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Abstract

We study how precipitation has affected food consumer price inflation (CPI), using dynamic panel estimation of food CPI Phillips curves across countries for 34 OECD member and candidate economies from 1985 to 2010 augmented with climate variables. We allow for nonlinear effects of precipitation on food CPI inflation, and also control for possible nonlinear effects of temperature. We find that precipitation has significant nonlinear effects on food CPI inflation. The coefficient of food CPI inflation on the linear precipitation term is significantly negative, and the coefficient on the quadratic precipitation term is significantly positive. Consequently, food CPI inflation increases as precipitation becomes very low and very high. Moreover, we find that temperature has no additional explanatory power for food CPI inflation over and above that of precipitation. We control for the effects of inflation expectations, the output gap and exchange rate changes on food CPI inflation, which are significant with the expected signs.

JEL-Codes: E310, E520, E580, Q480, Q580.

Keywords: climate change, precipitation, temperature, inflation, food prices.

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1. Introduction

We study how precipitation has affected food consumer price inflation (CPI) ex-post, via dynamic panel estimation of food CPI Phillips curves across countries for 34 OECD member and candidate economies from 1985 to 2010 augmented with climate variables. We allow for nonlinear effects of precipitation on food CPI inflation, and also control for the effects of temperature. We also control for the effects of the ouput gap, exchange rate changes and inflation expectations on food CPI inflation.

Changes in global precipitation are among the most important and least well-understood consequences of climate change, with increasing greenhouse gas emissions thought to affect the zonal-mean distribution of precipitation (Marvel and Bonfils, 2013). The main mechanisms for this are that increasing temperatures lead to an intensification of the hydrological cycle, and changes in atmospheric circulation patterns lead to poleward displacement of the storm tracks and subtropical dry zones (Marvel and Bonfils, 2013). The effects of climate change on the hydrological cycle are expected to increase the risk of heavy rainfall events and prolonged droughts (Lehmann et al., 2018). There is evidence of an intensification of daily rainfall extremes due to anthropogenic climate change (Min et al., 2011; Madakumbura et al., 2021; Fischer and Knutti, 2016; Kotz et al., 2022). The mean number of record-wet months globally has significantly increased over recent decades, broadly consistent with observed trends in mean rainfall (Lehmann et al., 2018). This is mainly due to changes in the northern middle to high latitudes, where record-wet months have occurred by up to 37% more frequently regionally. Southeast Asia has also seen more record-wet months, while Africa has seen more record-dry months (Lehmann et al., 2018). Increases in greenhouse gas emissions have contributed to the observed intensification of heavy precipitation events in around two thirds of Northern Hemisphere land areas covered by data (Min et al., 2011). Models seem to underestimate the observed increase in heavy precipitation with warming (Allan and Soden, 2008).

Recent evidence suggests that the frequency and intensity of heavy precipitation events have increased since the 1950s over most land area for which observational data are sufficient for trend analysis, and human-induced climate change is likely the main driver (International Panel on Climate Change (IPCC), 2021). Moreover, human-induced climate change has contributed to increases in agricultural and ecological droughts in some regions due to increased land evapotranspiration (IPCC, 2021).

The frequency of extreme heat events has increased with global warming, and is projected to increase further with future global warming. Extreme heat events, which occurred with a probability of 10% per year worldwide from 1850-1900, were already happening with a higher probability of 28% recently, and are projected to happen with still larger probabilities of 41%, 56% and 94% under global warming scenarios of 1.5°C, 2°C and 4°C above pre-industrial temperatures, respectively.[1] Human influence has likely increased the probability of increases in the frequency of concurrent heatwaves and droughts on the global scale since the 1950s (IPCC, 2021). Adverse climate events due to global warming, including more severe floods and droughts, can lead to large economic costs and disruptions (OECD, 2015).

Climate change is likely to affect inflation and the monetary policy transmission mechanism, and is therefore relevant for monetary policy (Smets, 2020; Network for Greening the Financial System (NGFS), 2020). Central banks are increasingly incorporating climate change

[1] See International Panel on Climate Change (2021) and Banque de France (2021).

considerations into their monetary and financial stability frameworks. Following the conclusion of its monetary policy strategy review, the ECB Governing Council stated its strong commitment to further incorporating climate change considerations into its monetary policy framework (ECB, 2021). The ECB Governing Council also decided to conduct theoretical and empirical analyses on the implications of climate change and climate policies for the economy and the transmission of monetary policy (ECB, 2021). Moreover, the ECB has developed economy-wide climate stress tests of banks based on climate scenarios of the NGFS (Alogoskoufis et al., 2021).

