**Inflation in times of global warming**

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**(NOT FOR CIRCULATION)**

1. **Introduction**

The post-pandemic surge of inflation to a four-decade high in many advanced and emerging markets has renewed interest in the drivers of inflationary pressures and prompted questions on inflation management strategies, including alternatives to the conventional monetary approaches (ref: Chris Giles, FT). While the consensus is strong with respect to the need for curbing excess demand-pull inflation by means of monetary tightening, adverse supply shocks that push prices up and output down create difficult policy trade-offs (Klomp 2020). A key tenet of modern monetary policymaking under flexible inflation-targeting (FIT) regimes is indeed to “look through” the first-round effects of supply shocks and to intervene only if their persistence threatens the stability of expectations and, so, inflation to become entrenched. On these lines, although the recent inflationary episode was mainly driven by a series of idiosyncratic developments - namely, supply-chain bottlenecks, changes in relative prices, and Russia’s invasion of Ukraine, possibly exacerbated by firms’ excessive market power (Stiglitz and Regmi 2022) – central banks eventually responded by sustaining high interest rates.

In the 2024 BIS Annual Economic Report, such forceful global tightening action is celebrated for it sent “a strong signal to markets, firms and workers that the central bank would do what it took to restore price stability” (BIS 2024, p. 46). As a result, “inflation is now again returning to the price stability region while economic activity and labour markets have proved resilient” (idib., p. 41). In academic circles, however, the firm adoption of a contractionary stance was generally seen as a blunt and unnecessarily costly revival of the monetarist doctrine, which overshadows alternative instruments of price stabilisation (see, for example, Stiglitz and Regmi 2022, Saraceno 2023, Weber and Wesner 2023). Correctly identifying the origins of inflation is key to tailoring an appropriate policy response.

As the bout of post-COVID19 inflation wanes, the debate on the appropriate response to trade-off inducing shocks remains appropriate in the context of another, increasingly concerning, source of future uncertainty. Climate change is an accelerating process that is expected to increase both the frequency and intensity of acute physical hazards (i.e., droughts, floods, wildfires, heatwaves, etc.) and the chronic deviation of meteorological variables from their historical means (i.e., rising averages in temperature, precipitation, and sea levels) (IPCC 2021). The physical risks deriving from these phenomena influence agents’ preferences and endowments with immediate implications for the price stability mandate of central banks around the world through a variety of supply- and demand-side channels (we review them in Section 2). In contrast to longer-run changes in climatic trends which influence the optimal monetary policy and r\*, extreme climatic events “are largely unpredictable and thereby bear resemblance to other shocks that unfold over the business cycle and to which monetary policymakers tend to adjust monetary policy” (NGFS 2024, p. 7). Either way, climate change is flaring up the debate over whether policymakers should respond to climate-related price shocks by looking through their early signs, by pre-emptive monetary tightening, or by loosening their stance. The answer depends on our understanding of the nature and the pattern of climate-related inflationary pressures.

This paper aims to contribute to this discussion by providing new empirical evidence on the effect of acute physical risk on inflation, employing a global panel dataset of monthly country-sector inflation from 1990 to 2023. A number of authors have started contouring the subject (among others, Faccia et al. 2021, Kotz et al. 2024, Cevik and Jalles 2024) and we add to this growing body of cutting-edge empirical findings in several ways.

First, we disaggregate the price data – specifically looking at 12 Consumer Price sub-indexes[[1]](#footnote-2) and 6 PPI sub-categories – to disentangle the idiosyncratic nature of weather shocks. Adopting a sectoral dimension allows us to zoom in on various market segments, distinguishing those immediately hit by the hazards from those affected at later stages, and therefore to identify the origins (cost-push vis a vis demand-pull) of aggregate inflation dynamics.

Secondly, we acknowledge the importance of the global production network in the propagation of price spillovers. While there is broad agreement that the degree to which sectoral prices respond to shocks is determined by the input-output structure of the economy, there is no evidence for the transmission mechanisms responsible for the inflationary effects of climate change. To fill this gap, we build upon the literature on sectoral propagation of shocks (…), recently applied to assess the impact of weather shocks and sectoral productivity by Zappalá (2024), to incorporate the input-output framework that factors in the indirect price spillover effects of weather shocks. We argue that omitting the sectoral, either national or international, transmission would produce a bias in the estimation of the sectoral price effect of climate shocks

In addition, we account for possible moderating factors emerging in both the monetarist and structuralist theory of inflation, such as and the monetary policy stance and the role of sectoral competition in the price setting mechanism (Weber and Wasner 2023). Lastly, we follow Faccia et al. (2021) to check for the presence of tipping points and we also test whether the price effect has been increasing over time by restricting the sample.

