Observed changes in climate can empirically identify long-run adaptation: the extensive vs intensive margins of energy demand

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Motivation

Empirically derived damage functions are typically estimated exploiting:

- idiosyncratic weather variation
- cross-sectional climatic exposure

The estimation of the impacts on the economy is hindered by:

- the temporal invariance of climate
- correlation of cross-sectional climate variation with other regional heterogeneity

Strong assumptions about dynamic processes:

- adaptation (adjusting among a set of technological opportunities, technological change)
- general equilibrium effects (adjustment of prices and factor reallocations)
- intensification of climate effects

In this work we test the hypothesis that we can observe meaningful climatic variation within units in the econometric framework.

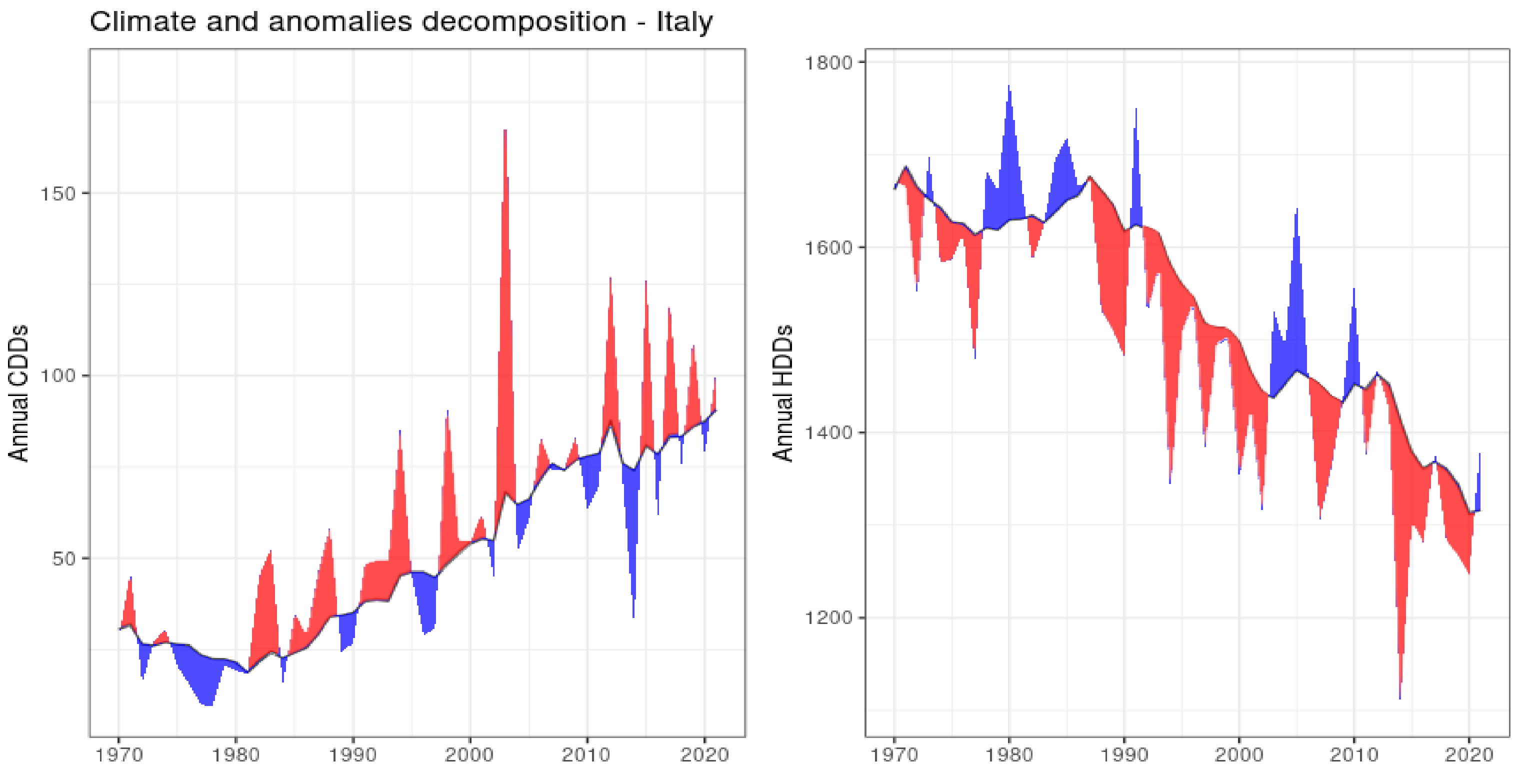
Theoretical framework: weather exposure decompositon

Climate (c): 10-year moving average the yearly observed weather (w).

$$c_{i,t} = \mathbb{E}_t w_{i,t} = \ell^{-1} \sum_{s=t-\ell}^{t-1} w_{i,s}$$

Weather anomaly (a): deviation of observed yearly w from c.

$$a_{i,t} = w_{i,t} - c_{i,t}$$



Theoretical framework: equations

	Weather model	Hybrid models	Proposed decomposition
Equation $y_{i,t} =$	$\alpha w_{i,t} + \mu_i + \varepsilon_{i,t}$	$\alpha w_{i,t} + \beta w_{i,t} \cdot z_i + \mu_i + \varepsilon_{i,t}$	$\gamma c_{i,t} + \eta a_{i,t} + \mu_i + \varepsilon_{i,t}$
Within trans. $y_{i,t} - \overline{y}_i =$	$\alpha \widetilde{w}_{i,t}$	$\alpha \widetilde{w}_{i,t} + \beta \widetilde{w}_{i,t} \cdot z_i$	$\gamma \widetilde{c}_{i,t} + \eta \widetilde{a}_{i,t}$
Interpretation	$\widehat{\alpha}$ response to meteorological exposure	$\widehat{\beta}$ heterogeneity in the response to meteorological exposure	$\widehat{\gamma}$ response to a persistent change in climate $\widehat{\eta}$ response to an unexpected weather anomaly

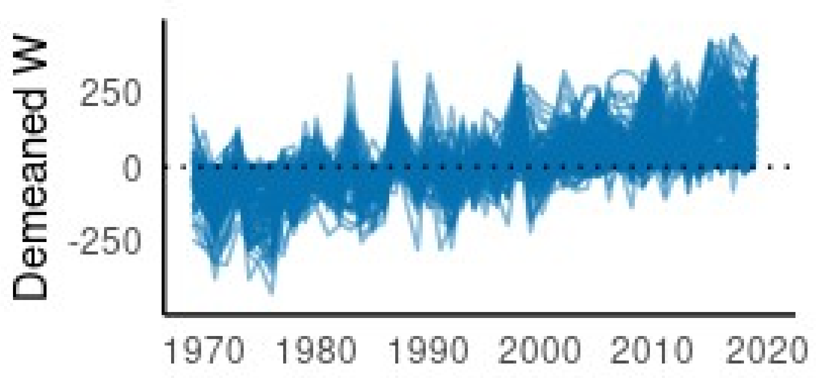
i and t index units and time;
w: weather variable; c: climate variable; a: weather anomaly variable;
z: spatially varying predictive variable;
μ: fixed effects

