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Heat and observed economic activity in the rich urban tropics

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Heat and activity in the tropics

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Abstract: We use space-and-time resolved mobility data to assess how heat impacts Singapore, a rich city-state and arguably a harbinger of what is to come in the urbanizing tropics. Singapore's offices, factories, malls, buses, and trains are widely air conditioned, its public schools less so. We document increased attendance and commuting to workplaces, malls, and the more air-conditioned schools on hotter relative to cooler days, particularly by low-income residents with limited use of adaptive technologies at home. Investment by rich cities may attenuate heat's pervasive negative consequences on productive outcomes, yet this may worsen the climate emergency in the long run.

Keywords: Urban heat, adaptive technology, defensive behaviour, heterogeneous impact, resilience of cities, tropics, climate change

Classification: Q54, O18, R40, J22

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Data and code availability statement: The footfall data are commercially available and purchasable from StarHub Ltd. Both the commuter and the Household Travel Survey microdata were obtained under non-disclosure from the Land Transport Authority. To allow verification, we will deposit the commuter data aggregated to our estimation samples in a public repository. All other data, including crowdsourced school-level air-conditioning usage, building-level likelihood of air conditioning at destination, and attendance and test scores at UWCSEA, as well as all computer code used to generate the results in this paper, are available on Dataverse `https://doi.org/10.7910/DVN/8XZFUK`. Moreover, upon reasonable request, the footfall data and the commuter and travel survey microdata are available on an NUS Department of Economics (or equivalent institutional) computer to replicate all published results from the deposited computer code.

1 Introduction

A growing economics literature documents adverse—and often sizeable—socioeconomic impacts of heat across a range of contexts including health, labour, education, and local economic output. Much of this literature examines US settings, extending over different climate zones and sometimes going back several decades. Graff Zivin and Neidell (2014) find that on days with a maximum temperature above 30 °C, US workers in occupations with climate exposure report reduced time allocated to work by as much as 14%. Deryugina and Hsiang (2014) find that each 1 °C increase in daily average temperature beyond 15 °C is associated with a 1.5% decline in US annual county-level income. Park *et al.* (2020) find that a 1 °F (0.6 °C) hotter US school year reduces PSAT test scores in the following year by 1%. Deschenes and Greenstone (2011) report that one additional day with a mean temperature above 32 °C raises the US annual mortality rate by 0.11%. Mullins and White (2019) estimate increases of 0.5% in mental-health emergency department visits and up to 0.8% in suicide rates per 1 °F rise in mean temperature over the month.[1]

A small part of this economics literature considers and finds a moderating role for defensive capital and other forms of adaptation (Heal and Park, 2016; Kahn, 2016).[2] Park *et al.* (2020) obtain school-level measures of air conditioning and find that such defensive investment offsets the effect of ambient heat. Moreover, heat disproportionately impacts minority students who are less likely to have access to air conditioning at school or home, or who can

[1] Recent work includes labour/firm productivity and human capital in developing countries (Zhang *et al.*, 2018; Somanathan *et al.*, 2021; Adhvaryu *et al.*, 2020; Garg *et al.*, 2020b; Graff Zivin *et al.*, 2020; Heyes and Saberian, 2022), as well as labour allocation in rural/farm settings (Jessoe *et al.*, 2018; Garg *et al.*, 2020a; Colmer, 2021; Liu *et al.*, 2023).

[2] Adaptation refers to measures taken to alleviate the detrimental effects of heat. We follow Barreca *et al.* (2016) and attribute "adaptation" to the widespread use of air conditioning in Singapore. Graff Zivin *et al.* (2018) include "avoidance behaviour, such as technological adoption, mobility, and cultural changes designed to buffer against the effects of climate (and) limit exposure to temperature extremes" (p.79).

draw on compensatory inputs (e.g., extra tutoring) when faced with lost learning. Barreca *et al.* (2016) document a century-wide decline in the US temperature-mortality relationship, with the attenuation after 1960 attributed to the diffusion of residential air conditioning. Chen and Yang (2019) find that summer heat is more detrimental to industrial output in China's low-temperature regions relative to high-temperature regions, suggesting that the latter regions have invested less in adaptation.

Other work finds limited historical adaptation. For example, in a cross-country study, Burke *et al.* (2015) find that productivity peaks at an annual mean temperature of 13 °C, declining strongly thereafter, and that "the relationship is globally generalizable [and] unchanged since 1960" (p.235).[3] Deschenes (2014) notes that "the available knowledge is limited, in part due to the few real-world data sets on adaptive behaviours [to heat]" (p.606). Dell *et al.* (2014) note: "Temperature shocks appear to have little effect in rich countries, although estimates for rich countries are not statistically precise" (p.753). It is in the context of this literature, and the environmental justice dimension that is developing within it, that we wish to contribute.

