

Inflation in times of global warming

Xolani Sibande* Serena Merrino †

August 12, 2025

ipsum

Keywords: Climate impacts, Input-output supply chain interlinkages, Production network, Spillovers, Weather shocks, Monetary Policy **JEL Codes:**E23, E32, E52, L14, O11, Q54, R15,

*Economic Research Department, South African Reserve Bank; Email: xolani.sibande@resbank.co.za.

†Economic Research Department, South African Reserve Bank and University College London, School of Slavonic and East European Studies, United Kingdom; Email: serena.merrino@resbank.co.za

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 aggregate inflation and prompted questions on the optimal response of the monetary authorities to deviations from target (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 average inflation-targeting regimes is indeed to “look through” transitory trade-off inducing supply shocks, especially if originated in specific markets, unless their persistence threatens the stability of expectations and inflation to become entrenched (...). On these lines, although the recent inflationary episode was supposedly 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, 2023) - central banks have responded by sustaining high interest rates purportedly to slay aggregate demand. In the latest BIS annual 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. ...). As a result, “inflation is now again returning to the price stability region while economic activity and labour markets have proved resilient” (idib., p. ...). In academic circles, however, the firm adoption of a contractionary stance is 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, 2023; Weber and Wasner, 2023). Correctly identifying the origins of inflation (along with producing reliable forecasts and indicators of future expectations) is key to tailoring an appropriate policy response.

As these shocks wane and inflation comes down, the two narratives on the origins of inflation remain appropriate in the context of another, increasingly concerning, source of future uncertainty. Climate change is an accelerating process that is expected to increase the frequency and intensity of both acute physical hazards (i.e., droughts, floods, wildfires, heatwaves, etc.)

and chronic deviations of meteorological variables from historical means (i.e., rising averages in temperature and precipitation) (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 the longer-run changes in climatic trends which influence the optimal monetary policy and r^* (Mukherjee and Ouattara, 2021), 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-induced inflationary pressures in the same old way — by vigorous monetary tightening.

This paper aims to contribute to this discussion by providing new evidence on the effect of acute climatic events on inflation employing a global panel dataset of monthly country-sector inflation from 2000 to 2023. We add to existing studies in several ways. First, we zoom in on 12 Consumer Price sub-indexes and 6 PPI sub-categories to disentangle the idiosyncratic nature (sectoral, cost-push vs demand-pull) of the impact of acute physical hazards (i.e., deviations in rainfall, temperature, and dryness).¹ Secondly, we acknowledge the importance of the production network in the propagation of price spillovers and aggregate inflation dynamics. 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 Zappala (2024), to develop an input-output framework that factors in the indirect price spillover effects of weather shocks. In addition, we follow current developments in the scholarship on inflation determinants by accounting for possible moderating and mediating factors, such as the role of sectoral

¹We 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).

competition in the price setting mechanism ([Weber and Wasner, 2023](#)) and the monetary policy stance.

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, such as the underlying nature of aggregate inflation, 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 localised effects of changing weather conditions but, even so, the sectoral dimension should be sufficiently sensible.²

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

²If, 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.

on prices. In particular, we focus here on a wide range of acute severe climatic events. 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.

2 Climateflation: A literature review

The past few years have witnessed growing efforts of the research community towards the empirical assessment of the socio-economic effects of climate change. Although the causal relation between climate and prices remains understudied, existing empirical works find that the response of aggregate inflation to climate change is varied. [Parker \(2018\)](#) and [Cevik and Jalles \(2023\)](#) highlight the importance of the type of climate-induced natural disaster, the country’s level of development and fiscal space in determining the direction and size of the inflation effect whereas, focusing at the effects of temperature deviations, [Mukherjee and Ouattara \(2021\)](#) and [Kotz et al. \(2024\)](#) document rising and persistent inflation, especially in lower-income countries.

