# The (Mis)Allocation Channel of Climate Change Evidence from Global Firm-level Microdata

Tianzi Liu Zebang Xu

Cornell University

STEG Annual Conference 2025, Oxford

# The Misallocation Channel of Climate Change

- Estimated macroeconomic consequences of climate change are significant:
  - $\rightarrow\,$  Burke et al. (2015):  $\quad$   $\approx$  23% of global GDP by 2100
  - $\rightarrow\,$  Bilal et al. (2024):  $\quad\approx\,$  50% of global GDP by 2100
  - $\rightarrow\,$  Usually modeled/identified as aggregate TFP losses since Nordhaus (1992).

Question: What are the micro-level channels behind these aggregate estimates?

• In an efficient economy, marginal products are equalized across firms.

Aggregate TFP = 
$$\underbrace{\text{"Technology"}}_{\text{Aggregation of physical productivity}}$$

Previous literature: climate change affects technology (~ physical productivity)

- Heat drags down labor productivity, disrupts transportation...
- Temperature  $\uparrow \rightarrow$  production possibility frontier contracts  $\rightarrow$  Lower TFP

#### What are the micro-level channels behind these aggregates?

• In a distorted economy, there is dispersion in marginal products across firms:.

This paper: climate change affects across-firm capital misallocation.

- Heat leads to inefficiencies: less productive firms ends up with too much capital
- Temperature  $\uparrow \rightarrow$  dispersion of "investment mistakes"  $\uparrow \rightarrow$  Lower TFP
- Climate change moves the economy further away from the efficient frontier

#### An illustrative example:

- Technology: machines are, on average, only 80% productive during heat shocks
- Misallocation: malfunctioned machines could have been more productive in plants with ACs!

### Literature

• Empirical climate econometrics: we propose measurable channel decomposition of how climate damages aggregate TFP;

 $\rightarrow\,$  This enables us to measure a new channel: the misallocation channel.

(Dell, Jones, and Olken 2012; Hsiang 2016; Deryugina and Hsiang 2017; Mérel and Gammans 2021; Carleton et al. 2022; Lemoine 2018)

• Macroeconomic modeling of climate change: we emphasize how firm heterogeneity shapes the cost of climate change.

(Nath 2023; Caggesse et al. 2024; Nath, Ramey, and Klenow 2023; Cruz and Rossi-Hansberg 2023;

Bakkensen and Barrage 2021; Casey, Fried, and Gibson 2022; Rudik et al. 2021)

• Climate and Long-run Development: we find the misallocation channel to be a key driver of cross-country TFP differences.

(Montesquieu 1748; Sachs and Warner 1997; Gallup, Sachs, and Mellinger 1999; Nordhaus 2006; Dell, Jones, and Olken 2012)

• **Misallocation**: we exploit temperature shocks as quasi-natural experiments to identify the environmental driver of misallocation.

(Hsieh and Klenow 2009; Sraer and Thesmar 2023; Bau and Matray 2023)

• Value of weather forecasts: we estimate the aggregate consequences of temperature forecast errors.

(Schlenker and Taylor 2021; Shrader 2023; Shrader, Bakkensen, and Lemoine 2023)

#### Main Idea:

• Climate-induced misallocation is an important (if not major) driver of aggregate climate damage

#### The Plan:

- 1. Causal evidence and reduced-form measurement of climate-induced misallocation
- 2. Projection of global welfare losses under future climate change scenarios
- 3. Explain and identify the mechanisms in a simple firm dynamics model
- 4. Quantitatively re-examine the impact of climate on comparative development, growth and income convergence

- A lower bound approach:
  - $\rightarrow$  focus only on across-firm misallocation within each region-sector n = (s, r).
- HK09 + all micro fundamentals can be affected by  $\tilde{T}_{rt}$  in an arbitrary but smooth way
- Total output is a CES aggregation of differentiated products,

$$Y_{nt} = \left(\int B_{ni} (\tilde{\mathbf{T}}_{rt}, \cdot)^{\frac{1}{\sigma_n}} Y_{nit}^{\frac{\sigma_n-1}{\sigma_n}} di\right)^{\frac{\sigma_n}{\sigma_n-1}},$$

