

Adapting to Heat Extremes with Unequal Access to Cooling: Evidence from India

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Introduction

Motivation

- Large evidence about the **welfare costs** of **extreme heat** for individuals
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 - \hookrightarrow If there is **imperfect** substitution \Rightarrow **inequality** in exposure to extreme heat

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⇒ Q2. Do air conditioners and evaporative coolers provide different level of protection?

This Paper

1. Examine **the heterogeneous technological responses** of households to hot days
 - Household ($> 200k$) panel data from **India** combined with high-quality **weather** information
 - Document the **extensive margin** response: **technology adoption**
 - Document the **intensive margin** response: **electricity consumption**

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2. Test whether technology determines **the level of protection** from extreme heat
 - Administrative **district-level** annual **mortality** data (all-age, all-causes)
 - Re-construct district-level **ownership rates** of air conditioners and evaporative coolers
 - Evaluate the **interactions** between ownership rates and extreme heat

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 - Evaluate the **interactions** between ownership rates and extreme heat
3. Determine the consequences of **technological inequality** in heat adaptation
 - Number of **prevented deaths**
 - Implications for policy: back-to-the-envelope **cost-benefit analysis**

- Extreme heat:

- ↪ Between March and May 2022: temperature reached 51°C

- ↪ Future: estimated up to 20 times more likely relative to 2022
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- **Cooling adaptation:**

- ↪ Rising incomes and temperatures ⇒ boost in cooling demand
(IEA, 2018; Davis et al. 2021; Pavanello et al. 2021, NC)

- ↪ One of the first countries to develop a **Cooling Action Plan** (2019)

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 - ↪ If similarly widespread, **air conditioners** would have prevented **47%** of heat-related deaths

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 - ↳ **Evaporative coolers** prevented **14%** of heat-related deaths
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- **Subsidising** air conditioners results as a **cost-effective** strategy to reduce heat-related mortality

1. Air-conditioning adoption, temperature and income

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↔ **Contributions:** alternative technologies, prevalence and adoption, heterogeneity

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4. Mediator effect of cooling technologies

(Barreca et al 2016, JPE; Park et al. 2020, AE; Somanathan et al. 2021, JPE; Hua et al. 2022, JPopE)

↪ **Contributions:** technological dimension, first application to mortality in India, cost-benefit analysis

- Household panel data: **Consumer Pyramid Dx survey (2014-2019)**:
 - Four-month air-conditioning and coolers ownership
 - Monthly electricity expenditure
 - Households' socio-economic and demographic characteristics
- District-level annual **mortality data**: **Civil Registration System (2014-2019)**
 - Digitalise the reports
 - All-age and all-causes, distinction between total, urban and rural deaths
- District-level data on **heat adaptation**: **Consumer Pyramid Dx survey (2014-2019)**
 - District and state-level penetration rates of air conditioners and evaporative coolers
- Population-weighted **climate data** from **ERA5** ($0.25^\circ \times 0.25^\circ$ cells):
 - Daily average temperature, daily total precipitation, daily specific humidity

Theoretical Framework

Set-up

A representative household maximises its utility function:

$$\max_{q_S, q_N, k, x} u = D[T, a, q_S, k] \cdot z[q_N, x] \quad \text{s.t. } y \geq p[q_S + q_N] + rk + x$$

↔ Assumption: (1) $\partial u / \partial D < 0$ (2) $\partial u / \partial z > 0$

- T = ambient temperature ($^{\circ}\text{C}$)
- q_S = electricity for cooling (kWh)
- k = space conditioning capital (total capacity, kWh)
- p = electricity price, r = discounted capital cost
- y = income, q_N = electricity for other uses, x = numeraire good
- a = loss of effectiveness ($^{\circ}\text{C} / \text{kWh}$)

Damage Function

The **damage function** is defined as follows:

- Higher-than-optimal indoor temperatures T^* incur a linear utility penalty D with marginal disutility coefficient δ

$$D = 1 - \delta \left(\frac{1}{A[q_S, k]} T - T^* \right)$$

where we assume that $A^{(-1)}T \geq T^*$

- For simplicity, let A being a **Leontieff** function

$$A = a^{(-1)} \min [q_S, k]$$

Solve the model:

- Closed-form solution for electricity consumption and cooling capital

$$q_S^*, \bar{k}, q_S^* = k^* \propto \sqrt{T} \sqrt{Y}$$

↔ importance of **temperature-income interactions**

↔ diminishing returns to adaptation

- **Income inequality** \Rightarrow how much a household can adapt
- Current assumption: no technological differences