This paper presents evidence for a rich nation in the tropics whereby heat does not appear to induce significant economic losses. We consider a wide range of data and ask how economic activity in Singapore today responds to typical fluctuations in heat. Despite its tropical climate generally being warm and humid, heat does vary. Even after mild seasonality is accounted for, some days are significantly hotter than others. In the context of urban adaptation to a warming climate, how heat impacts this newly affluent city-nation matters

[3]Mullins and White (2019) "find no evidence of adaptation on any of the margins we analyse: the estimates remain stable over time, air conditioning adoption levels, regions with hotter or colder average climate conditions, and areas with higher or lower incomes." Burke *et al.* (2018) report suicide rates rising by 0.7% in US counties and 2.1% in Mexican municipalities per 1 °C increase in monthly temperature, with the "effect similar in hotter versus cooler regions and has not diminished over time."

not only to its population of 6 million but arguably as one model for the fast urbanizing tropics that are home to 4 billion people (State of the Tropics, 2020). The evidence we present is consistent with significant adaptation. And even within rich Singapore, we find heterogeneous effects based on income.

We obtain mainly high-frequency urban activity data including the number of people visiting specific indoor and outdoor locations, based on "pinging" their mobile phones, and the universe of bus and rail trips made on public transit, detailed by geocoded origin and destination, that are linked to transit farecards with unique identifiers. Singapore is densely populated and public transit is by far the most popular form of urban transport. Our main measure of heat is the daily maximum heat index, which accounts for both temperature and relative humidity (Anderson *et al.*, 2013).

We find that on hotter relative to cooler days the occupancy of office buildings and malls generally rises—and it does not drop at any time of the day. For example, a 1 °C rise in the daily maximum heat index increases workday office occupancy by 0.4% (averaged over all hours, and by more in the early morning) and mall occupancy by 0.6% (and by more in the evening). We interpret the evidence as being consistent with ambient heat inducing workers to be at the office, and leisure-seekers to visit the mall, because of the prevalence of air conditioning.

The individual public-transit panel allows us to infer neighbourhood of residence and associated income. We find that departures from industrial locations are higher on hotter versus cooler days, particularly among workers who reside in low-income neighbourhoods. Hotter weather appears to *reduce* absences of such workers, consistent with industrial and office workplaces offering cooled shared spaces relative to their homes. We find that schools that offer more air-conditioned classrooms attract more student commuters as heat rises, particularly low-income students. Homes are costly to cool, especially so over typically hot tropical afternoons and for low-income apartment dwellers who are less willing or able to afford purchasing and using cooling equipment at home (Salvo, 2018). This gradient in income based on the origin of work and school trips is a novel result.

In sum, in the places and occupations that we look, including manufacturing and office workers, school children, and shoppers/diners at malls, we do not find an adverse impact of heat on economic activity. For a historical perspective, Lee Kuan Yew, founding Prime Minister of Singapore from 1959 to 1990, famously singled out the air conditioner as the most important invention of the 20th century. Lim Swee Say, the environment minister from 2001 to 2004, highlighted the role of defensive capital investment: "Air conditioning plays a crucial role in our economy. Without it, many of our rank-and-file workers would probably be sitting under coconut trees to escape from the heat and humidity, instead of working in high-tech factories" (Arnold, 2002).

One interpretation of our findings is that as investment in adaptive technologies develops, some of the pervasive negative consequences of heat on a variety of productive outcomes that have been documented in the literature might be less severe for rich cities. At the same time, while such technologies help address the short-run effects of climate change, growing demand for fossil fuels to power them can make the climate emergency worse in the long run. We caution that we examine ordinary dwellers going about their daily lives and do not focus on extreme weather, such as heatwaves. The daily maximum heat in our samples varies between 30 and 40 °C, a range to which OSHA (2016) assigns a "moderate" risk of heat-related illness. We do not examine outdoor workers who are directly exposed to ambient heat and radiation (Obradovich *et al.*, 2018; LoPalo, 2023). By activity at the workplace or school, we mean mobility and do not imply output, as we do not measure productivity directly. We thus measure work loss in the sense of work attendance—“labour supply” as in Hanna and Oliva (2015). We caution further that we study how economic activity responds to weather fluctuations given climate today and subject to existing technologies and current relative prices, not to projected climate, technologies, and policies in 2050, let alone 2100 (Zhang *et al.*, 2021).

2 Data and setting

Two main data sources. We use data on the flow of persons to assess how economic activity in Singapore responds to hotter weather. A footfall dataset contains the number of people visiting a location by hour, based on pinging the mobile phones of a major telecommunications firm’s subscribers (see details in the appendix). We acquired hourly footfall for June to August of 2016 and 2017 in major agglomerations of activity, including office towers, shopping malls, and public parks (Table A.1). Footfall tends to peak at noon at office towers and at 18:00 at malls and public parks (Figure A.1).