• Subject to demand, firms face capital distortions in production:

$$\max_{\substack{P_{nit}, K_{nit}, L_{nit}}} P_{nit} \underbrace{A_{ni}(\tilde{\mathbf{T}}_{rt}, \cdot) K_{nit}^{\alpha_{Kn}} L_{nit}^{\alpha_{Ln}}}_{Y_{nit}} - \left(1 + \tau_{ni}^{K}(\tilde{\mathbf{T}}_{rt}, \cdot)\right) R_{nt} K_{nit} - W_{nt} L_{nit}$$
$$\mathsf{MRPK}_{nit} := R_{nt} (1 + \tau_{ni}^{K}(\tilde{\mathbf{T}}_{rt}, \cdot))$$

• Any mechanisms causing ex-post capital return differences will show up as  $\tau_{ni}^{\kappa}(\mathbf{\tilde{T}}_{rt}, \cdot)$ .

## Measurement: Climate-TFP Accounting

• Under the standard assumption of joint log-normality between  $A_{nit}$ ,  $B_{nit}$  and  $(1 + \tau_{nit}^{K})$  in any cross-section, aggregate TFP of a region-sector n = (s, r) can be decomposed as:

$$\operatorname{og} \mathsf{TFP}_{n}(\widetilde{\mathbf{T}}_{rt}, \cdot) = \underbrace{\frac{1}{\sigma_{n} - 1} \operatorname{log} \left[ \mathbb{E}_{i} \mathsf{TFP}_{ni}(\widetilde{\mathbf{T}}_{rt}, \cdot)^{\sigma_{n} - 1} \right]}_{\mathsf{Technology}} - \underbrace{\frac{\alpha_{Kn} + \alpha_{Kn}^{2}(\sigma_{n} - 1)}{2} \operatorname{var}_{mrpk_{ni}}(\widetilde{\mathbf{T}}_{rt}, \cdot)}_{\mathsf{MRPK Dispersion Across Firms}}$$

- Dispersion in MRPK lowers aggregate TFP.
- All aggregate sufficient statistics are all smooth functions of  $\tilde{T}_{rt}$ , which yields:

$$\frac{d \log \mathsf{TFP}_n(\tilde{\mathsf{T}}_{rt}, \cdot)}{d\tilde{\mathsf{T}}_{rt}} = \frac{d \operatorname{Technology}_n(\tilde{\mathsf{T}}_{rt}, \cdot)}{d\tilde{\mathsf{T}}_{rt}} - \underbrace{\frac{\alpha_{Kn} + \alpha_{Kn}^2(\sigma_n - 1)}{2} \frac{d \operatorname{var}_{mrpk_{ni}}(\tilde{\mathsf{T}}_{rt}, \cdot)}{d\tilde{\mathsf{T}}_{rt}}}_{\text{The Misallocation Channel}}$$

We can measure the total effect of climate on var<sub>1+τ<sup>K</sup><sub>ni</sub></sub>(T
<sub>rt</sub>, ·) without taking a stance on the exact sources of the heterogeneity in τ<sup>K</sup><sub>ni</sub>(T
<sub>rt</sub>, ·).

$$\frac{d \log \mathsf{TFP}_n(\tilde{\mathbf{T}}_{rt}, \cdot)}{d\tilde{\mathbf{T}}_{rt}} = \frac{d \operatorname{Technology}_n(\tilde{\mathbf{T}}_{rt}, \cdot)}{d\tilde{\mathbf{T}}_{rt}} - \underbrace{\frac{\alpha_{Kn} + \alpha_{Kn}^2(\sigma_n - 1)}{2} \frac{d \operatorname{var}_{mrpk_{ni}}(\tilde{\mathbf{T}}_{rt}, \cdot)}{d\tilde{\mathbf{T}}_{rt}}}_{\text{The Misallocation Channel}}$$

To identify the misallocation channel, we use:

- Standard parameters drawn from the literature:  $\alpha_{Kn} = 0.35$ ,  $\sigma_n = 4$
- Firm-level microdata from 32 countries:  $\approx$  80 m. firm-year obs.
  - $\rightarrow\,$  Orbis Historic: 1995-2018 for 30 European countries
    - Good coverage of total sales in many countries
  - $\rightarrow$  China NBS + India ASI
    - Census for "above-scale" manufacturing firms
  - ightarrow Under Cobb-Douglas, we measure misallocation using

$$\mathsf{var}_{mrpk_{nit}} = \mathsf{var}\left[\mathsf{log}(\frac{\mathsf{Revenue}_{nit}}{\mathsf{Capital Stock}_{nit}})\right]$$

for each region-sector-year. (e.g. all firms within UKJ14, Manufacturing, 2024)