Most of the research on the effects of climate change and climate policy on macroeconomic variables so far has focussed on the effects on growth.[2] Kotz et al. (2022) studied the effect of precipitation on economic growth allowing for nonlinearity. Kotz et al. (2022) show that economic growth rates respond nonlinearly to total annual rainfall, and are reduced by increases in the number of wet days and in extreme daily rainfall, with high-income countries most affected. They conclude that anthropogenic intensification of daily rainfall extremes will have negative global economic consequences, which require further study in order to evaluate the costs of climate change. By contrast, higher total annual rainfall can increase growth in low-income agriculturally dependent economies (Kotz et al., 2022; Damania et al., 2020; Barrios et al., 2010). Controlling for nonlinear effects of precipitation, Burke et al. (2015) showed that economic productivity is nonlinear in temperature for both developed and developing countries, with productivity peaking at an annual average temperature of 13°C and declining strongly at higher temperatures (Burke et al., 2015).

Eurosystem work stream on climate change (2021) provides an overview of the evidence on the effects of climate change on inflation.[3] Parker (2018) finds that droughts and floods tend to increase headline CPI inflation. Kamber et al. (2013) find that a drought of the magnitude of that of early 2013 in New Zealand increases food CPI prices by around 1.0-1.5%, and wholesale electricity prices by up to 8%, but has no effect on retail electricity prices. Associated depressed economic activity results in falling prices for other non-tradable sectors, so that there is no significant effect on headline CPI. Buckle et al. (2007) also found no significant effect on consumer prices from droughts in New Zealand.

Faccia et al. (2020) use temperature anomaly data to study the effects of extreme temperatures on prices. They find that hot summers, where temperatures exceed a country's long-run mean by more than 1.5°C, are associated with an increase in food prices of around 0.2pp during the same summer quarter. De Winne and Peersman (2021) find that increases in global agricultural commodity prices caused by harvest or weather disruptions in other regions of the world significantly reduce economic activity, and that the effect is stronger in advanced countries. They conclude that the consequences of climate change on advanced economies through food prices could be larger than previously thought.[4]

Our paper contributes to the literature by providing ex-post empirical analysis of the effects of precipitation on food CPI inflation allowing for nonlinear effects, for a broad sample of OECD countries, and controlling for the effects of temperature.

We choose cross-country panel estimation of Phillips curves based on Jasova et al. (2019, 2020) in order to capture inflation dynamics well. Phillips curves are the standard way to model

[2] See Dell et al. (2014) for a survey on the effects of climate change on growth.
[3] The effects of climate policy in the form of carbon pricing on inflation has been studied in Konradt and Weder di Mauro (2021), McKibbin et al. (2021), Kaenzig (2021) and Moessner (2022).
[4] De Winne and Peersman (2016) find for the United States that adverse food commodity market shocks lead to an increase in food commodity prices and food CPI inflation, as well as a persistent fall in real GDP.

inflation dynamics in modern monetary policy analysis (Clarida et al., 1999; Smets, 2003; Woodford, 2003; Levin and Moessner, 2005). This approach allows to exploit cross-country variation to avoid the difficulties of identification present for country-specific estimates, as discussed by Reichlin (2018) and Forbes (2019) in the case of the output gap. Here we apply this approach to food CPI inflation, as in Moessner (2022), to capture food CPI inflation dynamics well by controlling for the effects of the output gap, exchange rate changes and inflation expectations.

We find that precipitation has significant nonlinear effects on food CPI inflation. The coefficient of food CPI inflation on the linear precipitation term is significantly negative, and the coefficient on precipitation squared is significantly positive. Consequently, food CPI inflation increases as precipitation becomes very low and very high. Moreover, we find that temperature has no additional explanatory power for food CPI inflation over and above that of precipitation. We also find that the effects of the output gap, exchange rate changes and inflation expectations on food CPI inflation are significant with the expected signs.

The remainder of the paper is organised as follows. Section 2 summarises the data, and Section 3 presents the method and results. Finally, Section 4 concludes.

