From Heatwaves to Cold Spells: How Extreme Temperature Events Shape Inflation in Germany

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Work in progress – Comments are wellcomed!

Motivation

> If we do not account for the impact of climate change on our economy, we risk missing a crucial part in our work to keep prices stable. – Christine Lagarde, 2022

- For centuries, thinkers theorized about how weather/climate affects human societies. $\Rightarrow$ reinforced by global warming.
- The literature has been heavily empirically focused in recent years.
- In addition, ***central banks*** are increasingly focusing on this issue, especially for inflation monitoring and forecasting (ECB (2024); Drudi et al. (2021)).
- Understanding the channels through which global warming affects prices is crucial for monetary policy.

Related Literature

- Large literature on the effects of temperatures on output.[1]
- Different concepts how to measure a temperature shock.
- Number of papers covering the effects on prices is limited: Faccia et al. (2021), Ciccarelli et al. (2023) Kotz et al. (2024) and Lucidi et al. (2024) all highlight common channels of temperatures primarily affecting food and/or energy prices.
- However, there are some disparities regarding the effects on overall inflation and the groups of countries affected.
- Many more elements of the literature investigate the effects on outcomes such as health, development, conflict, crime.[2]

⇒ Literature is all about **hot temperature extremes**!

[1] See Dell et al. (2014) for a detailed review.
[2] See Carleton and Hsiang (2016) for a review.

Climate Change is more than Hot Weather Extremes!

- Evidence shows that climate change also increases the ***risk of late spring frost*** particular in Europe and Asia.

$\Rightarrow$ One reason: A weakened or meandering jet stream

- The economic literature has so far overlooked this issue largely, despite its significant impact on agricultural production.

$\Rightarrow$ We provide a comprehensive framework discussing both, heat and cold shocks!

Research Questions

- What are the mechanisms that causally drive food and energy prices in Germany?

⇒ Possible explanations (demand vs supply side):

  - Rising food prices (because of bad agricultural conditions) lead to a rise in (food)inflation.
  - Decreasing energy demand during winter because of warm spells (declining (energy)prices).
  - Warm summer with lots of sunshine improve energy production by solar power.

- Is it sufficient to focus only on extreme hot temperatures? NO!

⇒ Need to define ***temperature shocks*** to analyze the full macroeconomic propagation.

Challenges Creating a Shock

- Both the annual German average temperature and the price index have trended upward $\Rightarrow$ complicates **identification**
- How to measure both extremes (hot and cold)?
- Isolation of the **unexpected component**:
  - Climate change (and trends) are known—agents adjust their expectations
  - Oscillations are hard to anticipate
- Many approaches rely on timely or geographically aggregated data, risking that extremes are averaged out

Our Contribution

- Novel shock identification based on high-frequency, highly granular data.
- We highlight the importance of distinguishing between heat and cold extremes.
- Application to German data, examining whether advanced countries' inflation is impacted by the weather already today (local projection).
- Behavioral New Keynesian three-sector model (appendix).

Data - Temperature

- The temperature data for Germany are taken from the ERA5 reanalysis dataset (Hersbach et al. (2020)), which integrates the simulations of the climate model with observed meteorological data to interpolate between weather stations.
- Data resolution: 0.1 ° x 0.1 ° (longitude and latitude) coordinate points + hourly frequency.
- Aggregate hourly data to daily frequency by calculating the 24h average; assign each coordinate point to the corresponding Landkreis (and Bundesland) using GADM spatial data.
- Calculate the daily average for each Landkreis, resulting in a daily time series at Landkreis level for Germany.

Economic Variables (Data)

Temperature Shock - Construction I

- Try to avoid weaknesses of typical concepts from the literature (using temperature levels, temperature anomalies, or number of extreme days).
- Relying on *static* thresholds is problematic when identifying shocks for every season.

