Climate Change, Firms, and Aggregate Productivity

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Introduction

- **Climate change** refers to long-term shifts in temperatures and weather patterns
- Key issue to formulate policies: predict the impact on society of future climate change.
- Our focus: **quantify the effects of temperature fluctuations on productivity**.
  - Studies using firm-level data from developing countries highlight negative impact of extreme temperature shocks (e.g., among others, Somanathan et al., JPE, 2021)
  - What about **developed countries**?
  - Through which **channels**? And how to **quantify aggregate implications?**
- This paper estimates the effect of temperature fluctuations on firm level outcomes in Italy.
  - Theoretical framework allows us to: i) Identify demand, efficiency and misallocation channels; ii) Quantify aggregate productivity losses; iii) Predict aggregate effects of future climate change, as well as its regional heterogeneity.

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Preview of Results

Preview of the (preliminary) results:

1. Extreme temperatures, either high or low, depress firm-level output, **with the negative effect of high temperatures very non-linear and convex**.
2. Extreme temperatures **reduce efficiency, and cause misallocation of capital**, while labour and other variable inputs reallocate efficiently. Demand channel has negligible effects.
3. Substantial negative effects of future climate change, steep non-linearity:
   - **2°C** increase from now to 2100 would reduce aggregate productivity by **1.8%**
   - **4°C** increase would reduce it by **6.4%**
   - **6°C** increase (SSP5-8.5 scenario) would reduce it by **14.5%**
4. Effect driven by lower efficiency (around 60%) and higher misallocation (around 40%).
5. Substantial **heterogeneity across regions**, exacerbates inequality.

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Literature Review

- **Macro:** Desmet and Rossi-Hansberg (2015); Conte et al. (2021); Cruz and Rossi-Hansberg (2021); Desmet et al. (2021), Rudik et al. (2021); Krusell and Smith (2022); Barrage and Nordhaus (2023); Bilal and Rossi-Hansberg (2023)
- **Micro:** Zhang et al. (2018); Adhvaryu et al. (2020); Somanathan et al. (2021); Colmer (2021); Custodio et al. (2021); Albert et al. (2022); Cascarano et al. (2022)
- **Micro-to-Macro:** Hsieh and Klenow (2009); Gopinath et al. (2017); Baqaee and Farhi (2020); Sraer and Thesmar (2020); Bau and Matray (2023)

Framework

Model: Demand

- Output Y is a CES aggregate of M firms:

$$Y = \left(\sum_{i=1}^{N} \left(e^{\boldsymbol{d_i(T_{g(i)})}} Y_i \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

- $\boldsymbol{e^{d_i(T_g(i))}}$ is a *temperature-dependent demand wedge* for firm i in grid-cell g
- Grid-cells are the finest geographical unit for which we have data on temperatures

Model: Supply

- The production function is Cobb-Douglas in inputs $\mathcal{X} \equiv \{K, L, M\}$:

$$Y_i = \boldsymbol{e^{z_i(T_{g(i)})}} \prod_{X \in \mathcal{X}} X_i^{\alpha^X}, \quad \text{with} \quad \sum_{X \in \mathcal{X}} \alpha^X = 1$$

- $\boldsymbol{e^{z_i(T_{g(i)})}}$ is a *temperature-dependent productivity wedge* for firm i in grid-cell g
- In our empirical application: K=capital, L=labour cost, M=cost of variable inputs.

Model: Firm's Problem

- Given demand and supply primitives, the problem of the firms can be cast as

$$\Pi_i = \max_{\{P_i, Y_i\}} P_i Y_i - \mathcal{C}(Y_i)$$

$$\text{s.t.} \quad Y_i = e^{(\sigma-1)d_i(T_{g(i)})} \left(\frac{P_i}{P}\right)^{-\sigma} Y$$

where

$$\mathcal{C}(Y_i) = \min_{X} \left\{ \sum_{X \in \mathcal{X}} \boldsymbol{e^{\tau_i^X (T_{g(i)})}} P^X X_i \;\middle|\; Y_i - e^{z_i(T_{g(i)})} \prod_{X \in \mathcal{X}} X_i^{\alpha^X} \right\}$$