- Assume that there exists two type of technologies $\theta \Rightarrow$ **conditional** maximisation utility problem
- Household invests only on one technology
- The two technologies only differ in **loss of effectiveness** a and **cost** r
- The optimal disutility due to temperature becomes:

$$D_{\theta}^* \propto \sqrt{r_{\theta}}, \sqrt{a_{\theta}}$$

- Coolers are **cheaper** than air conditioners ($r_C < r_{AC}$)
- If coolers are **less effective** at bringing thermal comfort ($a_{AC} < a_C$)
 \Leftrightarrow There is a **trade-off**

Moving to Empirical Analysis

Our empirical analysis:

1. Identify how Indian households are adapting and through which technology
↪ **revealed preferences**
2. Estimate the **marginal disutility** $\partial D / \partial T$
↪ mortality—temperature relationship
3. Determine **differences at reducing thermal discomfort** a_θ
↪ mortality—(temperature \times technology)

Heat Adaptation

The Choice of the Heat Adaptation Technology

- Our data feature allows to look at both **ownership** and **adoption** of cooling appliances
- The investment decision is a **slow adjustment** process \Rightarrow long lifetimes of cooling appliances
- Households invest based on **expectations** about climate \Rightarrow average weather over long periods
(Cohen et al. 2017)
- In our setting **adoption** occurs in a short period of time
 \hookrightarrow driven only by **economic development** but **conditional on climatic conditions** Trend State
- How we model **unobserved heterogeneity** determines the dimension of study

Empirical Framework

Estimating the impact of **temperature and income** on the **ownership** and **adoption** of the cooling appliances:

$$C_{ciw} = \gamma_0 + \gamma_1 \overline{CDD}_{d(i)w} + \gamma_2 l_{iw} + \gamma_3 g(P_{d(i)w}) + \lambda X_{iw} + \mu_k + \delta_w + \theta_{s(i)} y + \theta_{s(i)}^2 y^2 + \zeta_{iw}$$

- C_{ciw} : dummy if household i in wave w has a cooling appliance c
- $\overline{CDD}_{d(i)w}$: 10-year moving average of quarterly CDD in the previous decade
- l_{iw} : natural logarithm of quarterly income of household i
- Controls: second-degree polynomial of precipitation and household characteristics
- μ_k : unobserved heterogeneity (state or household FE)
- Additional fixed-effects: wave FE, quadratic state-year trend
- All regressions are weighted using survey weights that also correct for attrition

Evaporative coolers are climate sensitive, air conditioners respond only to income

	Both Appliances (1)	Air Conditioner (2)	Evaporative Cooler (3)
$\overline{\text{CDD}}$ (100s)	0.0146*** (0.002)	0.0000375 (0.001)	0.0145*** (0.003)
Log(Income)	0.0863*** (0.007)	0.0592*** (0.006)	0.0611*** (0.010)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
State FE, Wave FE	Yes	Yes	Yes
Quadratic State \times Year Trend	Yes	Yes	Yes
R ²	0.51	0.21	0.51
Observations	2442730	2442730	2442730

Notes: (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Air conditioners:

- Living in an urban area (↑↑)
- Hours of power availability during the day and ownership of generators (↑)
- Education level (↑↑), female head (↓), house materials (↑), head age (↓)

Coolers:

- Hours of **power availability** during the day and **ownership of generators** (↑↑)
- Education level (↑), female head (↓), house materials (↑), head age (↑)

Adoption is a matter of **economic development**

	Both Appliances (1)	Air-conditioning (2)	Evaporative Cooler (3)
$\overline{\text{CDD}}$ (100s)	-0.000666 (0.000)	0.000216 (0.000)	-0.000764* (0.000)
Log(Income)	0.0410*** (0.003)	0.0135*** (0.001)	0.0344*** (0.003)
Precipitations Controls	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Household FE, Wave FE	Yes	Yes	Yes
Quadratic Trend \times State	Yes	Yes	Yes
R ²	0.05	0.02	0.06
Observations	2432366	2432366	2432366

Notes: (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights..

