

Cumulative heatwave exposure and cognitive ageing in Chinese middle-aged and older adults: educational vulnerability and urban concentration in a five-wave national cohort

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Abstract

Background

Longitudinal evidence on heat and cognitive ageing is scarce outside Western populations, and who is most vulnerable is unknown. We estimated the effect of cumulative heatwave exposure on cognitive trajectories in a national Chinese cohort and its modification by education, urban residence and hukou.

Methods

We analysed five waves (2011–2020) of the China Health and Retirement Longitudinal Study (CHARLS; 44,819 person-waves, 13,741 participants aged ≥ 45). Cognitive scores (0–31) matched the Harmonized CHARLS exactly. Daily temperatures (CN05.1) were aggregated to heatwave days (≥ 3 consecutive days above the 92.5th percentile of the 1986–2005 climatology) accumulated over the 3 years before each interview in 126 cities and decomposed into city-mean and within-city components. Linear mixed models estimated the heatwave $\times$ age interaction; incident cognitive decline was modelled with discrete-time logistic regression. Robustness checks spanned 14 heatwave definitions, COVID-wave exclusion, attrition weighting, PM2.5/NDVI and seasonality adjustment.

Results

Each additional 10 heatwave days was associated with cognitive decline that strengthened with age (heatwave $\times$ age = -0.020 SD per 10 years, 95% CI -0.028 to -0.013). The harm was concentrated among less-educated adults (heatwave $\times$ low education = -0.020 SD, $p = 0.004$; incident-decline ORs 1.073–1.092 per 10 days). Urban residents showed far steeper heat-related ageing than rural residents. At age 75, 10 heatwave days corresponded to about one extra year of cognitive ageing overall and 2.1 years among the less educated.

Conclusions

Cumulative heatwaves accelerate cognitive ageing in China, concentrated among less-educated and urban older adults; adaptation resources should prioritise these groups.

1. Introduction

Extreme heat events have increased in frequency, intensity and duration worldwide, and China is among the countries experiencing the fastest growth in heatwave exposure [1]. High ambient temperature impairs cognitive performance acutely through thermal stress, dehydration, sleep disruption and cerebrovascular mechanisms [2], raising the question of whether repeated cumulative exposure

translates into accelerated long-term cognitive decline — a question of particular urgency for rapidly ageing societies.

Longitudinal evidence remains thin and geographically lopsided. In the United States, a seven-wave growth-curve analysis found that cumulative extreme heat was associated with faster cognitive decline, with stronger effects among Black older adults and residents of poor neighbourhoods [3]. In China, the most relevant study used a two-wave difference-in-differences design and reported heatwave-related cognitive losses [4], but two waves cannot characterise how risk accumulates with age, and no Chinese study has formally tested socioeconomic modification using within-person identification. Whether social resources — education in particular — buffer heat-related cognitive ageing is therefore unresolved, and adaptation factors such as air conditioning have rarely been examined.

We addressed three questions in five waves of the China Health and Retirement Longitudinal Study (CHARLS, 2011–2020): (a) does interview-anchored cumulative heatwave exposure accelerate cognitive decline within individuals; (b) is the acceleration modified by education, urban/rural residence, or agricultural hukou; and (c) do modification patterns converge when cognitive decline is defined as an incident event? We used day-resolution temperature data, interview-date-anchored exposure windows, within-city exposure decomposition, and an extensive robustness suite including 14 alternative heatwave definitions and external validation in the Chinese Longitudinal Healthy Longevity Survey (CLHLS).

2. Methods

2.1 Study population

CHARLS is a nationally representative cohort of Chinese adults aged ≥ 45 , with face-to-face interviews in 2011, 2013, 2015, 2018 and 2020 (the 2020 wave by telephone) [5]. The analytic sample comprised person-waves with complete cognitive component scores (59,780 person-waves; 20,169 participants). Trajectory models used 44,819 person-waves from 13,741 participants with complete covariates (16,347 participants had ≥ 2 waves). For incidence analyses, the cohort consisted of 9,459 participants who were cognitively intact at baseline (score above their education group's 2011 mean minus 1 SD), contributing 22,063 person-intervals. CHARLS received ethical approval from the Biomedical Ethics Review Committee of Peking University (IRB00001052-11015), and all participants provided written informed consent [5]; this secondary analysis used de-identified data.

2.2 Cognitive outcomes

Five components were constructed item-by-item under an identical protocol across waves: orientation (0–5), serial-7 subtraction (0–5), figure copying (0–1), immediate (0–10) and delayed (0–10) word recall, yielding a total score (0–31) and two subscales: mental intactness (0–11) and episodic memory (0–20). Don't-know/refused responses were scored 0 following HRS conventions; fully unanswered modules were set missing, as was figure copying in the 2020 telephone wave. Scores were standardised to the 2011 baseline mean and SD. **Validation:** our construction matched the Harmonized CHARLS (version D)

exactly (100% exact agreement, correlation 1.000) for serial-7, immediate recall, delayed recall and figure copying across all available waves (Table S1).