- $\boldsymbol{e^{\tau_i^X (T_{g(i)})}}$ are *temperature-dependent input-specific wedges* for firm i in grid-cell g

Model: Sales

- Firm i sales are

$$P_iY_i = e^{(\sigma-1)\overbrace{d_i(T_{g(i)})z_i(T_{g(i)})}^{\equiv \tilde{z}_i(T_{g(i)})}}\left(\frac{\sigma}{\sigma-1}\prod_{X\in\mathcal{X}}\left(\frac{e^{\tau_i^X(T_{g(i)})}P^X}{\alpha^X}\right)^{\alpha^X}\right)^{1-\sigma}P^{\sigma}Y$$

- Empirically testable relation between temperature and sales: mix of different effects.

Model: Aggregate TFP (1)

- Change in Solow residual given by

$$d\log Solow \approx \frac{Y}{GDP} \times d\log TFP$$

- Change in TFP given by

$$d\log TFP = \underbrace{d\log TFP^e}_{\Delta\text{ Efficient}} + \underbrace{\left(d\log TFP - d\log TFP^e\right)}_{\Delta\text{ Allocative Efficient}}$$

Model: Aggregate TFP (2)

- Change in aggregate TFP given by

  →

$$d\log TFP = d\log TFP\left(\boldsymbol{d_i(T_{g(i)})}, \boldsymbol{z_i(T_{g(i)})}, \boldsymbol{\tau_i^X(T_{g(i)})}; \sigma, \alpha_i^X, \boldsymbol{dT_{g(i)}}\right)$$

- Change in efficient TFP given by

  →

$$d\log TFP^e = d\log TFP^e\left(\boldsymbol{d_i(T_{g(i)})}, \boldsymbol{z_i(T_{g(i)})}; \sigma, \boldsymbol{dT_{g(i)}}\right)$$

- **Challenge:** Identify *temperature-dependent wedges* $\boldsymbol{d_i(T_{g(i)})}, \boldsymbol{z_i(T_{g(i)})}$ and $\boldsymbol{\tau_i^X(T_{g(i)})}$

Summary of identification strategy

- Regression of firm-level sales on temperature shocks identifies jointly $\boldsymbol{d_i(T_{g(i)}) + z_i(T_{g(i)}) + \tau_i^X(T_{g(i)})}$ (semi-parametric approach to allow for any non-linearity in these functions).
- Regression of firm-level marginal revenue products on temperature shocks identifies $\tau_i^X(T_{g(i)})$.
- Comparison of tradables and non-tradable firms helps to disentangle $d_i(T_{g(i)})$ from $z_i(T_{g(i)})$.
- Firm and Sector-Year fixed effects, region time trends, region specific Great Recession and Sovereign Crisis dummies control for possible confounding factors.

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Identification

Identification: Step 1

- We need to separate the effect of temperature between
  - demand-adjusted productivity wedge $e^{\tilde{z}_i(T_{g(i)})}$
  - input-specific wedges $e^{\tau_i^X(T_{g(i)})}$
- Assume that $e^{\tilde{z}_i(T_{g(i)})}$ and $e^{\tau_i^X(T_{g(i)})}$ take the follow functional forms:

$$e^{\tilde{z}_i(T_{g(i)})} \equiv e^{\tilde{z}_i + F_i^z(T_{g(i)})}, \quad \text{with} \quad Cov(\tilde{z}_i, F_i^z(T_{g(i)})) = 0$$

$$e^{\tau_i^X(T_{g(i)})} \equiv e^{\tau_i^X + F_i^X(T_{g(i)})}, \quad \text{with} \quad Cov(\tau_i^X, F_i^X(T_{g(i)})) = 0, \quad \forall X \in \mathcal{X}$$