Along with the diversity of climate-induced shocks, also the channels of price transmission are multiple and convoluted: for example, shocks can hit the supply or demand-side of the economy, directly or indirectly, they can be physical or non-physical, sudden or progressive, and they can travel upstream or downstream the economic system. This mix of possibilities means “no two physical hazard events have the same macroeconomic effects“ (NGFS 2024, p. 9) and that different weather shocks will likely hit different segments of the economy, often unevenly, causing volatility both in nominal and relative prices ([Buelens, 2024](#)). We attempt to conceptualise the mechanisms behind climateflation here. Climate-induced supply shocks. On the supply side, the climate influences some of the characteristics and effective availability of productive factors – such as impoverishment of natural resources, a more rapid depreciation of capital endowments, or reduction in labour - and total factor productivity, that encapsulates the role of technology, financing conditions, infrastructure, supply chain disruptions, etc. (NGFS, 2024).

Sectors characterised by an inherent exposure to weather-based risk are particularly sensitive

to the direct effect of local weather shocks. In farming, for example, changes in weather conditions impact negatively on agricultural productivity through workers' heat stress (De Lima et al., 2021), environmental degradation affecting crops and animal breeding (Liang et al., 2017) or increased use of pesticides and overall production costs (Savage 2024). Many authors have focused on the climate-food prices relationship. 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 strongest 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.

As the climate warms, disruptions in the water cycle are likely to hit water-intensive sectors, including not only agriculture but also electricity, manufacturing, and waterway transport (Buelens, 2024). Also, the higher demand for energy for cooling and warming, as climate becomes extreme, will increase its price as well as the chances of power disruptions (Mukherjee and Ouattara, 2021). An additional direct impact is observed in the NGFS (2023)'s report and relates to damages inflicted on ecosystems resulting in the loss of services, such as touristic, from these systems.

Direct adverse effects on productivity can also emerge due to reduced number of working hours or to presenteeism, due to heat stress and impaired health conditions among others (Graff Zivin et al. 2018, ILO 2019, Nath 2020, Pinna Pintor et al. 2024). Lower labour productivity can result in non-agricultural sectors too, particularly in presence of outdoor work (e.g. construction, tourism), but also in indoor settings (e.g. factories or offices) (ILO 2019). 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 additionally highlight the presence of seasonally heterogeneous 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 (Kotz et al., 2024), while warmer winter temperatures are associated with lower energy prices. Reduction in total factor productivity (Letta and Tol, 2019), 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 economic networks, where shocks that hit sectors or firms propagate through input-output linkages leading to large aggregate effects.³ [Acemoglu et al. \(2012\)](#) show that in the presence of intersectoral input–output linkages, microeconomic idiosyncratic shocks may lead to “cascade effects” whereby productivity shocks to a sector located in the early stages of the supply chain propagate not only to its immediate downstream customers, but also to the rest of the economy. [De Winne and Peersman \(2018\)](#) find that adverse weather impacts on agricultural production and food commodity prices can depress economic activity worldwide, including in high-income countries. [Zappala \(2024\)](#) 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 as a result of network effects.

The price transmission mechanism occurs along similar lines: upstream price changes – such as in agriculture and electricity - percolate downstream: “The producer price of an industry depends on both the prices/volume of its input suppliers and sector-specific productivity shocks. (...) Price shocks in the machinery industry affects the price of motor vehicles because of the production network coefficient.” ([Bilgin 2022](#), p. 14) Moreover, the mechanism is asymmetric because downstream prices adjust downward more rapidly than they would do upward, and at a lower passthrough rate. 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 cost pass-through. The latter will be stronger if it originates in “salient” commodities (e.g. oil, food). 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

³See 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); Huneus (2018); Lim (2018); Baqaee and Farhi (2019).

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) reveal that Euro Area inflation amplified through production networks after the pandemic. Depending on the elasticity of substitution between inputs, the reallocation of expenditure can mitigate the ripple effect of the production cost shock. If however demand remains stable, input price increases are otherwise passed on to consumers as cost-push inflation.⁴ 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.