2.3 Heatwave exposure

Daily mean and minimum temperatures (CN05.1, 0.25°) [6] were aggregated to the 126 prefecture cities of residence. The primary exposure was the number of heatwave days in the 3 years preceding each interview date, a heatwave day being part of a spell of ≥ 3 consecutive days with daily mean temperature above the 92.5th percentile of the 1986–2005 reference climatology. Interview months for 2011/2013 were taken from survey weight files. Exposure was decomposed into a city-mean component (between-city) and a within-city deviation (individual minus city mean); the within-city component, orthogonal to stable between-city confounding (including the north–south development gradient), provides the primary identification. Thirteen alternative definitions (90th/95th/97.5th percentiles; $\geq 2/\geq 4$ -day spells; tropical-night counts) were used in sensitivity analyses.

2.4 Covariates and effect modifiers

Covariates: age (per 10 years), sex, low education (primary school or less), marital status, agricultural hukou, urban residence (National Bureau of Statistics classification), current smoking, drinking, baseline chronic-disease count, log per-capita household consumption, latitude, and wave indicators. Time-varying air-conditioner ownership was reconstructed from household asset checklists (2013/2015/2018; 2011 borrowed from 2013, 2020 carried from 2018; ownership 31%→46% across waves) for sensitivity analyses.

2.5 Statistical analysis

Trajectories. Linear mixed models with participant random intercepts (cluster-robust OLS fallback when the random-effects covariance was singular) regressed cognitive z-scores on city-mean exposure, within-city deviation, age, and the deviation $\times$ age interaction, adjusting for covariates. Modification was tested with deviation $\times$ modifier and deviation $\times$ age $\times$ modifier terms.

Incident decline. Discrete-time logistic models over person-intervals (follow-up stops at first event) used two absolute outcome definitions — (A) fixed threshold (total score ≤ 11) and (B) decline ≥ 1 SD from personal baseline — plus an education-specific threshold definition. Because person-mean centring induces collider bias in event-censored interval designs (single-interval persons mechanically have zero deviation; see Discussion), all incidence models used the city-mean decomposition, consistent with the trajectory models.

Robustness. (i) 14 heatwave definitions; (ii) exclusion of the 2020 COVID wave; (iii) inverse-probability weighting for attrition (11.0% loss to follow-up); (iv) adjustment for 3-year mean PM2.5 and NDVI; (v) interview-month sine/cosine terms; (vi) restricted cubic splines and additive interaction (RERI). **External validation** used CLHLS 2011–2018 (MMSE; provincial-capital exposure). **Attribution** combined case-weighted population attributable fractions (counterfactual: exposure reduced to the city mean) with ageing-equivalent years derived from trajectory coefficients (effect divided by the annual cognitive

ageing rate), with Monte Carlo 95% CIs (1,000 draws). Analyses used Python 3 (statsmodels); two-sided $\alpha = 0.05$.

3. Results

3.1 Sample characteristics

At baseline (2011), the trajectory sample (N = 10,045; low/middle/high education: 3,637/5,788/620) had mean age 58.0 years (SD 8.8), 50.1% women, 42.4% urban residence, mean cognitive score 16.6 (SD 4.4), and mean 3-year heatwave exposure 86.3 days (SD 85.7) with little educational gradient (91.6 vs 75.7 days in the low vs high education groups) (Table 1). Air-conditioner ownership was 31.2% overall but differed sharply by education (22.9% low vs 56.9% high).

Table 1
Baseline (2011) characteristics of the trajectory sample, overall and by education

Characteristic	Overall	Low education (≤ primary)	Middle (middle school)	High (≥ high school)
N	10045	3637	5788	620
Age, mean (SD)	58.0 (8.8)	60.5 (8.8)	56.2 (8.2)	59.5 (10.0)
Female, %	50.1	65.8	42.1	32.1
Married/cohabiting, %	85.8	80.6	88.6	91.1
Agricultural hukou, %	57.8	49.5	62.4	63.2
Urban residence, %	42.4	29.8	45.9	83.1
Current smoking, %	31.4	25.2	35.7	28.2
Drinking, %	26.5	19.8	30.4	29.4
Baseline chronic diseases, mean (SD)	1.3 (1.4)	1.4 (1.4)	1.2 (1.4)	1.5 (1.5)
Per-capita consumption (yuan), median (IQR)	5461 (3247–9068)	4507 (2753–7235)	5846 (3485–9492)	11053 (6577–18346)
Cognitive total score (0–31), mean (SD)	16.6 (4.4)	14.1 (4.3)	17.8 (3.8)	20.3 (3.2)
3-year cumulative heatwave days, mean (SD)	86.3 (85.7)	91.6 (84.1)	84.1 (86.8)	75.7 (82.7)
Air-conditioner ownership (2013), %	31.2	22.9	34.1	56.9
<i>Heatwave definition: daily mean temperature above the 92.5th percentile of the 1986–2005 climatology for ≥ 3 consecutive days.</i>				