- Weather and Climate Data: Daily Temperature from ERA5  $(0.1^{\circ} \times 0.1^{\circ})$
- Medium-Range Weather Forecast Data (ECMWF)

# Average Effect of Temperature on MRPK Dispersion

We regress region-sector-level MRPK dispersion on the distribution of daily temperatures.

$$\mathsf{var}_{mrpk_{(s,r),t}} = \sum_{b \in B/(5 \sim 10^{\circ} C)} \lambda^{b}_{\sigma^{2}_{mrpk}} \times \mathsf{Tbin}^{b}_{r,t} + \delta_{\sigma^{2}_{mrpk}} \mathbf{X}_{s,r,t} + \theta_{c(r),s,t} + \eta_{s,r} + \varepsilon_{r,s,t}.$$

- r: region ("NUTS3"-level); s: sector (SIC industry group)
- $\mathbf{T}_{r,t} = { \text{Tbin}_{r,t}^{<-5^{\circ}C}, ..., \text{Tbin}_{r,t}^{>30^{\circ}C} }$  as days in temperature bins.
- $X_{s,r,t}$  is a vector of controls: number of firms, average sales and average MRPK
- $\eta_{s,r}$ : region-sector FE
- $\theta_{c(r),s,t}$ : country-sector-year FE
- SE clustered at the region level

Within each region-sector, weather patterns are **exogenous** to capital distortions conditional on FEs.

# Average Effect of Temperature on MRPK Dispersion



If we replace a 5-10°C (41°F to 50°F) day with a hotter-than-30°C (86°F) day in a year:

- The measured MRPK dispersion will increase by about 0.31 log points;
- The measured yearly TFP will decrease by about 0.11% through capital misallocation.  $\rightarrow~\approx$  40% of daily GDP

## Technology vs. Misallocation



• Technology only plays a minor role in aggregate climate damage! (only  $\approx \frac{1}{5}$  for heat shocks)



• Following Carleton et al. (2022), we interact the long-term annual average temperature of region *r* and average region-level GDP per capita with each temperature bin:

$$\sigma_{mrpk_{s,r,t}}^{2} = \sum_{b \in B_{/(5 \sim 10^{\circ} C)}} \lambda_{\sigma_{mrpk}}^{b} \times \operatorname{Tbin}_{r,t}^{b} + \sum_{b \in B_{/(5 \sim 10^{\circ} C)}} \lambda_{\sigma_{mrpk}}^{b,\overline{T}} \times \operatorname{Tbin}_{r,t}^{b} \times \overline{T}_{r} + \sum_{b \in B_{/(5 \sim 10^{\circ} C)}} \lambda_{\text{GDP}_{pc}}^{b} \times \operatorname{Tbin}_{r,t}^{b} \times \ln \overline{\text{GDP}_{pc,r}} + \delta_{\sigma_{mrpk}}^{2} \times \tilde{\mathbf{X}}_{s,r,t} + \alpha_{c,t} + \eta_{s,r} + \varepsilon_{s,r,t},$$
(1)

• The estimated first-order effect takes adaptation into account:

$$\frac{d\operatorname{var}_{mrpk_{s,r}}(\widetilde{\mathbf{T}}_{rt},\cdot)}{d\operatorname{Tbin}_{r,t}^{b}} \approx \lambda_{\sigma_{mrpk}^{2}} + \overline{T}_{r} \cdot \lambda_{\sigma_{mrpk}}^{\overline{\tau}} + \ln \overline{\operatorname{GDP}}_{pc,r} \cdot \lambda_{\operatorname{GDP}_{pc}}^{b}$$

# Heterogeneous Effect across Regional Income and Long-run Climate



In terms of the misallocation channel:

- Hotter and more developed regions suffer more damage by heat shocks.
- Cooler regions could even benefit from heat shocks.
- With Technology



Micro-level estimates using only firm-level data *quantitatively* match macro estimates (GDP per capita) quite well