A second dataset consists of public transit trips made in October to December of 2015 and 2016. Public bus and train (or a combination of both) jointly account for 64% of trips to work and for 72% of trips to school, compared with cars (owned, private hailed, taxi) which account for 27% and 19% of transport to work and school, respectively (DOS, 2019). The wide adoption of farecards enables us to track most commuters’ movements as they tap in and out on buses and in rail stations.

We observe the departure and arrival times and stops for every trip charged to a farecard, identified by a unique number, and its type, such as a concessionary student card. Workday commuting peaks in the early morning and evening, reaching 0.5 million trips during the hour starting at 18:00 (Figure A.2). We consider travel to various locations including a large zone reserved for industrial use, the Central Business District, malls, and schools (Figure 1). Malls are often near office towers and thus trips to such commercial areas at 8:00 are work related (non-food shops tend to open after 10:00).

The geocoded individual commuter panel when combined with housing characteristics enables us to analyse heterogeneity in the response to heat. In Singapore's structured housing market, dwelling type is informative of socioeconomic standing including access to home air conditioning (DOS, 2014; Salvo, 2020). To illustrate, mean annual household income per person varied widely in 2013, at \$9,300/person for 1- to 2-room apartments, \$20,900/person for 3-room apartments, and \$60,000/person for condominium apartments.[4]

We obtained the composition of dwelling types for each residential building in Singapore. For each bus/rail stop in a residential neighbourhood, we infer the affluence of the population it serves from the proportion of 1-3 room apartments among all dwellings in a given radius. Based on the typical daily first-departure and last-arrival stops associated with each farecard, we infer whether the cardholder lives in a low-income neighbourhood (Figure A.3).

In contrast with most workplaces and malls, schools are one of the last bastions in Singapore without widespread indoor cooling. In 2022, we surveyed 1500 university undergraduates on air conditioning use in their middle/high school classrooms years earlier,

[4]Air-conditioning penetration in 2013 ranged from 14% for 1-2 room apartments and 99% for condos, and is growing at the low end, e.g., 25% of 1-2 room apartments had cooling by 2018 (DOS, 2019).

overlapping with the commuter sample period. Because the typical survey respondent attended a middle school followed by a different high school, we have multiple (and consistent) responses for almost every school (∼200). The survey indicates that while most schools' classrooms did not use air conditioning, some schools enjoyed almost fully air-conditioned instruction (Figure A.3). We examine commuting on student cards to stops nearby schools and how this commuting varies with the extent of space cooling on offer.

Ambient environment. Singapore's tropical climate is warm and humid (Table A.1). The high relative humidity affects human thermoregulation by inhibiting the body's ability to dissipate metabolic heat from the skin into the environment (Lim *et al.*, 2008). Rather than specify air temperature and relative humidity as separate key regressors of interest, we focus our analysis on a heat index that combines the two variables (NWS, 1990, 2020). We compute an hourly heat index series that takes the one-hour temperature and one-hour relative humidity as its arguments; we then take the daily maximum realization of the computed one-hour heat index. The daily maximum heat index varies between 30 and 40 °C in our samples.

The heat index shows an amplification of temperatures (Buzan *et al.*, 2014). A 6 °C shift in the daily maximum temperature translates into a 10 °C shift in the daily maximum heat; moreover, fixing the temperature, the heat varies (Figure A.4). Substantial variation in daily maximum heat remains (8-10 °C) after we partial out year-month means to account for mild tropical seasonality and year-to-year changes.

3 Empirical models

Our footfall regression models, implemented by location type, take the general form

$$f_{lth} = \boldsymbol{W}_{th}\boldsymbol{\beta} + \alpha_h + \alpha_t + \alpha_l + \epsilon_{lth}, \tag{1}$$

where footfall f (in log) at location l on date t and hour h is regressed on date(-hour) specific weather and pollution covariates $\boldsymbol{W}_{th}$ (daily maximum heat, concurrent PM2.5, concurrent rainfall, concurrent wind speed), hour fixed effects (FE) α_h, day-type FE and year-month FE α_t, and location FE α_l. Day-type FE consist of two separate sets of day-of-week dummies, when schools are in session and during school vacations. $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$ are parameter vectors. We estimate models by OLS. Because the error ϵ_{lth} is potentially spatially correlated, we cluster the standard errors at the date level.