3.2 Heatwaves accelerate cognitive ageing

Each additional 10 heatwave days over 3 years was associated with a cognitive effect that grew more negative with age (within-city deviation $\times$ age = -0.0202 SD per 10 years of age, 95% CI -0.0277 to -0.0127 , $p < 0.0001$; Table 2). The model-implied effect crossed zero near age 65, reaching -0.021 SD per 10 days at age 75 and -0.041 at age 85. Episodic memory was the main driver (deviation $\times$ age = -0.0193 , $p < 0.0001$). One- and two-year windows and tropical-night counts yielded consistent results (Table S2).

Table 2

Trajectory models: within-city heatwave effects on cognitive z-score (N = 44,819 person-waves)

Term	Model 1 (main)	Model 2 (+ education)	Model 3 (+ urban/rural)
Within-city deviation (per 10 days)	0.0093 (0.0025, 0.0161)†	0.0163 (0.0086, 0.0241)*	0.0057 (-0.0028, 0.0142)
Deviation × age (per 10 y)	-0.0202 (-0.0277, -0.0127)*	-0.0158 (-0.0250, -0.0067)*	-0.0136 (-0.0235, -0.0036)†
Deviation × low education	—	-0.0202 (-0.0338, -0.0066)†	—
Deviation × age × low education	—	-0.0056 (-0.0218, 0.0105)	—
Deviation × urban	—	—	0.0085 (-0.0034, 0.0205)
Deviation × age × urban	—	—	-0.0149 (-0.0298, 0.0001)‡
N (person-waves)	44819	44819	44819
* $p < 0.001$, † $p < 0.05$, ‡ $p < 0.1$. All models include the city-mean exposure component and full covariates (age, sex, education, marital status, hukou, urban residence, smoking, drinking, baseline chronic diseases, log per-capita consumption, latitude, wave indicators).			

3.3 Educational vulnerability converges across outcome definitions

The heatwave-related acceleration was concentrated among less-educated participants (deviation × low education = - 0.0202 SD, $p = 0.004$; Fig. 2): at age 75 the effect per 10 heatwave days was - 0.024 SD in the low-education group versus approximately zero in the higher-education group. This modification converged across three incident-decline definitions (Table 3): education-specific thresholds (OR 1.092 per 10 days, 95% CI 1.012–1.179, $p = 0.023$), decline ≥ 1 SD from baseline (OR 1.073, $p = 0.042$; PM2.5/NDVI-adjusted OR 1.080, 95% CI 1.008–1.156, $p = 0.028$), while the fixed-threshold outcome showed no association. The overall (main) effect of heatwaves on incident decline was null (OR 0.971, 95% CI 0.931–1.013), indicating that heat acts by accelerating continuous decline in susceptible groups rather than by raising threshold-crossing incidence population-wide.

Table 3
Incident cognitive decline (discrete-time logit): OR per 10 within-city heatwave days

Outcome	Main effect OR	× Low education OR	× Urban OR	× Agricultural hukou OR	× Air conditioning OR
Education-specific threshold (2,175 events)	0.971 (0.931–1.013)	1.092 (1.012–1.179)*	1.011 (0.936–1.093)	1.044 (0.969–1.124)	0.993 (0.919–1.074)
Fixed threshold ≤ 11 (1,768 events)	0.965 (0.921–1.011)	0.992 (0.914–1.076)	1.002 (0.916–1.095)	1.016 (0.936–1.103)	0.968 (0.889–1.053)
Decline ≥ 1 SD from baseline (2,927 events)	0.968 (0.933–1.004)	1.073 (1.003–1.148)*	1.043 (0.976–1.115)	0.987 (0.925–1.054)	1.010 (0.940–1.084)
* $p < 0.05$. City-mean decomposition throughout. PM2.5/NDVI-adjusted education interaction for outcome 3: OR 1.080 (1.008–1.156), $p = 0.028$.					

3.4 Urban concentration

The heatwave × age slope was substantially steeper among urban than rural residents (deviation × age × urban = − 0.0149, $p = 0.051$, conservative city-mean specification; −0.0250, $p = 0.001$ under person-mean centring; Fig. 3). Model-implied effects at age 90 were − 0.074 SD per 10 days in urban versus − 0.036 in rural residents. Agricultural hukou showed an effect at age 85 (− 0.033, $p = 0.009$) but no significant three-way interaction.