# End-of-the-century Projections under SSP3-4.5 Warming Scenario

Under the assumption that  $\frac{d \operatorname{var}_{mpk_{nl}}(\tilde{\tau}_{\tau,\tau'})}{d\tilde{\tau}_{\tau}} = f(\operatorname{Long-run} \operatorname{Climate}, \operatorname{Income})$ , we project the effect of climate-induced misallocation on aggregate TFP loss by the end of the 21st century (2081-2100) for 4,881 regions in 172 countries worldwide.

$$\underbrace{\Delta_{r,EOC}^{\text{Mis, Loss} \text{ In TFP}}}_{\text{Misallocation Channel}} = \sum_{r} \omega_{rt} \frac{\alpha_{Kr} + \alpha_{Kr}^2 (\sigma_r - 1)}{2} \left[ \sigma_{mrpk}^2 \left( \tilde{\mathbf{T}}_{r,EOC}, \frac{d\sigma_{mrpk,r,EOC}^2}{d\tilde{\mathbf{T}}_{r,EOC}} \right) - \sigma_{mrpk}^2 \left( \tilde{\mathbf{T}}_{r,2019}, \frac{d\sigma_{mrpk,r,2019}^2}{d\tilde{\mathbf{T}}_{r,2019}} \right) \right]$$
$$= \underbrace{\text{Shock Effect}}_{2.13\%} + \underbrace{\text{Level Effect}}_{11.34\%} + \underbrace{\text{Income Effect}}_{19.46\%} + \underbrace{\text{Resid.}}_{3.8\%}$$

Figure: TFP Loss from Climate-Induced Misallocation



# Future TFP Loss under SSP3-4.5 Warming Scenario



- $\rightarrow$  Large spatial heterogeneity in projected damages from the misallocation channel:
  - Above 40 %: Tanzania, Malaysia, Honduras, and India.
  - 20-30 %: US, Argentina, and Spain.
  - Below 15 %: France, UK, Russia, and Canada.

- We want to explain why both the levels and shocks of temperature give rise to misallocation.
- A simple model with minimal ingredients: focusing on activities within (r, s).
- Firms: iso-elastic demand + Cobb-Douglas production
  - $\rightarrow$  Revenue Function:  $P_{it}Y_{it} = \hat{A}_{it}K_{it}^{\hat{\alpha}_K}L_{it}^{\hat{\alpha}_L}$

A Firm's productivity is heterogeneously impacted by temperature:



• Two sources of heterogeneity in  $\hat{\beta}_{it}$  :

 $\rightarrow \hat{\beta}_i \sim \mathcal{N}\left(\overline{\hat{\beta}_i}, \sigma_{\hat{\beta}}^2\right) \text{ is known by the firm: product characteristics and adaptability.}$  $\rightarrow \hat{\xi}_{it} \sim \mathcal{N}\left(0, \sigma_{\hat{\xi}}^2\right) \text{ is i.i.d.: the likelihood of extreme events scales with } (T_t - T^*).$ 

# MRPK and Temperature

• "Time-to-build" Capital  $\rightarrow$  investment depends on expected productivity:

$$k_{it+1} \propto \mathbb{E}_t[a_{it+1}] \propto \hat{\beta}_i \mathbb{E}_t[(T_{t+1} - T^*)]$$

• After all shocks are realized, relative MRPK is higher in the firms with higher unexpected changes in productivity:

$$mrpk_{it} - \overline{mrpk_{it}} = \frac{1}{1 - \alpha_N} (\hat{a}_{nit} - \mathbb{E}_{t-1}[\hat{a}_{nit}])$$
$$= \frac{1}{1 - \alpha_N} \left\{ (\hat{\beta}_i - \overline{\hat{\beta}_i}) \underbrace{(\mathcal{T}_{t+1} - \mathbb{E}_t[\mathcal{T}_{t+1}])}_{\text{T Forecast Error}} + \hat{\xi}_{it} \underbrace{(\mathcal{T}_t - \mathcal{T}^*)}_{\text{T Level}} + \hat{\varepsilon}_{it} \right\}$$

- Who gets lower *mrpk* with a heat shock in a warm place?  $(T_{t+1} \mathbb{E}_t[T_{t+1}] > 0, T_t T^* > 0)$ 
  - → Heat-averse firms with  $\hat{\beta}_i < \overline{\hat{\beta}_i}$ : failed to expect the low productivity caused by the temperature shock,  $T_{t+1} \mathbb{E}_t[T_{t+1}]$ .
  - $\rightarrow$  Unlucky firms with  $\hat{\xi}_{it}>$  0: failed to expect the low productivity caused by the damage sensitivity shock  $\hat{\xi}_{it}$ .
- What kind of firms have higher  $\hat{\beta}_i$  in the data? Larger in size/AC-equipped.

