Energy Research & Social Science 138 (2026) 104785

Contents lists available at ScienceDirect

Energy Research & Social Science

journal homepage: www.elsevier.com/locate/erss

Original research article

The thermostat of opportunity: Home air conditioning, its social gradient, and educational consequences

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ARTICLE INFO

Keywords:
Climate change adaptation
Air conditioning
Educational inequality
Academic achievement
PISA
Protective heat adaptation mechanisms

ABSTRACT

Rising global temperatures pose a significant threat to student cognitive functioning, positioning access to air conditioning (AC) as a critical adaptation mechanism. However, the unequal distribution of this resource threatens to establish a new line of educational inequality. While research has focused on school-based cooling, the home environment remains a critically understudied channel for heat-related learning losses, despite being the primary setting for independent study and sleep. To investigate the prevalence, social stratification, and academic implications of home AC access, we analyze data from the Programme for International Student Assessment spanning 2006–2022. The dataset comprises 576,786 fifteen-year-old students across 21 countries and five continents.

Our cross-national analysis reveals that while residential AC is diffusing globally, access remains strongly stratified by socioeconomic status. Consistent with the theory of Maximally Maintained Inequality, these socioeconomic gaps only begin to diminish in nations approaching market saturation. Furthermore, we identify a context-dependent relationship between home AC and academic achievement. In hotter climates, students with residential AC achieve higher test scores than those without, even after adjusting for socioeconomic covariates. This finding supports a heat-mitigation mechanism, suggesting that residential AC provides a protective shielding effect. Conversely, in cooler contexts, associations are negligible or negative. We conclude that as the climate crisis intensifies, the home learning environment must be recognized as a material determinant of educational equity and a key site for climate adaptation policy.

1. Introduction

Average global temperatures have risen markedly over recent decades, and the frequency and intensity of extreme heat events have increased in much of the world [1]. Among the many domains affected by this trend, education is increasingly recognized as a setting in which heat exerts measurable costs [2]. A growing body of research links elevated temperatures to lower cognitive performance, reduced learning, and lower test scores [3–6]. Air conditioning (AC) has emerged as one of the most effective forms of adaptation to these conditions, with research beginning to document its capacity to shield students from the adverse effects of heat on academic outcomes [2,7]. However, adaptation through AC is not equally available to all as access to cooling devices is socially stratified [2,8,9]. Hence, a “new line of inequality” has been described, separating those households able to insulate themselves from rising temperatures from those that cannot [10–12]. Where heat impairs learning and AC mitigates that impairment, unequal access to cooling becomes a channel through which climate change is likely to amplify pre-existing educational inequalities.

Despite the importance of this topic, existing research provides only a partial picture. Comparative cross-national evidence on residential AC prevalence among school-aged populations is scarce. Most existing studies focus on single national contexts, predominantly the United States or East Asian countries [2,7], and little is known about how prevalence has evolved over time across a broader set of countries. Socioeconomic gradients in AC ownership have been documented within several national contexts [2,8,9]. However, less is known about how the magnitude of these gradients varies across countries that differ in climate, level of economic development, and overall AC prevalence, or how they have evolved over time. Furthermore, evidence on AC as a

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https://doi.org/10.1016/j.erss.2026.104785
Received 4 February 2026; Received in revised form 15 May 2026; Accepted 28 May 2026

buffer against heat-related learning losses has concentrated almost exclusively on the school environment [2,7], treating school-based cooling as the primary policy lever. This narrow focus leaves the home environment critically understudied [13], where students spend the majority of their time and undertake substantial portions of their learning. Consequently, whether residential AC is associated with academic achievement, and whether this association varies cross-nationally in ways consistent with a heat-mitigation mechanism, remains an open question.

Against this background, we ask three sets of questions. First, we examine the prevalence of residential AC across countries and its evolution over time *(RQ1)*. Second, we ask to what extent AC access is stratified by family socioeconomic status *(RQ2a)*, how the magnitude of this stratification has evolved over time *(RQ2b)*, and how it varies across national contexts *(RQ2c)*. Third, we examine whether students with residential AC achieve higher test scores than those without *(RQ3a)*. Furthermore, we assess whether the magnitude of this association varies across countries in ways consistent with a heat-mitigation mechanism *(RQ3b)*, meaning it would be more pronounced in hotter contexts.

To address these questions, we draw on internationally harmonized data from the Programme for International Student Assessment (PISA) spanning the 2006 to 2022 cycles. The resulting analytical sample consists of 576,786 15-year-old students across 21 countries representing Asia, Europe, North America, South America, and Oceania. This paper makes three main contributions. First, it shifts the empirical focus from the school to the home environment. We provide systematic evidence on residential AC. Despite its theoretical and substantive importance for student learning, this setting has received little attention in the literature on heat and academic achievement. Second, the study adopts a comparative, cross-national perspective. Prior work has largely been confined to single countries. We instead leverage variation across 21 national contexts. This approach allows us to examine how AC prevalence, socioeconomic gradients, and the relationship between AC and achievement vary across countries. Third, our data offers extensive temporal coverage. This allows us to document both cross-sectional patterns and their evolution over a 16-year period. Consequently, across multiple years, we track changes in home AC prevalence, the magnitude of socioeconomic gradients, and the difference in academic achievement between students with and without access to residential AC.

This study is organized as follows. Section 2 provides the theoretical and empirical background on access to AC, its social stratification, and the achievement differences between students with and without residential cooling. Section 3 describes the datasets and the main variables used in the study and discusses our analytical strategy. Section 4 presents the main results for the three sets of research questions outlined above. Section 5 summarizes and discusses the key results and presents concluding remarks.

2. Theoretical considerations and prior research

2.1. The diffusion of AC

The global stock of residential AC has expanded rapidly over the past several decades. Sales of residential AC units tripled between 1990 and the late 2010s, reaching nearly 100 million units sold annually [8]. Roughly two-thirds of the 1.6 billion AC units installed globally are in residential buildings [14]. Adoption is projected to continue growing through mid-century. Falchetta et al. [14] estimate that the share of households worldwide with residential AC will rise from 27% in 2020 to 41% by 2050, corresponding to an increase from approximately 620 million to 900 million households with AC. Davis et al. [8] reach similar conclusions for their 16-country sample, projecting an increase from 35% of households in 2020 to 55% by 2050. The bulk of this growth is projected to occur in the Global South, with the largest absolute increases concentrated in South and South-East Asia and in sub-Saharan Africa [8,14]. Conversely, penetration in already saturated markets such as the United States, Australia, and Japan is expected to grow more moderately [14]. Three drivers underpin this expansion. First, rising mean temperatures and the increasing frequency and intensity of extreme heat events raise the demand for indoor cooling [1,14]. Second, sustained income growth in middle-income countries has brought AC within reach of a rapidly expanding share of households [8,15]. Third, urbanization, changes in building stock, and the urban heat island effect amplify cooling needs in densely populated areas [15].

Against this background, we expect residential AC prevalence among 15-yearolds to have increased in the countries studied over the 2006–2022 period, with substantial heterogeneity likely reflecting differences in climate and income level.

2.2. Socially stratified AC access

Prior research indicates that access to AC is not distributed evenly. Within countries, socioeconomically disadvantaged households show lower rates of AC ownership and use [2,8,9]. These gaps are expected to widen as energy costs rise and demand intensifies [14,16,17]. AC access has, thus, been described as a “new line of inequality” that separates those who can afford to insulate themselves from warming from those who cannot [10–12].