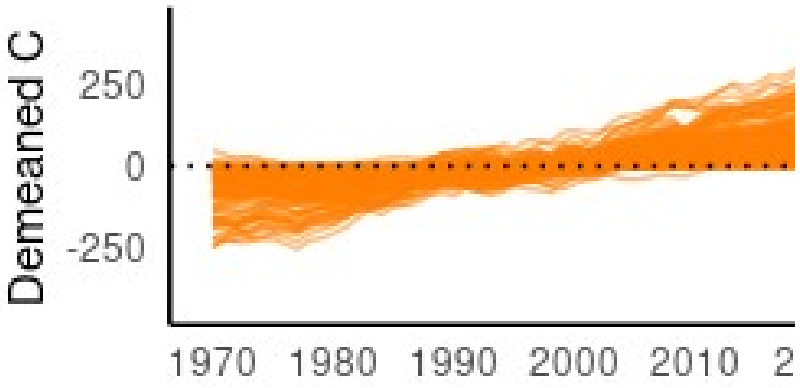
Preliminary data analysis: ERA5 country-year data

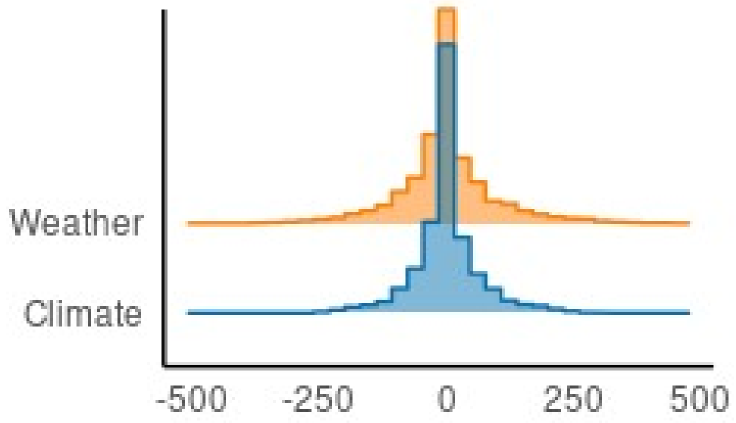
We test the hypothesis that we cannot observe meaningful climatic variation within the unit of the sample.

The blue (orange) line shows the trend in the de-meaned value of Cooling Degree Days (24°C) for each country in the original weather observation (climate moving average).

The two metrics have a similar distribution, suggesting meaningful statistical information can be extracted from within-country climatic variations.







min: -448 max: 440 sd: 92

min: -259 max: 316 sd: 63

Empirical setting

Dependent variable	Sectoral demand for electricity and fossil fuels
Scope	Global
Units	Countries (~135)
Time	1970-2019
N	~5.000-7.000
Weather/climate	Cooling Degree Days and Heating Degree Days
Comparable studies	Rode et al., (2021); De Cian and Sue Wing (2019).

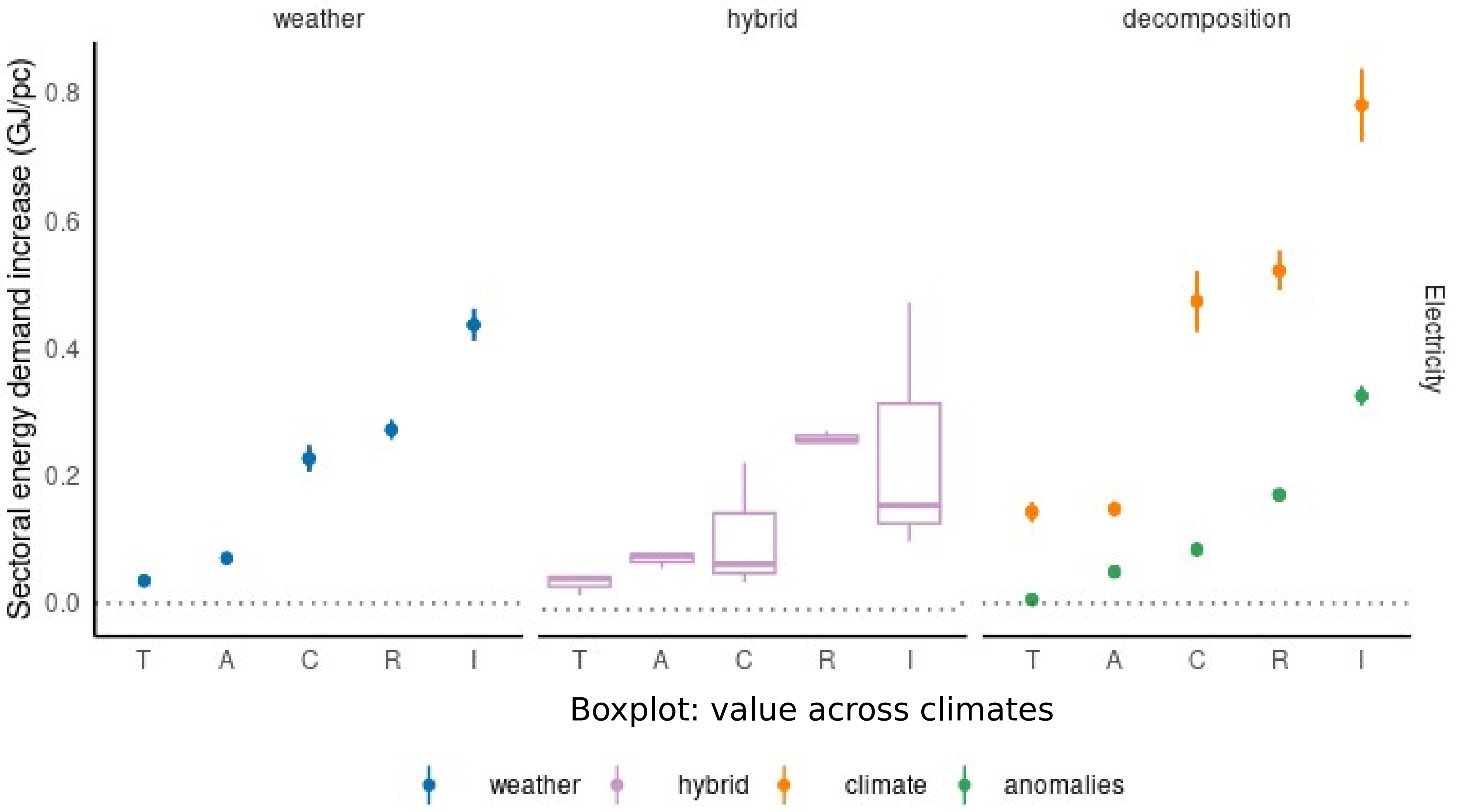
- Electricity and fossil fuel demand is estimated separately for each combination of sector *m* (Residential, Commerical, Industrial, Agricolture and Trasport).
- Climatic CDDs/HDDs and the vector of positive and negative anomalies are included in the same equation.
- The vector of anomalies is interacted with the level of climatic CDDs/HDDs: e.g. a positive anomaly in CDDs (eg +100 CDDs) influences energy demand differently in cold vs hot climates.