While the empirical analysis is global in essence, the econometric model will be also specified as a country-specific regression to examine the experience of a single economy: we choose South Africa. Southern Africa is a climate-sensitive region that is already experiencing significant deviations of rainfall and temperatures from long-term averages as well as severe droughts and floods (World Bank Climate Portal 2024), with implications for water availability and food security. From a socio-economic perspective, however, South Africa is the strongest country in the region, exhibiting a solid infrastructure and a well-diversified and emerging open economy fully integrated to global supply chains. Moreover, what makes South Africa a good case study is its high levels of market concentration and product regulation to validate the existence of profit-led inflation.

Notably, our sectoral approach does not downplay the macroeconomic relevance of climate risk. On the contrary, shedding light on how climate change affects specific segments of the economy and spills over to other sectors is key to understand macroeconomic processes and to envisage tailored policy responses. Relative price changes are also fundamental to the analysis of welfare costs, as heterogeneous households face different inflation rates depending on their income, wealth, and composition of their consumption basket. Thus, despite their merits, not only aggregate indexes can potentially smoothen out the variance from several inflation components, but they also conceal the true inflation costs that different consumers within the same country are susceptible to. Similarly, we are aware that a possible limitation of our study derives from the risk country-level data veil some of the local effects of changing weather conditions but, even so, the sectoral dimension should be sufficiently sensible.[[2]](#footnote-3)

Finally, the present analysis is limited to ‘climateflation’, first defined by Schnabel (2022) to conceptualise the ways in which physical risks caused by climate change put upside pressure on prices. Other aspects are important in determining the relation between weather and price movements, such as the impact of chronic rises in temperature averages, climate adaptation and mitigation policies, but these are beyond the scope of this paper.

**[PAPER OUTLINE**

Section 2: LR;

Section 3: Data + Methodology;

Section 4: Discussion of results;

Section 5: Model extensions;

Section 6: Conclusions and policy implications**]**

1. **Climateflation: a literature review**

Within the broad range of climate risks, acute physical risk[[3]](#footnote-4) refers to the potential for adverse consequences resulting from sudden, intense, and short natural hazards such as extreme weather events such as hurricanes, floods, or wildfires.

The past few years have witnessed growing efforts of the research community towards the empirical assessment of the economic effects of extreme weather, including on prices. For instance, Mukherjee and Ouattara (2021) and Kotz et al (2024) document that temperature shocks generate persistent inflation, especially in lower-income countries, whereas Parker (2018) and Cevik and Jalles (2024) highlight outcomes would also depend on the type of disaster, the country’s level of development and fiscal space. This mix of possibilities means “no two physical hazard events have the same macroeconomic effects“ (NGFS 2024, p. 9): different weather shocks will likely hit distinct segments of the economy, often unevenly, causing volatility both in nominal and relative prices (Buelens 2024). We attempt to conceptualise the transmission mechanisms underlying climateflation here.

**Climate-induced supply shocks.** On the supply side, abrupt climatic deviations influence some of the characteristics and effective availability of productive factors through capital destruction, productivity and production loss. Sectors characterised by an inherent exposure to weather are particularly sensitive to the **direct effect of weather shocks**. In farming, for example, extreme events impact negatively on both crops and animal breeding through workers’ heat stress (De Lima et al. 2021), environmental degradation (Liang et al 2017) or increased use of pesticides and overall production costs (Savage 2024). The obvious relation between the weather and the food system has prompted many authors to examine food prices dynamics closely. Faccia et al. (2021) find that upward temperature anomalies have an immediate impact on food prices; Kotz et al (2024) observe that the effects of global warming are stronger in the food component of inflation; Roberts and Schlenker (2013) find that crop yields are humped-shaped, with higher temperatures increasing yields up until a threshold, before having increasingly negative effects. Finally, according to Parker (2016) storms and floods lead to a short-lived but upward effect on food price inflation.