Identification: Step 2

- We can recover the temperature-elasticity of sales from

$$p_i y_i = \boldsymbol{(\sigma - 1) F_i(T_{g(i)})} - (\sigma - 1)\left(\log \mu + \sum_{X \in \mathcal{X}} \alpha^X (p^X + \tau_i^X - \log \alpha^X) - z_i \right) + \sigma p + y$$

- Where $F_i(T_{g(i)})$ is given by

$$F_i(T_{g(i)}) \equiv \left(F_i^z(T_{g(i)}) - \sum_{X \in \mathcal{X}} \alpha^X F_i^X(T_{g(i)}) \right)$$

Identification: Step 3

- We can recover the temperature-elasticity of input-specific wedges $e^{\tau_i^X(T_{g(i)})}$ from

$$e^{\tau_i^X + F_i^X(T_{g(i)})} P^X \mu = \alpha^x \frac{P_i Y_i}{X_i}$$
$$= MRPX_i, \quad \forall X \in \mathcal{X}$$

- Which in logarithms is

$$mrpx_i = \boldsymbol{F_i^X(T_{g(i)})} + \tau_i^X + p^X + \log \mu, \quad \forall X \in \mathcal{X}$$

Identification: Step 4

- We recover the temperature-elasticity of the demand-adjusted wedge as

$$\boldsymbol{F_i^z(T_{g(i)})} = \frac{1}{\sigma - 1} F_i(T_{g(i)}) + \sum_{X \in \mathcal{X}} \alpha^X F_i^X(T_{g(i)})$$

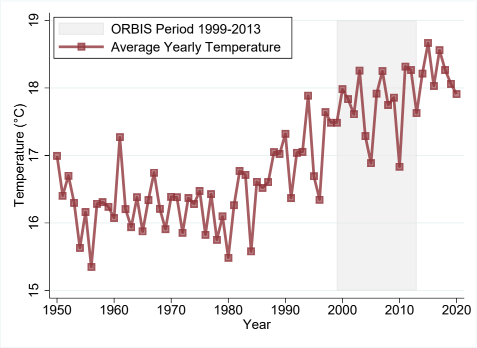
Data

Datasets

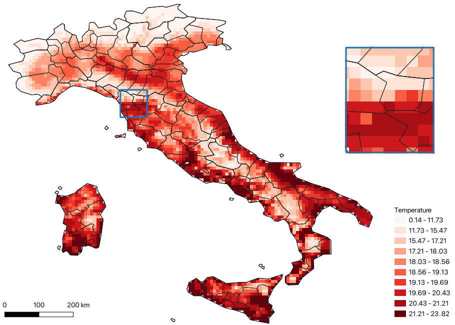
- Firm-level data: Italian Orbis data (quasi Census)
  - Balance sheet panel data from 1999-2013
  - Approximately 1 million firms, 4.3 million observations, 75% of aggregate gross output.
- **Climate data:** Copernicus
  - E-OBS daily gridded ($0.1° \times 0.1°$) meteorological data for Europe since 1950
  - Daily data on temperature, rainfall, humidity, wind speed, pressure, ...
- Merge: using firms' postcode and grid cells' latitude and longitude (minimum distance)

Temperatures over Time and Across Space

(a) Yearly Temperature, Italy



(b) Yearly Temperatures, 1999



Empirical Analysis

Empirical Specification

- Main regression

$$\text{Outcome}_{it} = \sum_{\ell} \beta_\ell T^{\ell}_{g(i)t} + \boldsymbol{\delta' X_{it}} + \alpha_i + \gamma_{s(i)t} + \varepsilon_{it}$$

- Observation is firm i, in grid-cell $g(i)$, and sector $s(i)$, at year t
- β_ℓ is the coefficient of interest
- $\boldsymbol{X_{it}}$: average rainfalls $R_{g(i)t}$, regions-time trends, Great Recession and Sovereign Debt Crisis dummies.
- α_i and $\gamma_{s(i)t}$ are firm and sector-time fixed effects
- ε_{it} clustered at grid-cell level