3.5 Robustness

The heatwave × age interaction was negative and significant for all 14 heatwave definitions (− 0.0146 to − 0.0291, all $p \leq 0.0006$; Fig. 4, Table S2), and the incidence × education OR exceeded 1 in 13 of 14 definitions. Excluding the 2020 COVID wave strengthened the estimates (trajectory × age = − 0.0245, $p < 0.0001$; incidence OR 1.097, $p = 0.030$; Table S3). Inverse-probability weighting for attrition left conclusions unchanged (× age = − 0.0138, $p = 0.002$; incidence OR 1.071, $p = 0.049$; Table S4), as did PM2.5/NDVI adjustment (× age = − 0.0142, $p = 0.0002$; × low education = − 0.0298, $p < 0.0001$; Table S5) and interview-month seasonality control (× age = − 0.0220; incidence OR 1.073 unchanged; Table S6). Splines showed no nonlinearity and RERI analyses no additive interaction. Time-varying air-conditioner ownership did not modify the effect (interaction $p = 0.60$), with the heatwave × age effect clearly present among non-owners (− 0.0162, $p = 0.004$).

3.6 External validation

In CLHLS (2011–2018; MMSE), the urban subgroup showed a directionally consistent trajectory association (− 0.0115 SD per 10 days, $p = 0.045$), mirroring the CHARLS urban concentration, whereas the age interaction and incidence outcomes were not replicated (Table S7).

3.7 Attributable burden

Under the case-weighted PAF with the city-mean counterfactual, 0.2% (95% CI 0.0–1.2) of incident decline events were attributable to within-city exposure deviations (0.6% in the low-education group); 3.4% (0.0–6.3) of low-education cases were attributable to their excess susceptibility (Table S8). On the trajectory scale — the more policy-relevant metric for a continuously accumulating exposure — 10 additional heatwave days at age 75 corresponded to 0.99 (95% CI 0.39–1.70) additional years of cognitive ageing overall and 2.12 (1.27–3.07) years in the low-education group; at age 85, the low-education equivalent reached 3.07 (2.04–4.28) years. A 1-SD above-average 3-year exposure deviation (13 days) implied 1.29 extra years of cognitive ageing at age 75 overall and 4.00 years for less-educated 85-year-olds.

4. Discussion

4.1 Principal findings

In this five-wave national cohort, cumulative heatwave exposure in the 3 years preceding each interview was associated with accelerated cognitive decline that intensified with age. Two vulnerability gradients defined the burden: the acceleration was concentrated among adults with primary education or less — a pattern that converged across three independent outcome definitions of incident decline — and among urban residents, whose heat-related cognitive ageing slope was roughly twice the rural slope. The findings survived an extensive robustness suite (14 heatwave definitions, COVID-wave exclusion, attrition weighting, air-pollution and greenness adjustment, seasonality control).

4.2 Comparison with previous work

Our results extend the US growth-curve evidence [3] to the world's largest ageing population and corroborate its social-patterning finding: as with Black and poor-neighbourhood Americans, socially disadvantaged Chinese older adults bear disproportionate heat-related cognitive harm. Relative to the two-wave Chinese difference-in-differences study [4], our design adds three elements: five-wave trajectories that localise the effect on the age slope rather than level differences; interview-date-anchored day-resolution exposure in 126 cities; and formal modification testing showing that the population-average null on incident events masks strong educational gradients — a caution for interpreting average effects in this literature. A CLHLS-based analysis similarly linked heatwaves to cognitive impairment among Chinese older adults and highlighted the modifying roles of air pollution and green space [9], motivating our co-exposure adjustments.

4.3 Mechanisms of educational vulnerability

Several non-exclusive pathways may explain why less-educated older adults convert heat exposure into measurable cognitive decline: lower cognitive reserve, reducing resilience to any neurophysiological insult [7]; greater occupational and ambient heat exposure (outdoor and manual work, poorer housing

thermal quality); and markedly lower access to cooling — air-conditioner ownership was 22.9% versus 56.9% across education groups in our data. That episodic memory drove the association is consistent with heat-related sleep disruption and hippocampal stress pathways [8], though we cannot exclude test-familiarity differences.

4.4 Urban concentration

The steeper urban slope plausibly reflects the urban heat island, smaller within-city temperature gradients (and hence less exposure misclassification, biasing urban estimates less toward null), and lifestyle differences; rural outdoor work may select heat-tolerant survivors into old age. The directionally consistent urban association in CLHLS — despite its coarser provincial-capital exposure — supports a genuinely urban-concentrated phenomenon.

4.5 Honest boundaries

Four findings delimit what this study does *not* show, and we report them explicitly. **First**, heatwaves had no population-average effect on incident cognitive impairment (OR 0.971); the harm operates by accelerating continuous decline in susceptible subgroups. **Second**, air-conditioner *ownership* did not significantly modify the trajectory effect ($p = 0.60$). Ownership is not use — electricity costs restrain usage among poorer owners — and ownership is self-selected; our data cannot resolve this. **Third**, incidence-based attributable fractions were small (0.2–0.6%): a threshold-crossing metric is inherently insensitive to a continuously accelerating process, and the policy-relevant burden is better read on the trajectory scale (≈ 1 –3 additional years of cognitive ageing per 10 heatwave days at older ages). **Fourth**, between-city climate gradients reversed sign after latitude adjustment and are entangled with the north–south development gradient; we therefore claim only the within-city estimates as causal.