Two complementary frameworks from the sociology of inequality help to structure expectations about how the socioeconomic gradient should evolve. The theory of Maximally Maintained Inequality (MMI; [18]), originally developed to explain educational expansion, predicts that advantaged groups are the first to adopt a desirable, diffusing resource. Consequently, inequalities in access narrow only after these advantaged groups approach saturation, allowing disadvantaged groups to finally catch up. Applied to AC, MMI implies that socioeconomic gradients in access should only start to attenuate at very high prevalence levels. The theory of Effectively Maintained Inequality (EMI; [19]) extends this logic to the qualitative dimension of access: even when gaps in binary access close, advantaged groups secure higher-quality variants of the resource. For AC, this suggests that even where ownership rates converge, inequalities may persist along dimensions such as the number of cooled rooms, cooling capacity, energy efficiency, and duration of use. Although these specific factors are not the focus of the present study, they critically condition the interpretation of any observed convergence in overall ownership.

Beyond the question of stratified access, AC sits within a broader system of differential climate adaptation. The climate justice and environmental justice literature draws on the IPCC framework, which decomposes vulnerability into exposure, sensitivity, and adaptive capacity [20]. Within this framework, disadvantaged groups are seen to face a compounded disadvantage. Specifically, they tend to be more exposed to climate hazards and more sensitive to that exposure due to pre-existing vulnerabilities, while also possessing a lower capacity to adapt. Residential AC is thus best understood not as an isolated technology but as one component of adaptive capacity within this wider system, in which exposure and protection are jointly stratified along socioeconomic lines [11,14].

These considerations yield three expectations corresponding to social inequalities in AC access. First, we expect a positive socioeconomic status (SES) gradient in residential AC access. Second, we expect the magnitude of this gradient to vary across national contexts and over time. The theory of MMI implies an relationship between overall AC prevalence and the social gradient, with SES gaps narrowing only as ownership reaches saturation. Furthermore, these gradients may be sharper in hotter countries where the functional value of AC is higher and households face stronger incentives to invest. Conversely, gradients may be more compressed in economically developed countries where higher general living standards bring AC within reach of lower-SES households [17].

2.3. Heat, academic achievement, and the home environment

A substantial and growing literature documents negative effects of elevated temperatures on cognitive performance and academic achievement [3–6]. Several non-mutually exclusive mechanisms might explain these findings. Physiologically, heat stress is associated with reduced cerebral blood flow and the impaired delivery of oxygen and nutrients to the brain [21,22]. Additionally, heat leads to dehydration and disrupted thermoregulation that can significantly compromise cognitive functioning [22]. Heat exposure also degrades sleep quality, with downstream consequences for memory consolidation, attention, and next-day learning [23]. At the cognitive and behavioral level, high temperatures reduce the ability to concentrate, increase fatigue and irritability, and lower the willingness or capacity to engage in effortful tasks such as studying or completing homework [3,24]. Finally, heat may operate through indirect channels including increased absenteeism, reduced instructional time, and adverse effects on teachers as well as students [2,25].

Empirical work consistent with these mechanisms documents associations between reduced academic performance and elevated classroom temperatures [26–28], short-term heat events around the time of testing [3,4,29], and cumulative long-term heat exposure during the school year [2,6,25]; for systematic reviews see Venegas Marin et al. [5] and Vasilakopoulou and Santamouris [6]. Park et al. [2] show that adverse effects of heat exposure only emerge above a thermal threshold of roughly 21 °C (70 °F) and intensify progressively with higher temperatures. In his study on the US context, Park [3] finds that taking an exam when temperature is around 32 °C (90 °F) results in 13% of a standard deviation lower performance relative to more moderate a more moderate temperature of 24 °C (75 °F). Graff Zivin et al. [30] find even stronger adverse effects in China, linking a 1 °C increase in temperature during the exam period to drops in total test scores by 2.91% of a standard deviation.

The expanded deployment of air conditioning is increasingly recognized as a potential shielding mechanism against the negative effects of heat [12,14,15,31]. Specifically, evidence from the United States and Japan shows that AC in schools substantially attenuates heat-related declines in test scores [2,7]. Research on AC as a buffer against heat has, however, concentrated overwhelmingly on the school environment, treating school-based cooling as the primary policy lever [2,7]. Yet students spend the majority of their time outside school, and a nontrivial share of learning, such as homework, exam preparation, independent reading, and increasingly, online instruction, takes place at home. Sleep, which is critical for memory consolidation and next-day cognitive functioning, occurs at home and is highly sensitive to indoor temperature [23]. To the extent that residential heat exposure impairs these processes, the home environment constitutes a second, largely unexamined channel through which temperature shapes academic outcomes [13]. Importantly, socioeconomic gradients in residential AC are likely to be steeper than those in school-based AC. Residential AC is a largely private good, tied directly to household income and the ability to pay for electricity [11,12], while school-based AC is usually publicly funded and affected by collective institutions such as taxation and school finance policy [32]. The case for residential AC as a buffer is further strengthened by the differential-exposure component of climate vulnerability discussed above. Specifically, disadvantaged students are not only less likely to have residential AC, but they are also more likely to live in neighborhoods with higher ambient temperatures due to denser built environments, limited green space, and the urban heat island effect [16,33,34]. The buffering value of residential AC, where available, may therefore be particularly significant for those students who would otherwise be subject to the highest levels of environmental heat exposure.

Taken together, these insights lead to two specific expectations regarding the AC–achievement link. First, we expect students with residential AC to achieve higher test scores than those without. However, because both AC ownership and academic achievement are strongly stratified by SES [22,35,36], it is critical to account for socioeconomic background. Without doing so, observed differences may simply reflect these underlying compositional disparities rather than a shielding effect of AC. We therefore estimate differences that are adjusted for individual-level demographic and socioeconomic covariates. Second, we expect the achievement difference between students with and without AC to be more pronounced in hotter countries. Such a pattern would be consistent with a heat-mitigation mechanism, where the functional value of cooling is highest in high-exposure environments.

3. Materials & methods

3.1. Data

We utilize data from the 2006, 2009, 2012, 2015, 2018, and 2022 administrations of the PISA [37–42]. The sampling design employed across the various data collection waves closely resembles the methodology outlined below for PISA 2022. The PISA 2022 involved a two-stage stratified sampling design to obtain a representative sample of 15-year-old students enrolled in educational institutions within participating OECD and partner countries [42]. In the first stage, schools were systematically selected with probabilities proportional to their estimated size. Within each selected school, a random sample of age-eligible students was drawn in the second stage. The target population was 15-year-old students, defined as those aged between 15 years and 3 months to 16 years and 2 months at the beginning of the testing period. For more information on the sampling, see OECD [43].

We utilized data from these specific waves because students in selected countries were asked whether their homes were equipped with AC. During this period, the item was administered to students across 21 countries spanning Europe, the Americas, Asia, and Oceania. Because not all countries participated in every PISA assessment cycle, and because the AC question was not consistently administered across all waves, our resulting data structure is an unbalanced panel. Table 1 lists the country-years utilized in our study, displaying only those instances where a country both participated in a given PISA cycle and administered the AC question. In total, our dataset yields 73 country-year observations. Coverage ranges from countries appearing only once (e.g., Australia, Hong Kong, Hungary, Indonesia) to those with data available across six time points (e.g., Bulgaria, Italy, South Korea, Thailand, Turkey). In total, the sample comprises 612,318 students, with country-year specific sample sizes ranging from 4498 (Bulgaria in 2006) to

Table 1
Availability of the air conditioning item by country and PISA assessment cycle.