Temperature Shock - Construction II

- We count particular hot/cold days within a month.
- Determine hot/cold days using ***rolling thresholds*** based on the daily temperature distribution for the specific month over the past 5 years. $\Rightarrow$ classify a day as hot if it exceeds the 90th percentile, or cold if below the 10th percentile.
- Monthly shock series for hot and cold extremes for each Landkreis.[3]

$$heat\_shock\_county_t^i = \sum_{d=1}^{n_t} I(T_{d,t}^i > ut_t^i) - \underbrace{N_t \times 0.1 \times 0.2}_{\text{expected number of hot days}}$$

$$cold\_shock\_county_t^i = \sum_{d=1}^{n_t} I(T_{d,t}^i < lt_t^i) - \underbrace{N_t \times 0.1 \times 0.2}_{\text{expected number of cold days}}$$

Diagnostics

[3] Aggregation: population weighted average (by Landkreis) to aggregate the time series to the macro level.

Econometric Framework

- Local Projection method Jordà (2005) to estimate impulse response functions.
- Single time series regression is estimated for each horizon h, going from 0 to 24.
- We argue that calender seasons matter, leading to our main model version:

$$ln(y_{t+h}) - ln(y_{t-1}) = \alpha_h + \sum_{j=1}^{4}(\beta_h^j \text{hot\_shock}_t \times D_t^j + \gamma_h^j \text{cold\_shock}_t \times D_t^j) + \sum_{l=1}^{12} \delta_{h,l} \mathbf{X_{t-l}} +$$

$$\phi_h t + \psi_h t^2 + \epsilon_{t+h}$$

Identifying Assumptions

- To truly identify a *causal* effect, we rely on natural experimental variation in climate. Fuchs-Schündeln and Hassan (2016) and try to rule out endogeneity concerns (OVB, reverse causality).
- Time series approach instead of pure cross section to reduce OVB $\Rightarrow$ assumption that each population is comparable to itself over time.
- The high temporal resolution of our analysis further reduces the risk of potential short-term confounding factors.
- Limited number of control variables to avoid "bad control" Angrist and Pischke (2009) or "overcontrolling" Dell et al. (2014).
- Reverse causality less of an issue due to the typical assumption that weather patterns, being governed by geophysical processes, are exogenous to economic activity ($\Rightarrow$ Granger causality test).

Evidence - Food Prices by Season on Impact

Table: Effects on Impact - Food Inflation

	Food Inflation			
	Horizon 0	Horizon 1	Horizon 2	Horizon 3
Hot Winter	-0.11	-0.40*	-0.51***	-0.36**
	(0.13)	(0.22)	(0.18)	(0.18)
Hot Spring	-0.03	-0.16	-0.32*	-0.30
	(0.13)	(0.21)	(0.19)	(0.21)
Hot Summer	0.07	0.30***	0.39***	0.29*
	(0.07)	(0.11)	(0.12)	(0.15)
Hot Fall	-0.04	-0.33	-0.40*	-0.20
	(0.14)	(0.21)	(0.22)	(0.21)
Cold Winter	0.07	0.28	0.29	0.10
	(0.16)	(0.21)	(0.20)	(0.22)
Cold Spring	0.24	0.50**	0.58**	0.68**
	(0.15)	(0.20)	(0.24)	(0.27)
Cold Summer	0.08	0.24	-0.04	0.08
	(0.13)	(0.17)	(0.20)	(0.22)
Cold Fall	0.04	0.16	-0.17	-0.02
	(0.15)	(0.19)	(0.18)	(0.21)
Time Trends	Yes	Yes	Yes	Yes
Observations	288	287	286	285
R^2	0.26	0.36	0.38	0.38