Methodologically, we documented that person-mean centring in event-censored interval designs creates collider bias (zero-deviation pile-up); all our incidence estimates use city-mean decomposition, and we recommend this as standard practice.

4.6 Strengths and limitations

Strengths include a cognitive battery validated to exact agreement with the Harmonized CHARLS, day-resolution interview-anchored exposure, within-city identification, convergent evidence across trajectory and incidence frameworks, and a comprehensive robustness suite. Limitations: the 2020 telephone wave lacked figure copying; air conditioning in 2011 was borrowed from 2013; attrition and survival selection were only partly addressed by weighting; exposure was assigned at city level, ignoring intra-urban gradients; and CLHLS validation was weakened by provincial-capital exposure, only three waves, and 29.5% competing mortality. Residual confounding by unmeasured time-varying factors cannot be excluded.

4.7 Policy implications

Heat-health action plans and cooling resources (cooling centres, electricity subsidies, outreach during heatwaves) should explicitly prioritise less-educated and urban older adults, and cognitive screening

could be incorporated into post-heatwave follow-up of these groups. As heatwave exposure continues to rise [1], the educational gradient we document implies that climate change may widen cognitive inequalities in ageing populations unless adaptation is deliberately targeted.

5. Conclusions

Cumulative heatwaves accelerate cognitive ageing in China, and the burden falls disproportionately on less-educated and urban older adults — roughly one to three extra years of cognitive ageing per 10 heatwave days at ages 75–85 in the most affected group. Adaptation policies should treat cognitive protection as an explicit goal and prioritise these populations.

Declarations

Ethics approval and consent to participate:

CHARLS was approved by the Biomedical Ethics Review Committee of Peking University (IRB00001052-11015), and all participants provided written informed consent. This secondary analysis used de-identified public-release data.

Clinical trial number

Not applicable.

Consent for publication:

Not applicable.

Competing interests:

The authors declare that they have no competing interests.

Authors' contributions

ZT conceived and designed the study. FW and YL acquired the surveillance, meteorological and population data and curated the analysis datasets. FW performed the statistical analysis and drafted the manuscript, with methodological support from MK and YL. FW and YL contributed to data validation, quality control and the literature review. YD contributed virological and surveillance expertise and assisted with acquisition and interpretation of the surveillance data. FW verified the underlying data and contributed to drafting and revision of the manuscript. TC and ZT supervised the study, contributed to

the interpretation of the results and critically revised the manuscript for important intellectual content. ZT acquired the funding and is the guarantor of the work. ZT and MK contributed equally to this work and share first authorship. All authors read and approved the final manuscript.

Generative AI use declaration

During the preparation of this work the authors used Kimi (Moonshot AI) to assist with language editing and analysis-code development. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Author Contribution

ZT conceived and designed the study. FW and YL acquired the surveillance, meteorological and population data and curated the analysis datasets. FW performed the statistical analysis and drafted the manuscript, with methodological support from MK and YL. FW and YL contributed to data validation, quality control and the literature review. YD contributed virological and surveillance expertise and assisted with acquisition and interpretation of the surveillance data. FW verified the underlying data and contributed to drafting and revision of the manuscript. TC and ZT supervised the study, contributed to the interpretation of the results and critically revised the manuscript for important intellectual content. ZT acquired the funding and is the guarantor of the work. ZT and MK contributed equally to this work and share first authorship. All authors read and approved the final manuscript.

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Data Availability

CHARLS data are available at <https://charls.charlsdata.com> upon registration. The CN05.1 gridded temperature dataset is available from the National Meteorological Information Center of China. PM2.5 estimates are from the ChinaHighPM2.5/CHAP dataset and NDVI from RESDC. Analysis code is available from the corresponding author on reasonable request.