	2006	2009	2012	2015	2018	2022
Argentina	–	✓	✓	–	–	–
Australia	–	–	–	–	–	✓
Brunei Darussalam	–	–	–	–	✓	✓
Bulgaria	✓	✓	✓	✓	✓	✓
Canada	✓	✓	✓	✓	✓	–
Croatia	✓	–	✓	✓	✓	✓
Dominican Republic	–	–	–	✓	✓	✓
Hong Kong	–	–	–	–	–	✓
Hungary	–	–	–	–	–	✓
Indonesia	✓	–	–	–	–	–
Italy	✓	✓	✓	✓	✓	✓
Japan	–	✓	–	–	–	✓
Malaysia	–	✓	✓	–	✓	✓
Philippines	–	–	–	–	✓	✓
Portugal	–	✓	✓	✓	✓	–
Romania	✓	–	–	–	–	✓
Singapore	–	✓	✓	✓	✓	✓
South Korea	✓	✓	✓	✓	✓	✓
Thailand	✓	✓	✓	✓	✓	✓
Turkey	✓	✓	✓	✓	✓	✓
Viet Nam	–	–	✓	✓	–	✓

31,073 (Italy in 2012). A comprehensive breakdown of the country-specific student sample sizes is available in Table B1 in the Appendix.

3.2. Operationalization

For our analyses concerning the prevalence of AC and the socioeconomic gaps in AC access, the primary outcome variable is the presence of an AC system in the student's home. In most PISA assessment cycles, this information was captured via a dichotomous item: students were asked, "Which of the following are in your home?", and could respond "yes" or "no" to AC. However, in the 2022 cycle, the questionnaire in certain countries was expanded to ask for the specific number of AC units. To establish a consistent metric across all measurement points, we harmonized these responses into a standard binary indicator of access (1 = yes, 0 = no). Table B2 in the Appendix details the exact question wording as well as the country-specific formulations of the response options.

For our analyses regarding achievement differences between children in homes with and without air conditioning, the outcome variable is academic achievement. PISA evaluates the extent to which 15-year-old students can extrapolate their knowledge in mathematics, reading, and science, and apply it to real-world scenarios [44]. Our study utilizes data from six PISA cycles spanning 2006 to 2022. Across these waves, the major domain of assessment rotates systematically: the primary focus was science in the 2006 and 2015 cycles, reading in 2009 and 2018, and mathematics in 2012 and 2022. We operationalize academic achievement using the plausible values of mathematics test scores [45,46]. Due to space constraints and highly similar performance patterns across subjects, our main text focuses exclusively on mathematics; however, results utilizing the reading and science domains are displayed as robustness checks in the Appendix. The cognitive assessments consist of a mixture of multiple-choice and constructed-response questions, which are grouped around passages depicting real-life situations. To cover the domains comprehensively, PISA utilizes several hours of total test items. Because no single student takes the entire test, different combinations of items are distributed across multiple test forms. These forms are completed by a sufficient number of students to enable robust estimations of proficiency and psychometric analyses across all countries and relevant subgroups [44]. To account for this matrix test design, Item Response Theory models are used to scale the results and generate the plausible values. These values are then transformed onto a standardized PISA reporting metric with a mean of 500 and a standard deviation of 100. This specific baseline metric is historically anchored to the performance of participating OECD countries during the cycle when a given subject was first established as the major domain [47].

Furthermore, we use the highest level of parental education as our proxy for students' socioeconomic background.[1] Specifically, our SES measure is equal to one if at least one parent holds a university degree and zero otherwise. This dichotomization was selected to ensure cross-national comparability [49]. Because an alternative, occupation-based SES measure suffers from a higher rate of missing data compared to our education-based indicator, we provide these results exclusively as a robustness check in the Appendix.

We include several additional control variables in our regression models. Student gender is operationalized based on self-reports (boy or girl), and age is measured in years. Discrimination against immigrant populations and ethnic minorities in the housing market can result in these groups ending up in homes that are, on average, less well-equipped, including a lack of air conditioning [50–53]. Because immigrant and minority status also correlate with education and income in many countries [54,55], failing to account for this could lead us to falsely attribute these systemic effects to AC. Therefore, we utilize the dataset's existing classification of students as native, first-generation, or second-generation immigrants—based on the student's and parents' countries of birth—as a proxy for minority status. Because this variable exhibits a high share of missing values (1.8–4.7% across the various survey cycles), we included a separate "missing" category to retain these observations in our analyses. To control for home resource availability, we include binary indicators for computer availability (1 = yes, 0 = no) and internet access (1 = yes, 0 = no), alongside a categorical measure for the number of books at home (0–10, 11–25, 26–100, 101–200, 201–500, or more than 500 books). Finally, if residential AC correlates with other measures of housing quality that affect academic performance, omitting broader housing controls may upwardly bias the estimated effect of AC. To capture these parallel housing conditions, we include indicators for whether the student has their own room (1 = yes, 0 = no) and a quiet place to study (1 = yes, 0 = no), as well as a categorical measure for the number of bathrooms in the home (none, one, two, or three or more).

With the exception of the quiet place to study (not surveyed in 2022) and the number of bathrooms (not surveyed in 2006), all control variables are consistently available across all included PISA cycles.[2]

3.3. Country-level data

We calculated mean annual temperatures by averaging monthly satellite-based meteorological data [56,57].[3] Specifically, we utilized the ERA5-Land monthly averaged data (at 2 m height above surface) covering the period from 1950 to the present. To retrieve these data and spatially assign them to national boundaries, we employed several R packages [58–61]. Specifically, our computational workflow consisted of three primary steps. First, we systematically queried the Copernicus Climate Data Store via an application programming interface to download global, monthly-averaged 2-m temperature reanalysis data in gridded format for the years 2005 through 2021. Second, we imported these gridded files as spatio-temporal raster layers and harmonized their coordinate reference systems with national polygon boundaries to ensure accurate geographic overlay. Finally, we performed a two-stage aggregation: we calculated the annual mean temperature for each spatial grid cell by averaging across the twelve monthly layers, and subsequently extracted the national spatial averages by calculating the mean value of all grid cells falling strictly within each country's borders. This process yielded a harmonized country-year dataset that was then exported for our statistical analyses.

To proxy national economic development, we use Gross Domestic Product (GDP). We assigned the corresponding GDP per capita value (PPP, constant 2021 international $) to each country-year observation based on World Bank data [62]. Finally, to estimate the national prevalence of air conditioning, we aggregated the PISA student-level data. For each country and assessment cycle, we calculated the proportion of students residing in households equipped with air conditioning.

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[1] Because the item capturing AC at home is included as a country-specific wealth indicator in the construction of the PISA index of economic, social and cultural status (ESCS) [48], we opted against using this widely utilized index as our measure of SES.

[2] In the Appendix, we additionally control for school-level resources (e.g., instruction hindered by a lack of infrastructure) and school type (public or private) for the PISA cycles where this information is available. However, because these data are reported by school principals, they exhibit a substantially higher rate of missing values than our individual-level variables. To minimize potential bias, we utilize these variables exclusively as robustness checks.

[3] For further robustness, we incorporated four additional climate measures: the monthly mean temperature during the month of the assessment, the number of hot days (exceeding 26.5 °C) in the three calendar years prior to the PISA assessment, the number of hot days (exceeding 26.5 °C) during the testing month, and the mean relative humidity (calculated from temperature and dewpoint temperatures) for the full calendar year preceding the assessment. The results utilizing these alternative measures are presented in the Appendix.