Main Regressor

- For **main regressor** $T^{\ell}_{g(i)t}$ we follow Somanathan et al. (2021)
- Aggregate daily temp. to annual counting the number of days within different temp. bins
- We use temp. bins defined as

$$\{(-\infty, 5), [5, 15), [15, 30), [30, 35), [35, 40), [40, \infty)\}$$

- Vector $\mathbf{T}$ summarizes the temp. distribution over the year

$$\mathbf{T} = \{T^1, T^2, T^3, T^4, T^5, T^6\}$$

  which counts number of days within each bin

- This is calculated for every geography g and year t

Summary Statistics of Days Within Temperature Bins (1999-2013)

	Temperature Bins					
	$(-\infty, 0°C]$	$(0°C, 15°C]$	$(15°C, 30°C]$	$(30°C, 35°C]$	$(35°C, 40°C]$	$(40°C, \infty)$
Variable						
Mean	1.86	118.48	196.87	42.55	5.19	0.04
Median	0	127	192	44	3	0
Min	0	19	2	0	0	0
Max	164	284	321	95	56	10

Avg. Effect of Temperature on Firms: Sales and Inputs

Dependent Variable	**Sales**	**Materials**	**Labor**	**Capital**
Temperature Bins				
$(-\infty, 5°\text{C})$	-0.156***	-0.157***	-0.143***	-0.076***
	(0.031)	(0.053)	(0.034)	(0.043)
$[5°\text{C}, 15°\text{C})$	0.011	0.014*	-0.000	0.007
	(0.010)	(0.014)	(0.008)	(0.009)
$[30°\text{C}, 35°\text{C})$	-0.018*	-0.032**	0.001	0.005
	(0.010)	(0.016)	(0.009)	(0.012)
$[35°\text{C}, 40°\text{C})$	-0.052***	-0.080***	0.008	0.004
	(0.019)	(0.031)	(0.019)	(0.021)
$[40°\text{C}, +\infty)$	-0.842***	-0.896***	-0.421**	-0.021
	(0.223)	(0.304)	(0.196)	(0.235)
Fixed Effects	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,587,926	4,635,108	3,692,934	4,260,946

Take Away: Inverted U-shaped pattern. Response of materials $\approx$ wages $>$ capital

Avg. Effect of Temperature: Firms on Marginal Products

Dependent Variable	**MRPM**	**MRPL**	**MRPK**
Temperature Bins			
$(-\infty, 5°C)$	-0.038	0.001	-0.080*
	(0.035)	(0.027)	(0.046)
$[5°C, 15°C)$	0.005	-0.009	-0.010
	(0.007)	(0.007)	(0.011))
$[30°C, 35°C)$	0.007	-0.012*	-0.018
	(0.008)	(0.006)	(0.012)
$[35°C, 40°C)$	0.013	-0.023	-0.054**
	(0.016)	(0.014)	(0.024)
$[40°C, +\infty)$	-0.202	-0.024	-0.610**
	(0.174)	(0.161)	(0.263)
Fixed Effects	✓	✓	✓
Controls	✓	✓	✓
Observations	4,587,926	3,686,465	4,235,847

Take Away: Inverted U-shaped pattern. Response of MRPK $>$ MRPL $\approx$ MRPM

Avg. Effect of Temperature on Firms: Demand-Adjusted Productivity

- Now we can recover effect of temperatures on demand-adjusted productivities
  - We use $\sigma = 4$, implying a markup of $\approx 30\%$
  - Production function elasticities $\{\alpha^x\}_{x \in \{M,L,K\}}$ from cost shares: $\{0.53, 0.36, 0.11\}$

	Temperature Bins				
	$(-\infty, 5)$	$[5, 15)$	$[30, 35)$	$[35, 40)$	$[40, \infty)$
β_ℓ^z	-0.061	0.003	-0.008	-0.002	-0.358

Het. Effect of Temperature on Firms: Demand vs Productivity (1)