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Figures

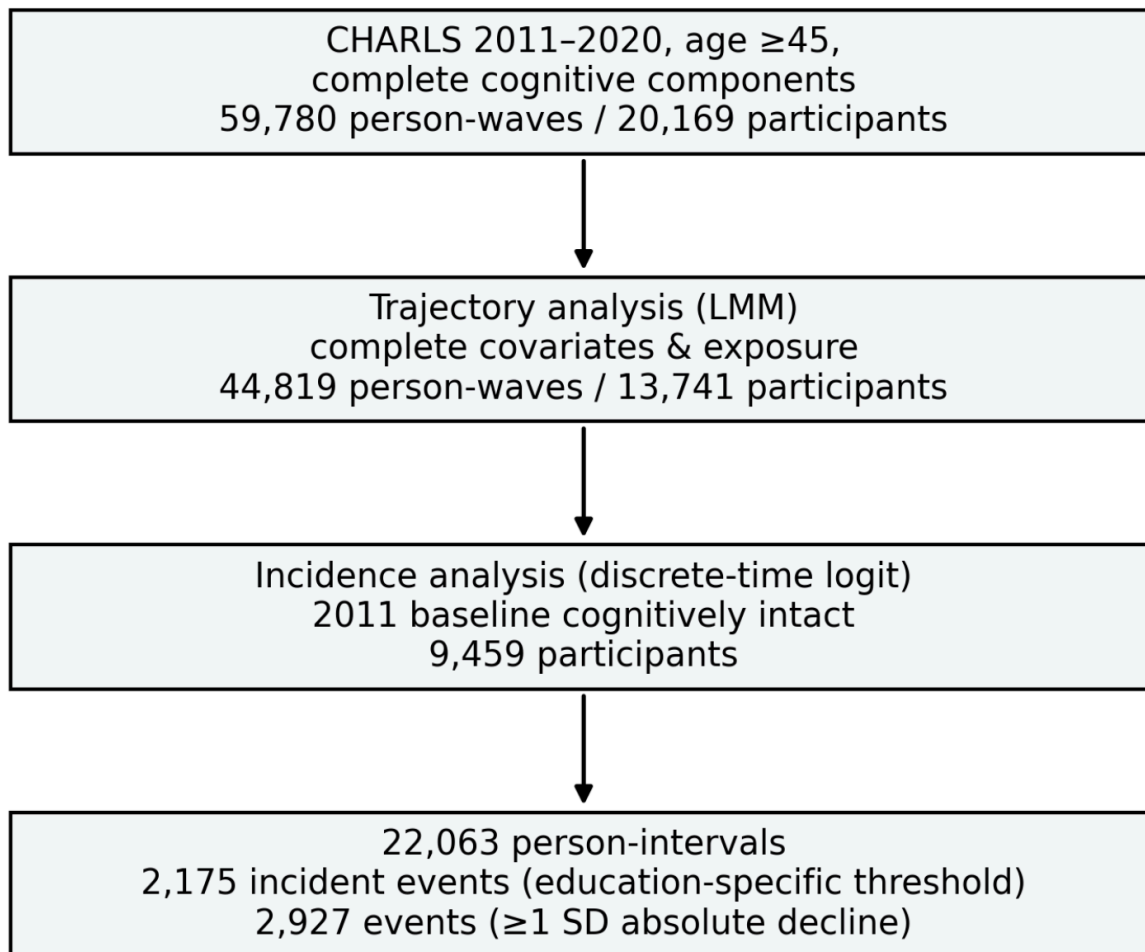


Figure 1

Analytic sample flowchart.