Besides agriculture, climate disasters are likely to hit water-intensive sectors, such as electricity, manufacturing, and waterway transport (Buelens 2024), while damage to infrastructure, natural resources, and properties can undermine the provision of services (NGFS 2023, [Duba 2024](https://theconversation.com/extreme-weather-in-south-africa-is-disrupting-tourism-research-tracks-the-impact-on-coastal-areas-232172))

Non-agricultural activity can be also undermined by reduced labour productivity, particularly in presence of outdoor work (e.g. construction, tourism) (Graff Zivin et al. 2018, ILO 2019, Nath 2020, Pinna Pintor et al. 2024). Acevedo et al. (2020) documents that higher temperatures significantly lower labour productivity in heat-exposed sectors but they have no significant effect in non-heat exposed industries, including in hot climate countries. Some authors additionallyhighlight the presence of seasonally heterogenous pressures, such that increases in hotter months and regions reduce the growth rate of labour productivity and GDP (Colacito et al. 2019) and possibly cause larger inflationary impacts, while warmer winter temperatures are associated with lower energy prices (Kotz et al. 2024). Reduction in total factor productivity via disrupting technology, financing conditions, and supply chains (Letta and Tol 2019, NGFS 2024) or damages and faster depreciation of capital assets (Bakkensen and Barrage 2018) have also been documented.

In all these cases, higher costs of production in the affected sectors are transmitted downstream as higher end-user and wholesale prices. There is a growing body of literature that highlights the role of production networks in the shock transmission mechanism: shocks that hit sectors or firms in the early stages of the supply chain propagate to the rest of the economy through input-output linkages leading to “cascade effects” and aggregate changes.[[4]](#footnote-5) The international and intersectoral propagation of weather shocks has been assessed empirically **but only in terms of output and productivity**. De Winne and Peersman (2018) warn that harvest-induced spikes to agricultural commodity prices depress economic activity, including in high-income countries. Zappalá (2024) uses the input-output framework to examine the productivity shock transmission across sectors and shows that, although agriculture is harmed the most and earlier, downstream sectors – even if foreign - suffer from substantial and persistent losses because of network effects.

The price transmission mechanism occurs along similar lines, with changes in input prices – such as in agriculture and electricity - percolating downstream. In contrast to production, in the inflation diffusion network the central nodes are the upstream industries that by supplying intermediate inputs to others, lead to pipeline pressures and cost pass-through. In the euro area, Peersman (2022) estimates that shifts in international food prices between 1961 and 2016, caused by harvest shocks, explain 30% of euro-area inflation volatility. Also, Ciccarelli et al (2023) document that temperature increases raise EU inflation in food and services, possibly due to higher sensitivity of services, such as health and tourism, to food or weather. Di Giovanni et al. (2022) reveals that the Euro Area post-pandemic inflation was amplified by production networks. Moreover, the mechanism is **asymmetric** because prices increase more rapidly and sizably than they decrease.

The price propagation will be stronger if it originates in "salient" commodities or primary goods, whose inelastic demand and supply make their price more volatile. Depending on the inputs’ elasticity of substitution, the reallocation of expenditure can mitigate the ripple effect of the production cost shock. Otherwise, input price increases are passed on to consumers as cost-push inflation.[[5]](#footnote-6)

Weber and Wasner (2023) posit that in advanced economies firms with big **market power** have contributed to recent inflation by amplifying the initial supply disruptions in essential sectors, such as food and energy: in other words, the initial cost-push dimension of the price rise unleashes a structural – or conflict - inflation component.

Even if weather events are temporary, a sequence of severe compound shocks can generate durable implications that affect medium-run inflation, expectations, wages ("second-round effects"), and the conduct of monetary policy (Reis and Watson 2010, BIS 2022). For example, more frequent climate shocks will make it more difficult to disentangle permanent from transitory shocks (NGFS, 2021). According to Mukhejee and Ouattara (2021), in developing countries price effects persist several years after the initial shock due, for instance, to poor integration into global markets and weak import substitution effects.