- **Q:** How to separate demand and productivity effects of temperatures?
  - Firms selling tradable goods less subject to local temperature-related demand shocks
  - Most of their demand comes from grid-cells other than theirs
  - Hence, any extra effect of temperature for non-tradables must come from demand
- Regression framework

$$\text{Outcome}_{it} = \sum_{\ell} \beta_{1,\ell} T^{\ell}_{g(i)t} + \sum_{\ell} \beta_{2,\ell} T^{\ell}_{g(i)t} \times I^{NT}_{s(i)t} + \boldsymbol{\delta' X_{it}} + \alpha_i + \gamma_{s(i)t} + \varepsilon_{it}$$

  - $I^{NT}_{s(i)t}$ is a dummy equal 1 if sector s is above median trade volumes in WIOT
  - $\beta_{2,\ell}$ is the coefficient of interest

Het. Effect of Temperature on Firms: Demand vs Productivity (2)

Dependent Variable	**Sales**	**Sales**
Temperature Bins		
$(-\infty, 0°\text{C}]$	-0.156***	-0.132**
$(0°\text{C}, 15°\text{C}]$	0.011	0.020
$(30°\text{C}, 35°\text{C}]$	-0.018*	-0.024*
$(35°\text{C}, 40°\text{C}]$	-0.052***	-0.071**
$(40°\text{C}, +\infty)$	-0.842***	-0.866***
Temperature Bins$\times I^{NT}_{s(i)}$		
$(-\infty, 5°\text{C}]$		-0.044
$(5°\text{C}, 15°\text{C}]$		-0.022
$(30°\text{C}, 35°\text{C}]$		0.016
$(35°\text{C}, 40°\text{C}]$		0.047
$(40°\text{C}, +\infty)$		0.069
Fixed Effects	✓	✓
Controls	✓	✓
Observations	4,587,926	4,587,926

Take Away: Non-tradables affected as tradables → demand margin weak

Het. Effect of Temperature on Firms: Demand vs Productivity (2)

Dependent Variable	**Sales**	**Sales**
Temperature Bins	→	→
Temperature Bins $\times I_{s(i)}^{NT}$		
$(-\infty, 5°C)$		-0.044
		(0.052)
$[5°C, 15°C)$		-0.022
		(0.014)
$[30°C, 35°C)$		0.016
		(0.015)
$[35°C, 40°C)$		0.047
		(0.031)
$[40°C, +\infty)$		0.069
		(0.389)
Fixed Effects	✓	✓
Controls	✓	✓
Observations	4,587,926	4,587,926

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Aggregate Implications

Micro to Macro Link

- Aggregate **TFP changes** due to temperatures can be expressed as

$$\begin{aligned}\Delta \log TFP &\approx \Delta \log TFP\left(\tilde{z}_i(T_{g(i)}), \tau_i^X(T_{g(i)}); \boldsymbol{\Delta T_{g(i)}}\right)\\ &= \Delta \log TFP\left(\sum_{\ell} \boldsymbol{\beta_\ell^{\tilde{z}} T_{g(i)}^{\ell}}, \sum_{\ell} \boldsymbol{\beta_\ell^{X} T_{g(i)}^{\ell}}; \boldsymbol{\Delta T_{g(i)}}\right)\end{aligned}$$

- **Efficient TFP changes** due to temperatures can be expressed as

$$\begin{aligned}\Delta \log TFP^e &\approx \Delta \log TFP\left(\tilde{z}_i(T_{g(i)}); \boldsymbol{\Delta T_{g(i)}}\right)\\ &= \Delta \log TFP^e\left(\sum_{\ell} \boldsymbol{\beta_\ell^{\tilde{z}} T_{g(i)}^{\ell}}; \boldsymbol{\Delta T_{g(i)}}\right)\end{aligned}$$

- **Counterfactual:** Change in TFP due to a daily $\boldsymbol{\Delta T_{g(i)}}$

Climate change and extreme temperatures: Counterfactual Distribution of Days Within Temperature Bins