$$q_{i,t}^{m} = \gamma_1^m cdd_{i,t}^C + \gamma_2^m hdd_{i,t}^C + \boldsymbol{\eta}_1^{m,j} \mathbf{cdd}_{i,t}^A \cdot cdd_{i,t}^C + \boldsymbol{\eta}_2^{m,j} \mathbf{hdd}_{i,t}^A \cdot hdd_{i,t}^C + \pi^m x_{i,t,m} + \mu_i^m + \tau_t^m + \varepsilon_{i,t}^m \quad (1)$$

- Fixed effects by units and time control for time-invariant and time-specific unobservables.
- Regional non-linear time trends control for long-term development pathways in the outcome.
- The preferred specification is estimated in levels. Equations in first-differences are also tested.

Results: energy demand

Electricity demand response to CDDs by sector

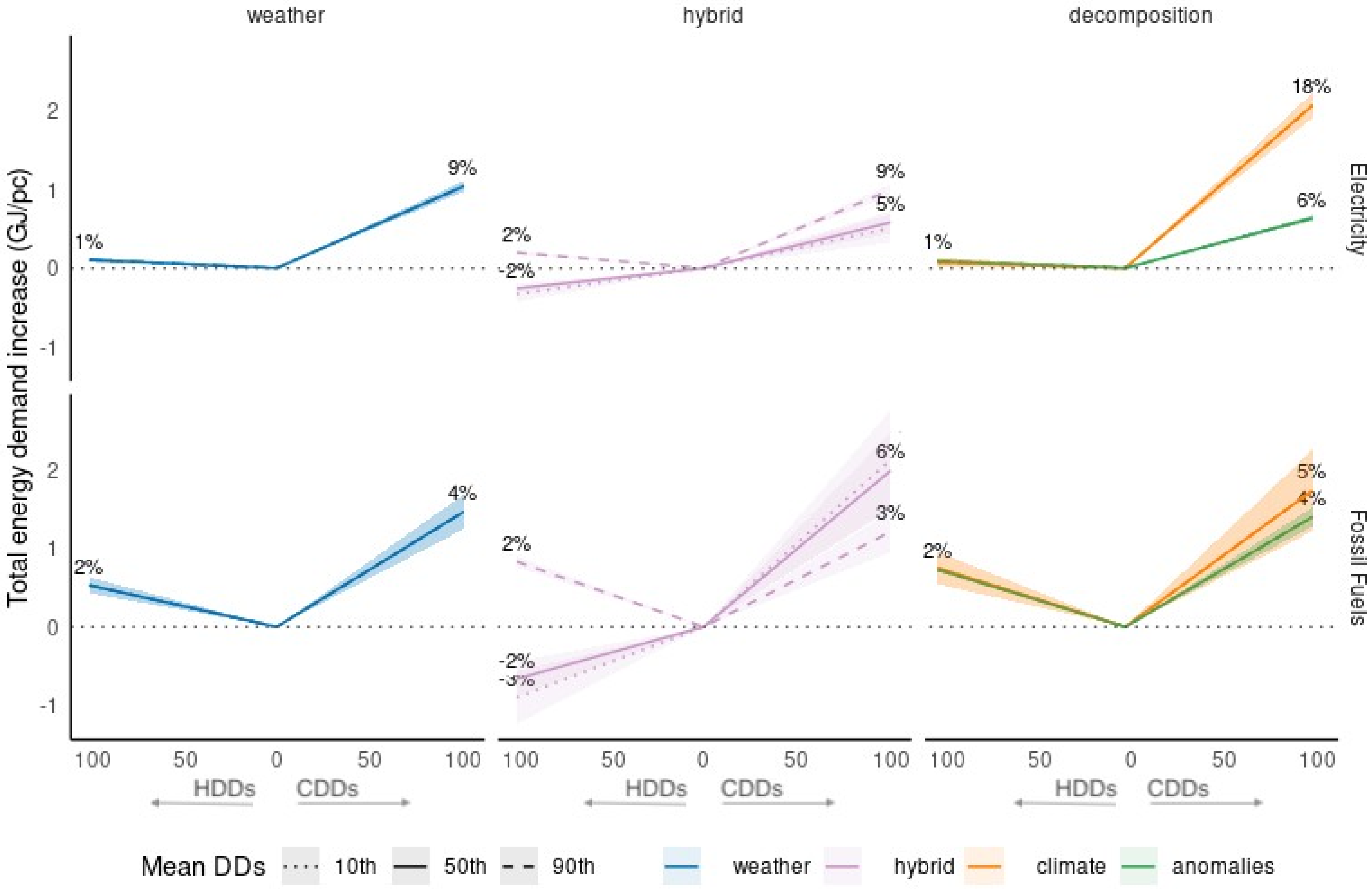


Boxplot: value across climates

T: Transport;
A: Agricolture;
C: Commerical;
R: Residential;
I: Industrial

Results: energy demand

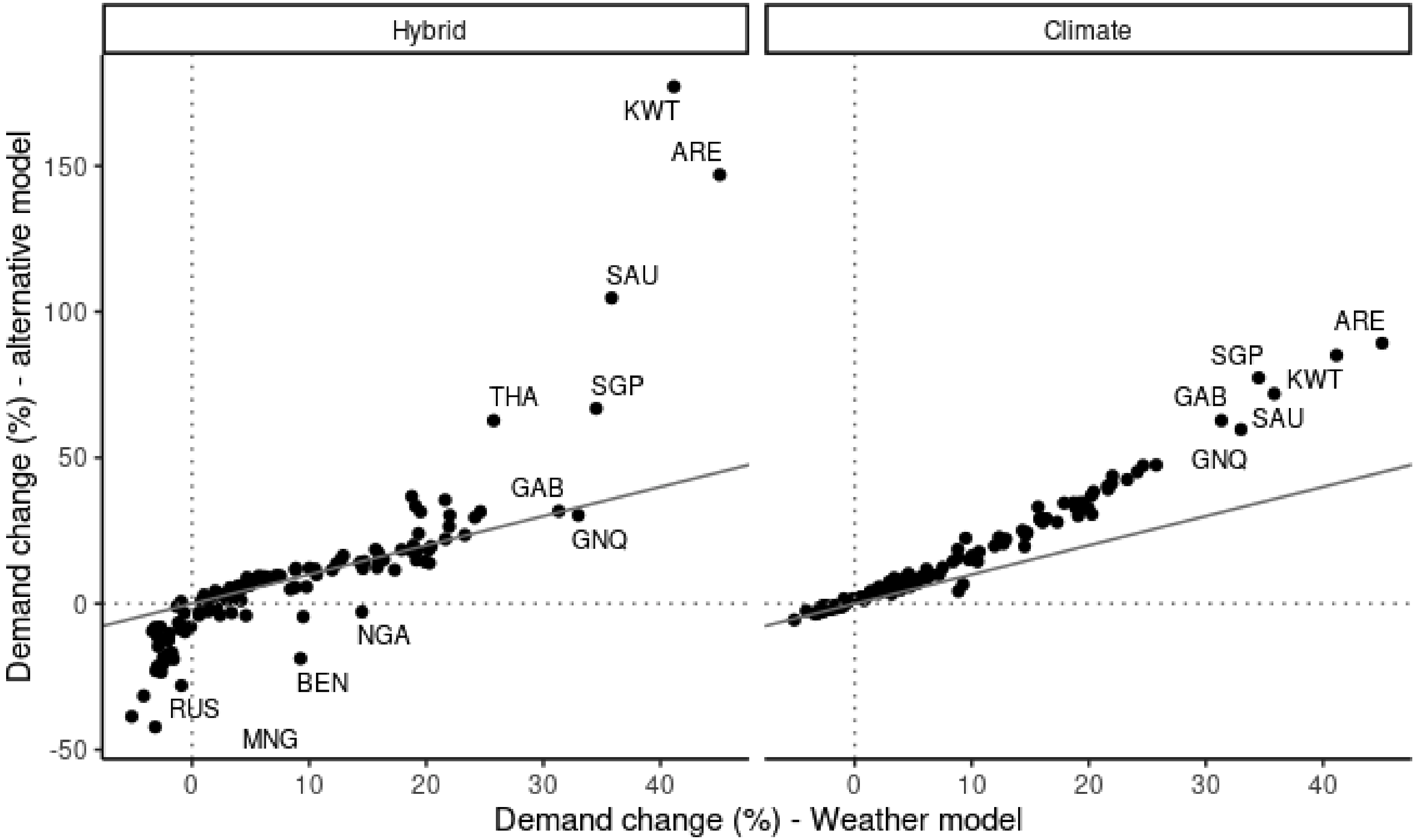
Total energy demand respose by cold/hot exposure and fuel



Projections: energy demand

Country-level changes in energy demand in 2050 under RCP 4.5 across 13 GCMs (median) with respect to 2010-2014:

- Global change in electricity demand for adpatation in the preferred model is 2-3 times higher than classical models.
- Impacts result from climatic shifts, while impacts of future weather anomalies are not accounted



Global energy demand change in 2050				
	RCP	**Weather**	**Hybrid**	**Decomposition**
Electricity	4.5	14%	20%	37%
	8.5	21%	42%	56%
Fossil fuels	4.5	3%	~0%	4%
	8.5	5%	2%	7%

Discussion

Implications:

- Energy demand is an archetype of a broader class of impacts of climate change
- Assumption that we cannot extract a climatic signal from the historical record can be relaxed in other settings

Caveats:

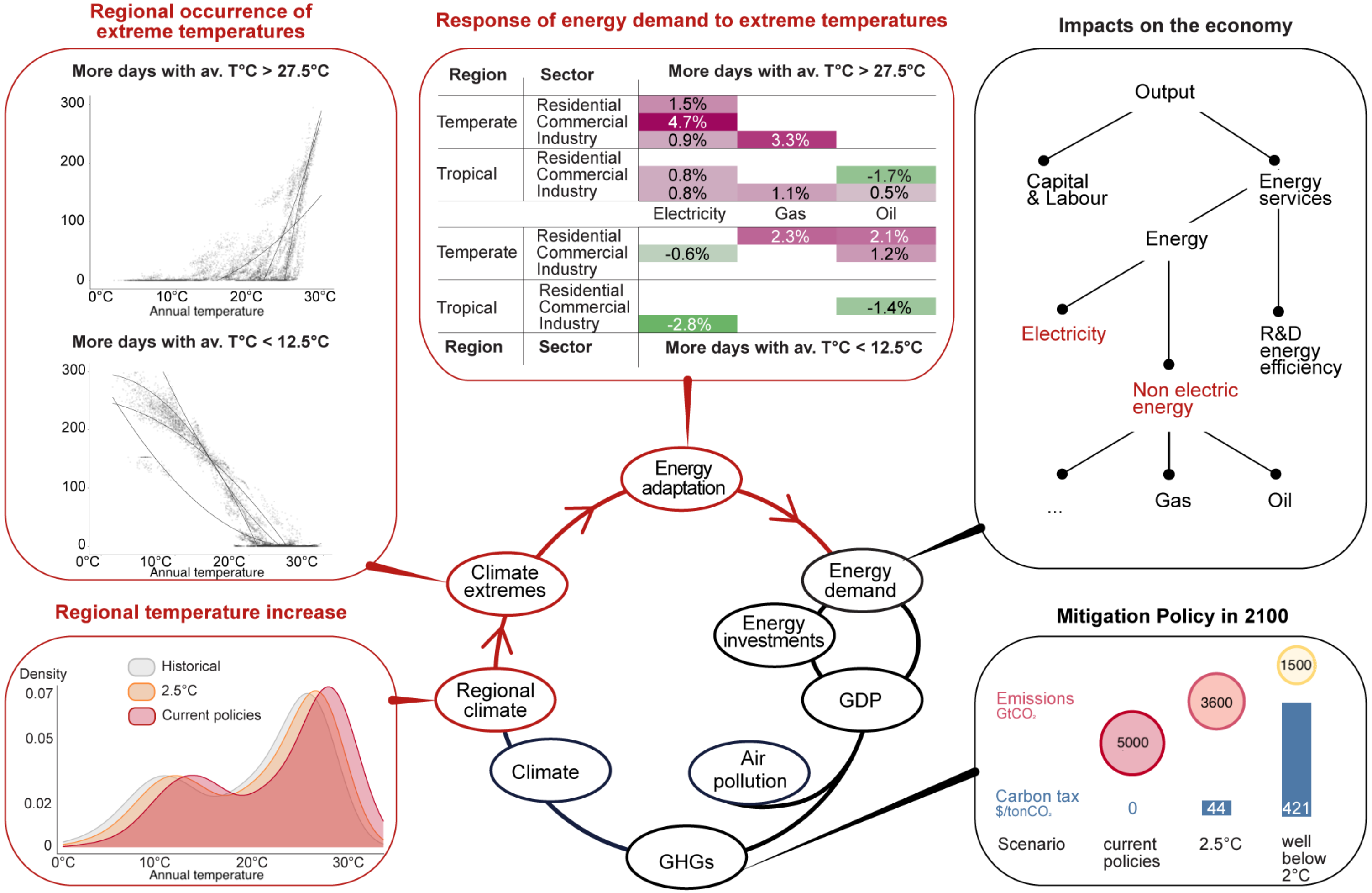
- Limited representation of sub-annual impacts (e.g. peak demand)
- Energy efficiency and fuels/technology substitution only considered implicitly

Future work:

- Interaction effects that can account for adaptive capacity (eg: capital stock accumulation)
- Method for projections of future anomalies (possibly exploiting GCM inter-annual variability)
- Include shocks in IAMs to evaluate impacts on energy supply and emissions.