**Climate-induced demand shocks.** Beyond driving cost-push inflation up, acute physical hazards can also shift household preferences and human needs, and by extension demand patterns. For example, the higher demand for energy for cooling and warming can increase its price, as well as the chances of power shortages (Mukherjee and Ouattara 2021). Consumption shifts towards disaster-related goods can push sectoral prices up – especially in the presence of structural rigidities in the shrinking sectors. Furthermore, Ferrante et al (2023) note that the post-pandemic inflationary effects of the consumption reallocation from services to goods were amplified by the heterogeneous price rigidities across sectors: industries that produce goods have more flexible prices than those that produce services and so the reduction in service supply was accompanied by only modest declines in prices. Thus, another important question is whether climate change spurs demand in sectors with relatively more flexible prices than shrinking sectors.

Another way climate change affects demand is through Keynesian supply shocks: when extreme weather depresses economic activity, declining real disposable incomes, wealth, and confidence might also cause a fall in demand and consequently prices for non-tradable sectors (Kamber et al 2013). In a cross-country analysis of 48 advanced and emerging economies, Faccia et al. (2021) find that upward temperature anomalies have a swift upward effect which turns insignificant or even negative in the medium term, possibly due to the negative demand effect. Distinguishing by type and intensity of climate shocks, Kabundi et al (2022) find that, while droughts tend to push inflation up because of rising food prices, floods curb demand and so inflation. The second-round deflationary effect of Keynesian-type supply shocks depends not only on the size of the initial negative impact on output but also on the income and wealth elasticity of demand. Particularly in developing countries where food constitutes the largest share of the consumer basket, higher food prices reduce the money available for other items, stifling broader consumer spending.

* 1. **A conceptual map**

Figure 1 summarises the price spillovers that follow a weather shock (i.e., deviation of temperature from its historical mean). The upper diagram shows the case of a weather shock hitting the end of the supply chain (i.e., downstream). The shock can either shift consumer preferences away from the focal sector with deflationary but localised effects (resulting in *Effect A*) or push sectoral inflation up through higher demand or production costs (*Effect B*) – in the case of essential or substitute goods with increased post-disaster demand. Regardless of whether the shock alters demand- or supply-side forces, it will affect the price in the focal sector directly but will not propagate up the supply chain (from customers to suppliers).[[6]](#footnote-7) For example, if an extreme weather event depresses tourism, lower prices in the hospitality sector shall not affect the price of its suppliers (i.e. food or construction industry).

The lower diagram represents the transmission mechanism of a weather shock hitting an upstream sector (i.e., energy or agriculture). A physical hazard is not expected to decrease demand for primary goods – so the negative demand effect is not contemplated in this case. Yet, an upstream weather shock can translate into inflation via either higher demand or higher production costs in the focal sector. In both cases, the aggregate price effect results from two channels of transmission: a direct channel, whereby the weather shock changes the price in the focal sector directly through sector-specific supply or demand forces (*Effect C*), and one indirect channel, whereby the price change travels downstream to any other sector that purchases inputs from the focal sector (*Effect D*: network weather shock). The cross-sector sum of these effects will result into aggregate inflation. At this point, the adverse supply shock can travel further via a Keynesian-type propagation that depresses demand, with subsequent deflationary effects (*Effect E*)

**Figure 1**. Flow chart of price propagation from weather shocks

A close-up of a white background

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A diagram of a diagram

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Given the complex interplay of upward and downward forces on prices, the overall reaction of inflation to weather shocks depends on which countervailing dynamic dominates the sum of the marginal effects. If the shock hits sectors downstream only, the aggregate effect on inflation (A + B) will not be clear a priori, although it is expected to remain confined to the focal sectors. If the shock hits the upstream supply chain, then the aggregate effect (C + D) is most likely inflationary and could turn deflationary with a lag and under certain conditions. Moreover, “a negligible or null effect of local weather shocks on a given sector may be amplified or mitigated by weather shocks hitting other sectors with strong commercial interlinkages” (Zappalá 2024, p. 15). Climate change is therefore highly sectoral by nature. If our understanding is correct, we expect to observe one or several of the five patterns described in the table below.