Overall, relative price adjustments that pass through to broad-based inflation (“first-round effects”) can generate durable implications for medium-run inflation, expectations, wages (“second-round effects”), and the conduct of monetary policy [Reis and Watson (2010); BIS 2022]. At the same time, as noted by NGFS (2021), more frequent climate shocks will make it more difficult to disentangle permanent from transitory shocks. Moreover, food inflation is often perceived by households as a signal of future inflation, which will be then embedded in their expectation formation. All these factors induce central banks to intervene. According to Mukherjee and Ouattara (2021), in developing countries, price effects persist several years after the initial shock. The reasons can be multiple: first, poor integration into global markets implies weak import substitution effects (i.e., a failed local harvest is not easily substituted with food imports) and, secondly, food prices in developing countries depend on weather more than in advanced countries where the relative contribution of wages, physical capital, energy, and transport costs is substantially higher.

Climate-induced demand shocks. Beyond driving cost-push inflation up, the climate can also shift household preferences and human needs (e.g. cooling or warming) and by extension demand patterns. For example, depressed economic activity (i.e., declining income, wealth, and confidence) might cause falling prices for non-tradable sectors (Kamber et al., 2013). 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.

⁴If 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.

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 lower demand. 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. In the aftermath of a weather shock, consumption patterns may adapt in ways that prompt relative price fluctuations among sectors, such as from hospitality and travel to technology. Explained in Figure 1.

In contrast to the spillover effects of supply-side shocks, demand shocks do not give rise to price transmission from customers to suppliers despite the presence of sectoral interlinkages: for example, if as a result of a weather shock consumers' demand for hospitality falls, this will likely affect the price of the focal sector (i.e., hospitality sector) without altering the price of its suppliers (i.e. food or construction industry).⁵

Furthermore, Ferrante et al (2023) note that the post-pandemic inflationary effects of the demand reallocation from services to goods were amplified by the sectoral heterogeneity in price rigidity: industries that produce goods have more flexible prices than those that produce services and so service-producing sectors reduce production swiftly, with only modest declines in prices. Thus, another important question to understand the origins of aggregate inflation is whether climate change spurs demand in sectors with relatively more flexible prices than shrinking sectors.

In summary, a weather shock translates into idiosyncratic inflation via three channels: (i) on the demand-side, the price effect is ambiguous and depends on the sector-specific demand response to the weather shock; on the supply-side, (ii) a sector-specific weather shock changes the price in that sector directly and, lastly, (iii) by affecting the price of any other sector that supply inputs to the focal sector, it travels downstream (network weather shock). The cross-sector sum of these effects will result into aggregate inflation.

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 ([Parker](#),

⁵A 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).