**Proposition:** MRPK Dispersion The variance of *mrpk<sub>it</sub>* across firms in a given period is:

$$\sigma_{mrpk,(r,s),t}^{2} = \left(\frac{1}{1-\alpha_{N}}\right)^{2} \operatorname{Var}(\hat{a}_{nit} - \mathbb{E}_{t-1}[\hat{a}_{nit}]) \\ = \left(\frac{1}{1-\alpha_{N}}\right)^{2} \left[\underbrace{(\mathcal{T}_{r,t} - \mathcal{T}^{*})^{2}}_{\text{Level Effect}} \sigma_{\hat{\xi},(r,s)}^{2} + \underbrace{(\mathbb{F}\mathbb{E}_{t}[\mathcal{T}_{t+1}])^{2}}_{\text{Forecast Error Effect}} \sigma_{\hat{\beta},(r,s)}^{2} + \sigma_{\varepsilon,(r,s)}^{2}\right]$$

• MRPK dispersion  $\propto$  TFP volatility  $\longleftarrow$  endogenously generated by climate conditions.

How would climate change lead to larger misallocation?

- Given everything else unchanged, a higher  $\sigma^2_{\hat{\xi},(r,s)}$  and  $\sigma^2_{\hat{\beta},(r,s)}$  lead to more capital misallocation
- Larger deviation from optimal temperature:  $(T_{r,t} T^*)^2$
- Larger unexpected temperature shocks:  $(\mathbb{FE}_t[\mathcal{T}_{t+1}])^2$

## Forecast Error Effect

$$\sigma_{mrpk,(r,s)t}^{2} \propto \mathsf{Var}(\hat{a}_{nit} - \mathbb{E}_{t-1}[\hat{a}_{nit}]) \propto \left[\underbrace{(\mathbb{FE}_{t}[\mathcal{T}_{t+1}])^{2}\sigma_{\beta}^{2}}_{\mathsf{Forecast Error Effect}} + \underbrace{(\mathcal{T}_{r,t} - \mathcal{T}^{*})^{2}\sigma_{\xi}^{2}}_{\mathsf{Level Effect}}\right]$$

- Mid-range temperature forecast data (1-month ahead forecast) from ECMWF.
- Misallocation is worse if the temperature forecast is inaccurate (TWFE residualized):



• a 1°C error in temperature forecast for all months  $\rightarrow$  0.5 % of annual aggregate TFP loss

## Level Effect: Temperature as volatility shocks

$$\sigma_{mrpk,(r,s)t}^{2} \propto \mathsf{Var}(\hat{a}_{nit} - \mathbb{E}_{t-1}[\hat{a}_{nit}]) \propto \left[\underbrace{(\mathbb{FE}_{t}[\mathcal{T}_{t+1}])^{2}\sigma_{\beta}^{2}}_{\mathsf{Forecast Error Effect}} + \underbrace{(\mathcal{T}_{r,t} - \mathcal{T}^{*})^{2}\sigma_{\xi}^{2}}_{\mathsf{Level Effect}}\right]$$

We test whether firm-level TFP volatility varies non-linearly with the level of temperature in the region-sector panel:

$$\mathsf{Var}_{(s,r),t}(\hat{a}_{it} - \hat{a}_{it-1}) = \alpha + \beta f(T_{r,t}) + \eta_{s,r} + \delta_{c(r),t} + \varepsilon_{s,r,t},$$

by using the "first-differenced" TFPR shocks.

- Firms' TFP volatility goes up in regions that are too hot or too cold.