		Temperature Bins					
		$(-\infty, 0°C]$	$(0°C, 15°C]$	$(15°C, 30°C]$	$(30°C, 35°C]$	$(35°C, 40°C]$	$(40°C, +\infty)$
Warming Scenario	*Variable*						
1999-2013	Mean	1.86	118.48	196.87	42.55	5.19	**0.04**
	Median	0	127	192	44	3	0
	Min	0	19	2	0	0	0
	Max	164	284	321	95	56	10
$1°C$	Mean	1.12	104.84	198.35	51.04	9.53	**0.13**
	Median	0	114	193	52	6	0
	Min	0	8	4	0	0	0
	Max	153	282	326	105	64	17
$2°C$	Mean	0.64	91.76	198.61	58.11	15.46	**0.43**
	Median	0	102	193	59	11	0
	Min	0	0	11	0	0	0
	Max	140	281	326	105	70	32
$4°C$	Mean	0.21	67.10	197.01	65.51	32.55	**2.614**
	Median	0	78	194	65	32	1
	Min	0	0	31	0	0	0
	Max	111	283	314	117	103	52

Aggregate Productivity Loss

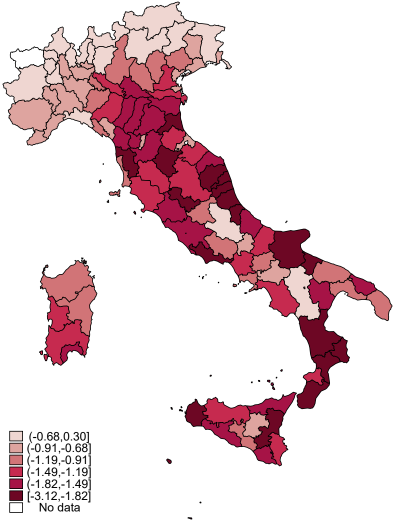
- Decompose the **total aggregate productivity loss** due to temperatures into
  1. An **efficient** component
  2. A **misallocation** component
- Look at different warming scenarios: $1°$C, $2°$C (baseline), $4°$C. Also consider $6°$C (SSP5-8.5 scenario) and $8°$C.

	Aggregate Productivity Loss		
	Δ*Total*	Δ*Efficient*	Δ*Misallocation*
$1°$C	0.8%	0.5%	0.3%
$2°$C	1.8%	1.0%	0.8%
$4°$C	6.4%	3.7%	2.7%

Comparison w.r.t. other papers: →

Take Away: (1) substantial losses, (2) losses convex in temp., (3) misallocation important

Regional Productivity Losses for 2°C Warming Scenario



→

Conclusion

Conclusion

- We propose a structural framework to:
  - Disentangle different channels of climate change
  - Understand the aggregate effects on TFP
- We document causal link between climate change and firm outcomes
  - We uncover an inverted U-shaped patter
  - Important heterogeneity across firms
- Quantify aggregate productivity implications of climate change
- Work in progress
  - Adaptation effects
  - Sources of efficiency losses
  - Extend to other European countries

Appendix: Aggregate TFP

- Change in aggregate TFP given by

←

$$\Delta \log TFP \approx \sum_{i=1}^{N} \lambda_i \left(e^{\tilde{z}_i(T_{g(i)})}, e^{\tau_i^X(T_{g(i)})}\right) \sum_{X \in \mathcal{X}} \frac{\alpha^X}{e^{\tau_i^X(T_{g(i)})}} \Omega_t^X \left(e^{\tilde{z}_i(T_{g(i)})}, e^{\tau_i^X(T_{g(i)})}\right)$$
$$\times \left[\left(\sigma \frac{e^{\tau_i^X(T_{g(i)})}}{\Omega_t^X \left(e^{\tilde{z}_i(T_{g(i)})}, e^{\tau_i^X(T_{g(i)})}\right)} - (\sigma - 1) \right) \left(\frac{\partial \tilde{z}_i(T_{g(i)})}{\partial T_{g(i)}} - \sum_{X \in \mathcal{X}} \alpha^X \frac{\partial \tau_i^X(T_{g(i)})}{\partial T_{g(i)}} \right) + \frac{\partial \tau_i^X(T_{g(i)})}{\partial T_{g(i)}} \right] \Delta T_{g(i)}$$