For our key variable of interest, heat, we favour the daily maximum realization to proxy for a day's overall heat exposure, noting that days with high maxima tend to exhibit high medians and hot mornings (Figures A.23 and A.25). The interpretation is that early in the morning (or the night before), when one is making plans for the day, one already has a sense of whether a given day is shaping up to be unseasonably hot or cool. We favour heat entering linearly because we are inferring responses over variation that does not span too wide a range.[5]

Because we observe a proxy for a commuter's income group based on their residential neighbourhood, our commuter regression models expand on the above, as follows

$$f_{lthy} = \boldsymbol{W}_{th}\boldsymbol{\beta} + \boldsymbol{W}_{th} lowIncome_y \boldsymbol{\beta}_y + \alpha_y + \alpha_h + \alpha_t + \alpha_l + \epsilon_{lthy}, \tag{2}$$

[5]We drop the wind control from $\boldsymbol{W}_{th}$ when using an alternative heat definition that accounts for wind. We include robustness tests where we specify concurrent heat, heat lagged by one hour, or the maximum heat realization in the morning. We also include specifications with maximum heat in the preceding days.

in which commuter flows (log of the count of arrivals or departures, or arrivals and departures pooled together) f are aggregated to the location-date-hour-income group level, $lowIncome_y$ is a dummy equal to 1 when the observation relates to commuting by residents of low-income neighbourhoods, and we include interactions between this demographic characteristic and a subset of environmental conditions (heat, PM2.5, and rainfall for added flexibility). A low-income fixed effect enters via α_y. $\boldsymbol{\beta}_y$ is a parameter vector capturing a differential response to environmental variation. Our findings are robust to dropping the income-PM2.5 and income-rain interactions.

To specifically model daily commuting by students through stops serving middle/high schools, we implement three variants of (2). The first variant follows (2) closely but collapses the hourly student flows to the schoolday t (by school stop l and by income group y) level. A second variant replaces the ambient environment-student income interactions $\boldsymbol{W}_t lowIncome_y$ with ambient environment-school cooling interactions $\boldsymbol{W}_t AC_l$, and further collapses the data across both income groups, specifically:

$$f_{lt} = \boldsymbol{W}_t \boldsymbol{\beta} + \boldsymbol{W}_t AC_l \boldsymbol{\beta}_{AC} + \alpha_t + \alpha_l + \epsilon_{lth}, \tag{3}$$

Here the interactions are between stop-level school-weighted air conditioning and the same environmental conditions (heat, PM2.5, and rainfall). Regressor AC_l in levels is subsumed in the location FE α_l (and recall that we have an air-conditioning measure for most schools). A third variant follows the first in keeping observations at the school stop-schoolday-income group level, but now includes a set of triple ambient environment-student income-school cooling interactions, $\boldsymbol{W}_t lowIncome_y AC_l$ (besides all two-variable interactions).

4 Results

Indoor work (and some leisure). Table 1 reports the impact of a day's heat on overall activity in offices and malls, measured by mobile-phone footfall across all times of the day, and separately by workday and non-workday. A 1 °C rise in the daily maximum heat index increases office workday, mall workday, and mall non-workday footfall by 0.4%, 0.5%, and 0.6%, respectively.[6] We obtain an insignificant impact of heat on activity in offices on non-workdays, for which average footfall is one-seventh that on workdays (not reported).

Panels a and b of Figure 2 show the impact of heat on office and mall footfall distributed over a workday. The positive point estimates throughout underscore the aggregate results, i.e., people are not merely shifting the timing of their activities within the day. Noting that malls often locate by office towers and open to shoppers only late morning, early-morning estimates are driven by work-related decisions, including whether and when to go to work. A 1 °C rise in the daily maximum heat index increases morning office and mall footfall by 0.7% and 0.5%, respectively. We find that Singaporeans—at the currently observed heat range—are more likely to go to their indoor workplaces in the early morning on hot days relative to cooler days. Similarly, we find evidence against the hypothesis that offices are less busy during the afternoon on hotter days. Instead, ambient heat may induce workers to remain at the office, possibly because of the prevalence of space cooling.[7]

The bus/rail ridership data complement the footfall data, adding an income dimension. The bottom panel of Table 2 shows that transit flows on workdays at the industrial zone and at commercial areas by low-income residents grow 0.2-0.3% per +1 °C heat relative to

[6]We convert a table's estimates in log points to percent impact. All figures show 95% confidence intervals of percent changes.

[7]We also reject adverse impacts of heat on the duration a phone is at a location (Figure A.13).

that of high-income residents. As with Table 1, the top panel shows the heat impact for both income groups combined, when we omit the low-income × environment interactions from model (2). Even though the commuter sample focuses on public transit and misses private travel, the point estimate for both income groups in the industrial zone (+0.4%) is comparable to Table 1's work-related footfall estimates (which in turn miss the income dimension). Importantly, we can reject adverse heat impacts.[8]

Again narrowing in on specific time intervals (and examining directional travel), panel e of Figure 2 shows that the impact of heat on work-related commercial-area arrivals in the early morning of workdays is similar to the impact on mall footfall, specifically +0.5% per +1 °C for the high-income group—and larger for low-income residents (+0.8%; also see Table A.5). Effects on early-evening industry departures are larger, with +1.3% for the high-income group and +1.6% for the low-income group per +1 °C heat (Figure 2, panel d).