## Quantitative Results: Calibration

We run the following model-induced regression to calibrate the sensitivity dispersion parameters:

$$\sigma_{mrpk,(s,r),t}^{2} = \sigma_{\xi}^{2} \cdot (T_{r,t} - \hat{T}^{*})^{2} + \sigma_{\beta}^{2} \cdot \mathsf{MSFE}_{r,t} + \iota_{s,r} + \iota_{c(r),s} + \varepsilon_{s,r,t},$$
(2)

	(1)	(2)
$(T_{r,t}-\hat{T}^*)^2$	0.0045***	0.0042***
	(0.0008)	(0.0007)
MSFE <sub>r,t</sub>	0.0120**	0.0124**
	(0.0055)	(0.0052)
Region-Sector FE	Yes	Yes
Country-Year FE	Yes	No
Country-Sector-Year FE	No	Yes
Observations	121,561	121,004
$R^2$	0.876	0.909

- Using the model, we will revisit the classic question through the misallocation channel: How much does temperature affect productivity and income inequalities in development?
  - → We pair our micro estimates with gridded climate data (ERA5) and weather forecast data (ECMWF) for all regions worldwide since 1981.

#### Quantitative Results: Cost of Climate-Induced Misallocation

• With Cobb-Douglas aggregators, the Global TFP can be written as:

$$\log \mathsf{TFP}_t^{\mathsf{Global}} = \sum_r \omega_{rt} \log \mathsf{TFP}_{rt}.$$

• Using 1981-2019 averages, the global cost of climate-induced misallocation is around 9.1%.



## The Changing Cost: Climate Change and Forecast Improvements

- From  $t_0 = 1981$  to  $t_1 = 2019$ : hotter climate but better forecasts.
- Combining both leads to a 2.49% net increase in the cost of climate-induced misallocation.



# The Changing Cost: Climate Change and Forecast Improvements

• A 0.2% of TFP increase from small but steady increase in mid-range weather forecast accuracy



- According to Georgeson et al. (2017), the investment cost of weather information services is about 0.08% of global GDP.
- Potential benefits are at least 0.2%, implying a benefit-cost ratio greater than 2.

#### Temperature and Cross-/Within-Country Productivity Differences

• We match our model-generated country-year estimates with TFP data from the Penn World Table (PWT) 10.01.



(b) Within-country: Macro Data vs. Model



- On average, the model estimates  $\Delta^{T,\text{Mis}} \log \text{TFP}_{c,t} \Delta^{T,\text{Mis}} \log \text{TFP}_{\text{US},t}$  predicts the macro data  $\ln \text{TFP}_{c,t} \ln \text{TFP}_{\text{US},t}$  very well in the cross-section.  $\longrightarrow \beta \approx 1$  !
- The misallocation channel accounts for 9% of the TFP dispersion across countries and 5% of the TFP variation within a country.

### Climate Change Slows Down Aggregate TFP Growth

- Global TFP would have been 2.36 p.p. higher if  $\Delta_{\text{Global}}^{T,\text{Mis}} \log \text{TFP}_t$  stays at the 1981 level.
- This is equivalent to a 36% increase of cumulative growth since 1981.



(b) Contribution to Cumulative Growth since 1981



#### Increasing Misallocation Hinders Income Convergence

• To measure income inequality, we follow Gaubert et al. (2021) and adopt a population-weighted, between-country variance of income per capita:

$$V_{\text{Global},t} = \sum_{r} \omega_{rt} \left( \ln \text{GDPpc}_{rt} - \sum_{r} \omega_{rt} \ln \text{GDPpc}_{rt} \right)^2$$
(3)

- Actual income convergence:  $V_{\text{Global},t}$  declines from 2.09 to 0.83.
- Without climate-misallocation:  $\widetilde{V}_{Global,t}$  declines from 2.02 to 0.71.
- The misallocation channel accounts for an increasing share of the surviving income inequalities
  - $\rightarrow\,$  from about 3% in 1981 to 14% in 2019



(b) Contribution of Climate-Induced Misallocation



- Established the first causal estimates and projections of the misallocation channel of climate change
  - $\rightarrow\,$  A major channel for aggregate climate damage
  - $\rightarrow$  36.7% TFP Losses by EOC under SSP 3-4.5
- Quantitatively studied how climate-induced volatility and weather forecast errors can result in capital misallocation in a firm dynamics model
  - $\rightarrow\,$  The varying cost of climate-induced misallocation match well with macro data at the country-level.
  - $\rightarrow$  Climate-induced misallocation accounts for an important part of comparative development, growth and income inequality across countries.
- Policies to manage climate-induced misallocation:
  - $\rightarrow\,$  Mitigating global warming:  $\approx$  22% TFP loss can be avoided under RCP 2.6 compared to RCP 7
  - $\rightarrow\,$  Improving mid-range temperature forecast accuracy
  - $\rightarrow\,$  Reducing damage heterogeneity across units:
    - More "equity" across firms  $\rightarrow$  higher aggregate efficiency