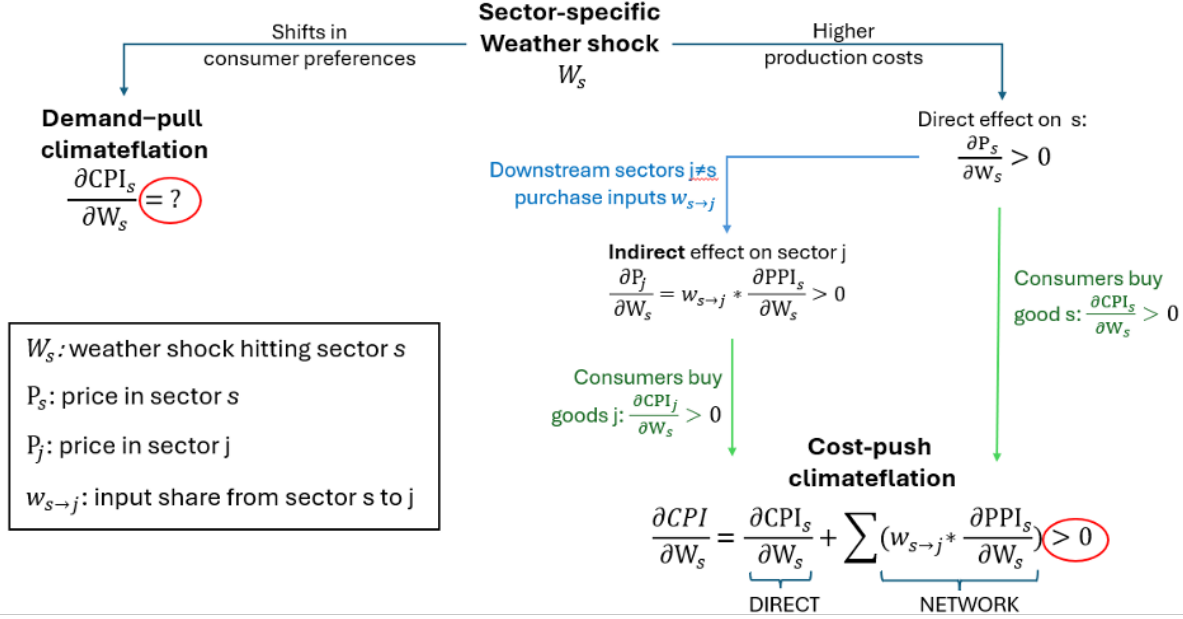


Figure 1: Flow chart of price propagation from weather shocks

2018). 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 inter linkages” (Zappala, 2024). Climate change is therefore highly sectoral by nature.

3 Data

3.1 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. By matching the 12 CPI categories which classify consumer expenditure to the standard taxonomy of industrial sectors (UN 2008), we derive sectoral retail prices – see Table 1.⁶ 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 2000-2023 (details on

⁶We exclude ‘Alcohol and Tobacco’ prices as well as ‘Other’ prices due to the impossibility of properly matching these products to a particular industrial sector.

data availability per country-sector are in Table A1 in the Appendix).

Table 1: Matching price categories to industrial sectors

No.	CPI category	Industry Classification
1	Headline	All economic activities
2	Energy	Electricity, gas, steam and air conditioning supply
3	Food and Beverages	Agriculture, forestry and fishing
4	Clothing	Manufacturing
5	Housing	Real estate activities
6	Household goods	Manufacturing
7	Transport	Transportation and storage
8	Health	Human health and social work activities
9	Recreation	Arts, entertainment and recreation
10	Education	Education
11	Communication	Information and communication
12	Hotels	Accommodation and food service activities

3.2 Weather shocks

To account for the sector-specific exposure to weather shocks, [Zappala \(2024\)](#) 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).

3.3 Input-output linkages

4 Methodology

We build on the network econometrics methodology of [Acemoglu et al. \(2016\)](#), who develop an empirical framework to study the impact of various types of domestic shocks, and the applications by [Zappala \(2024\)](#) and [Das et al. \(2021\)](#).

4.1 Identification of climate-induced network shocks.

In our analysis of inflation propagation, network shocks are computed from the interaction of the vector of weather shocks hitting a specific sector in the global production network and a vector of downstream weights reflecting the focal sector's input purchases from other sectors j . Hence, these network shocks can be domestic ($W_{s,c,t}^D$) and foreign ($W_{s,c,t}^F$) based on the supplier's origin with respect to the focal sector and they will only propagate downstream.

$$W_{s,c,t}^D = \sum_{j \neq s} w_{sc,jc,t}^D W_{s,c,t}, \text{ where } w_{sc,jc,t}^D = \frac{\text{input}_{jc \rightarrow sc,t}}{\text{totalinput}_{all \rightarrow s,t}}, \text{ and} \quad (1)$$

$$W_{s,c,t}^F = \sum_j \sum_{k \neq c} w_{sc,jk,t}^F W_{k,t}, \text{ where } w_{sc,jk,t}^F = \frac{\text{input}_{jc \rightarrow sk,t}}{\text{totalinput}_{all \rightarrow s,t}}. \quad (2)$$

$w_{sc,jc,t}^D$ and $w_{sc,jk,t}^F$ are coefficients of the Leontief matrix, defined as the input share going from sector j in country c or k (depending on whether the weather shock is foreign or domestic) to the focal sector s in country c at time t . 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.