Newey-West standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

IRFs

Evidence - Energy Prices by Season on Impact

Table: Effects on Impact for Energy Prices

	Energy Inflation			
	Horizon 0	Horizon 1	Horizon 2	Horizon 3
Hot Winter	-0.18	-0.64**	-0.88**	-0.87*
	(0.19)	(0.27)	(0.43)	(0.44)
Hot Spring	-0.37	-0.30	-0.67*	-1.04**
	(0.24)	(0.35)	(0.35)	(0.44)
Hot Summer	0.15	-0.13	0.28	-0.51
	(0.15)	(0.31)	(0.38)	(0.41)
Hot Fall	-0.12	-0.06	-0.57*	-0.59*
	(0.17)	(0.22)	(0.29)	(0.31)
Cold Winter	0.28	0.33	-0.07	-0.25
	(0.19)	(0.28)	(0.34)	(0.47)
Cold Spring	-0.17	0.06	0.04	0.00
	(0.15)	(0.27)	(0.39)	(0.40)
Cold Summer	0.18	-0.17	0.16	-0.18
	(0.22)	(0.47)	(0.45)	(0.63)
Cold Fall	0.19	0.47	0.30	0.10
	(0.24)	(0.34)	(0.45)	(0.55)
Time Trends	Yes	Yes	Yes	Yes
Observations	288	287	286	285
R^2	0.45	0.43	0.45	0.46

Newey-West standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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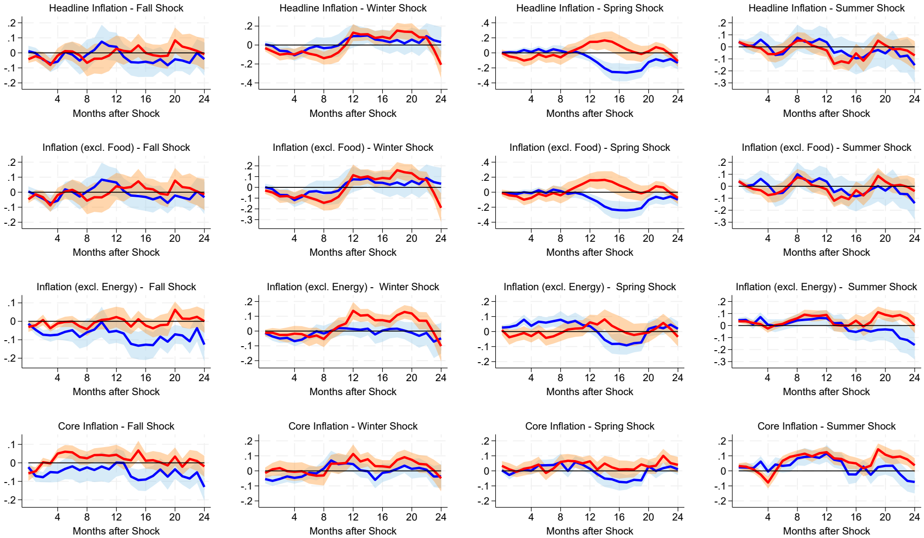
Evidence - Headline and Core Inflation



Robustness Checks

- Supply vs. Demand Effects
- Drought Events
- Nonlinear Effects
- Growing Season
- Further checks
  - Comparison with Temperature Anomalies
  - Different Weightings
  - Different learning periods
  - Year on Year Inflation

$\Rightarrow$ Overall, our core results/channels remain robust across specifications

Supply vs. Demand Effects I

- Are price movements caused by supply or demand movements? [Ciccarelli and Motta, 2024]
- Re-estimating model with total industrial and energy production [Lucidi et al., 2024]
- Total production declines during hot spring and summer periods as well as during cold fall and winter periods
- Energy production responds positively to cold fall and winter periods, even though renewables decline

⇒ Co-movement of energy production and prices: Demand side dominates

Regression Results

Supply vs. Demand Effects II

- To support this claim we also look at consumption.
- We rely on heating and cooling degree days (HDD, CDD) [Lucidi et al., 2024] as proxies for temperature-related energy needs.
- We construct dummies indicating whether the number of HDDs or CDDs in a given year has increased or decreased compared to the previous year.
- We interact these dummies with are cold/heat shock variable.
- Example: When HDD falls, a heat shock is expected to reduce heading needs lowering gas demand

⇒ Warmer-than-usual winters reduce heating needs, and thus lower energy demand.