**Table 1.** The price effect of weather shocks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Aggregate effect | Shock type | Disaggregated effect | Observed effects | Interpretation |
| Inflationary | Demand-pull inflation | B > A |  | Increased demand in one or multiple downstream sectors (D1), due to shift in preferences, implies opposite effects coexist.  If the positive effect dominates, core inflation rises too. |
| Traditional supply shock | B |  | Decreased productivity in one or multiple downstream sectors in push prices up.  If the shock hits multiple sectors, it can give rise to core inflation. |
| Cost-push inflation | C + D |  | Higher prices in salient commodities percolate downstream through direct and network effects.  Headline inflation rises. |
| Deflationary | Negative demand shock | A > B |  | Decreased demand in one or multiple downstream sectors (D1), due to shift in preferences, implies opposite effects coexist.  If the negative effect dominates, core inflation goes down too. |
| Keynesian supply shock | E | -with a lag | The initial supply shock is followed by depressed demand (especially in downstream sector) |

1. **Data**
   1. **Prices**

We build a global dataset of monthly Consumer Price Indexes and sectoral sub-indexes sourced from Haver Analytics. We use non-seasonally adjusted data due to better coverage and we remove seasonal effects. Inflation is calculated as the annualised growth rate of price levels in the last three months relative to the previous three months,[[7]](#footnote-8) as follows:

By matching the ten CPI categories[[8]](#footnote-9) which classify consumer expenditure to the EORA taxonomy of industries (Lenzen et al. 2012, Lenzen et al. 2013), we derive sectoral retail prices – see Table 2. Our sample covers 151 countries from January 1980 to December 2023; however, to make the panel more balanced, we restrict the analysis to the period …-2023 (details on data availability per country-sector are in Table A1 in the Appendix).

**3.2 Climate data (Xolani)**

- use temperature and precipitation data from the global reanalysis ERA-5 dataset compiled by the European Centre for Medium-Range Weather Forecasts (Mu˜noz Sabater, 2019). ERA-5 is available on a 0.25×0.25 resolution grid cell, at hourly frequency, from 1950 to the present.

- To preserve as much variability as possible, transformation are computed at grid cell level and only then averaged over country using weights (Hsiang, 2016), also accounting for fractional grid cells that partially fall within a country. The last step involves summing or averaging over days within coarser time intervals.

To account for the **sector-specific weather exposure**, Zappalá (2024) weighs grid-cell data by the proportion of agricultural and non-agricultural economic activities. Hence, to measure the exposure of the agricultural sector, grid-cell data is weighted by the proportion of each grid cell under cropland using the Global Agricultural Lands dataset (Ramankutty et al., 2010). In all other sectors, such granular information is not available and so exposure is accounted by aggregating grid-cell level information weighted by population weights from the Landscan dataset (Bright and Coleman, 2001).

* I compute the annual number of days that belongs to the top/bottom pth-percentile of each grid-specific distribution over the fifty-year period (where p ∈ {1; 5; 10}). These events should be interpreted as abnormally cold and hot, or dry and wet, compared to the country-specific climatic norm and so they should implicitly account for the influence of long-run adaptation to climatic conditions

**🡪 2 weather shocks for each country: one weighted by crops (W\_agri) and one weighted by night-light (W\_non-agri)**

**3.3 Input-output data**

Intersectoral (including cross-border) trade linkages are a crucial channel identified in the inflation network. To measure them, we use Input-Output (IO) data from the Eora26 dataset (Lenzen et al. 2012, Lenzen et al. 2013), which displays info on commercial transactions at basic prices, aggregated by 26 sectors, in 189 countries from 1990 to 2023.

To analyse sectoral linkages among countries in the Eora26 dataset – specifically how much sectors purchase from each other – we use the so-called ‘transactions’ matrix, which captures intermediate demand flows between all country-sector pairs (in thousand USD). We further aggregate the data to match the sectoral CPI data, as described in Table 2. Thus, while Headline CPI inflation relates to the totality of the 26 sectors captured in the IO tables, each sectoral price index only matches one or a few sectors.