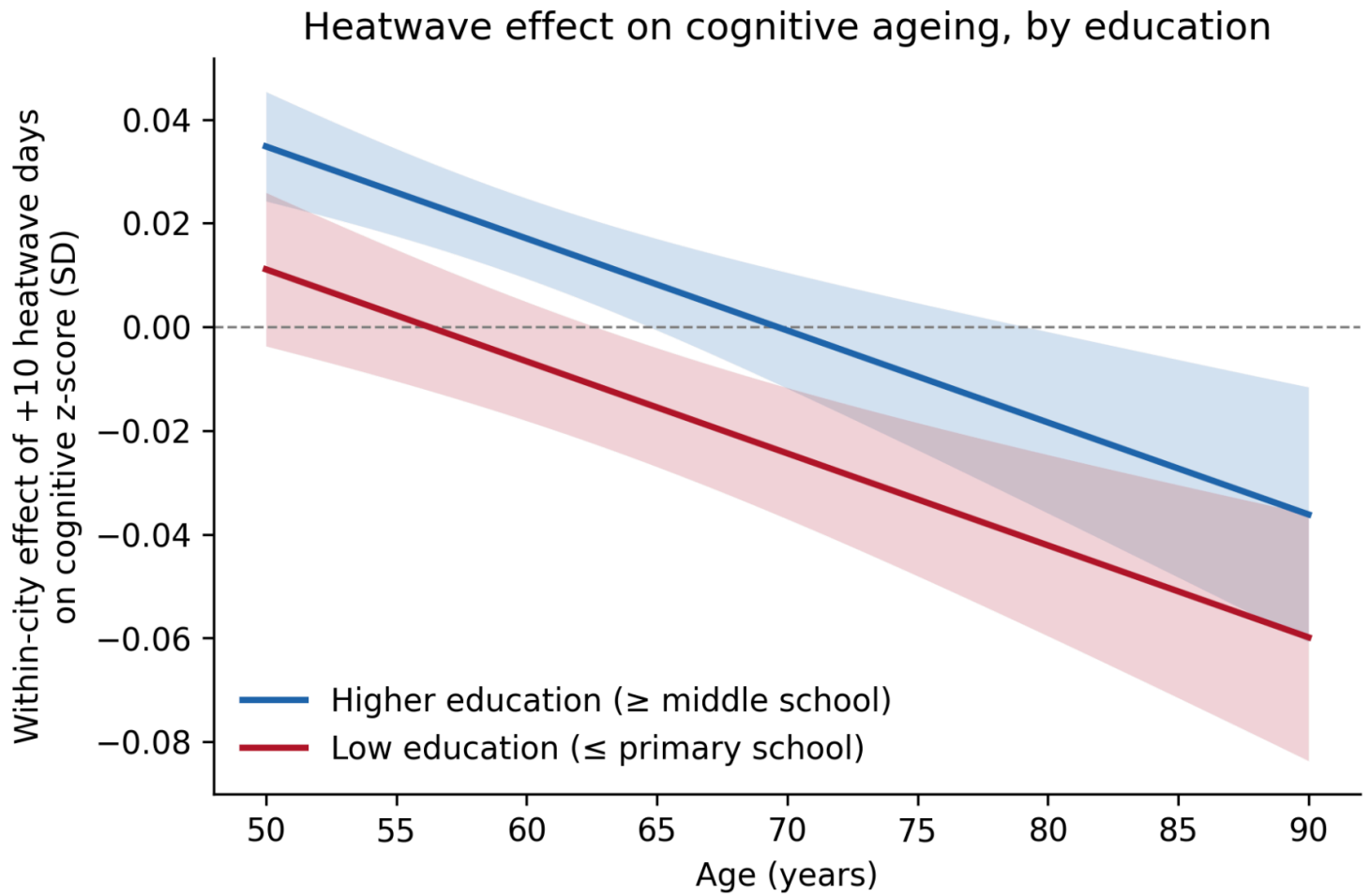


Figure 2

Heatwave effect on cognitive z-score by age and education. Within-city effect of +10 heatwave days; delta-method 95% CIs.