3.4. Missing data

The proportion of students with missing values on at least one model variable is consistently low across all cycles (2006: 4.7%; 2009: 4.7%; 2012: 5.7%; 2015: 7.3%; 2018: 7.4%; 2022: 5.0%). Table B4 in the Appendix details the exact percentage of missing values for all model variables by PISA assessment cycle. Generally, missing data rates for individual variables remain below 5%, with immigration status exhibiting the highest share of missingness (ranging between 1.8 and 4.7%). For the air conditioning variable, missing values fluctuate between 1.7 and 3.7% overall. A more detailed examination of missing AC data—disaggregated by country, year, and student socioeconomic status reveals that the share of missing values remains below 5% in the vast majority of country-year observations (see Table B3 in the Appendix). The lowest missing rates were recorded in Singapore and South Korea (0.4% in 2009), while the highest was observed in the Dominican Republic (12.3% in 2015). Furthermore, among students with available data on parental education, those with non-tertiary-educated parents exhibit higher missing rates for the AC variable compared to their peers with tertiary-educated parents. However, given the generally low proportion of missing values—both overall and within specific SES subgroups—alongside the small absolute differences between these groups, we do not expect this to introduce substantial bias into our analyses. If any bias were present, it would likely result in an underestimation of group differences, as we anticipate that students who lack the resource (like AC) may be more prone to leaving the question blank.

Consequently, we conducted complete case analyses, utilizing listwise deletion for students with missing data on any of the model variables. The final analytical sample comprises 576,786 students (2006: $N = 82{,}121$; 2009: $N = 97{,}435$; 2012: $N = 100{,}598$; 2015: $N = 80{,}736$; 2018: $N = 99{,}066$; 2022: $N = 116{,}830$) nested within 73 country-year observations across 21 countries and six assessment cycles. A detailed breakdown of the analytical sample sizes for each country and assessment year is provided in Table B1 in the Appendix. Within this final sample, country-year observations range from a minimum of 3986 students (Bulgaria, 2009) to a maximum of 29,946 students (Italy, 2009).

3.5. Analytical strategy

In all analyses, we employ the Stata *repest* package [63] to account for the complex sampling design, survey weights, and the use of plausible values for academic achievement. Because the survey utilizes a stratified sampling approach, the package accurately estimates sampling variances by applying replicate weights, specifically balanced repeated replication techniques. Additionally, it handles the multiply imputed plausible values by averaging the estimator across them and integrating the resulting imputation error into the final variance estimate.

We proceed with our analysis in five distinct steps to answer our research questions. First, to address how AC prevalence differs between countries and how it has changed over time, we estimate the mean prevalence of AC among adolescents across countries and assessment years. Specifically, we calculate the fraction of students with home AC for each country-year available in the PISA data, with standard errors clustered at the school level. This yields 73 separate estimates.

Second, to answer our research question regarding social inequalities in AC access, we examine the SES gap in AC prevalence across countries and over time. We calculate the fractions of adolescents with AC access among students with tertiary-educated and non-tertiary-educated parents. We define the SES gap in AC as the country-year-specific difference between these fractions, resulting in 73 estimates. These estimates are derived from separate bivariate linear probability models, with standard errors clustered at the school level.

Third, to assess the relationship between within-country SES gaps in AC and country-level characteristics, we follow a two-step approach: The estimation of country-year specific SES gaps in home AC access described above represents the first step. In the second step, we use these inequality estimates at the country-year level as the dependent variable and regress them on AC prevalence, mean temperature, and GDP at the same level using ordinary least squares (OLS) regressions. To account for estimation uncertainty in the first step and to assign greater influence to more precise observations, we weight these regressions using the inverse of the estimated standard errors of the SES gaps [64]. As Giesecke and Kohler [65] note, this method is particularly suitable for data structures like ours, where the number of micro-level observations within each macro-level unit is large, but the overall number of macro-level observations is comparatively small. Furthermore, they argue that the two-step procedure deliberately brings the scarcity of macro-level data points to the researcher's attention. Consequently, this method serves as a robust alternative to a traditional one-step random-effects framework in such situations, primarily because it relies on much weaker distributional assumptions. We restrict these analyses to the 17 countries with at least two observation points, excluding Australia, Indonesia, Hong Kong, and Hungary. This yields various regression models based on 69 country-year estimates. We estimate models including one country-level indicator at a time, specifically AC prevalence, yearly mean temperature, and GDP (Models 1–3). We then estimate a model including all three country-level characteristics simultaneously (Model 4). Subsequent models introduce either country dummies or year dummies to account for time-invariant, country-specific characteristics and time-varying, globally common trends, respectively (Models 5–6). The final model includes both country and year dummies simultaneously (Model 7).

Fourth, to address the question of achievement gaps between students with and without home AC, we estimate covariate-adjusted AC test score gaps via OLS regressions for each available country-year combination, resulting in 73 estimates with standard errors clustered at the school level. The dependent variables are the plausible values in mathematics representing academic achievement. Specifically, we control for students' age, gender, parental SES, immigration status, computer availability, internet access, number of books at home, having their own room, having a quiet place to study, and the number of bathrooms.[4]

Fifth, similar to the procedure described for SES gaps, we apply a two-step approach to estimate the influence of mean temperature on the AC test score gaps. We again restrict the sample to the 69 country-year estimates from countries with at least two observations. In the second step, the estimated AC differences in test scores are regressed on the country-level mean temperature. These models are similarly weighted using the inverse of the standard errors of the first-step AC test score differences. The modeling sequence is similar to the previous approach, first testing country-level mean temperature individually (Model 1), then adding country and year dummies separately (Models 2–3), and finally incorporating both country and year dummies in a single model (Model 4).

4. Results

4.1. AC prevalence

Fig. 1 reveals substantial cross-national heterogeneity in the prevalence of air conditioning. While nearly all respondents in Australia (92.3%), Hong Kong (98.5%), South Korea (97.7%), and Japan (95.5%) reported possessing home AC in 2022, rates are significantly lower in countries such as Thailand, Turkey, Vietnam, Romania, the Dominican Republic, Hungary, and Malaysia where prevalence hovers around 40–60%. The lowest prevalence in 2022 is observed in the Philippines (35.3%).

Furthermore, among countries with multiple observation points, the

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[4] Unadjusted AC test score gaps, without controlling for covariates, are presented in Figure A3 in the Appendix.