**Table 2.** Matching sectoral price and IO data

|  |  |  |
| --- | --- | --- |
|  | Price index | Eora26 |
| 1 | Headline | 1-26 |
| 2 | Energy | 7: Petroleum, Chemical and Non-Metallic Mineral Products; 13: Electricity, Gas and Water |
| 3 | Food and Beverages | 1: Agriculture; 2: Fishing; 4: Food & Beverages; |
| 4 | Clothing | 5: Textiles and Wearing Apparel |
| 5 | Housing | 14: Construction; 15: Maintenance and repair |
| 6 | Household goods | 6: Wood and paper; 9: Electrical and machinery; 11: Other manufacturing |
| 7 | Transport | 10: Transport equipment; 19: Transport |
| 8 | Health | 23: Education, Health and Other Services |
| 9 | Education | 23: Education, Health and Other Services |
| 10 | Communication | 20: Post and Telecommunications |
| 11 | Hotels | Hotels and Restaurants |

Considering about 90% of entries are small transactions (<$1M) that only account for <0.6% of total value, we filter them out to focus on the significant linkages in the global supply chain (as shares of a sector’s total inputs). Finally, we build a 5-year moving average of the IO data,[[9]](#footnote-10) a slowly time-variant measure that smooths shorter-term noise.

* Possibility that production network endogenously responds to the shock itself - Kunze (2021) shows a small and negligible shift of sectoral interlinkages after tropical cyclones.

**4. Methodology**

**4.1 Identification of network weather shocks**

In our analysis of inflation propagation, we build on the network econometrics methodology of AAK (2016) and applications by Zappalá (2024) and Das et al. (2021).

Network weather shocks are weather shocks hitting a sectordifferent from the focal sector and travelling indirectly to the latter through input purchases. Thus, each network shock can affect the focal sector to the extent of its input purchases from the affected sector. The sectoral transmission depends, therefore, on the relative importance of each supplier sector for the focal sector.

These shocks are computed multiplying the matrix of global weather shocks (as seen in Section 3.2) by the focal sector’s input purchases (from Section 3.3). For each sector *s* in every country *c*, network shocks can be either domestic *D or* foreign *F*, based on the supplier’s origin, and agri and non-agri, based on the type of input hit by the weather shock, such that:

(1)

(2)

Finally, the *total* network shock is defined as the sum of the network shocks:

**4.2 Econometric modelling.** We quantify the relative importance and persistence of the two channels of transmission of the weather shock - direct and network – on sectoral inflation by estimating a heterogeneous 3D fixed-effect model (Equation 3) and impulse response functions by local projections (Equation 4):

(3)

(4)

The dependent variable is inflation in sector *s* in country *c* and time *t*, measured as the growth rate of the price level, such that *s* = (PPI and sub-indices, CPI and sub-indices).

On the RHS, the first term is past inflation (given inflation expectations are not available at sectoral level); the coefficients are heterogeneous slopes – which are estimated jointly in a fully saturated model – representing the sector-specific *direct effect* of weather shocks on inflation and allow us to observe the differential responses by sector; in other words, if is statistically significant, then the weather shock has a direct price effect on the focal sector 𝑠 in country 𝑐 at time 𝑡.

The second term on the RHS captures the *network effect*, that is the response of sectoral inflation to the weather shock working through the global production network. In the regressions, we consider each of the three network shocks defined above, such that n = 𝐷, F, 𝑇𝑜𝑡. The relative impact that shocks originating in different parts of the network have on a sector’s inflation are given by the estimates of .

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

For example, let us consider a single country-sector specific regression, such that the focal sector *s* is ‘2: Energy’ and the country *c* is South Africa (ZAF):

where

In all periods in which a weather shock hits South Africa, it enters the equation twice:

1. As a direct weather shock to the energy sector: was weighted by night-time lights
2. As a domestic network weather shock: was weighted by night-time lights and by - which is the focal sector (2, ZAF)’s input from all other non-Agri sectors in South Africa (non-agri, ZAF).
3. is the weather shock weighted by cropland exposure and further wighted by - which is the focal sector (2, ZAF)’s input from the agri sector in South Africa (agri, ZAF).

In all periods in which a weather shock hits a foreign country, say *f* = Afghanistan (AFG) it enters the equation twice:

1. As an indirect weather shock to the foreign agri sector, is weighted by the local cropland area and by weight which is the focal sector (2, ZAF)’s input from Afghanistan’s agri sector (agri, AFG)
2. As an indirect weather shock to the foreign nonAgri sectors, is weighted by the local area population and by weight which is the focal sector (Agri.ZAF)’s input from Afghanistan’s non-Agri sectors (non-Agri.AFG).
3. Clearly, recurrence of weather shocks in different parts of the world can have a compound effect on domestic/sectoral inflation.