⇒ Colder-than-usual winters increase heating needs, and thus increases energy demand.

Regression Results

Conclusion

- Temperature surprises matter as a true macroeconomic shock for the German economy.
- Heat and cold surprises, as well as seasonal variation, matter.
- Headline inflation is driven by energy prices
- Droughts, nonlinear effects, and renewable energy adoption also matter, affecting both demand and supply channels.

References

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Carleton, T. A. and Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304):aad9837.

Ciccarelli, M., Kuik, F., and Hernández, C. M. (2023). The asymmetric effects of weather shocks on euro area inflation.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature*, 52(3):740–798.

Drudi, F., Moench, E., Holthausen, C., Weber, P.-F., Ferrucci, G., Setzer, R., Nino, V. D., Barbiero, F., Faccia, D., Breitenfellner, A., et al. (2021). Climate change and monetary policy in the euro area. *ECB Occasional Paper Series No 271*.

ECB (2024). Economic, financial and monetary developments. *ECB Economic Bulletin, Issue 2/2024*.

Faccia, D., Parker, M., and Stracca, L. (2021). Feeling the heat: extreme temperatures and price stability.

Fuchs-Schündeln, N. and Hassan, T. A. (2016). Natural experiments in macroeconomics. In

Data - Economic Variables

- Data on consumer prices and output is taken from Eurostat.
- Monthly data starting in January 1996 and ending in December 2021.
- Focus on the Harmonised Index of Consumer Prices and its five main components (processed food, non-processed food, services, energy and non-energy industrial goods) + Core Inflation excluding food and energy.
- Complementary data is sourced from different databases (INKAR, Agorameter, GADM).

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Temperature Shock - Some Diagnostics

Table: Summary Statistics for Temperature Shocks

						Ljung-Box test	
	T	Mean	SD	Min	Max	Q-stat	p-value
Combined Shock	312	0.78	4.02	−6.17	12.59	16.43	0.87
Hot Days	312	0.58	3.50	−3.09	15.58	28.43	0.24
Cold Days	312	0.20	3.69	−3.09	15.50	30.73	0.16

Temperature Shock - Some Diagnostics

Table: Predictability of the shock series – Granger causality tests

		Inflation	Food Inflation	Energy Inflation
Combined Shock	χ^2	4.04	5.88	10.38
	$p(\chi^2)$	0.671	0.44	0.11
Hot Days	χ^2	9.17	4.60	10.19
	$p(\chi^2)$	0.16	0.60	0.12
Cold Days	χ^2	7.85	4.16	10.72
	$p(\chi^2)$	0.25	0.66	0.10

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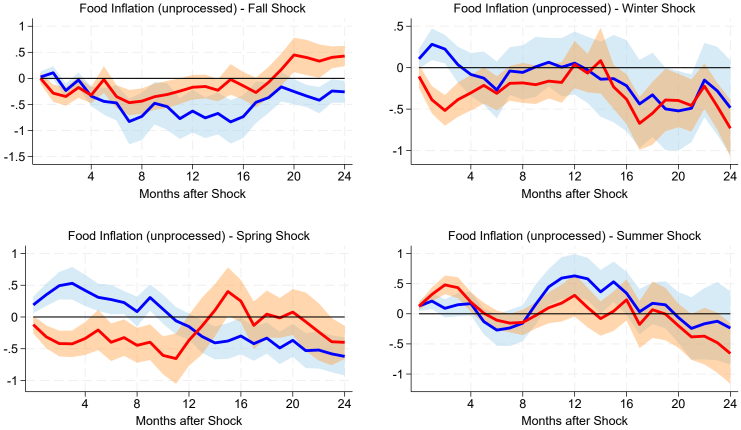
Evidence - Food Prices by Season