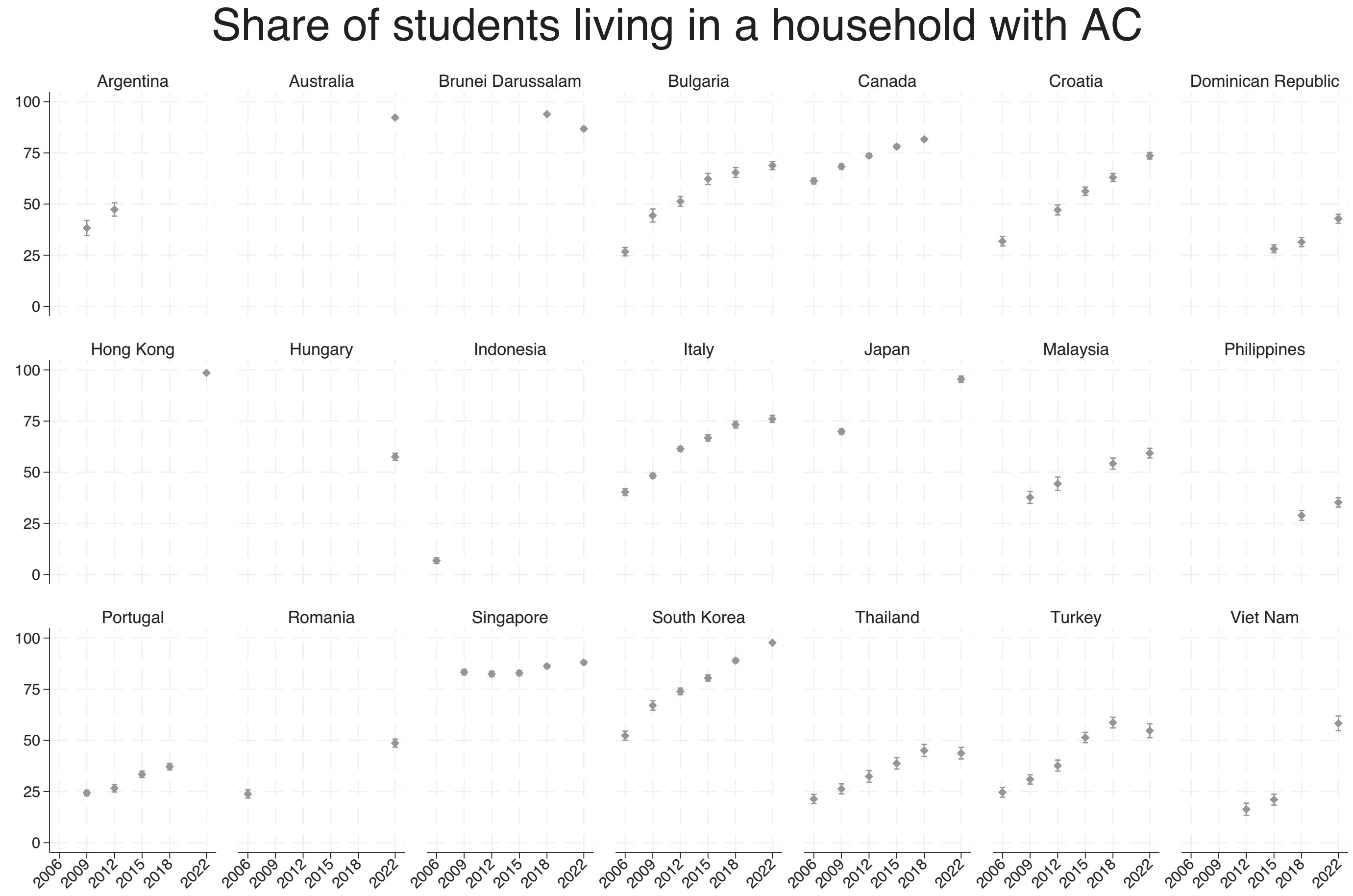

Fig. 1. Proportion of students reporting home air conditioning by country (across PISA assessment cycles). Note: 95%-confidence intervals are displayed. $N =$ 576,786. Source: PISA 2006, PISA 2009, PISA 2012, PISA 2015, PISA 2018, PISA 2022, our own calculations.

proportion of students reporting home AC ownership has steadily increased over time. This trend is particularly evident in Bulgaria, Thailand, and Turkey. Consequently, based on the observed nations, there appears to be a broader global trend toward wider AC diffusion. Indeed, some countries such as Japan and South Korea have already almost reached saturation. Table B5 in the Appendix presents the country-specific proportions for each year, alongside the absolute and relative changes between the earliest and most recent observation years.

4.2. Social inequalities in AC access

We find pronounced and statistically significant ($p < 0.05$) SES related disparities in home AC access: students from families with non-tertiary educated parents are less likely to have AC at home in almost all countries in the sample (see Fig. 2, with the exceptions of Hong Kong in 2022 and Brunei Darussalam in 2018). In several of the observed countries, these SES gaps in home AC persist over time. The largest absolute percentage differences are observed in Thailand. While a narrowing of the SES gap in AC access over time is evident in several nations, such as South Korea, Thailand, and Turkey, the percentage-point difference remains substantial in many others. Even in 2022, gaps exceeding 10 to 20 percentage points are common. In certain countries, such as Portugal and Singapore, these socioeconomic disparities appear remarkably persistent over time. Recalling Fig. 1, it becomes apparent that countries with high overall AC prevalence exhibit smaller or statistically insignificant SES gaps in household access. This is exemplified by Japan, South Korea, Hong Kong, and Australia in 2022.

Relating the SES gaps in home AC at the country-year level to country-year AC prevalence, mean temperature, and GDP reveals distinct patterns (Table 2). The bivariate models indicate that SES gaps in residential AC access are smaller where AC is more widespread (Model 1), where temperatures are higher (Model 2), and where GDP is higher (Model 3). In Model 4, we jointly include all three predictors. While the coefficients of AC prevalence and mean temperature remain qualitatively similar to the corresponding bivariate models, the GDP coefficient drops sharply and loses significance. The introduction of country fixed effects in Model 5 confirms that AC prevalence remains a robust within-country predictor of the SES gap in AC access, whereas the mean temperature association loses significance. The latter can plausibly be explained with relatively low within-country temperature variation across PISA waves. The coefficients in Model 6 (year fixed effects only) closely mirror those in Model 4, indicating that common temporal trends do not drive the pooled associations. Including both country and year fixed effects (Model 7) confirms the robust association between within-country AC prevalence and the social gradient in AC access and that temperature and GDP play no independent role.

4.3. Test score differences between children with and without AC access

Fig. 3 displays the mathematics test score gaps between students with and without home AC. Examining the trends over time, these achievement gaps remain remarkably stable in most countries, lacking any clearly discernible universal trajectory. Notable exceptions are Singapore, which exhibits a growing disparity, and Brunei Darussalam, where the gap has narrowed over time. In terms of magnitude, the statistically significant gaps ($p < 0.05$) typically fall within a range of -20 to $+20$ points on the PISA mathematics scale (which has a standard deviation of 100). The most pronounced disparity is observed in Hong