Our results remain **robust** to several alternative specifications:

- Alternative time and time-invariant fixed-effects
- Clustering standard errors at state level
- Changing CDD thresholds
- Specifying CDD up to degree 3 polynomials
- Logit and multinomial logit specification (for ownership)

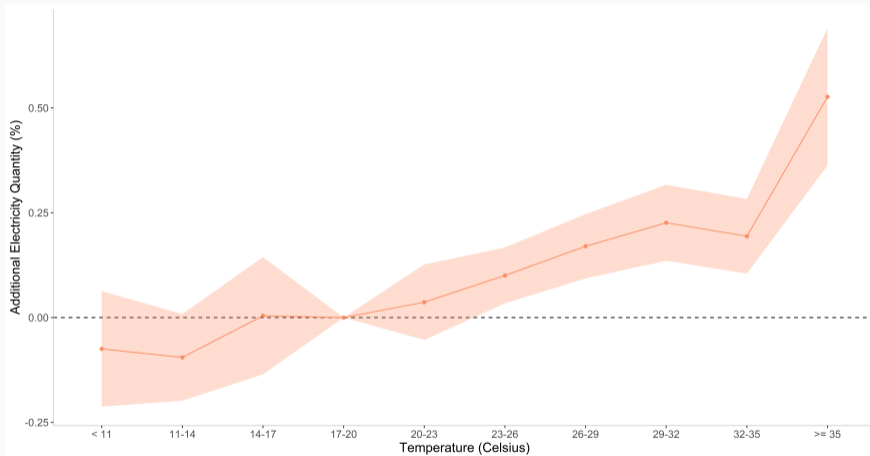
- Consumption electricity in response to temperature is a **short-term** decision
- **Technology modulates** household response
- Using the monthly information we observe the **causal effect** of short-term variation in temperature
- **Heterogeneity** in the response should be confirmatory of the **distribution** of the technologies

Estimating the impact of **temperature** on electricity quantity:

$$Q_{imy} = \alpha + \sum_{j=1}^k \theta_j T_{d(i)my}^j + \beta_2 f(P_{d(i)my}) + \beta_3 l_{imy} + \mu_i + \delta_{my} + \epsilon_{imy}$$

- Q_{imy} : natural logarithm of electricity quantity of household i in month m and year y
- $T_{d(i)my}$: 3°C bins of daily average temperature in district d (17-20 as reference category)
- Controls: second-degree polynomial of total precipitation and natural logarithm of monthly income
- Fixed-effects: household FE (μ_i) and month-year FE (δ_{my})
- All regressions are weighted using survey weights that also correct for attrition

Temperature-electricity



An additional day ≥ 35 °C (wrt 17 – 20) increases electricity consumption by **0.53%**

We test the **heterogeneity** of the response across different sub-samples

	Rural			Urban		
	Poor (1)	Middle (2)	Rich (3)	Poor (4)	Middle (5)	Rich (6)
≥ 35	0.00387*** (0.001)	0.00329*** (0.001)	0.00530*** (0.001)	0.00607*** (0.001)	0.00749*** (0.001)	0.00973*** (0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.02	0.01	0.01	0.05	0.04	0.09
Observations	550374	1636916	414634	511879	3242848	1960647
Avg. kWh	59.85	92.59	148.77	75.37	116.80	208.83
$\Delta(\text{kWh})$	+0.23	+0.30	+0.79	+0.40	+0.87	+2.03

Notes: (1) to (6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Our results remain **robust** to alternative specifications:

- Alternative time and time-invariant fixed-effects
- Electricity quantity in levels
- Clustering standard errors at state level
- Specifying temperature as 5-degree bins, up to degree 3 polynomials, as Cooling Degree Days (CDD)
- CRU rather than ERA5 climate data

Protective Effects

Estimating the impact of **temperature** on mortality:

$$M_{dt} = \alpha_0 + \sum_j \theta_j T_{dtj} + \sum_k \delta_k P_{dtk} + \sum_h \beta_h H_{dth} + \mu_d + \rho_t + \lambda_{r(d)}t + \lambda_{r(d)}^2 t^2 + \epsilon_{dt}$$

- M_{dt} : natural logarithm of mortality rate in district d and year y
- $T_{d(i)my}$: 5°C bins of daily average temperature in district d (15-20 as reference category)
- Fixed-effects: district FE (μ_d), year FE (ρ_t), climatic region \times quadratic trend ($\lambda_{s(d)}t + \lambda_{s(d)}^2 t^2$)
- Square root of district population used as weight for the regression
(Barreca et al. 2016, JPE; Burgess et al. 2017)
- Additional regressions: (1) interaction **warmest \times most humid bin**

The Role of Cooling

Estimate an augmented regression model:

$$M_{dt} = \alpha_0 + \sum_{j=1}^8 \theta_j T_{dtj} + \sum_{l=1}^2 \gamma_l T_{dt}^{\geq 35} \times C_{dtl} + \sum_{l=1}^2 \phi_l C_{dtl} + \\ + \sum_k \delta_k P_{dtk} + \sum_h \beta_h H_{dth} + \mu_d + \rho_t + \lambda_{r(d)} t + \lambda_{r(d)}^2 t^2 + \epsilon_{dt}$$