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

$$W_{s,c,t}^{Tot} = W_{s,c,t}^D + W_{s,c,t}^F \quad (3)$$

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 4) and impulse response functions by local projections (Equation 5):

$$\pi_{s,c,t} = \alpha \pi_{s,c,t-1} + \beta_S W_{s,c,t} + \sum_n \beta_n W_{s,c,t}^n + \Gamma_{s,c} + \gamma_{s,t} + \epsilon_{s,c,t} \quad (4)$$

$$\pi_{s,c,t+h} = \beta_s^h W_{s,c,t} + \sum_n \beta_n^h W_{s,c,t}^n + \Gamma_{s,c} + \gamma_{s,t+h} + \epsilon_{s,c,t+h} \quad (5)$$

The dependent variable $\pi_{s,c,t}$ is inflation in product category (or sector) s in country c and time t , measured as the growth rate of the price level, such that $s = (\text{PPI and sub-indices, CPI and sub-indices})$.

On the right side, the first term $\pi_{s,c,t-1}$ is past inflation (given inflation expectations are not available at sectoral level); the variable $W_{c,t}$ measures the weather shock hitting country c at time t , while the β_s 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 β_s is statistically significant, then the weather shock $W_{c,t}$ has a direct price effect on the focal sector s in country c at time t .

The second term on the right side captures the spillover or 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 β_j . In order to make meaningful comparisons across those coefficients, each shock variable W_t^j 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 socio economic 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, $\epsilon_{s,c,t}$ is the error term. For

robustness purposes, additional specifications of Equation 4 and Equation 5 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 .

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 et al. (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 4 and Equation 5, such that $c = \textit{SouthAfrica}$ and Equation 6 and Equation 7 are cross-sector panel data regressions.

$$\pi_{s,t} = \beta_s W_t + \sum_{j \neq s} \beta_j W_{s,t}^j + \Gamma_s + \gamma_{s,t} + \epsilon_{s,t} \quad (6)$$

$$\pi_{s,t+h} = \beta_s^h W_t + \sum_{j \neq s} \beta_j^h W_{s,t}^j + \Gamma_s + \gamma_{s,t+h} + \epsilon_{s,t+h} \quad (7)$$

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.

5 Results

6 Conclusion

References

- Acemoglu, D., Akcigit, U., and Kerr, W. (2016). Networks and the Macroeconomy: An Empirical Exploration. *NBER Macroeconomics Annual*, 30(1):273–335.
- Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The Network Origins of Aggregate Fluctuations. *Econometrica*, 80(5):1977–2016.
- Bakkensen, L. and Barrage, L. (2018). Climate shocks, cyclones, and economic growth: Bridging the micro-macro gap. Technical report, National Bureau of Economic Research.
- Buelens, C. (2024). Climate change and its implications for prices and inflation. *Quarterly Report on the Euro Area (QREA)*, 23(1):23–40.
- Cevik, M. S. and Jalles, J. T. (2023). *Eye of the Storm: The Impact of Climate Shocks on Inflation and Growth*. International Monetary Fund.
- Ciccarelli, M., Kuik, F., and Hernández, C. M. (2023). The asymmetric effects of weather shocks on euro area inflation.
- Colacito, R., Hoffmann, B., and Phan, T. (2019). Temperature and Growth: A Panel Analysis of the United States. *Journal of Money, Credit and Banking*, 51(2-3):313–368.
- Das, M. S., Magistretti, G., Pugacheva, E., and Wingender, M. P. (2021). *Sectoral Shocks and Spillovers: An Application to COVID-19*. International Monetary Fund.
- De Lima, C. Z., Buzan, J. R., Moore, F. C., Baldos, U. L. C., Huber, M., and Hertel, T. W. (2021). Heat stress on agricultural workers exacerbates crop impacts of climate change. *Environmental Research Letters*, 16(4):044020.
- De Winne, J. and Peersman, G. (2018). Agricultural price shocks and business cycles-a global warning for advanced economies. Technical report, CESifo Working Paper.
- Faccia, D., Parker, M., and Stracca, L. (2021). Feeling the heat: Extreme temperatures and price stability.