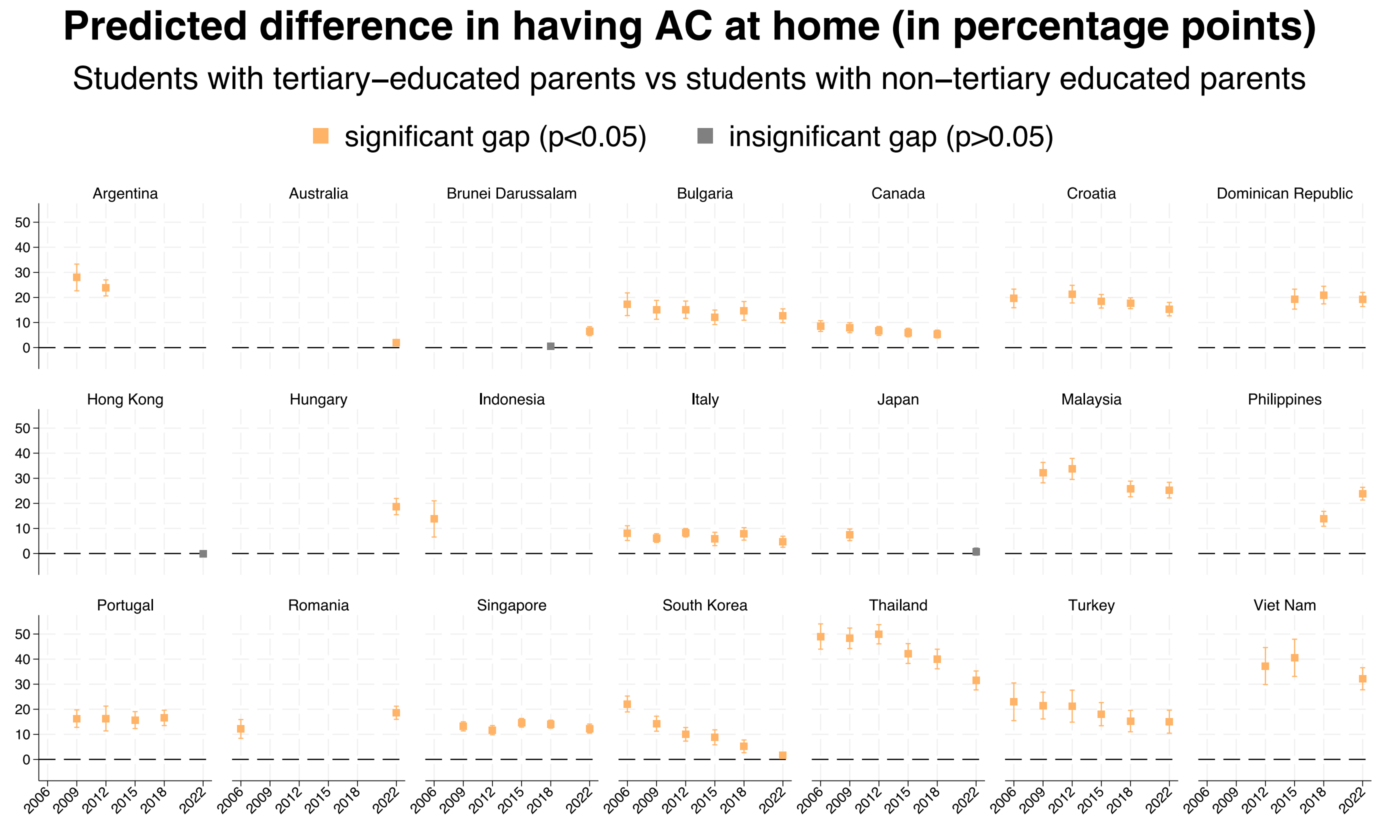

Fig. 2. Socioeconomic inequalities in home air conditioning access by country (across PISA assessment cycles). Note: 95%-confidence intervals are displayed. N = 576,786. Source: PISA 2006, PISA 2009, PISA 2012, PISA 2015, PISA 2018, PISA 2022, our own calculations.

Table 2
Association of country-year socioeconomic inequalities in home air conditioning access and country-year AC prevalence, temperature, and GDP.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
AC prevalence	−0.34***			−0.28***	−0.24***	−0.26***	−0.34***
Mean temperature		0.47***		0.44***	0.76	0.46***	0.85
GDP (in 1000 $)			−0.17***	−0.05	−0.03	−0.06	−0.08
Intercept	35.73***	7.53***	22.57***	27.75***	24.77	26.37***	26.82
Country dummy	no	no	no	no	yes	no	yes
Year dummy	no	no	no	no	no	yes	yes
R^2	0.49	0.17	0.21	0.62	0.94	0.63	0.94

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$.
$N = 69$ country-years (17 countries).
Source: PISA 2006, PISA 2009, PISA 2012, PISA 2015, PISA 2018, PISA 2022, World Bank (2004), Copernicus Climate Change Service (2022); our own calculations.

Kong, where the achievement gap reaches approximately 40 points in favor of students with AC access at home. The direction and statistical significance of these test score gaps vary substantially across the sampled nations. A predominantly significant and positive association—indicating higher test scores among students with home AC—is evident in Argentina, Brunei Darussalam, Hong Kong, Malaysia, and Singapore, with only isolated exceptions in specific observation years. Conversely, a significant negative relationship, wherein students without home AC perform better, is consistently found in Canada, Italy, Portugal, and Turkey. Furthermore, for a large cluster of countries—specifically Australia, Bulgaria, Croatia, the Dominican Republic, Hungary, Indonesia, Japan, the Philippines, and South Korea—the achievement gaps are generally small and not statistically significant at the 5% level across most years. Focusing specifically on the most recent wave of data in 2022 highlights distinct regional patterns. Significant positive test score gaps in the 2022 cycle are concentrated almost exclusively in East and Southeast Asian educational systems, namely Brunei Darussalam, Hong Kong, Malaysia, Singapore, Thailand, and Viet Nam. Conversely, among the participating nations in 2022, significant negative gaps are observed only in Italy and Turkey.

Finally, we examine how the country-year AC test score gaps in mathematics relate to country-year specific mean temperatures (see Table 3). In the initial single-indicator model (Model 1), mean temperature exhibits a statistically significant coefficient ($p < 0.05$) of 0.94. This suggests that each additional degree of mean temperature is linked with a widening of the AC test score gap. Model 3, which includes only year fixed effects, returns a coefficient (0.86) essentially identical to Model 1, indicating that common temporal shocks and secular trends do not substantially affect the association. When we introduce country fixed effects instead (Model 2), the coefficient estimate increases substantially to 5.39, implying that within the same country, hotter PISA years (1 °C increase from the country-specific mean) are associated with wider AC tests score gaps. Model 4 adds both country and year fixed effects. The point estimate of 4.03 remains close in magnitude to Model 2 but falls just short of conventional significance ($p = 0.058$), which we attribute to the limited degrees of freedom available once both sets of