- C_{dtl} : penetration rate in district d of technology l
- Additional regressions: interactions with (1) bins of humidity, (2) warmest \times most humid bin
- **Drawback:** no quasi-experimental design
 - \hookrightarrow **Key for identification:** the two shares do not have to correlate with other drivers of mortality
 - \hookrightarrow **Robustness:** log of income per capita, log of income per capita \times all bins, ownership rates \times with all bins

Only air conditioners are **effective** against extreme heat

	Air conditioner (1)	Evaporative Cooler (2)	Both Appliances (3)
AC \times T (≥ 35)	-0.0270*** (0.009)		-0.0206** (0.009)
Cooler \times T (≥ 35)		-0.00769* (0.004)	-0.00629 (0.005)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quadratic Trend \times Region	Yes	Yes	Yes
R ²	0.05	0.05	0.05
Observations	2753	2753	2753

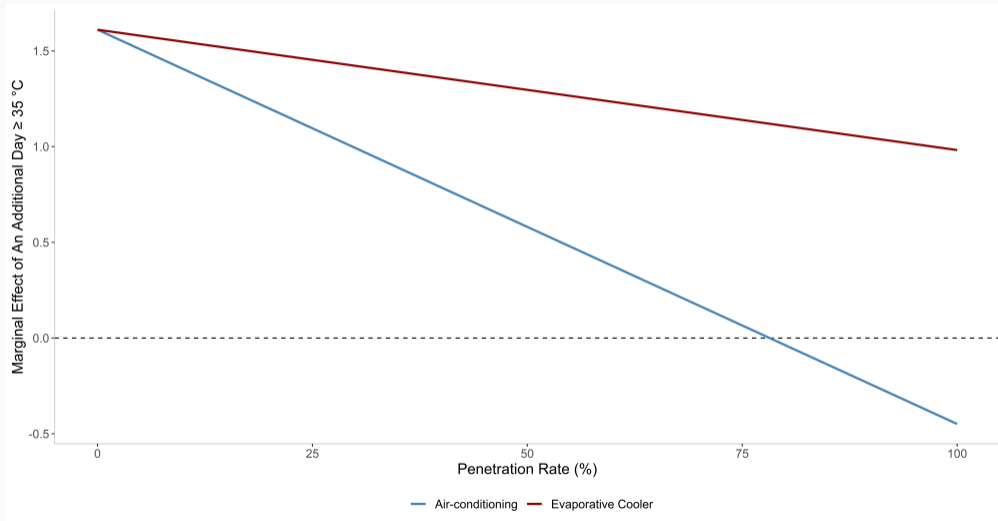
Notes: (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Our results remain **robust** to alternative specifications:

- Temperature \times Humidity Humidity
- State-level ownership rates State
- Clustering standard errors at state level
- Interactions with all temperature bins All Bins
- Including district-level income per capita, and interactions of income with temperature bins Income

Discussion

Residual Effect of Extreme Heat



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- Uttar Pradesh:

- ↪ income = 14844 rupees, CDD = 454 degree-days

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- **Uttar Pradesh:**

- ↪ income = 14844 rupees, CDD = 454 degree-days
- ↪ increase by **30% p.p. in evaporative cooler** penetration rate (25% to 55%)

Residual Effect of Extreme Heat

Let's make an example:

- **Delhi:**

- ↪ income = 42183 rupees, CDD = 465 degree-days
- ↪ increase by **30% p.p. in air-conditioning** penetration rate (25% to 55%)
- ↪ heat-related mortality from extreme heat reduced by **52%**

- **Uttar Pradesh:**

- ↪ income = 14844 rupees, CDD = 454 degree-days
- ↪ increase by **30% p.p. in evaporative cooler** penetration rate (25% to 55%)
- ↪ heat-related mortality from extreme heat reduced by **12%**

Avoided Deaths

Without adaptation \Rightarrow **0.865 million annual excess deaths** due to extreme heat ($\geq 35^\circ\text{C}$)

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- Annual percentage of **avoided deaths** in the period 2014-2019:

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- Annual percentage of **avoided deaths** in the period 2014-2019:

\hookrightarrow With heat adaptation \Rightarrow **21%**

Avoided Deaths

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- Annual percentage of **avoided deaths** in the period 2014-2019:
 - \hookrightarrow With heat adaptation \Rightarrow **21%**
- **Annual gross welfare gains** from heat adaptation in the period 2014-2019
 - $\hookrightarrow 0.865 \times 21\% \times \text{VSL} = \$33 \text{ billion} \Rightarrow$ **2.18% of the annual GDP**
 - \hookrightarrow **66%** of these benefits is due to evaporative coolers \Rightarrow 6 times more widespread than air conditioners

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- What would have happened if air conditioners were **as widespread as** evaporative cooler?
 - \hookrightarrow Air-conditioning **alone** \Rightarrow Annual percentage of **avoided deaths** = **47%**
 - \hookrightarrow Annual gross welfare gains = **\$73 billion** \Rightarrow **4.9% of the annual GDP**
 - \hookrightarrow Estimates for the United States = **\$85 – \$185 billion** ([Barreca et al. 2016, JPE](#))

Implications for Policy

- Subsidise air conditioners may be a very **expensive policy**
 - ↪ The annualised cost is around 3083 rupees (\$37)
 - ↪ **100% subsidy** for having same rate of coolers = **\$3.02 billion**
 - ↪ Annual cost of additional **electricity expenditure** = **\$0.57 billion**
 - ↪ Annual **social cost of additional emissions** = **\$0.003 billion**
- But air conditioners appear as a **cost-effective solution**
 - ↪ **Benefits largely offset the costs**
 - ↪ Technology costs can be reduced with investment in **innovation** United States
- Evaporative coolers seems a **stop-gap** solution
 - ↪ Better an evaporative cooler than no cooling

Conclusion

Conclusion

- There exists a **trade-off** between accessibility to cooling and health protection
- **Technology layer** in the heat adaptation inequality for low- and middle-income households
- Only rich urban households adopt and use the most effective technology
- Trade-off also for policy makers
- **Questions:**
 - ↔ do competing strategies in other setting (e.g. agriculture) have similar inequality consequences?
 - ↔ is there a trade-off between adaptation and mitigation?
 - ↔ is the technological gap specific of India?

Thank you for your attention! **Any questions?**

Examples of evidence about the welfare costs of extreme heat:

- Mortality and morbidity

(Deschenes and Greenstone 2011, AEJ; Barreca et al. 2016, JPE; Burgess et al. 2017; Heutel et al. 2021, RESTAT; Carleton et al. 2022, QJE)

- Learning

(Park et al. 2020, AEJ; Zivin et al. 2020, JEEM; Park 2022, JHR)

- Mental health and mood

(Noelke et al. 2016, ER; Baylis 2020, JPubE; Hua et al. 2022, JPopE)

- Labour productivity

(Dasgupta et al. 2021, Lancet; Somanathan et al. 2021, JPE)

- Aggressive behaviour and crime

(Ranson et al. 2015, JEEM; Baysan et al. 2019, JEBO; Blakeslee et al. 2021, JEBO)

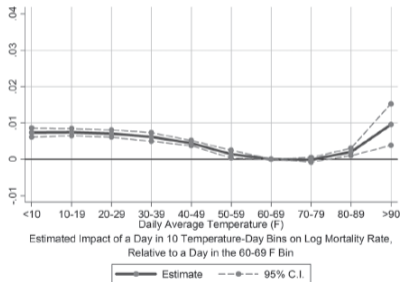
Mediating Effects of Air-conditioning

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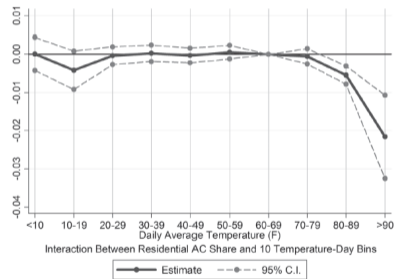
Mortality

(Barreca et al. 2016, JPE)