The evidence suggests that (i) hotter weather *reduces* work absences of those living in low-income neighbourhoods, consistent with industrial and office workplaces offering cooled spaces, and (ii) this "co-benefit" shrinks among high-income residents, possibly because they are more able and willing to cool their homes. All work-related estimates on the low-income × heat interaction in Tables 2, A.3 and A.5 are positive and similarly valued (again, at the daily level or for specific peak hours of arrival and departure, respectively). Consistent with the evidence above, Figure A.7 shows increased commuting to the Central Business District on hotter workdays, particularly in the low-income group.

[8]Table A.3 examines arrivals and departures separately. Estimates are not the same across arrivals and departures, though they are noisy. For high-income residents, the choice between taking public or private transit as the weather warms may differ when leaving home for work versus returning home from work. The morning peak for workplace arrivals exceeds the late-afternoon peak for workplace departures, consistent with some people taking different travel modes within a day (Figures A.5 and A.6).

Indoor leisure. When we consider commercial-area activity on workday evenings and on non-workdays, the response to heat variation tends to grow. Plausibly, leisure-related visitors have more freedom in deciding how to spend their time. For instance, a 1 °C rise in the daily maximum heat index increases mall footfall at 20:00-22:59 by 1.1% both on workdays and non-workdays (panel b of Figures 2 and A.8).[9] Malls may be more attractive on hot days because of the cooling attribute their services offer.

Non-workday leisure-related public transit by low-income residents grows 0.7% per +1 °C heat relative to that in the high-income group (Table 2). For non-workdays, the impact of heat on public-transit ridership is insignificant across both income groups yet negative for high-income residents. One interpretation is that on hot weekends and public holidays, high-income shoppers/diners may be increasingly likely to travel on private transit, which only our footfall measure of Table 1 captures, i.e., all mall goers irrespective of their travel mode being bus, train, car, walking, etc.[10]

The results suggest that people are more likely to visit malls when it is hot, particularly those on relatively low incomes. The difference between the responses of residents of low- and high-income neighbourhoods suggests that whereas high-income people additionally seek relief from heat by staying in air-conditioned homes or going to malls by car, low-income people may avoid heat exposure by riding public transit to publicly available air-conditioned spaces. Singapore's malls are air conditioned, as are its buses and trains. Of the 26 national libraries, which are popular with seniors, 20 are housed inside malls, and another 3 building-sized libraries are adjacent to malls. Recall that ranking neighbourhoods by increasing share of 1-3 room dwellings, low-income status is interpreted as a commuter's neighbourhood being

[9]Recall the 0.6% increase, over all times of the day, on mall non-workday footfall per +1 °C (Table 1).
[10]Table A.5 shows an insignificant impact on high-income resident flows on workday evenings.

in the upper quartile with most 1-3 room apartments (which have the lowest access to air conditioning). Even those lower-income households with access to an air conditioner at home may prefer not to use it in order to save on electricity bills.[11]

School attendance. We use concessionary student cardholders commuting on schooldays to and from stops nearby schools to proxy for student attendance. The top panel of Table 3 shows model (2) estimates specific to student flows through school stops (summed within schoolday). In this first variant, there is no significant differential response to heat according to income group—and again we reject adverse effects. A possible explanation is that, unlike indoor workplaces and malls, Singapore's schools still offer limited cooling.[12]

When we estimate model (3)—the second variant, in the middle panel—we do find a differential response based on classroom cooling. Absent classroom climate control, heat does not impact attendance, yet as space cooling shifts from 0 to 1 (fully air-conditioned instruction), middle/high schoolers are more likely to attend school. A 1 °C rise in the daily maximum heat index increases student commuting by 2.6% when classrooms offer a cooling co-benefit. One possible reason is that staying home on a hot day, with parents unable or unwilling to run an air conditioner throughout school hours, becomes less attractive.

The bottom panel of Table 3 suggests that this mechanism is particularly strong for low-income students who are offered air-conditioned classrooms. This third variant complements the second in suggesting that schools offering a cooling co-benefit are differentially attractive on hotter vs. cooler days among students who reside in low-income neighbourhoods.

[11]Electricity accounts for 3.2% of expenditure among households in the bottom quintile of Singapore's income distribution compared with 1.8% for those in the top quintile (Salvo, 2018). Salvo (2018) finds that the electricity demand response to heat grows with income and air-conditioner adoption.

[12]Table A.4 replicates Table 3 but examines arrivals and departures separately.