2. Data

We use data on precipitation and temperature (in °C) from the replication dataset of Burke et al. (2015), whose source is the University of Delaware dataset of Matsuura and Willmot (2012), which contains 0.5 degree gridded monthly average temperature and total precipitation data for all land areas. Burke et al. (2015) aggregate these 0.5 degree grid cell estimates to the country-year level, weighted by population density in the year 2000 using data from the Gridded Population of the World. We use this measure of population density weighted total annual precipitation in decimeters (dm) from the replication dataset of Burke et al. (2015).

Data on food consumer price indices (CPI) indices (food and non-alcoholic beverages) are based on data from the OECD, national sources and BIS calculations. Data on output gaps (as a percentage of potential GDP) are from the OECD. Global commodity prices are taken as the IMF all commodity price index. Data on professionals' survey-based CPI inflation expectations are from Consensus Economics surveys for next-year headline CPI inflation expectations. Nominal effective exchange rate indices (trade-weighted broad indices, annual averages) are from the BIS, with an increase indicating an appreciation of the domestic currency.

Our sample of countries consists of 34 economies, the OECD economies Austria, Australia, Belgium, Canada, Chile, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Hungary, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Mexico, the Netherlands, Norway, New Zealand, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland and the United States, and the OECD candidate country Bulgaria.

The sample period is from 1985 to 2010 at annual frequency.

3. Method and results

We quantify the effects of precipitation on inflation via dynamic panel regressions of Phillips curves according to

$$\pi^{f}_{it} = \rho\, \pi^{f}_{it-1} + \lambda_1\, \mathrm{prec}_{it} + \lambda_2\, \mathrm{prec}^{2}_{it} + \phi\, outputgap_{it} + \alpha_i + \beta_t + \varepsilon_{it.} \qquad (1)$$

This approach is based on Jasova et al. (2019, 2020) and Moessner (2022), using dynamic panel estimation of food CPI Phillips curves in order to capture food CPI inflation dynamics well. It is augmented with the climate variable precipitation in country i at time t, prec_{it}, in order to study its additional effects, as well as with precipitation squared, prec^{2}_{it}, to allow for nonlinearity. Phillips curves are the standard way to model inflation dynamics in modern monetary policy analysis.

In our baseline specification of equation (1) π^{f}_{it} denotes year-on-year (y/y) food CPI inflation in percent, calculated from log differences in food consumer price indices in country i at time t. Moreover, $outputgap_{it}$ denotes the output gap in country i at time t. Our baseline model includes country fixed effects, α_i, to capture unobserved heterogeneities across countries that might affect food CPI inflation. We also include annual time fixed effects, β_t, to control for the effects of global factors, such as global trends or shocks. We use fixed effect panel estimations and robust standard errors clustered at the country level.

The estimation results of equation (1) are shown in column I of Table 1. The coefficient on the output gap is significant at the 1% level with the expected sign. The coefficient on the linear precipitation term is negative and significant at the 5% level. We also find evidence of nonlinearity. The coefficient on precipitation squared is positive and also significant at the 5% level. Consequently, food CPI inflation increases as precipitation decreases to very low levels of precipitation (close to drought levels), and food CPI inflation increases as precipitation increases to very high levels of precipitation (close to flood levels).

Values of total annual precipitation for the sample used in equation (1) range from around 1.98dm to 19.09dm, with a mean precipitation level of 8.57dm. Figure 1 shows the effect of precipitation on food CPI inflation for this range of precipitation levels minus that at the mean precipitation level, in percentage points (pp) based on the coefficients of column I of Table 1. We can see that for very high precipitation levels food CPI inflation is up to around 2.6pp higher than at the mean precipitation level. For very low precipitation levels, food CPI inflation is up to around 1.8pp higher than at the mean precipitation level.