Without Air-conditioning



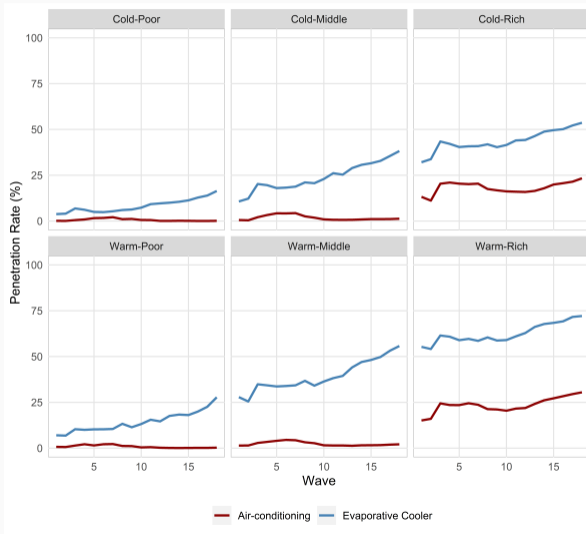
With Air-conditioning



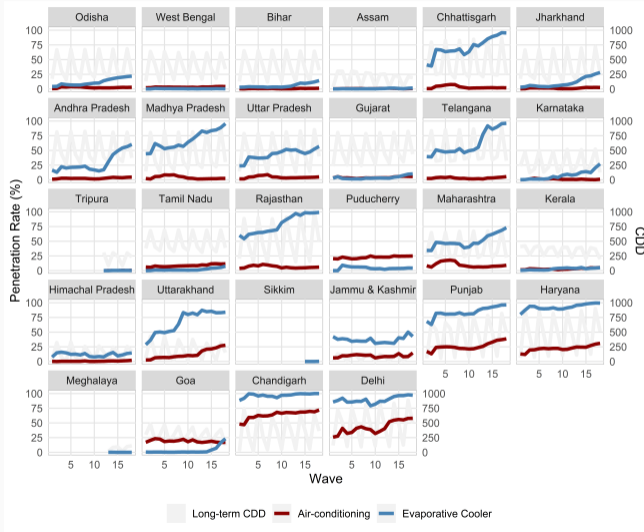
Further evidence: learning achievements, labour productivity and mental health

(Park et al. 2020, AE; Somanathan et al. 2021, JPE; Hua et al. 2022, JPopE)

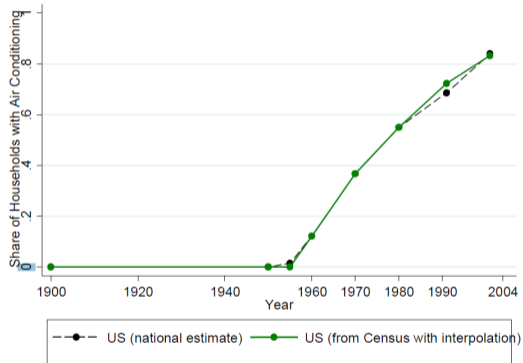
Trends in Ownership Rates by Income and Climate

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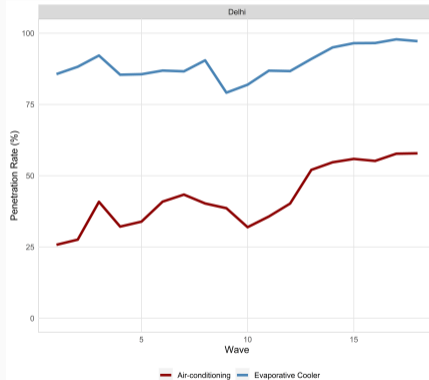
Trends in Ownership Rates by States

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United States (1900-2004)



Delhi (2014-2019)



Air-conditioners is not climate sensitive even for high-income families

	Both Appliances (1)	Air Conditioner (2)	Evaporative Cooler (3)
$\overline{\text{CDD}}$ (100s)	-0.0373*** (0.010)	-0.0101 (0.001)	-0.0423*** (0.013)
Log(Income)	0.0637*** (0.010)	0.0547*** (0.006)	0.0363** (0.015)
$\overline{\text{CDD}} \times \text{Log(Income)}$	0.00548*** (0.001)	0.00107 (0.001)	0.00600*** (0.002)
Precipitations, Household Controls	Yes	Yes	Yes
State FE, Wave FE	Yes	Yes	Yes
Quadratic State \times Year Trend	Yes	Yes	Yes
R ²	0.51	0.21	0.51
Observations	2442730	2442730	2442730

Notes: (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Still climatic conditions do not matter for adoption

	Both Appliances (1)	Air Conditioner (2)	Evaporative Cooler (3)
$\overline{\text{CDD}}$ (100s)	-0.00723** (0.003)	0.00151 (0.001)	-0.00943*** (0.003)
Log(Income)	0.0383*** (0.003)	0.0140*** (0.002)	0.0310*** (0.003)
$\overline{\text{CDD}} \times \text{Log(Income)}$	0.000693** (0.000)	-0.000137 (0.000)	0.000914*** (0.000)
Precipitations, Household Controls	Yes	Yes	Yes
Household FE, Wave FE	Yes	Yes	Yes
Quadratic State \times Year Trend	Yes	Yes	Yes
R ²	0.05	0.02	0.05
Observations	2442730	2442730	2442730