- Change in efficient TFP given by

←

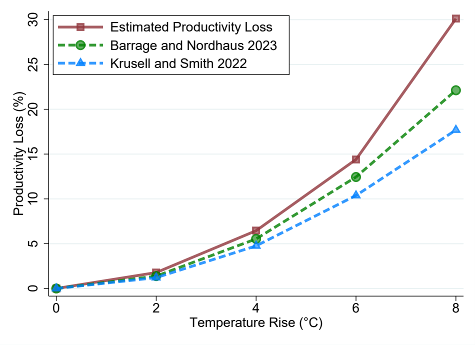
$$\Delta \log TFP^e \approx \sum_{i=1}^{N} \lambda_i^e \left(e^{\tilde{z}_i(T_{g(i)})}\right) \frac{\partial \tilde{z}_i(T_{g(i)})}{\partial T_{g(i)}} \Delta T_{g(i)}$$

Het. Effect of Temperature on Firms: Demand vs Productivity (2)

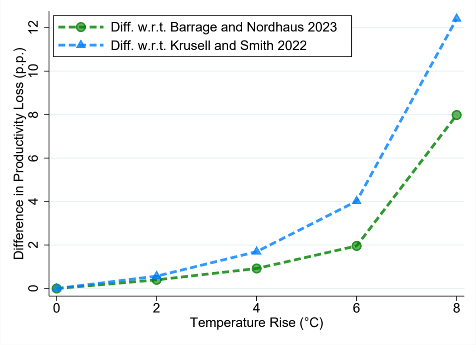
Dependent Variable	**Sales**	**Sales**
Temperature Bins		
$(-\infty, 5°C)$	-0.156***	-0.132**
	(0..031)	(0.041)
$[5°C, 15°C)$	0.011	0.020
	(0.010)	(0.013)
$[30°C, 35°C)$	-0.018*	-0.024*
	(0.010)	(0.014)
$[35°C, 40°C)$	-0.052***	-0.071**
	(0.019)	(0.028)
$[40°C, +\infty)$	-0.842***	-0.866***
	(0.223)	(0.294)
Temperature Bins$\times I^{NT}_{s(i)}$	←	←
Fixed Effects	✓	✓
Controls	✓	✓
Observations	4,587,926	4,587,926

Take Away: Non-tradables affected as tradables → demand margin weak

Comparison with Nordhaus Program



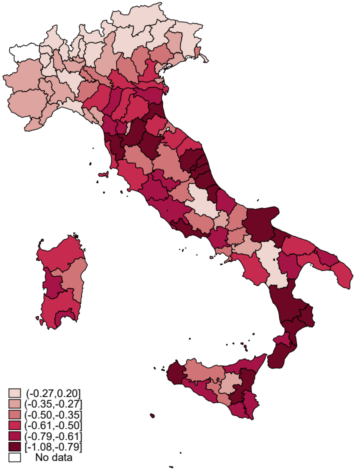
(a) Productivity Loss Across Models



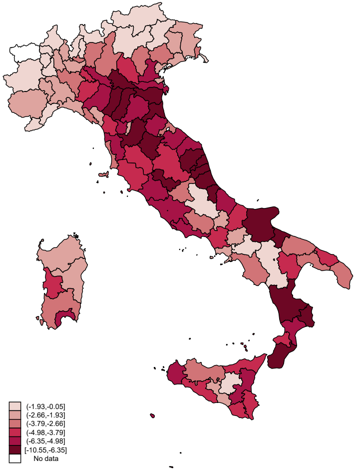
(b) Diff. in Productivity Loss Across Models

←

Regional Productivity Losses for $1°$C and $4°$C Warming Scenario



(a) $1°$C Warming Scenario



(b) $4°$C Warming Scenario

←