- Kabundi, A., Mlachila, M., and Yao, J. (2022). How persistent are climate-related price shocks? implications for monetary policy.
- Kamber, G., McDonald, C., and Price, G. (2013). Drying out: Investigating the economic effects of drought in New Zealand. Technical report, Reserve Bank of New Zealand Wellington.
- Klomp, J. (2020). Do natural disasters affect monetary policy? A quasi-experiment of earthquakes. *Journal of Macroeconomics*, 64:103164.
- Kotz, M., Kuik, F., Lis, E., and Nickel, C. (2024). Global warming and heat extremes to enhance inflationary pressures. *Communications Earth & Environment*, 5(1):116.
- Letta, M. and Tol, R. S. J. (2019). Weather, Climate and Total Factor Productivity. *Environmental and Resource Economics*, 73(1):283–305.
- Liang, X.-Z., Wu, Y., Chambers, R. G., Schmoldt, D. L., Gao, W., Liu, C., Liu, Y.-A., Sun, C., and Kennedy, J. A. (2017). Determining climate effects on US total agricultural productivity. *Proceedings of the National Academy of Sciences*, 114(12).
- Mukherjee, K. and Ouattara, B. (2021). Climate and monetary policy: Do temperature shocks lead to inflationary pressures? *Climatic Change*, 167(3-4):32.
- Parker, M. (2018). The Impact of Disasters on Inflation. *Economics of Disasters and Climate Change*, 2(1):21–48.
- Peersman, G. (2022). International food commodity prices and missing (dis) inflation in the euro area. *Review of Economics and Statistics*, 104(1):85–100.
- Ramankutty, N., Heller, E., and Rhemtulla, J. (2010). Prevailing Myths About Agricultural Abandonment and Forest Regrowth in the United States. *Annals of the Association of American Geographers*, 100(3):502–512.
- Reis, R. and Watson, M. W. (2010). Relative goods’ prices, pure inflation, and the Phillips correlation. *American Economic Journal: Macroeconomics*, 2(3):128–157.

- Schnabel, I. (2022). Monetary policy and the great volatility. In *Speech by Isabel Schnabel, Member of the Executive Board of the ECB, at the Jackson Hole Economic Policy Symposium Organised by the Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming*, volume 27.
- Stiglitz, J. E. and Regmi, I. (2023). The causes of and responses to today's inflation. *Industrial and Corporate Change*, 32(2):336–385.
- Weber, I. M. and Wasner, E. (2023). Sellers' inflation, profits and conflict: Why can large firms hike prices in an emergency? *Review of Keynesian Economics*, 11(2):183–213.
- Zappala, G. (2024). Estimating sectoral climate impacts in a global production network. Technical report, mimeo.

A Appendix

A.1 Inflation rates

Table A1: Summary statistics of sectoral inflation rates (%)

Sector	Mean	Standard Deviation	Minimum	Maximum	Observations
	4.62	7.85	-30.83	155.93	25,609
	4.77	11.61	-56.81	439.44	19,946
	1.92	15.65	-93.80	439.44	21,127
	0.28	12.51	-205.33	479.26	17,937
	4.64	11.59	-181.37	399.72	20,058
	4.15	32.25	-1,076.50	1,433.41	11,115
	3.83	8.14	-146.81	157.37	20,843
	4.96	9.05	-71.98	439.44	14,756
	3.01	8.16	-45.61	439.44	17,187
	4.46	10.41	-69.62	439.44	20,347
	3.70	11.24	-92.64	166.83	19,856