Notes: (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Middle-income households adopt evaporative coolers

	Air Conditioner			Evaporative Cooler		
	Poor (1)	Middle (2)	Rich (3)	Poor (4)	Middle (5)	Rich (6)
Log(Income)	0.00320*** (0.001)	0.00752*** (0.001)	0.0437*** (0.003)	0.0184*** (0.004)	0.0324*** (0.004)	0.0159*** (0.004)
Precipitations, Household, CDD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE, Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend \times State	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.01	0.01	0.03	0.10	0.07	0.02
Observations	485084	1219147	485420	485084	1219147	485420

Notes: (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Income elasticity **varies** between urban and rural areas

	Air Conditioner		Evaporative Cooler	
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
Log(Income)	0.00554*** (0.001)	0.0342*** (0.003)	0.0316*** (0.003)	0.0284*** (0.004)
Precipitations, Household, CDD Controls	Yes	Yes	Yes	Yes
Household FE, Wave FE	Yes	Yes	Yes	Yes
Quadratic State \times Year Trend	Yes	Yes	Yes	Yes
R ²	0.01	0.03	0.07	0.06
Observations	786354	1646012	786354	1646012

Notes: (1)-(4) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Income elasticity **varies** with climatic conditions

	Air Conditioner			Evaporative Cooler		
	Cold (1)	Mild (2)	Warm (3)	Cold (4)	Mild (5)	Warm (6)
Log(Income)	0.0152*** (0.003)	0.0134*** (0.002)	0.0128*** (0.002)	0.0122*** (0.005)	0.0370*** (0.004)	0.0435*** (0.005)
Precipitations, Household, CDD Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE, Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic State \times Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.02	0.03	0.01	0.08	0.08	0.05
Observations	829670	739207	863489	829670	739207	863489

Notes: (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Heterogeneity based on **technology**

	Air Conditioner (1)	Evaporative Cooler (2)
≥ 35	0.0112*** (0.002)	0.00469*** (0.001)
Precipitations Controls	Yes	Yes
Household Income	Yes	Yes
Household FE	Yes	Yes
Month-Year FE	Yes	Yes
R ²	0.05	0.01
Observations	785745	3707868
Avg. kWh	241.65	135.08
$\Delta(\text{kWh})$	+2.71	+0.63

Notes: (1) and (2) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

Focusing on high-income families

	Poor-Middle		Rich	
	Air Conditioner (1)	Evaporative Cooler (2)	Air Conditioner (3)	Evaporative Cooler (4)
≥ 35	0.00123 (0.002)	0.00350*** (0.001)	0.0147*** (0.003)	0.00909*** (0.002)
Precipitations Controls	Yes	Yes	Yes	Yes
Household Income	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
R ²	0.01	0.01	0.06	0.02
Observations	161766	226428	538787	1018452
Avg. kWh	130.99	110.46	278.43	185.33
$\Delta(\text{kWh})$	+ 0.16	+0.39	+4.09	+1.68

Notes: (1)-(4) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are conducted using survey weights.

	FE (1)	FE (2)	FE (3)	FE (4)
T (≥ 35)	0.00943*** (0.002)		0.00996*** (0.002)	0.000320 (0.003)
H (0 – 3)		0.000660 (0.003)	-0.000505 (0.003)	-0.000102 (0.003)
H (≥ 18)		-0.000102 (0.001)	0.000756 (0.001)	0.000110 (0.001)
T (≥ 35) \times H (≥ 18)				0.000123*** (0.000)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quadratic Trend \times Region	Yes	Yes	Yes	Yes
R ²	0.03	0.02	0.03	0.04
Observations	3908	3908	3908	3908

Notes: (1)-(4) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Heat-related deaths mostly occur in **rural areas**

	Rural		Urban	
	(1)	(2)	(3)	(4)
T (≥ 35)	0.00909** (0.004)	-0.00191 (0.005)	0.00549* (0.003)	0.00229 (0.004)
T (≥ 35) \times H (≥ 18)		0.000153** (0.000)		0.0000533 (0.000)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quadratic Trend \times Region	Yes	Yes	Yes	Yes
R ²	0.03	0.04	0.02	0.02
Observations	2520	2520	1549	1549

Notes: (1)-(4) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district rural and urban population.