The (Mis)Allocation Channel of Climate Change Evidence from Global Firm-level Microdata

Draft: https://www.zebangxu.com/climate\_allocation.pdf tl567@cornell.edu zx88@cornell.edu

$$\mathsf{var}_{\mathit{mrpk}_{(s,r),t}} = \sum_{b \in B/(5 \sim 10^{\circ} C)} \lambda^{b}_{\sigma^{2}_{\mathit{mrpk}}} \times \mathsf{Tbin}^{b}_{\mathit{r},t} + \delta_{\sigma^{2}_{\mathit{mrpk}}} \mathbf{X}_{s,r,t} + \theta_{c(r),s,t} + \eta_{s,r} + \varepsilon_{r,s,t}.$$

- r: region ("NUTS3"-level); s: sector (SIC divisions).
- $\mathbf{T}_{r,t} = { \text{Tbin}_{r,t}^{<-5^{\circ}C}, ..., \text{Tbin}_{r,t}^{>30^{\circ}C} }$  as days in each temperature bins.
- **X**<sub>s,r,t</sub> is a vector of control: number of observed firms, average firm-level sales and average MRPK across firms.
- $\eta_{s,r}$ : region-sector FE;  $\theta_{c(r),s,t}$ : country-sector-Year FE; SE clustered at region level..

#### ▶ Go Back

# The Technology Channel

We next turn to estimate how temperature affect the aggregate "physical productivity":

Technology Channel = 
$$\frac{1}{\sigma_n - 1} \frac{d \log \left[\mathbb{E}_i \mathsf{TFP}_{ni}(\tilde{\mathsf{T}}_{rt}, \cdot)^{\sigma_n - 1}\right]}{d \tilde{\mathsf{T}}_{rt}}$$

• This is an "elasticity of the average", not the "average elasticity" à la OLS:

$$\underbrace{\frac{d \log \mathbb{E}_{i} \left[\mathsf{TFP}_{ni}(\tilde{\mathbf{T}}_{r,t}, \cdot)^{\sigma_{n}-1}\right]}{d\tilde{\mathbf{T}}_{r,t}}}_{\text{Elasticity of the Average}} = \mathbb{E}_{i} \left[\underbrace{\frac{\mathsf{TFP}_{nit}^{\sigma_{n}-1}}{\mathbb{E}_{i}[\mathsf{TFP}_{nit}^{\sigma_{n}-1}]}}_{\text{Share}_{t}^{t}} \cdot \underbrace{\frac{d \log \mathsf{TFP}_{ni}(\tilde{\mathbf{T}}_{r,t}, \cdot)^{\sigma_{n}-1}}{d\mathbf{T}_{r,t}}}_{\text{Elasticity}_{it}}\right] \neq \underbrace{\mathbb{E}_{i} \left[\frac{d \log \mathsf{TFP}_{ni}(\tilde{\mathbf{T}}_{r,t}, \cdot)^{\sigma_{n}-1}}{d\mathbf{T}_{r,t}}\right]}_{\text{Average Elasticity}_{it}}$$

- OLS could bias the estimate of the average downward for heat shocks
  - $\rightarrow$  Larger firms are likely more resilient to heat, cov (Share<sup>E</sup><sub>it</sub>, Elasticity<sub>it</sub>) > 0.
  - $\rightarrow$  We draw caution to the practice of using (unweighted) micro-level OLS estimates to make an interpretation of the aggregate impact.
- Instead, the CES index can be consistently identified via PPML with the following moment condition:

$$\mathsf{E}_{i}\big[\frac{1}{\sigma_{n-1}}\widetilde{\mathsf{TFP}}_{nit}^{\sigma_{n}-1} \mid \widetilde{\mathsf{T}}_{rt}, \eta_{i}, \mathsf{log}(P_{nt}Y_{nt}), \kappa_{c(r)st}\big] = \exp\big[\beta \widetilde{\mathsf{T}}_{rt} + \eta_{i} + \delta \operatorname{log}(P_{nt}Y_{nt}) + \kappa_{c(r)st}\big],$$