Next step: update of the adaptation-energy feedbacks

Inclusion of the energy-adaptation loop in the WITCH model



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Increased energy use for adaptation significantly impacts mitigation pathways

Francesco Pietro Colelli, Johannes Emmerling, Giacomo Marangoni, Malcolm N. Mistry & Enrica De Cian

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5535 Accesses | **4** Citations | **170** Altmetric | Metrics

New calibration data will allow to:

- Include larger combination of sectors-fuels-regions
- Focus on larger set of climate indicators
- Compare impacts to other modeling approaches (coupling building model to IAMs)

Thank you!

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ENERGYA

http://www.energy-a.eu

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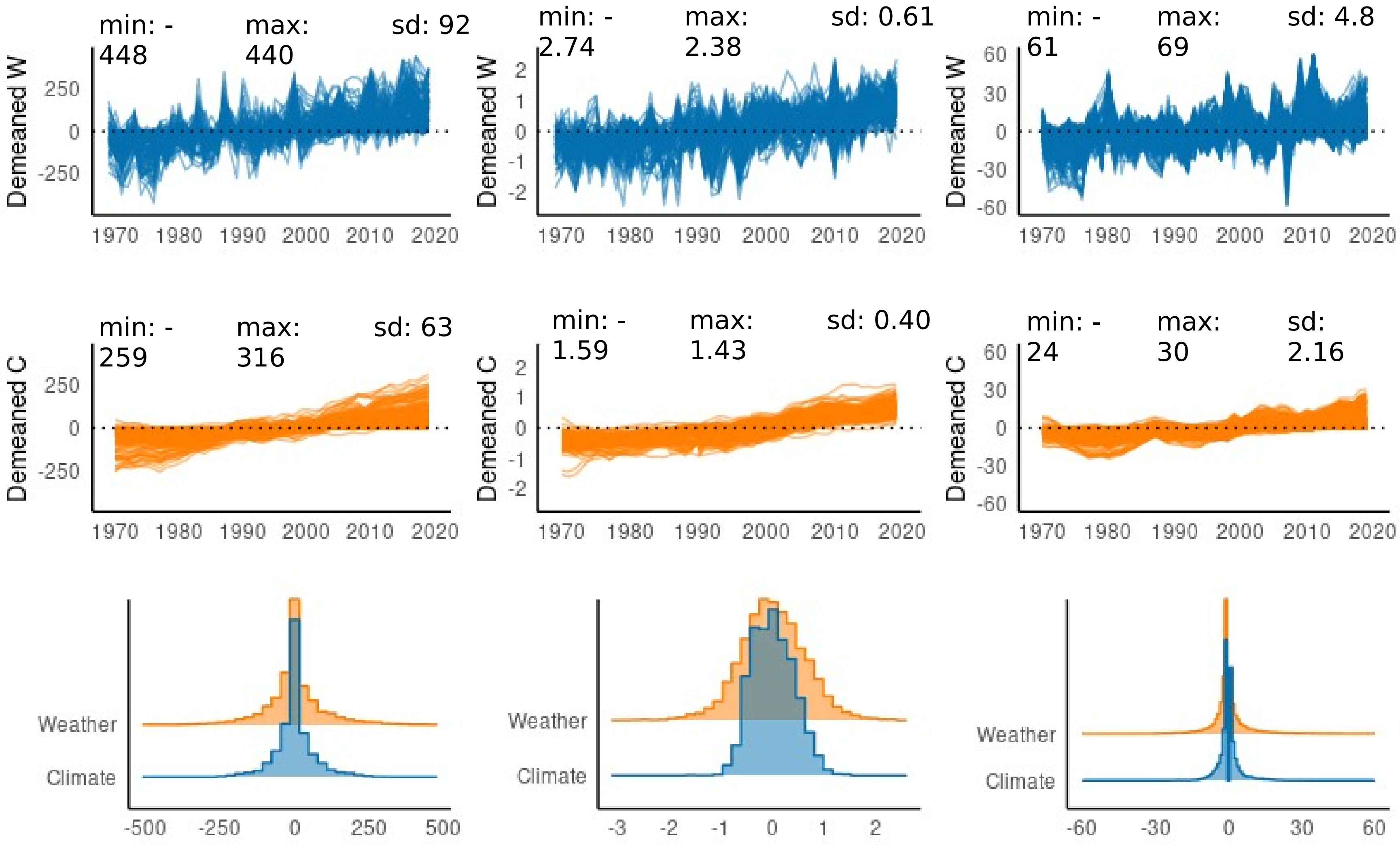
Preliminary data analysis