Urban parks. Recent economics research studies the value of urban parks and forests, including potential cooling properties of urban trees (Panduro *et al.*, 2018; Tan, 2022; Han *et al.*, 2022). We note briefly that we find evidence consistent with this literature (and provide details in the appendix). Table 1 shows that visits to public parks grow by 0.6% on workdays and by 0.9% on non-workdays per 1 °C rise in heat. Narrowing in on specific time intervals, a 1 °C rise in the daily maximum heat index increases public-park footfall by 0.8% at 17:00-19:59 and 1.2% at 20:00-22:59 on workdays, and by 1.2% at 17:00-19:59 and 1.6% at 20:00-22:59 on non-workdays (Figure A.11).[13]

5 Discussion

We discuss the implications and limitations of our study. A growing literature in economics examines historical weather fluctuations and finds that ambient heat can have large adverse effects on public health and other socioeconomic outcomes. This literature looks for evidence of adaptation, which IPCC (2007) defines—and Barreca *et al.* (2016) reproduces—as "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (p.6). Some of the economics research finds substantial harm to human systems from heat fluctuations under the actual climate, even for people working in climate-controlled environments. The takeaway from those studies is that ambient heat has pervasive effects and that adaptation opportunities are limited.

[13] The appendix provides further evidence from student-level panels on attendance and test scores at a large school with extensive climate control, large-scale household travel surveys, retail sales quantity indices, and morbidity and mortality statistics. Each additional dataset spans multiple years.

In addition to the studies cited in the introduction, consider the two leading heat impact studies of work environments. In a setting where "protection from heat is limited to the use of windows and some fans" (p.1803), Somanathan *et al.* (2021) find a 3% drop in a Gujarati cloth weaver's output for a 1 °C rise in daily maximum temperature. In a very different workplace characterized by "close to full application of the most obvious technological solution to mitigate temperature effects" (p.239), Heyes and Saberian (2019) report a 1.2% drop in the likelihood that a US immigration judge's decision is favourable to an applicant for a 1 °C rise in daily mean temperature.[14]

Against this backdrop, we view our in-depth study of how heat impacts Singapore as making a contribution. The urban tropics, and that in equatorial Asia in particular, are vast, densely populated, and fast growing—and remain relatively under-studied. Singapore seeks to remain a high-value manufacturing hub, not just a services economy. We examine high-frequency variation in heat, with the daily maximum varying by as much as 10 °C within month of sample. Following decades of economic expansion, Singapore's offices, factories, malls, buses, and trains are air conditioned, its public schools much less so. While rich on average, Singapore's population includes households on lower incomes with poor access and limited use of residential air conditioning, allowing us to investigate unequal responses to heat.

In the urban—and mainly indoor—workplace, commercial, educational, and transit spaces where we look, we do not detect a fall in activity on hotter relative to cooler days.

[14]Barreca et al. write "these adjustments can take the form of alterations in the uses of existing technologies or the invention of new technologies" (p.106) and describe the state of knowledge about adaptation as poor. Heyes and Saberian write of their takeaway: "The decision-makers that we observe work *indoors* and protected in their workplace by climate-control at a level typical of good-quality US Federal government buildings in the twenty-first century... With regard to biological adaptation to prevailing conditions, judges move around very little—they are largely attached to a single court location" (p.239, original emphasis).

To the contrary, we estimate that heat leads to increases in footfall at, and commuting to, offices, industry, malls, and the more air-conditioned among schools. Our interpretation is that cooling from the ambient heat is bundled in the services that these destinations offer to workers, shoppers, diners, and students. We find that cooling co-benefits are particularly attractive to low-income residents with limited access or use of adaptive technology at home.

We emphasize that by activity we mean mobility. Even if workers are at the workplace more, we do not observe if their output is affected—we leave on-the-job productivity to subsequent research.[15] We further caution that we do not study work hours or on-the-job productivity in occupations with high climate exposure and limited on-the-job access to defensive capital such as construction and landscaping. We also note that our analysis does not suggest there are positive effects of heat on overall welfare even in Singapore; although employers and retailers may value workers and shoppers showing up, there may be costs to not being at home, for example, older relatives not being looked after.

Applied to Singapore's 3.2 million services and manufacturing workers at work for 45 hours per week (MOM, 2017), impacts on the order of -1 to -3% as reported by the studies above in differing work environments translate loosely into a loss of 1.4 to 4.2 million weekly workplace hours for every unseasonable +1 °C variation in ambient heat that week. It is against this benchmark that we compare our results of a zero—*positive* even—impact on Singapore's predominantly indoor economic activity. Taking our +0.4% estimate of office footfall (Table 1, column 1) to fix ideas, we instead obtain a gain of 0.6 million weekly workplace hours per +1 °C rise in heat.

[15] Where we do have some measure of "productivity," specifically on test scores and retail sales, we do not detect adverse impacts from heat (Tables A.14 and A.16).

Taking our +0.6% estimate of mall footfall (Table 1, column 3—non-workdays to focus on non-work related visits), and applying this to 1.6 million mall visitors per day across all of Singapore's malls,[16] we estimate a positive variation of 9400 visitors daily for every 1 °C rise in the daily maximum heat index. Stretching this back-of-the-envelope to the 10 °C range of variation that we observe within month of sample, we obtain a difference of +94,000 mall goers on the hottest vs. the coolest of Singapore's days.