In order to make meaningful comparisons across those coefficients, each shock variable is divided by its own standard deviation. We include country-sector fixed effects to account for the time-invariant unobserved heterogeneity of each sector in each country, like the capacity constraints of electricity production in South Africa and the labour productivity of the manufacturing sector in China, that influence countries’ average sectoral inflation; the inclusion of spatial effects also allows us to disentangle plausibly random weather fluctuations from long-term climate, which is likely correlated with other socioeconomic characteristics. Sector-month fixed effects instead capture sector-specific time trends, such as technological innovations, or shocks, such as the 2008 financial crisis, Russia’s invasion of Ukraine, or El Niño events.

Standard errors are clustered at the country level to account for spatial correlation of the error terms across sectors in the same country over time. Finally, is the error term.

For robustness purposes, additional specifications of equation 3 and 4 will include country time trends while another version will exclude network shocks and other controls to gauge the importance of both in the estimate of direct effects.

We take non-linearity into account by using state-dependent local projections with a smooth threshold, following Auerbach and Gorodnichenko (2012). Weather deviations just below the threshold are incorporated but given lower weight, while larger anomalies are given greater weight. This method has the advantage of increasing the number of observations in the state-dependent estimate and making the results less sensitive to the choice of a fixed threshold. 🡪 see [Baleyte et al (2024](https://extranet.parisschoolofeconomics.eu/docs/monnet-eric/bbmm-temperature-shocks-cepr-dp19682.pdf))

**4.3 Extensions**

The effect of **monetary policy** can also be accounted for by dividing our sample into inflation-targeting and non-inflation-targeting countries using the information from Fratzscher and others (2020). Alternatively, the moderating effect of monetary policy on aggregate inflation can be integrated by multiplying the weather shock by the real interest rate change.

**4.4 Climateflation in South Africa**

In the last step, we repeat the above estimations by narrowing down the focus on South Africa. To this end, we adjust Equation 2 and 3, such that *c = South Africa* and Equation 5 and 6 are cross-sector panel data regressions.

(5)

(6)

To test whether sectoral **market competition/concentration** influences the extent to which weather shocks impact prices (Weber and Wasner 2023), we will extend the above by interacting the weather variable with a measure of industry concentration in South Africa, such as the Herfindahl-Hirschman Index, or sectoral profits-to-GVA.

**6. Conclusions**

- Inform MP

- Sectoral distribution of economic effects of climate physical risk

- Limits

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Table A1. CPI data availability by country and sector.

1. We use the COICOP price classification, that is a United Nations international reference framework for grouping household consumption expenditures on goods and services within homogeneous categories (UNSD, 1991). [↑](#footnote-ref-2)
2. If, for example, the shock hits only one of the nine provinces of South Africa, and raises food prices there, local food inflation will show up in the national food price index if the affected province’s food sector has a large enough share or if it travels to other regions through intra-national trade. If, instead, the local sector share is negligible (price-taker), local inflation is likely to disappear. [↑](#footnote-ref-3)
3. These risks are distinguished from chronic physical risks, which are associated with longer-term, gradual shifts in climate patterns. [↑](#footnote-ref-4)
4. See Long and Plosser (1983); Shea (2002); Gabaix (2011); Acemoglu et al. (2012); Di Giovanni et al. (2014); Acemoglu et al. (2016); Magerman et al. (2016); Grassi (2017); Huneeus (2018); Lim (2018); Baqaee and Farhi (2019). [↑](#footnote-ref-5)
5. If demand is perfectly elastic, producers will be forced to fully absorb the shock. On the contrary, if demand is perfectly inelastic, consumers will be forced to buy the good whatever the price is. [↑](#footnote-ref-6)
6. A few authors study demand shocks’ transmission across sectoral production and highlight specific conditions whereby upstream propagation may arise (Acemoglu et al. 2012, Arata and Miyakawa 2022). [↑](#footnote-ref-7)
7. To check robustness, we also estimate the model with month-on-month and 12-month inflation rates. [↑](#footnote-ref-8)
8. We exclude ‘Recreation’, ‘Alcohol and Tobacco’ prices as well as ‘Other’ prices due to the impossibility of properly matching these products to a particular industrial sector. [↑](#footnote-ref-9)
9. The MA uses data from the two years before and two years after (when available). [↑](#footnote-ref-10)