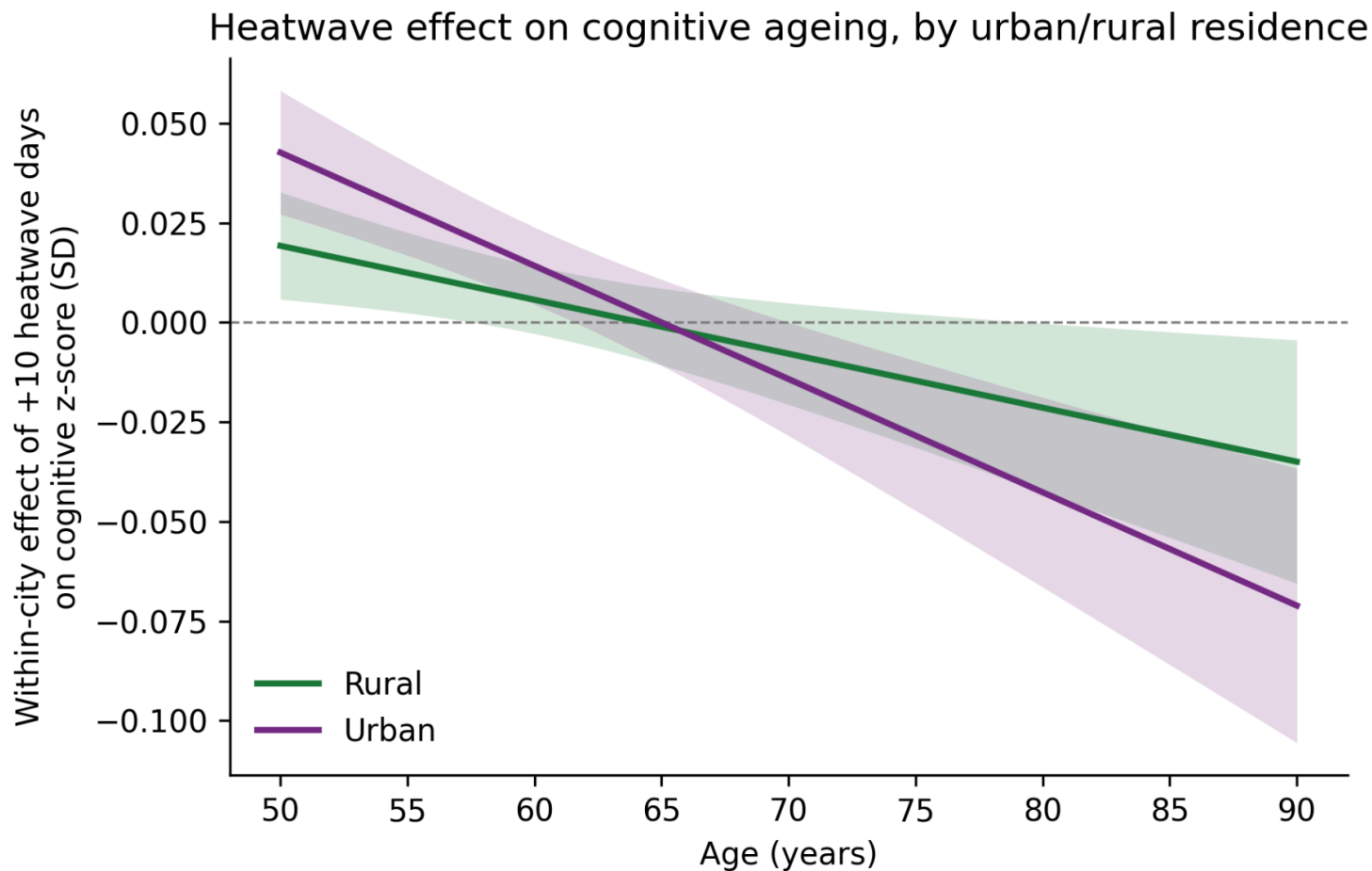


Figure 3

Heatwave effect on cognitive z-score by age and urban/rural residence. Within-city effect of +10 heatwave days.

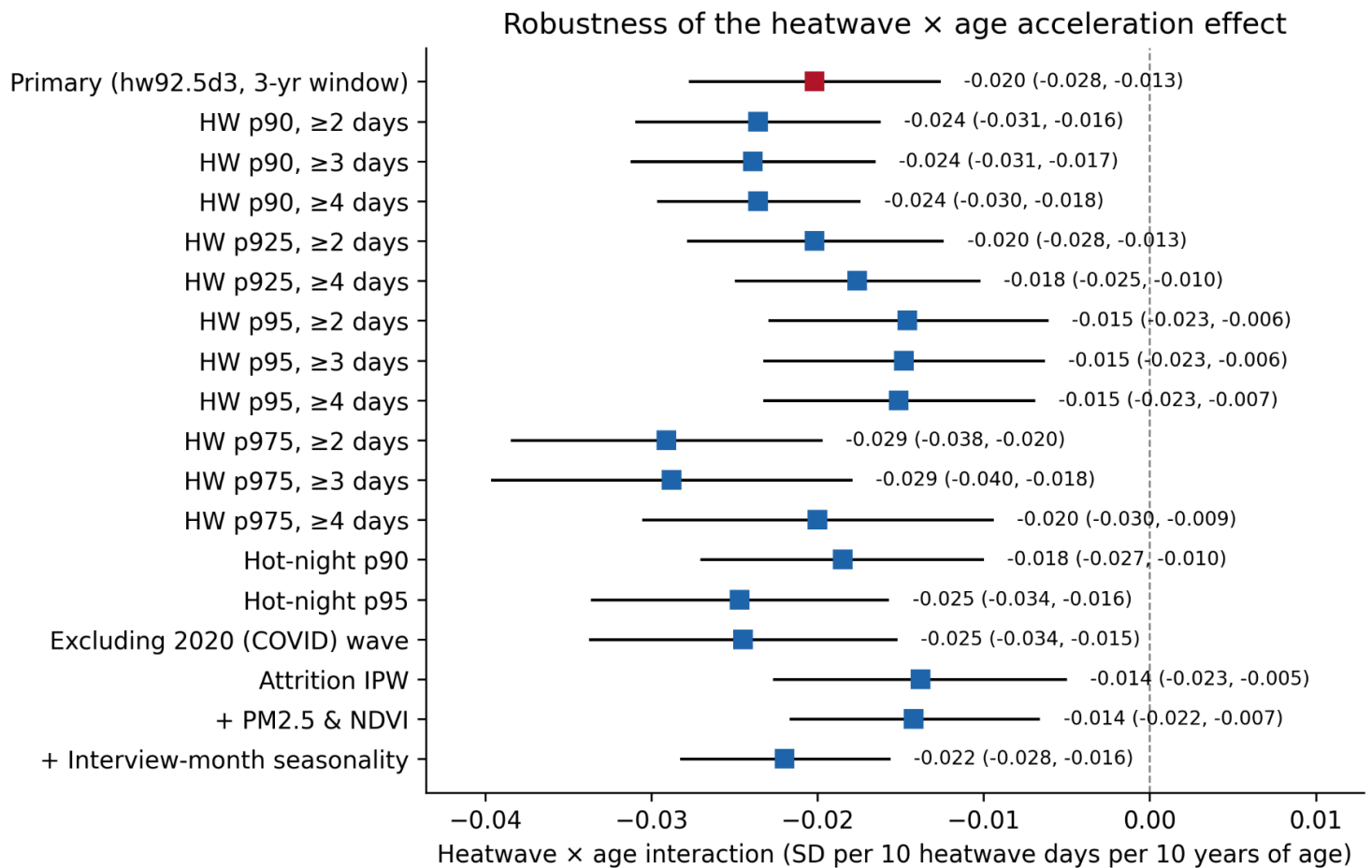


Figure 4

Robustness of the heatwave × age interaction. Results across 14 heatwave definitions, COVID-wave exclusion, attrition IPW, co-exposure adjustment and seasonality control.

Supplementary Files

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