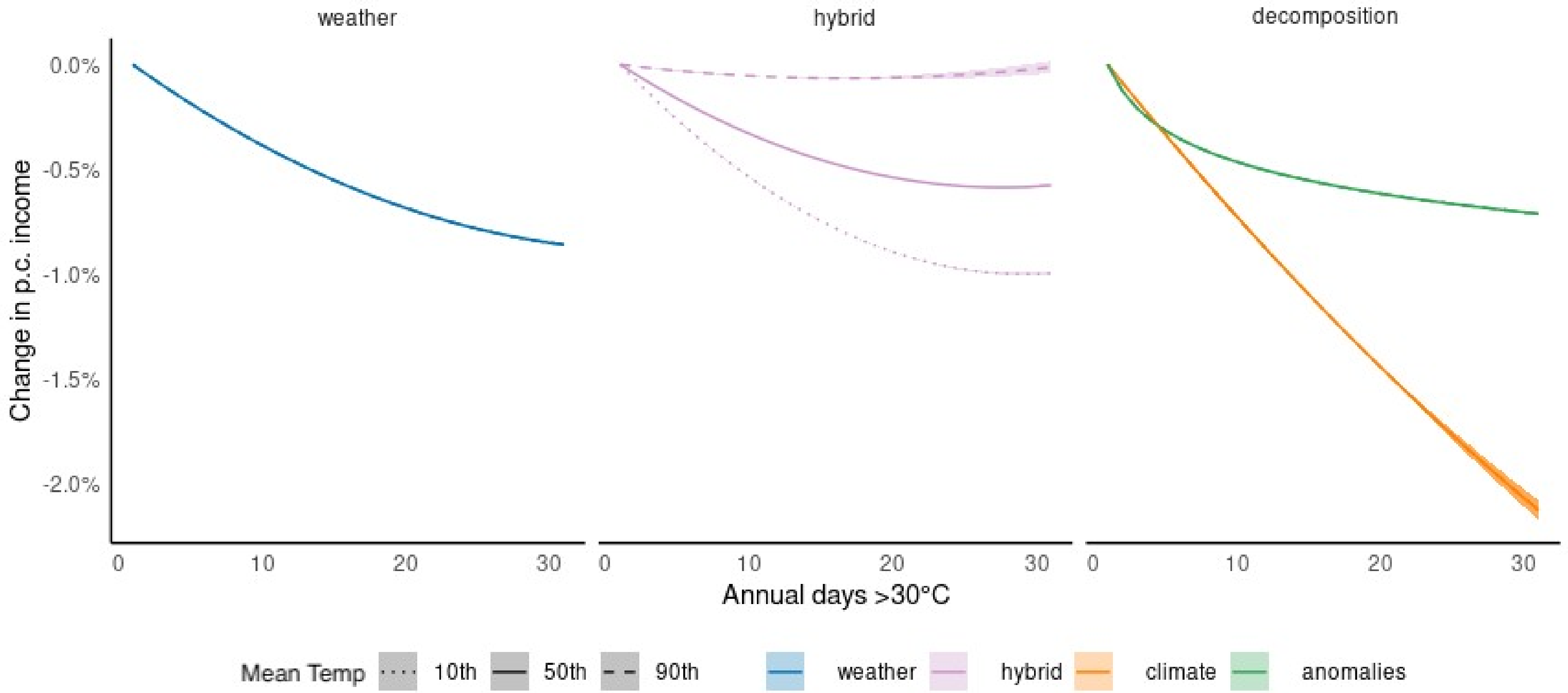
Setting 1 — Cooling Degree Days

Setting 2 — Annual temperature

Setting 3 — Annual bin daily T >30°C



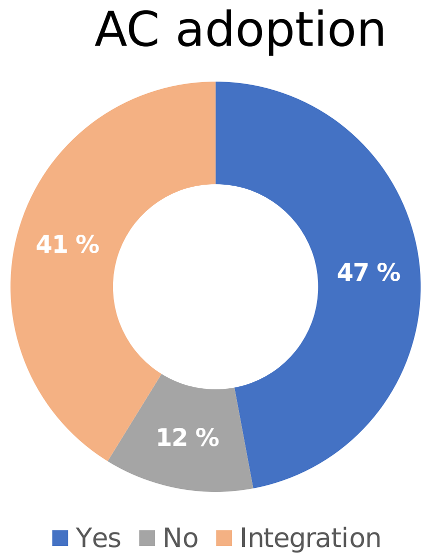
Additional results: US counties’ per capita income

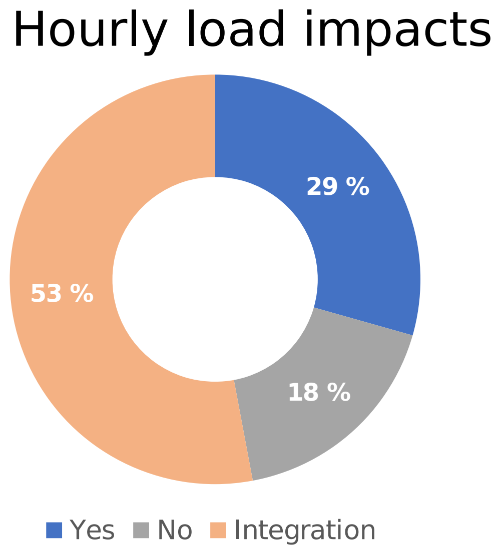


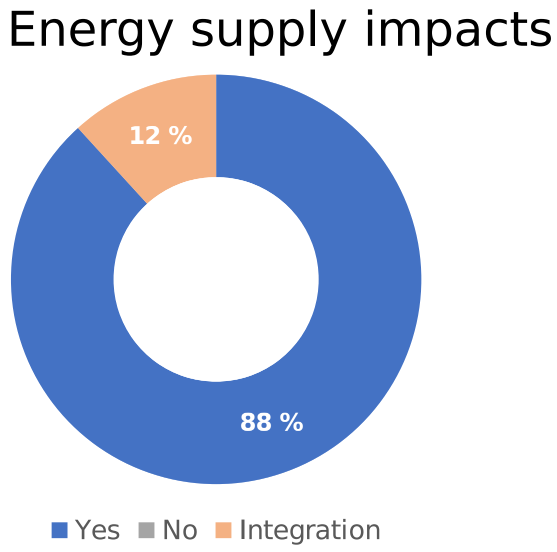
The weather model over-estimates the marginal damage from additional warming relative to the hybrid (heterogeneous marginal effect) model.
However, the hybrid model estimates how long-run adaptation affects the response to temporary hot exposure, while our decomposition shows how a shock due to permanent hot exposure differs from one due to temporary hot exposure.

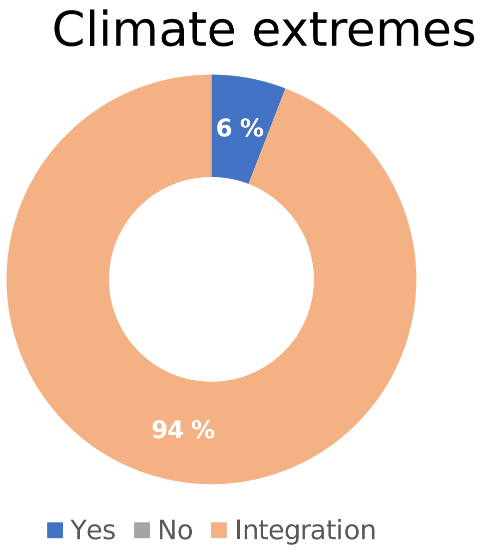
Future directions in modeling energy for adaptation