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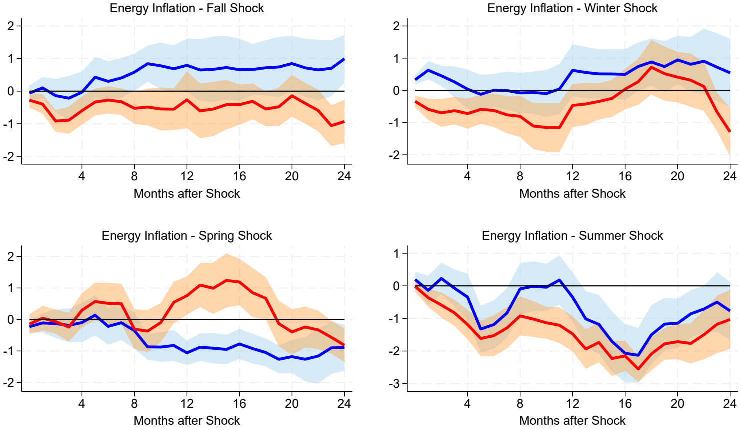
Evidence - Energy Prices by Season



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Supply vs. Demand Effects III

Table: Effects on Impact - Production and Energy Supply

	IP	IP-Energy	Solar	Wind (onshore)	Renewables Total	Conventional Total
Hot Spring + Summer	-0.27*	0.17	1.15***	0.01	-0.03	0.33
	(0.15)	(0.20)	(0.36)	(0.70)	(0.25)	(0.20)
Hot Fall + Winter	0.13	-0.81***	1.67***	0.90	0.74**	-0.44**
	(0.11)	(0.20)	(0.74)	(0.76)	(0.35)	(0.17)
Cold Spring + Summer	-0.15	0.77***	0.21	1.82**	0.38	0.19
	(0.19)	(0.21)	(0.50)	(0.80)	(0.31)	(0.17)
Cold Fall + Winter	-0.32*	0.57***	0.57	-2.24**	-1.01**	0.47**
	(0.16)	(0.22)	(1.01)	(1.07)	(0.47)	(0.23)
Add. Control Variables	Yes	Yes	No	No	No	No
Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	299	299	95	95	95	95
R^2	0.28	0.35	0.59	0.42	0.50	0.61

Newey-West standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Supply vs. Demand Effects IV

Table: Effects on Impact - Energy Demand

	Gas Consumption	Electricity Consumption
Heat shock $\times \mathrm{HDD}_{\text{negative}}$	-7.43***	-0.46
	(2.49)	(0.66)
Heat shock $\times \mathrm{CDD}_{\text{positive}}$	0.04	0.77
	(3.03)	(0.75)
Time Trends	Yes	Yes
Observations	143	143
R^2	0.70	0.81

Newey-West standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Drought

- We investigate the effects of drought conditions in conjunction with temperature shocks.
- We use aggregated precipitation data for Germany obtained from the Deutscher Wetterdienst (DWD) and constructed a drought indicator variable based on the Standardized Precipitation Index (SPI) at a monthly resolution.
- We define a drought as at least two consecutive months of unusually low precipitation [Felbermayr and Gröschl, 2014] [Bodenstein and Scaramucci(2025)].

⇒ Negative correlation between SPI and the occurrence of hot temperature shocks for spring and summer.

- We replicate the estimation, but differentiating only between the spring–summer and fall–winter periods, and allowing the drought dummy to interact with the heat-related temperature shock.