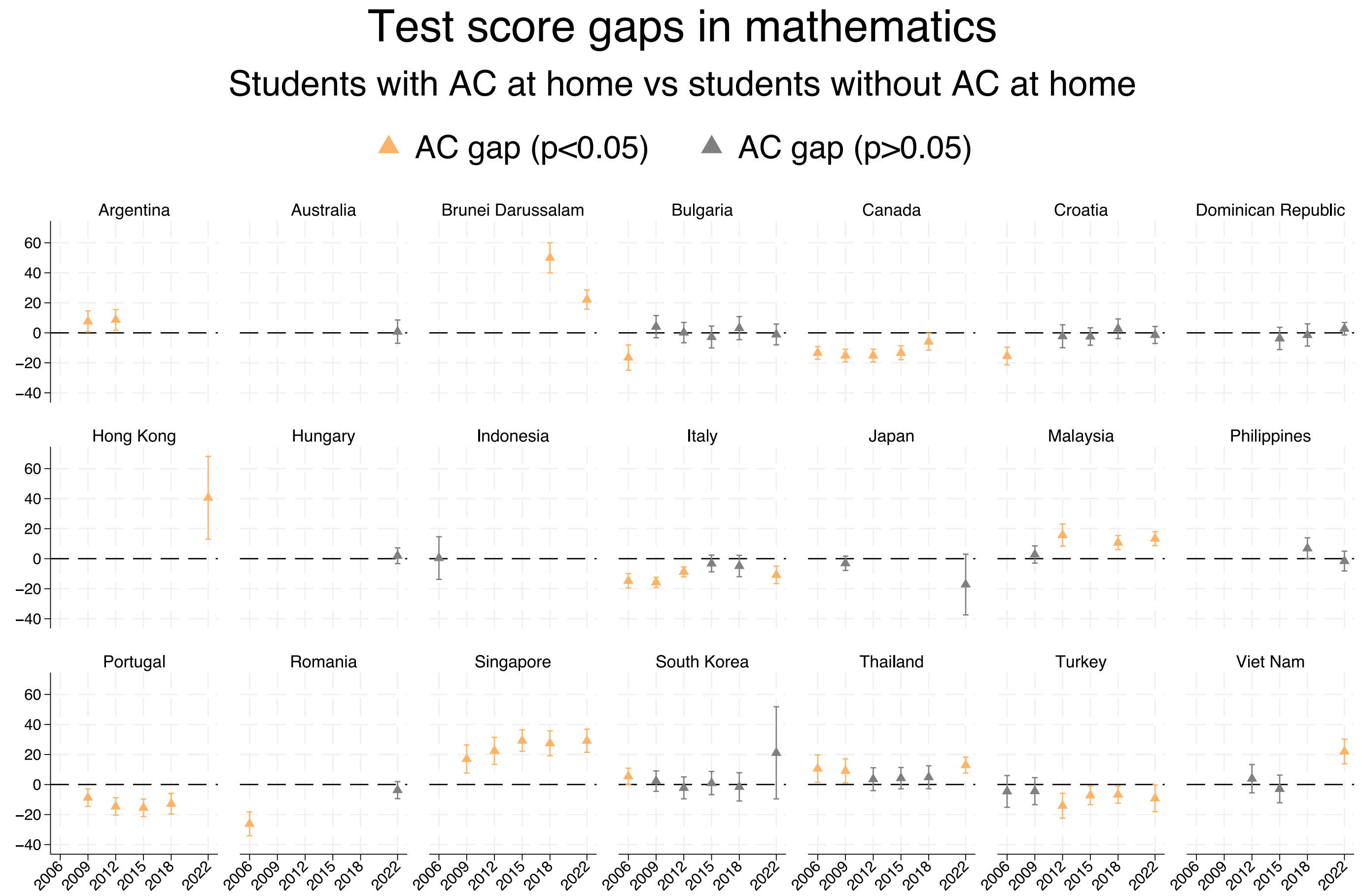

Fig. 3. Mathematics test score gaps between students with and without home air conditioning by country (across PISA assessment cycles). Note: 95%-confidence intervals are displayed. N = 576,786. Source: PISA 2006, PISA 2009, PISA 2012, PISA 2015, PISA 2018, PISA 2022, our own calculations.

Table 3

Association of country-year AC test score gaps in mathematics and country-year temperature.

	Model 1	Model 2	Model 3	Model 4
Mean temperature	0.94***	5.39***	0.86***	4.03
Intercept	−14.27***	−70.12***	−17.59***	−52.54
Country dummy	no	yes	no	yes
Year dummy	no	no	yes	yes
R^2	0.46	0.85	0.49	0.86

Note: * p < 0.05, ** p < 0.01, *** $p < 0.01$.
N = 69 country-years (17 countries).
Source: PISA 2006, PISA 2009, PISA 2012, PISA 2015, PISA 2018, PISA 2022, Copernicus Climate Change Service (2022); our own calculations.

dummies are absorbed in a panel of 69 country-years. Taken together, the results indicate a robust and sizeable within-country association between temperature and AC-related achievement gaps.

4.4. Robustness checks

We conducted a series of additional analyses to verify the robustness of our findings. First, we employed an alternative SES measure based on parental occupational status. Within each country and year, we constructed quintiles among students with valid occupational status data and compared the lowest quintile (Q1) with the top quintile (Q5). The results are highly consistent with those obtained using parental education (Figs. A1 and A2 in the Appendix).

Second, we replicated our analyses for reading and science (Figs. A4 and A5 in the Appendix). The results closely mirror those for mathematics, indicating that our findings are not domain specific.

Third, we re-estimated our models using alternative climate measures: the number of days exceeding 26.5 °C in the three years prior to the test, the mean temperature during the test month, the number of days exceeding 26.5 °C during the test month, and the relative humidity in the calendar year preceding the test (Tables B6–B13 in the Appendix). The results are consistent with our primary findings based on annual mean temperature.

Fourth, we introduced additional controls for school-type (private versus public) and school infrastructure (based on a questionnaire item asking to what extent a lack of infrastructure, such as adequate cooling or heating systems, hinders instruction). Because these items were only included in specific survey years and introduce further missing data, these analyses rely on a reduced sample. The results (Fig. A6 in the Appendix) remain substantially similar to our main findings.

Fifth, the observed negative coefficients of home AC on test scores in certain countries (e.g., Italy, Portugal, and Canada) might reflect regional sorting within these nations. In Italy, for instance, this finding may reflect pronounced within-country heterogeneity regarding test scores, social status, and AC prevalence, such as the distinct North-South divide [66]. Specifically, in the South, SES and average test scores are generally lower, yet home AC is more prevalent than in the North due to climatic conditions. This raises the broader question of whether our findings vary significantly across regions within countries and, if so, whether such regional variation might induce spurious correlations at the national level. To address this concern, we adopt a two-pronged approach. First, we leverage regional identifiers available in PISA data for 9 countries (encompassing a total of 27 country-years) and repeat our analyses separately for each region within these countries (note that in some cases, such as Turkey and Bulgaria, regional data are provided but the regions themselves are anonymized). The corresponding results are depicted in Figs. A8–A43 in the Appendix. AC prevalence shows considerable within-country differences (e.g., between Sicily and Trentino in Italy), yet an upward trend over time is visible across nearly all regions. SES gaps in AC access remain largely consistent across regions within most countries and years, with notable exceptions including the Northern Territory and Tasmania in Australia and the National Capital Region and Cordillera Administrative Region in the Philippines. The regional AC achievement gaps, in general, closely mirror the country level gaps. Second, to also include countries and years lacking regional identifiers, we used the school ID as a clustering variable, estimating the AC test score gap separately for each school within every country-year. Because within-school estimates vary substantially due to small sample sizes, we plotted the 25th, 50th, and 75th percentiles of the distribution of school-specific estimates per country-year, thereby mitigating the influence of outliers (Fig. A7 in the Appendix). The median of this distribution aligns closely with our main results. We interpret these findings as evidence that our reported national-level AC effects are not heavily distorted by within-country sorting, particularly since region-specific analyses continue to yield predominantly negative AC test score gaps in countries such as Italy, Portugal, and Canada.

Sixth, to test whether the AC–test score association varies across temperatures using an alternative method, we pooled the data from all countries and survey years, using the median of the plausible values as the outcome. These OLS regressions include the individual-level controls, year and country dummies, the yearly mean temperature, and an interaction between AC and temperature, with standard errors clustered at the country level (Table B14 in the Appendix). We find a significantly negative main effect of AC and a significantly positive interaction effect: only as temperatures rise above roughly 20 °C do children with home AC exhibit better test scores than those without.

Overall, these robustness checks yield results highly consistent with our main analyses, substantiating the validity of our primary findings.

4.5. Limitations

A primary limitation of this study is its reliance on (repeated) cross-sectional observational data, which limits strict causal claims [67]. To clarify which of the limitations discussed below are most consequential for our estimates, we present a simplified causal model of the home AC–achievement relationship as a directed acyclic graph (DAG, Fig. A44 in the Appendix). The DAG encodes our assumed mediation structure (home AC affects test scores via indoor temperature) and the main confounding paths through SES and outdoor temperature. We refer to the DAG where it sharpens the interpretation of specific limitations.