Potential update of novel empirical evidence into existing models



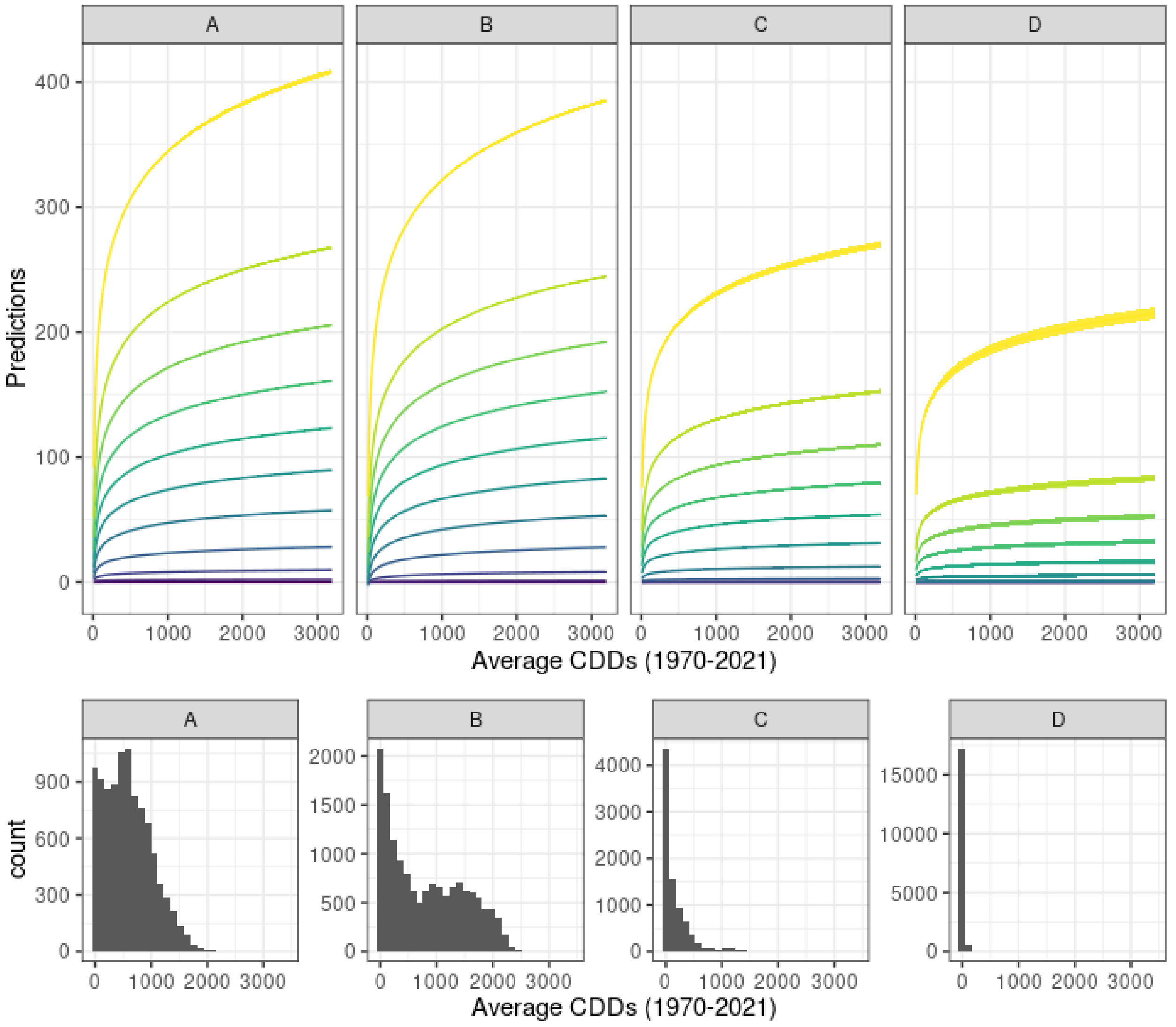






Models considered:
IAMS: WITCH, REMIND, TIMER-IMAGE, COFFE-TEA, MESSAGEix, FUND, GCAM, AIM-Hub, DNE21+, E3ME-FTT, EPPACGE;
GCE: ENVISAGE, GEM-E3, ICES
PE-Energy: TIMES, POLES, PROMETHEUS

sStatistical emulator of future CDD anomalies



Regression model of each quantile of the positive/negative anomalies, dependent on historical CDDs, conditional on the climate zone:

- The plot shows the predicted levels (95th confidence interval very narrow).
- Only Climates A (Tropical) and B (Arid) are characterized by hot historical annual CDDs >2000.
- Nevertheless, the relationship is predicted for each climate zone for the full range (0-3500) CDDs, in order to make sure any possible combination of future CDDs by climate zone is assigned to its synthetic pair

Electricity demand: weather specification

Dependent Variable:			ln_en_pc		
Model:	(Res)	(Com)	(Ind)	(Tra)	(Agr)
Variables					
hdd15	3.26×10^{-5}	0.0002^{***}	$9.04 \times 10^{-5***}$	6.1×10^{-5}	0.0002^{***}
	(3.5×10^{-5})	(4.84×10^{-5})	(3.36×10^{-5})	(6.82×10^{-5})	(4.21×10^{-5})
cdd24	0.0008^{***}	0.0009^{***}	0.0009^{***}	0.0018^{***}	0.0012^{***}
	(8.12×10^{-5})	(0.0002)	(0.0001)	(0.0002)	(0.0003)
ln_gdp_pc	4.178^{***}	0.1084^{**}	0.5331^{***}	0.2797^{***}	0.0076
	(0.1269)	(0.0482)	(0.0406)	(0.0472)	(0.0599)
ln_gdp_pc_sq	-0.2035^{***}	0.0393^{***}	0.0020	0.0372^{***}	0.0354^{***}
	(0.0068)	(0.0030)	(0.0030)	(0.0035)	(0.0044)
Fixed-effects					
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	5,597	5,155	5,624	3,810	2,879
R^2	0.97061	0.93536	0.94505	0.87346	0.94075
Within R^2	0.34583	0.12093	0.20789	0.09957	0.07120

Heteroskedasticity-robust standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Electricity demand: decomposition specification

Dependent Variable:			ln_en_pc		
Model:	(Res)	(Com)	(Ind)	(Tra)	(Agr)
Variables					
hdd15_clim	-5×10^{-5}	0.0002^{**}	7.9×10^{-5}	2.7×10^{-7}	0.0001^{**}
	(5.61×10^{-5})	(8.2×10^{-5})	(5.51×10^{-5})	(8.87×10^{-5})	(4.73×10^{-5})
cdd24_clim	0.0016^{***}	0.0018^{***}	0.0017^{***}	0.0037^{***}	0.0047^{***}
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0006)
ln_gdp_pc	4.222^{***}	0.1152^{**}	0.5115^{***}	0.2258^{***}	-0.0469
	(0.1267)	(0.0484)	(0.0412)	(0.0476)	(0.0589)
ln_gdp_pc_sq	-0.2063^{***}	0.0380^{***}	0.0031	0.0391^{***}	0.0365^{***}
	(0.0068)	(0.0031)	(0.0031)	(0.0035)	(0.0044)
cdd24_pos_anom	0.0005^{***}	0.0003	0.0007^{***}	0.0012^{***}	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
hdd15_pos_anom	5.97×10^{-5}	0.0002	4.5×10^{-5}	4.41×10^{-5}	0.0003^{***}
	(5.91×10^{-5})	(9.98×10^{-5})	(7.22×10^{-5})	(0.0002)	(0.0001)
Fixed-effects					
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	5,597	5,155	5,624	3,810	2,879
R^2	0.97113	0.93594	0.94550	0.87486	0.94259
Within R^2	0.35735	0.12883	0.21439	0.10956	0.10002