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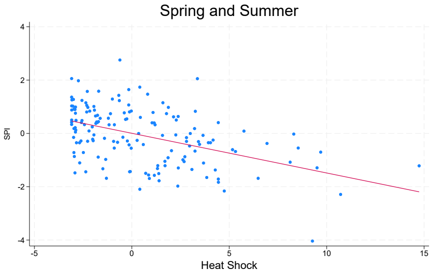
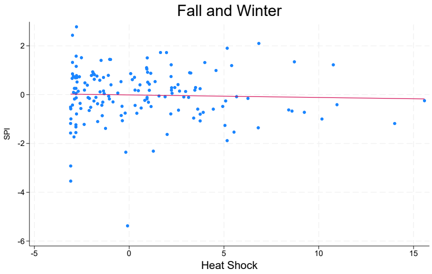
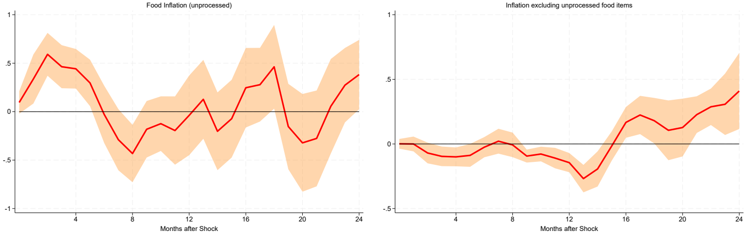
Drought Events





Drought Events



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Nonlinear Effects

- *Idea*: 1–2 hot days may have minimal effects on agriculture and food prices, whereas 8–9 or more days within a month can have a significantly larger negative (or positive) impact.

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Growing Season

- We examine the effects of temperature shocks during the crop growing season.
- We used aggregated data for Germany from the World Bank Climate Change Knowledge Portal, which provides the start and end dates of the yearly growing season.
- The start of the growing season is defined as the day of the year that reflects the first span of at least 6 consecutive days with a daily mean temperature above 5 °C.
- We create a dummy variable that indicates whether a month falls within the growing season or not.
- We are estimating a similar regression as in our benchmark scenario, but with growing instead of the calendar seasons.
- Further, we include sun duration and precipitation per month as additional controls.

⇒ Hot temperature shocks only impact food prices when they occur during summer, a period characterized by high absolute temperatures.

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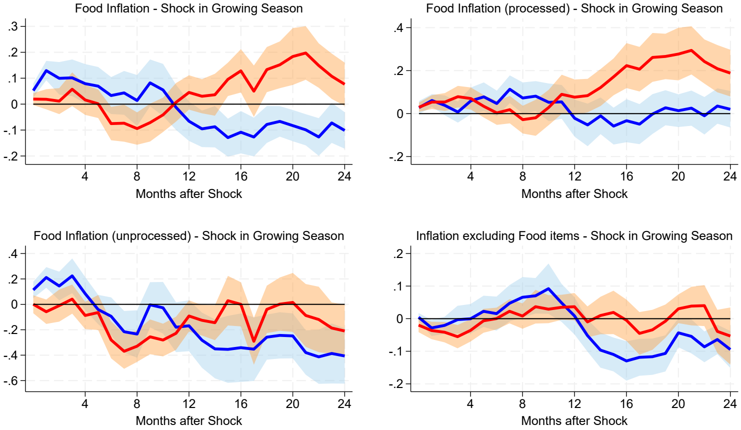
Growing Season



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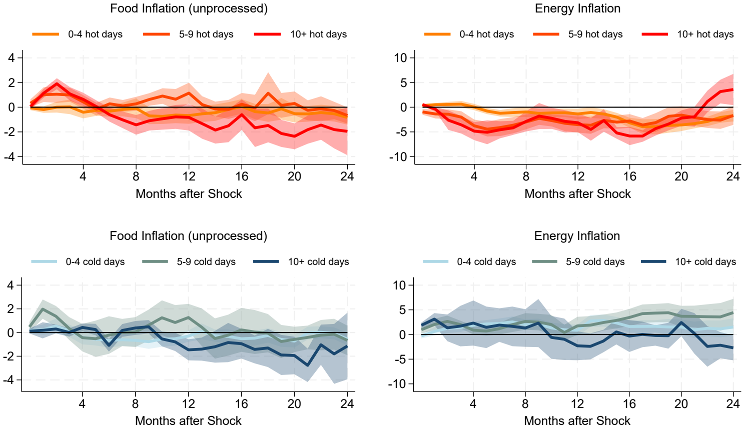
Nonlinear Effects



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