Regarding geographic representation, while this study offers a broad comparative overview, the 21 countries included do not constitute a random sample of the global population. They are predominantly middle- to high-income nations that opted into specific PISA questionnaire items. Expanding the geographic scope to include a broader range of climatic and economic contexts will be crucial to further test the generalizability of these patterns.

Furthermore, our main analyses operate at the national level, a relatively coarse spatial scale that does not fully capture within-country variation [16,68] in the interactions between local climate conditions and the impact of home AC. Although we conducted robustness checks at the regional and school level, these classifications likely still represent too high a level of aggregation, as heat exposure and the benefits of AC plausibly vary on a micro-level, even within single cities or municipalities [9,69,70]. In terms of the DAG, this amounts to residual confounding by outdoor temperature: our national-level measures only block this backdoor path to the extent that within-country variation in heat exposure is limited, and unobserved local differences in heat exposure linked to AC prevalence may bias the estimated AC achievement gap [16,71]. Assuming heat exposure is negatively linked to academic achievement [25] and that hotter localities within countries tend to have higher AC prevalence, this residual confounding would attenuate our estimates toward zero, though the ultimate direction and magnitude depend on the specific local relationships between heat exposure and AC adoption.

Additionally, our dataset lacks direct information on the presence of AC in students' schools [2,7]. The DAG is again informative: under the assumed structure, school AC affects test scores but is associated with home AC primarily through shared dependence on SES. Conditional on adequately measured SES, school AC therefore does not act as a confounder, and its unobservedness is not in itself a threat to identification. This logic does, however, depend on the assumption that school AC is not additionally driven by local outdoor temperature or by neighborhood-level sorting beyond what our SES controls capture. Our robustness checks controlling for a proxy of school infrastructure—which left the estimated home AC gaps substantively unchanged—offer some reassurance in this regard.

A further limitation concerns the binary AC indicator, which precludes distinctions between whole-house cooling and single-room units and lacks data on effective cooling capacity. Crucial qualitative dimensions of cooling inequality [19] therefore remain uncaptured.

Finally, the linearity assumption underlying our country-year analyses linking mean temperature to AC-related test score gaps (Table 3) might be oversimplified. AC is plausibly of modest relevance in cool climates and becomes increasingly consequential as temperatures rise into ranges where heat interferes with sleep, attention, and cognition [25]. Under a non-linear relationship, our linear estimates represent variance-weighted averages of slopes across very different segments of the temperature distribution and likely understate the effect in the warmer range where AC matters most. The same logic applies to the within-country estimates: although country fixed effects yield a substantially larger coefficient, this too is a weighted average and likely larger still in hotter countries. With 69 country-year observations, however, we have limited leverage to estimate flexible non-linear specifications.

Future research should therefore prioritize more disaggregated analyses [33,71,72] and richer functional-form specifications. For example, by using municipal-level data or temperature information based on exact school and household coordinates. Ideally, such studies would also utilize longitudinal panel data to better isolate causal mechanisms, despite the substantial difficulties involved in securing such high-resolution data for international comparative educational research.

5. Discussion

This study provides a comprehensive cross-national analysis of the prevalence, social stratification, and academic implications of residential air conditioning among adolescents. Leveraging data from 21 countries across five continents, we identify distinct patterns of diffusion and inequality that contribute to an emerging understanding of climate adaptation as a sociological phenomenon.

Regarding RQ1, our analysis reveals a clear global trajectory toward increased AC adoption [12,14,15,31]. This upward trend, however, masks substantial cross-national heterogeneity. While some East Asian contexts such as Japan and South Korea have reached near-universal coverage, diffusion in other regions remains lower. Global technological adaptation to rising temperatures is therefore advancing, but its pace is highly context-dependent, driven by a combination of climatic necessity and national economic capacity.

With respect to social stratification (RQ2a, RQ2b, RQ2c), we find that AC access is socially stratified in nearly all analyzed countries: students from higher socioeconomic backgrounds have significantly greater access [2,8,9]. Contrary to the expectation of a uniformly widening *new line of inequality*, however, we do not observe a consistent expansion of this social gradient over time. Instead, our results lend strong support to the theory of MMI [18]: once country and year fixed effects are accounted for, the primary driver of narrowing SES gaps is national AC prevalence itself. In countries approaching market saturation, distinct ceiling effects emerge as access becomes universal, corroborating findings from the US context [8]. The new line of inequality described in recent literature [10] may thus represent a transient phase of the diffusion process that narrows as the technology becomes a standard household utility.

The relationship between AC access and academic achievement (RQ3a, RQ3b) presents a more nuanced and context-dependent picture. The achievement gap between students with and without AC varies significantly by climate. In hotter regions (Hong Kong, Singapore, Malaysia), students with residential AC consistently achieve higher test scores, even after adjusting for parental SES and home environment variables — supporting the heat-mitigation hypothesis: in high-exposure environments, AC may serve as a crucial form of thermal capital shielding cognitive functioning and independent learning from heat [2,13]. Conversely, in temperate or cooler contexts (Canada, Italy, Portugal), the association is either negligible or paradoxically negative. We argue that these divergent effects highlight context-dependent measurement and unobserved variable bias [48]. In temperate or Mediterranean countries, AC may serve as a proxy for unobserved poor housing quality: wealthier households can bypass artificial cooling through superior housing, natural ventilation, green space, or better insulation, so the AC variable likely captures residual structural disadvantages not fully absorbed by our SES and home-resources controls. Drawing on the environmental justice and cooling poverty literature, AC in these climates may also represent a reactive measure by households living in heat traps such as poorly insulated housing or urban heat islands [73,74]. This may explain why students with AC in cooler regions perform worse: the appliance proxies a disadvantaged residential environment that affects learning through channels other than heat, such as poor air quality or overcrowding [13].

In conclusion, this study suggests that the global expansion of residential air conditioning is incrementally altering the material conditions under which academic achievement is produced. The findings indicate that while the diffusion of AC is a widespread phenomenon, the associated social stratification appears to follow a predictable cycle. In accordance with the theory of MMI [18], the socioeconomic *thermal divide* may represent a transitional phase of climate adaptation that tends to diminish only as national markets approach saturation. Furthermore, the academic implications of residential cooling seem to be ostensibly contingent upon the local climatic context. In hotter regions, home AC may be increasingly functioning as a form of *thermal capital* essential for maintaining cognitive performance [13]. Conversely, in temperate zones, its presence may serve as a proxy for substandard housing or urban heat vulnerability rather than a direct academic asset. As climate volatility increases, these results suggest that the home environment should be more systematically integrated into social science analyses of educational equity. Recognizing indoor thermal conditions as a potential determinant of student outcomes may require a shift toward context-specific policy interventions that address both technological disparities and broader structural deficiencies in residential housing quality.

List of abbreviations

AC	Air Conditioning
DAG	Directed Acyclic Graph
EMI	Effectively Maintained Inequality
ESCS	PISA index of economic, social and cultural status
GDP	Gross Domestic Product
IPCC	Intergovernmental Panel on Climate Change
MMI	Maximally Maintained Inequality
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PISA	Programme for International Student Assessment
PPP	Purchasing Power Parity
RQ	Research Question
SES	Socioeconomic Status

CRediT authorship contribution statement

Richard Nennstiel: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christian König:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization.

Funding sources

This work was supported by the Swiss National Science Foundation under grant agreement TMSGI1_211627.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.erss.2026.104785.

Data availability

The data are accessible to researchers upon completion of data usage agreements with the respective data providers. Replication materials to reproduce the analyses are available at: https://osf.io/943pc/.

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