For robustness, we add inflation expectations and nominal effective exchange rate changes to equation (1), in order to capture inflation dynamics via the Phillips curve better, but at the cost of reducing the sample size due to data availability issues,

$$\pi^{f}_{it} = \theta\, \pi^{e}_{it} + \rho\, \pi^{f}_{it-1} + \lambda_1\, \mathrm{prec}_{it} + \lambda_2\, \mathrm{prec}^{2}_{it} + \phi\, outputgap_{it} + \mu\, \Delta NEER_{it} + \alpha_i + \beta_t + \varepsilon_{it.} \qquad (2)$$

Here, π^{e}_{it} denotes next-year CPI inflation expectations from Consensus Economics surveys, y/y in percent; $\Delta NEER_{it}$ is the y/y change in the nominal effective exchange rate in percent, calculated from the log change in the nominal effective exchange rate, with an increase indicating an appreciation of the domestic currency. The results of equation (2) are shown in column II of Table 1. The coefficient on the linear precipitation term remains negative, with a lower magnitude and significance level of 10%. We also continue to find evidence of nonlinearity. The coefficient on precipitation squared remains of similar magnitude and positive, at a higher significance level of 1%. Our results are therefore generally robust to including inflation expectations and nominal effective exchange rate changes. We also find that the effects of the output gap, exchange rate changes and inflation expectations on food CPI inflation are significant with the expected signs in both equations (1) and (2). The output gap, inflation expectations and exchange rate depreciations all have significant positive effects on food CPI inflation.

As a further robustness check, we replace time fixed effects by y/y changes in the global commodity price index, π_t^{com},

$$\pi_{it}^{f} = \theta\, \pi_{it}^{e} + \rho\, \pi_{it-1}^{f} + \lambda_1\, \mathrm{prec}_{it} + \lambda_2\, \mathrm{prec}_{it}^2 + \phi\, outputgap_{it} + \mu\, \Delta NEER_{it} + \eta\, \pi_t^{com} + \alpha_i + \varepsilon_{it.} \qquad (3)$$

The results of equation (3) are shown in column III of Table 1. The coefficients on the linear and quadratic precipitation terms remain very similar to those in the baseline specification (column I of Table 1). We consequently find that our results for the effects of precipitation on food CPI inflation are robust to replacing time fixed effects by global commodity price inflation.

As a further robustness check, we also control for the effect of temperature, T_{it}, and of temperature squared, T_{it}^2, in equation (1), since idiosyncratic changes in local precipitation can be correlated with changes in local annual temperatures (Aufhammer et al., 2013; Burke et al., 2015),[5]

$$\pi_{it}^{f} = \rho\, \pi_{it-1}^{f} + \lambda_1\, \mathrm{prec}_{it} + \lambda_2\, \mathrm{prec}_{it}^2 + \gamma_1\, T_{it} + \gamma_2\, T_{it}^2 + \phi\, outputgap_{it} + \alpha_i + \beta_t + \varepsilon_{it.} \qquad (4)$$

The results of equation (4) are shown in column I of Table 2. We can see that the coefficients on both the linear and quadratic temperature terms are insignificant. Consequently, temperature has no additional explanatory power over and above that of precipitation. The coefficients on the linear and quadratic precipitation terms remain very similar to those in the baseline specification shown in column I of Table 1. We therefore find that our results for the effects of precipitation on food CPI inflation are robust to also controlling for potential nonlinear temperature effects.

We similarly add linear and quadratic temperature terms to equations (2) and (3). These results are shown in columns II and III of Table 2, respectively. The coefficients on both the linear and quadratic temperature terms are again insignificant. The coefficients on the linear and quadratic precipitation terms are very similar to those shown in columns II and III of Table 1, so that our results are robust to the inclusion of temperature also for these specifications.

4 Conclusions

We study how precipitation has affected food consumer price inflation ex-post, using dynamic panel estimation of Phillips curves across countries for 34 OECD member and candidate economies from 1985 to 2010 augmented with climate variables. We allow for nonlinear effects of precipitation on food CPI inflation, and also control for possible nonlinear effects of temperature.

[5] See also IPCC (2021) who find that human influence has likely increased the chance of increases in the frequency of concurrent heatwaves and droughts on the global scale since the 1950s.

We find that precipitation has significant nonlinear effects on food CPI inflation. The coefficient of food CPI inflation on the linear precipitation term is significantly negative, and the coefficient on precipitation squared is significantly positive. Consequently, food CPI inflation increases as precipitation becomes very low (closer to drought levels) and very high (closer to flood levels). Moreover, we find that temperature has no additional explanatory power for food CPI inflation over and above that of precipitation. We also control for the effects of inflation expectations, the output gap and exchange rate changes on food CPI inflation, which are significant with the expected signs. The output gap, inflation expectations and exchange rate depreciations all have significant positive effects on food CPI inflation.