A.2 Countries and month-sectors in sample

Table A2: Countries and month-sectors in the sample

Country	Number of month-sectors
Albania	1,621
Algeria	604
Angola	287
Argentina	125
Armenia	483
Aruba	127
Austria	2,086
Azerbaijan	200
Bahrain	1,181
Bangladesh	216
Belarus	448
Belgium	2,160
Belize	780
Benin	2,160
Bhutan	560
Bolivia	1,233
Botswana	1,593
Brazil	1,944
Brunei	910
Bulgaria	2,376
Burkina Faso	1,728
Cambodia	1,640
Cameroon	737
Canada	1,728
Chad	790
Chile	2,215
China	1,528
Colombia	1,728
Congo - Kinshasa	320
Costa Rica	1,944
Croatia	2,160
Cyprus	1,606
Czechia	2,376
Côte d'Ivoire	2,160
Denmark	1,808
Dominican Republic	2,239
Ecuador	2,258
Egypt	1,331
El Salvador	1,143
Equatorial Guinea	202
Estonia	2,160
Ethiopia	680
Fiji	1,251
Finland	1,879
France	2,376
Georgia	1,856
Germany	2,376
Ghana	2,119
Greece	1,939
Guatemala	1,644
Guinea-Bissau	1,804
Honduras	1,692
Hong Kong SAR China	1,296
Hungary	848
Iceland	2,115
India	558
Indonesia	950
Iran	760
Iraq	310
Ireland	2,376
Israel	1,944
Italy	2,359
Jamaica	2,115
Japan	1,512

Country	Number of month-sectors
Jordan	1,991
Kenya	1,134
Kuwait	704
Kyrgyzstan	1,750
Laos	1,030
Latvia	2,376
Lebanon	1,204
Lesotho	1,068
Lithuania	2,376
Luxembourg	2,376
Macao SAR China	1,825
Malaysia	1,791
Maldives	1,798
Mali	1,814
Malta	1,056
Mauritius	1,726
Mexico	2,026
Moldova	495
Mongolia	1,390
Montenegro	1,144
Morocco	1,030
Mozambique	298
Myanmar (Burma)	550
Namibia	2,067
Nepal	440
Netherlands	1,944
Nicaragua	920
Niger	2,160
Nigeria	2,082
North Macedonia	2,000
Norway	2,376
Oman	1,990
Pakistan	1,281
Palestinian Territories	1,575
Panama	1,125
Paraguay	2,160
Peru	1,512
Philippines	2,160
Poland	1,920
Portugal	2,376
Qatar	472
Romania	1,480
Russia	1,331
Rwanda	1,020
Samoa	927
Saudi Arabia	1,216
Senegal	1,951
Serbia	1,397
Seychelles	1,270
Singapore	1,944
Slovakia	2,091
Slovenia	2,371
South Africa	2,014
South Korea	2,376
Spain	2,347
Sri Lanka	387
Sudan	183
Suriname	251
Sweden	1,728
Switzerland	1,728
Taiwan	1,512
Tajikistan	211
Tanzania	880
Thailand	1,484
Timor-Leste	504
Togo	2,160
Trinidad & Tobago	2,037
Tunisia	1,654
Uganda	1,235
Ukraine	2,205

Country	Number of month-sectors
United Arab Emirates	1,150
United Kingdom	2,376
United States	1,512
Uruguay	2,160
Uzbekistan	40
Venezuela	32
Vietnam	1,403
Zambia	1,035