We noted earlier that recent studies document adverse and often sizeable impacts of ambient heat on morbidity and mortality. For example, White (2017) reports that a day over 80 °F (27 °C) is associated with a same-day 3.5% increase in emergency department visits in California, and significant heat impacts are found using US Medicare and German health data (Heutel *et al.*, 2021; Karlsson and Ziebarth, 2018). Motivated by these studies, we examined publicly available morbidity and mortality data for Singapore.

While our health data are not rich as in the cited health studies, the evidence we present in Tables A.17 and A.18 suggests that heat is not a significant cause of morbidity and mortality in Singapore—insofar as the current climate is concerned. We view this supplementary public health analysis as supportive of our main findings on heat-coping behaviours, and is consistent with adaptation inferred in some studies (Barreca *et al.*, 2016; Heutel *et al.*, 2021). The non-negative impacts that we find for a rich city-state acclimatized/adjusted to its tropical climate may offer a hopeful message on urban adaptation to a hot climate (C40, 2023).

[16] Table A.3 shows a sample mean of 460 public-transit arrivals/hour/income group/commercial area (on non-workdays, but workdays are similar). Multiplying by 13 hours (10:00-22:59) × 2 (income groups) × 80 commercial areas, and dividing by 0.6 (in the Household Travel Survey 40% of visitors walk or ride a car to the mall), yields 1.6 million visitors (ignoring people who arrive multiple times on a day).

We offer a back-of-the-envelope in the appendix which assumes that health damage from heat fluctuations in Jakarta can be moderated to levels observed in Singapore by increasing access to space cooling. Indonesia's capital city, with a population of 10 million, lies 900 km southeast of Singapore and has a similar climate, yet an income per capita one-seventh that in Singapore and low penetrations of air conditioning in residences, workplaces, malls, and community centres (Pavanello *et al.*, 2021; Savills Research, 2021). Only to provide an indication of costs relative to the benefits under simple, plausible assumptions, we focus on mortality among the elderly and assume that widespread provision of spaced-cooled community centres reduces heat-induced deaths in Jakarta to rates comparable to Singapore, for which we were not able to reject zero. We find that heat damage of $0.20 to $1.4 billion per year can be reduced through defensive investments of $0.25 billion per year.

We conclude with another word of caution. Space cooling and moving life indoors comes at considerable private and external costs. Our objective has been to investigate, from revealed behaviour, how a rich nation in the tropics has thus far adjusted to its current climate. Yet the climate is changing. In the four decades to 2014, the annual numbers of "warm days" and "warm nights" in Singapore have grown by 50 days and 72 nights, with an annual mean temperature increase of 1.1 °C over the period (NCCS, 2015). Our objective has not been to speculate on the costs of further adaptation to future global warming (Sherwood and Huber, 2010).

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Table 1: The impact of heat on footfall over all time intervals

	Offices	Malls		Public parks	
	Workdays 7:00-19:59	Workdays 7:00-22:59	Non-workdays 7:00-22:59	Workdays 7:00-22:59	Non-workdays 7:00-22:59
Log hourly footfall	(1)	(2)	(3)	(4)	(5)
Daily max. heat index (1 °C)	0.0039**	0.0052**	0.0063**	0.0056**	0.0085*
	(0.0018)	(0.0022)	(0.0032)	(0.0029)	(0.0048)
Number of observations	4992	10,240	4480	4096	1792
Number of regressors	32	37	29	34	26
R-squared	0.9519	0.9346	0.9497	0.8702	0.9203
Mean of dep. var. levels (1000s)	1.1700	1.7621	2.3154	8.7401	9.6649

Notes: This table shows results for 5 OLS regressions, per model (1). An observation is a location-date-hour triple on either workdays or non-workdays, as indicated, during all time intervals. Non-workdays are Saturdays, Sundays, and public holidays; workdays are all other days. The dependent variable is the log hourly footfall at an office tower (3 locations), a shopping mall (5 locations), or a public park (2 locations). See the appendix for estimates on other environmental conditions and for results at pay-for-entry parks. All regressions control for concurrent PM2.5, rainfall, wind speed, hour-of-day fixed effects (FE), day-type FE; year-month FE, and location FE. Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table 2: The income-resolved impact of heat on commuter activity over all time intervals

	Industrial zone	Commercial areas	
	Workdays	Workdays	Non-workdays
	6:00-22:59	7:00-22:59	10:00-22:59
Log hourly public transit flows	(1)	(2)	(3)
Effects across both income groups			
Daily max. heat index (1 °C)	0.0037	0.0016*	-0.0028
	(0.0027)	(0.0009)	(0.0027)
Number of regressors	35	113	102
Effects by income group			
Daily max. heat index (1 °C)	0.0028	0.0003	-0.0065**
	(0.0029)	(0.0010)	(0.0029)
Low-income group × max. heat	0.0018**	0.0026***	0.0073***
	(0.0008)	(0.0009)	(0.0019)
Overall heat on low-income	0.0046*	0.0029***	0.0009
	(0.0026)	(0.0010)	0.0028
Number of regressors	38	116	105
R-squared	0.9894	0.9333	0.9434
Number of observations	4352	326,979	116,336
Mean of dep. var. levels (1000s)	1.2635	0.8986	0.9438