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Tables

Effects of precipitation on food CPI inflation			**Table 1**
Dep. Var.: π^{f}_{it}			
	I	II	III
π^{f}_{it-1}	0.3972***	0.1195**	0.1781***
$prec_{it}$	-0.5831**	-0.3883*	-0.4668*
$prec^{2}_{it}$	0.0297**	0.0256***	0.0291**
$outputgap_{it}$	0.1920***	0.2347***	0.4199***
π^{e}_{it}		1.0849***	1.0465***
$\Delta NEER_{it}$		-0.0984***	-0.1064***
π^{com}_{t}			-0.0002
constant	5.4682***	-0.1012	1.2512
observations	697	404	404
number of countries	34	34	34
time fixed effects	yes	yes	no
R2 within	0.429	0.658	0.439
R2 between	0.797	0.611	0.395

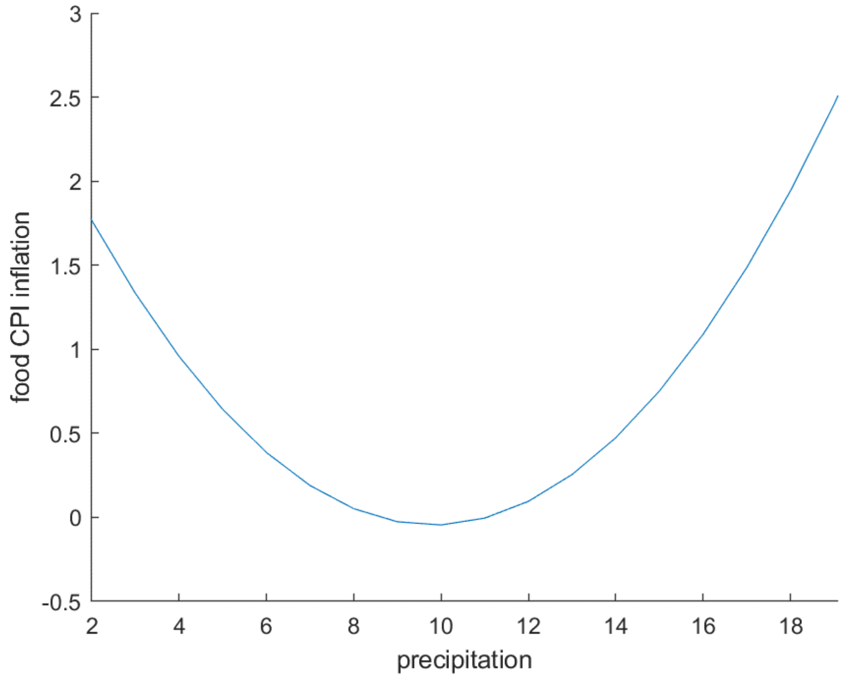
Note: Fixed effects panel estimation; sample period: 1985-2010. ***/**/* denote statistical significance at 1/5/10% confidence level. Robust standard errors clustered at the country level.

Effects of precipitation on food CPI inflation, with temperature			**Table 2**
Dep. Var.: π^{f}_{it}			
	I	II	III
π^{f}_{it-1}	0.3993***	0.1199**	0.1718***
$prec_{it}$	-0.5693**	-0.3830*	-0.4428*
$prec^{2}_{it}$	0.0285**	0.0248***	0.0272**
$temp_{it}$	0.0144	0.1509	0.0911
$temp^{2}_{it}$	0.0281	0.0037	0.0135
$outputgap_{it}$	0.1898***	0.2265***	0.3910***
π^{e}_{it}		1.0955***	1.0987***
$\Delta NEER_{it}$		-0.0989***	-0.1051***
π^{com}_{t}			0.0013
constant	2.1967	-2.2815	-1.7962
observations	697	404	404
number of countries	34	34	34
time fixed effects	yes	yes	no
R2 within	0.435	0.659	0.443
R2 between	0.379	0.482	0.248

Note: Fixed effects panel estimation; sample period: 1985-2010. ***/**/* denote statistical significance at 1/5/10% confidence level. Robust standard errors clustered at the country level.

Figures

Figure 1: Effect of precipitation on food CPI inflation minus effect at mean precipitation



Notes: Based on column I of Table 1; population density weighted total annual precipitation in decimeters (dm) from the replication dataset of Burke et al. (2015); effect on food CPI inflation in percentage points.