A.3 Climate shocks

Table A3: Summary statistics of climate shocks

Variable	Mean	Standard Deviation	Minimum	Maximum	Observations
Precipitation (mm)					
Land-weighted precipitation (deviation from mean)	0.45	73.38	-400.59	1,066.71	75,936
Population-weighted precipitation (deviation from mean)	0.51	74.11	-405.46	1,113.97	75,936
Land-weighted precipitation shock (90th percentile)	95.74	82.17	-114.82	1,066.71	12,658
Land-weighted precipitation shock (10th percentile)	-64.12	46.59	-400.59	62.42	12,873
Population-weighted precipitation shock (90th percentile)	95.81	83.89	-87.73	1,113.97	12,659
Population-weighted precipitation shock (10th percentile)	-64.52	47.83	-405.46	40.40	12,869
Land-weighted precipitation shock (95th percentile)	116.13	92.51	-11.72	1,066.71	6,329
Land-weighted precipitation shock (5th percentile)	-66.63	48.00	-400.59	36.35	6,732
Population-weighted precipitation shock (95th percentile)	116.11	94.23	-11.63	1,113.97	6,330
Population-weighted precipitation shock (5th percentile)	-67.20	49.38	-405.46	40.40	6,712
Land-weighted precipitation shock (99th percentile)	116.13	92.51	-11.72	1,066.71	6,329
Land-weighted precipitation shock (1st percentile)	-66.63	48.00	-400.59	36.35	6,732
Population-weighted precipitation shock (99th percentile)	5.90	4.58	-0.18	20.56	6,376
Population-weighted precipitation shock (1st percentile)	-6.03	4.84	-24.92	0.39	6,375
Temperature (°C)					
Land-weighted temperature (deviation from mean)	0.12	5.29	-26.18	21.12	75,936
Population-weighted temperature (deviation from mean)	0.12	5.18	-24.92	20.56	75,936
Land-weighted temperature shock (90th percentile)	5.72	4.46	-1.32	21.12	12,726
Land-weighted temperature shock (10th percentile)	-5.70	4.63	-26.18	2.01	12,701
Population-weighted temperature shock (90th percentile)	5.58	4.41	-1.05	20.56	12,730
Population-weighted temperature shock (10th percentile)	-5.56	4.53	-24.92	1.84	12,703
Land-weighted temperature shock (95th percentile)	6.06	4.63	-0.06	21.12	6,385
Land-weighted temperature shock (5th percentile)	-6.17	4.96	-26.18	0.16	6,373
Population-weighted temperature shock (95th percentile)	5.90	4.58	-0.18	20.56	6,376
Population-weighted temperature shock (5th percentile)	-6.03	4.84	-24.92	0.39	6,375
Land-weighted temperature shock (99th percentile)	6.06	4.63	-0.06	21.12	6,385
Land-weighted temperature shock (1st percentile)	-6.17	4.96	-26.18	0.16	6,373
Population-weighted temperature shock (99th percentile)	5.90	4.58	-0.18	20.56	6,376
Population-weighted temperature shock (1st percentile)	-6.03	4.84	-24.92	0.39	6,375

A.4 Matching sectoral price and IO data

Table A4: Matching sectoral price and Input-output data (Eora26)

Price Index	Input-output classification	Input-output Sector
Headline	1-26	All sectors
Energy	7,13	Petroleum, Chemical and Non-Metallic Mineral Products, Electricity, Gas and Water
Food and Beverages	1, 2, 4	Agriculture, Fishing, Food & Beverages
Clothing	5	Textiles and Wearing Apparel
Housing	14, 15	Construction, Maintenance and repair
Household goods	6, 9, 11	Wood and paper, Electrical and machinery, Other manufacturing
Transport	10, 19	Transport equipment, Transport
Health	23	Education, Health and Other Services
Education	23	Education, Health and Other Services
Communication	20	Post and Telecommunications
Hotels	18	Hotels and Restaurants

A.5 Stationarity tests

Table A5: Im-Pesaran-Shin unit-root test for main variables

variable	Statistic	p-value
Inflation rate	-148.56	0.00
Abnormally cold temperature shock (1st percentile)	-94.17	0.00
Abnormally hot temperature shock (99th percentile)	-36.49	0.00
Abnormally cold temperature shock (5th percentile)	-94.17	0.00
Abnormally hot temperature shock (95th percentile)	-36.49	0.00
Abnormally cold temperature shock (10th percentile)	-91.95	0.00
Abnormally hot temperature shock (90th percentile)	-69.64	0.00
Abnormally dry precipitation shock (1st percentile)	-173.14	0.00
Abnormally wet precipitation shock (99th percentile)	-61.01	0.00
Abnormally dry precipitation shock (5th percentile)	-173.14	0.00
Abnormally wet precipitation shock (95th percentile)	-61.01	0.00
Abnormally dry precipitation shock (10th percentile)	-174.51	0.00
Abnormally wet precipitation shock (90th percentile)	-87.69	0.00