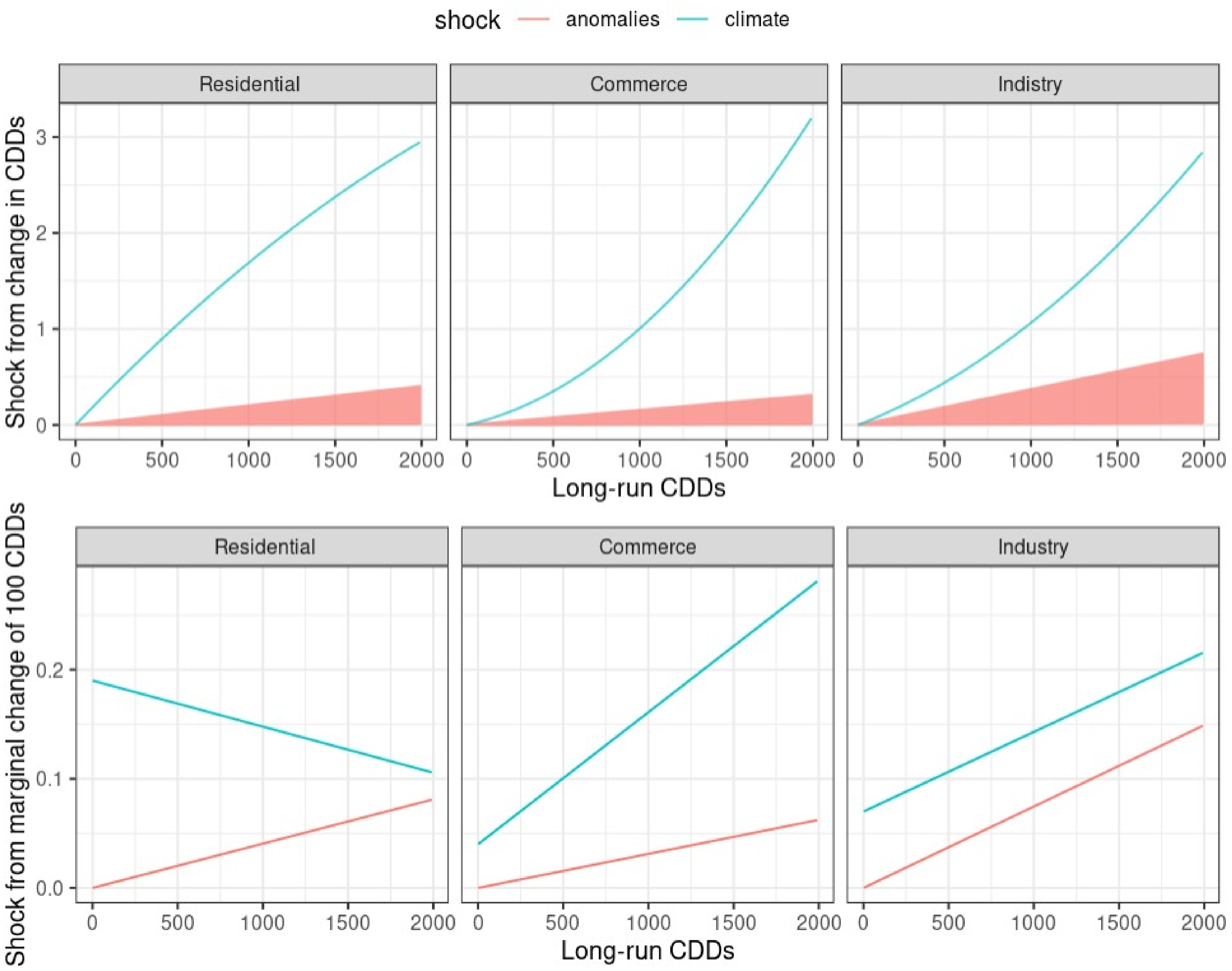
Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Electricity demand: quadratic decomposition specification

Dependent Variable:			ln_en_pc		
Model:	(Res)	(Com)	(Ind)	(Tra)	(Agr)
Variables					
hdd15_clim	-0.0005***	-0.0004***	-0.0001*	-0.0014***	-0.0003***
	(6.58×10^{-5})	(9.81×10^{-5})	(8.53×10^{-5})	(0.0001)	(9.24×10^{-5})
cdd24_clim	0.0019***	0.0004	0.0007**	0.0037***	0.0030**
	(0.0002)	(0.0004)	(0.0003)	(0.0006)	(0.0012)
hdd15_clim square	$1.33 \times 10^{-7***}$	$1.31 \times 10^{-7***}$	$5.29 \times 10^{-8*}$	$3.52 \times 10^{-7***}$	$1.13 \times 10^{-7***}$
	(1.27×10^{-8})	(2.51×10^{-8})	(2.73×10^{-8})	(3.52×10^{-8})	(3.44×10^{-8})
cdd24_clim square	$-2.11 \times 10^{-7**}$	$6.05 \times 10^{-7***}$	$3.65 \times 10^{-7**}$	$-9.04 \times 10^{-7***}$	1.59×10^{-6}
	(8.73×10^{-8})	(1.51×10^{-7})	(1.43×10^{-7})	(2.07×10^{-7})	(1.41×10^{-6})
ln_gdp_pc	4.004***	1.250***	0.9691***	-1.358***	-0.3354
	(0.1290)	(0.1737)	(0.1349)	(0.3305)	(0.2130)
ln_gdp_pc_sq	-0.1934***	-0.0551***	-0.0280***	0.1346***	0.0510***
	(0.0070)	(0.0120)	(0.0083)	(0.0269)	(0.0160)
cdd24_clim × cdd24_pos_anom	$4.06 \times 10^{-7***}$	3.12×10^{-7}	$7.46 \times 10^{-7***}$	$8.01 \times 10^{-7***}$	2.94×10^{-8}
	(1.21×10^{-7})	(2.44×10^{-7})	(2×10^{-7})	(2.79×10^{-7})	(7.57×10^{-7})
hdd15_clim × hdd15_pos_anom	$3.2 \times 10^{-8*}$	$9.31 \times 10^{-8***}$	2×10^{-8}	3.38×10^{-8}	$9.38 \times 10^{-8**}$
	(1.78×10^{-8})	(3.38×10^{-8})	(2.44×10^{-8})	(5.35×10^{-8})	(3.84×10^{-8})
Fixed-effects					
iso3	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	5,597	5,155	5,624	3,810	2,879
R^2	0.97159	0.93420	0.94595	0.87406	0.94124
Within R^2	0.36756	0.10515	0.22081	0.10382	0.07898

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Empirical results: climate vs anomalies



Impact for positive anomalies ranging from 10 to 500 CDDs