Heat-related deaths mostly occur in district with a **higher share of poor individuals**

	Below Median		Above Median	
	(1)	(2)	(3)	(4)
T (≥ 35)	0.00430*	0.00410	0.0173***	0.00147
	(0.003)	(0.003)	(0.004)	(0.006)
T (≥ 35) \times H (≥ 18)		0.0000199		0.000168**
		(0.000)		(0.000)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quadratic Trend \times Region	Yes	Yes	Yes	Yes
R ²	0.04	0.04	0.06	0.07
Observations	1369	1369	1384	1384

Notes: (1)-(4) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

State-level Ownership Rates [Back](#)

	Temperature			Humidity			Temperature \times Humidity		
	Air Conditioner (1)	Cooler (2)	Both (3)	Air Conditioner (4)	Cooler (5)	Both (6)	Air Conditioner (7)	Cooler (8)	Both (9)
AC \times T (≥ 35)	-0.0444*** (0.013)		-0.0373*** (0.014)						
Cooler \times T (≥ 35)		-0.0109** (0.005)	-0.00770 (0.005)						
AC \times H (≥ 18)				-0.00228 (0.005)		-0.00521 (0.005)			
Cooler \times H (≥ 18)					-0.000857 (0.002)	-0.000746 (0.002)			
AC \times T (≥ 35) \times H (≥ 18)							-0.000390** (0.000)		-0.000397** (0.000)
Cooler \times T (≥ 35) \times H (≥ 18)								-0.0000427 (0.000)	-0.00000122 (0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend \times Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.05	0.06	0.06	0.05	0.06	0.07	0.05	0.06	0.06
Observations	2753	2753	2753	2753	2753	2753	2753	2753	2753

Notes: (1)–(9) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Performance during Very Hot and Humid Days [Back](#)

Again only air conditioners are **effective** against extreme hot and humid days

	Humidity			Temperature × Humidity		
	Air conditioner (1)	Cooler (2)	Both (3)	Air conditioner (4)	Cooler (5)	Both (6)
AC × H (≥ 18)	-0.000662 (0.002)		-0.000685 (0.002)			
Cooler × H (≥ 18)		0.000507 (0.001)	0.000538 (0.001)			
AC × T (≥ 35) × H (≥ 18)				-0.000422*** (0.000)		-0.000384*** (0.000)
Cooler × T (≥ 35) × H (≥ 18)					-0.0000512 (0.000)	-0.0000238 (0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Trend × Region	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.05	0.05	0.05	0.06	0.06	0.06
Observations	2753	2753	2753	2753	2753	2753

Notes: (1)-(6) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Interactions with all Temperature Bins

[Back](#)

	Air Conditioner (1)	Evaporative Cooler (2)	Both (3)
AC \times T (≤ 10)	0.00109 (0.009)		-0.000206 (0.009)
Cooler \times T (≤ 10)		0.0000828 (0.003)	0.000279 (0.003)
AC \times T (10 — 15)	-0.0114* (0.006)		-0.0102 (0.007)
Cooler \times T (10 — 15)		-0.00219 (0.004)	-0.000694 (0.004)
AC \times T (20 — 25)	-0.00499 (0.004)		-0.00523 (0.004)
Cooler \times T (20 — 25)		-0.00195 (0.002)	-0.00153 (0.002)
AC \times T (25 — 30)	-0.00293 (0.005)		-0.00278 (0.005)
Cooler \times T (25 — 30)		0.000724 (0.002)	0.00104 (0.002)
AC \times T (30 — 35)	-0.00903 (0.006)		-0.0101 (0.006)
Cooler \times T (30 — 35)		0.00309 (0.002)	0.00365* (0.002)
AC \times T (≥ 35)	-0.0246** (0.010)		-0.0155 (0.011)
Cooler \times T (≥ 35)		-0.00752 (0.005)	-0.00646 (0.005)
Precipitation Terciles	Yes	Yes	Yes
Humidity Bins	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quadratic Trend \times Region	Yes	Yes	Yes
R ²	0.05	0.06	0.06
Observations	2753	2753	2753

Notes: (1)-(3) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

	FE (1)	FE (2)
AC \times T (≥ 35)	-0.0208** (0.009)	-0.0178* (0.010)
Cooler \times T (≥ 35)	-0.00636 (0.005)	-0.00629 (0.005)
Income Per Capita	Yes	Yes
Income \times Temperature Bins	No	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Quadratic Trend \times Region	Yes	Yes
R ²	0.05	0.06
Observations	2753	2753

Notes: (1)-(2) clustered standard errors at district level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are weighted by the square root of district population.

Rapson (2014, JEEM)

