Cevik and João Tovar Jalles. This changes everything: Climate shocks and sovereign bonds∗. *Energy Economics*, 107:105856, 2022.

Matteo Ciccarelli and Fulvia Marotta. Demand or supply? an empirical exploration of the effects of climate change on the macroeconomy. *Energy Economics*, 129:107163, 2024.

Matteo Ciccarelli, Friderike Kuik, and Catalina Martínez Hernández. The asymmetric effects of weather shocks on euro area inflation. 2023.

Ulrich Cubasch, GA Meehl, GJ Boer, RJ Stouffer, M Dix, A Noda, CA Senior, S u Raper, and KS Yap. Projections of future climate change. In *Climate Change 2001: The scientific basis. Contribution of WG1 to the Third Assessment Report of the IPCC (TAR)*, pages 525–582. Cambridge University Press, 2001.

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

Tatyana Deryugina and Solomon M Hsiang. Does the environment still matter? daily temperature and income in the united states. Technical report, National Bureau of Economic Research, 2014.

Donata Faccia, Miles Parker, and Livio Stracca. Feeling the heat: extreme temperatures and price stability. 2021.

Joshua Graff Zivin and Matthew Neidell. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26, 2014.

Jongrim Ha, M. Ayhan Kose, and Franziska Ohnsorge. One-stop source: A global database of inflation. *Journal of International Money and Finance*, 137:102896, October 2023.

Climate IPPC. Intergovernmental panel on climate change. *CC BY*, 4, 2021.

Òscar Jordà. Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182, 2005.

Francesco Simone Lucidi, Marta Maria Pisa, and Massimiliano Tancioni. The effects of temperature shocks on energy prices and inflation in the euro area. *European Economic Review*, page 104771, 2024.

Filippo Natoli. The macroeconomic effects of temperature surprise shocks. *Bank of Italy Temi di Discussione (Working Paper) No*, 1407, 2023.

Valerie A Ramey. Macroeconomic shocks and their propagation. *Handbook of macroeconomics*, 2:71–162, 2016.

Brigitte Roth Tran. Sellin'in the rain: Weather, climate, and retail sales. *Management Science*, 69(12):7423–7447, 2023.

Elisabeth Vogel, Markus G Donat, Lisa V Alexander, Malte Meinshausen, Deepak K Ray, David Karoly, Nicolai Meinshausen, and Katja Frieler. The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, 14(5):054010, 2019.

8 Appendix

To relax any concerns that economic activity is driving deviations in temperatures we estimate equation 4. The following tables present the results across all lags.

	Estimate	Std. Error	P-Value
Intercept	0.11259	0.11529	0.3297
IP	-0.02108	0.04688	0.6534
IP_{t-1}	-0.03380	0.07311	0.6443
IP_{t-2}	0.12482	0.07420	0.0937
IP_{t-3}	-0.10659	0.07446	0.1535
IP_{t-4}	0.01201	0.07509	0.8730
IP_{t-5}	-0.01427	0.07400	0.8472
IP_{t-6}	0.03894	0.04707	0.4089

Table 2: Exogeneity Test Results for Germany

	Estimate	Std. Error	P-Value
Intercept	0.14930	0.06597	0.0244
IP	-0.00089	0.02682	0.9736
IP_{t-1}	-0.01733	0.04183	0.6790
IP_{t-2}	0.04614	0.04246	0.2781
IP_{t-3}	-0.03891	0.04260	0.3619
IP_{t-4}	-0.00794	0.04296	0.8536
IP_{t-5}	0.00629	0.04234	0.8819
IP_{t-6}	-0.00098	0.02693	0.9709

Table 3: Exogeneity Test Results for Spain

	Estimate	Std. Error	P-Value
Intercept	0.02354	0.05494	0.6687
IP_t	0.01020	0.00500	0.0424
IP_{t-1}	-0.00659	0.00566	0.2454
IP_{t-2}	-0.00404	0.00566	0.4766
IP_{t-3}	0.00541	0.00568	0.3410
I_{t-4}	0.00057	0.00568	0.9196
IP_{t-5}	-0.00142	0.00568	0.8029
IP_{t-6}	0.00104	0.00501	0.8356

Table 4: Exogeneity Test Results for India

Indicators	Germany	Spain	India
Mean	0.08	0.15	0.05
Standard Deviation	1.87	1.08	0.69
Skewness	-0.19	-0.09	0.23
Kurtosis	0.17	0.13	0.73
Autocorrelation	0.15	0.24	0.36
ADF Statistic	-7.69	-8.61	-11.29
ADF p-value	0.00	0.00	0.00

Table 5: Summary statistics for the temperature shocks

Table 6: Data summary

Variable	Source	Frequency	Sample
Germany & Spain			
Consumer Price Index	World Bank	monthly	2000M1-2023M12
Food Index	World Bank	monthly	2000M1-2023M12
Energy Index	World Bank	monthly	2000M1-2023M12
Producer Price Index	World Bank	monthly	2000M1-2023M12
Core inflation Index	World Bank	monthly	2000M1-2023M12
Industrial Production Index	Eurostat	monthly	2000M1-2023M12
India			
Consumer Price Index	MoSPI[1]	monthly	2011M1-2023M12
Food Index	MoSPI	monthly	2011M1-2023M12
Energy Index	MoSPI	monthly	2011M1-2023M12
Producer Price Index	World Bank	monthly	2000M1-2023M12
Core inflation Index	MoSPI	monthly	2011M1-2023M12
Industrial Production Index	MoSPI	monthly	2000M1-2023M12

[1] MoSPI stands for Ministry of Statistics and Programme Implementation, India