#### The Technology Channel: OLS vs PPML



(a) OLS: Average Elas., biased towards small firms

#### (b) PPML: Elast. of Average, welfare relevant

 $eta_{\mathsf{OLS}}^{>30\,^{\circ}\,\mathsf{C}} pprox -0.1 \quad << \quad eta_{\mathsf{PPML}}^{>30\,^{\circ}\,\mathsf{C}} pprox -0.02$ 



### Heterogeneous Effect: Misallocation + Technology



• The misallocation channel almost always plays the dominating role in the total aggregate imapct!



- Projection Data Source:
  - $\rightarrow~$  Changes in daily temperature distributions and long-run temperature:
    - Near-surface air temperature projection in SSP3-7.0 from CMIP-6 (ensemble average of 26 models).
  - $\rightarrow~$  Changes in Income:
    - OECD Env-Growth model (Dellink et al. 2017)
    - Aggregation Weight: grid-level projected SSP-3 GDP (Wang and Sun 2022)

▶ Go Back

# Burke, Hsiang and Miguel 2015

Their finding: Country-level economic production is smooth, non-linear, and concave in temperature with a maximum at 13°C.



# Firm-level Evidence: Heterogeneity of $\beta_i$ and MRPK Responses

$$mrpk_{it} - \overline{mrpk_{it}} = \frac{1}{1 - \alpha_N} \left\{ \underbrace{(\hat{\beta}_i - \overline{\hat{\beta}_i})\eta_t^T}_{\text{Temp}} + \underbrace{\hat{\xi}_{it}(T_t - T^*)}_{\text{Damage Sensitivity}} + \hat{\varepsilon}_{it} \right\}$$

We run the empirical counterpart:

$$\log(MRPK_{r,s,i,t}) = \sum_{b \in B/\{5-10^{\circ}C\}} \lambda_b \times \mathsf{Tbin}_{r,t}^b + \sum_{b \in B/\{5-10^{\circ}C\}} \lambda_{b,\hat{\beta}\text{-proxy}} \times \mathsf{Tbin}_{r,t} \times \hat{\beta}\text{-proxy}_{it}^{r,s} + \delta \mathbf{X}_{i,t}$$
(4)  
+  $\delta_i + \alpha_{s,c(r),t} + \varepsilon_{s,c(r),i,t}, \qquad \hat{\beta}\text{-proxy} \in \{\mathsf{Relative Size, AC}\}.$ 

• Given it's hard to observe  $\hat{\beta}_i$ , we use two proxies:

 $\rightarrow$  Relative Size $_{it}^{r,s} := \log K_{it}^{s,r} - \overline{\log K_{it}}^{s,r}$  (Larger firms are more heat tolerant)

 $\rightarrow$  AC<sup>r,s</sup><sub>it</sub> = 1 if ever reported an AC installation (a proxy for adaptability, only in India ASI)

 λ<sub>b,β-proxy</sub>, are identified by comparing firms within the same country-sector exposed to identical temperature shocks but show differential response in (log) MRPK.

 $\rightarrow~$  A  $\lambda_{b,\hat{\beta}\text{-proxy}}>0$  : relatively higher MRPK responses to shocks for heat-tolerant firms

# Firm-level Evidence: Heterogeneity of $\beta_i$ and MRPK Responses



(b) Heterogeneous Effect from Firm Adaptability (AC)

- An additional 30°C day relative to baseline:
  - $\rightarrow$  makes a 1-SD larger firm having 0.1% higher MRPK compared to the average firm.
  - $\rightarrow$  makes an AC-equipped firm having 0.2% higher MRPK compared to those without ACs.
- $\lambda_{b,\hat{\beta}-\text{proxy}} > 0$  for heat shocks

# Firm-level Evidence: Heterogeneity of $\beta_i$ and MRPK Responses

- This explains why richer regions suffer larger climate-induced misallocation  $\rightarrow$  larger heterogeneity in firm-level sensitivity!
- Across Firms within a region-sector:  $\sigma_{\hat{\beta}}^2 \propto \sigma_k^2 \propto {\sf GDP}_{\it pc}$