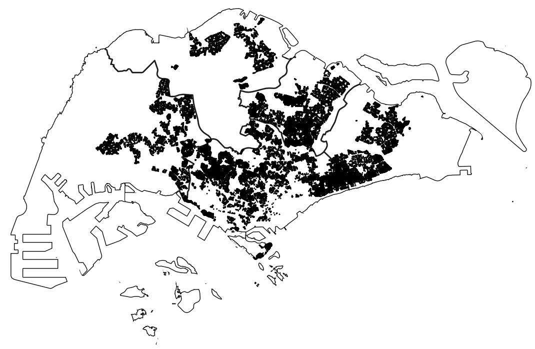
Notes: The bottom panel shows results for 3 OLS regressions, per model (2), and the top panel implements these same regressions when we omit the low-income × environment interactions from the model. An observation is a date-hour-income group triple in column 1 or a location-date-hour-income group tuple in columns 2-3, on either workdays or non-workdays, as indicated, during all time intervals. The dependent variable is the log hourly sum of bus/rail arrivals and departures in the industrial zone (a single aggregated location) or in a commercial area (80 mall/office locations). All regressions control for concurrent PM2.5, rainfall, wind speed, hour-of-day FE, day-type FE, year-month FE, and a low-income-group dummy. The bottom panel includes income-PM2.5 and income-rain interactions. Columns 2-3 further include location FE. Results are similar in the top panel if we collapse the data across both income groups. Given relatively modest commuting at selected times, we specify the average hourly public transit flows within quarter-of-sample as regression weights (specific to the location type and workdays/non-workdays). Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table 3: Heat, student income, school cooling, and attendance

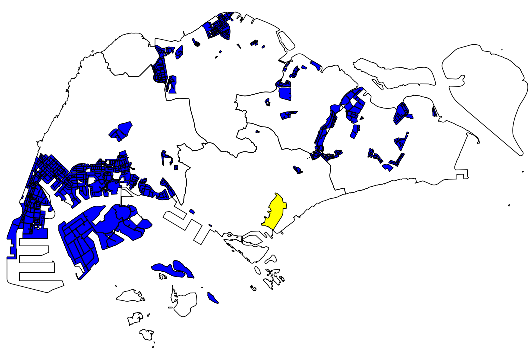
Log daily public transit flows by students at stops nearby schools	Sum of arrivals and departures (1)	Sum of arrivals and departures+1 (2)
By student income group		
Daily max. heat index (1 °C)	0.0081	0.0046
	(0.0079)	(0.0070)
Low-income group × max. heat	-0.0013	0.0041
	(0.0026)	(0.0035)
Overall heat on low-income	0.0068	0.0087
	(0.0087)	(0.0078)
No. of obs. (stop-schoolday-income)	168,647	185,422
Mean of dependent var. in levels	81.1465	74.8052
By school cooling		
Daily max. heat index (1 °C)	-0.0002	-0.0003
	(0.0117)	(0.0111)
School cooling × max. heat	0.0258**	0.0256*
	(0.0129)	(0.0137)
Overall heat with full cooling	0.0256**	0.0253**
	(0.0100)	(0.0103)
No. of observations (stop-schoolday)	76,214	79,301
Mean of dependent var. in levels	157.7588	151.6176
By student income and school cooling		
Daily max. heat index (1 °C)	0.0035	0.0019
	(0.0117)	(0.0110)
Low-income group × max. heat	-0.0042*	-0.0015
	(0.0022)	(0.0027)
School cooling × max. heat	0.0147	0.0133
	(0.0126)	(0.0126)
Low-income group × cooling × heat	0.0091***	0.0116***
	(0.0005)	(0.0005)
No. of obs. (stop-schoolday-income)	145,653	158,602
Mean of dependent var. in levels	82.5484	76.8088

Notes: This table shows results for 6 OLS regressions across three panels. An observation is a school stop-schoolday-income group triple in the top and bottom panels, per model (2) summed over hours within a schoolday, or a school stop-schoolday pair in the middle panel, per model (3). Across estimation samples, the stops serve 170-200 schools (cooling is missing for a minority of schools). The dependent variable is the log daily sum of arrivals and departures by students; in column 2, we add 1 before taking logs to account for a minority (∼5%) of zero-valued observations. All regressions control for concurrent PM2.5, rainfall, and wind speed, day-type FE, year-month FE, and school-stop FE. In the middle and bottom panels, the school-weighted stop-level cooling measure is expressed as a proportion; it is subsumed in the school stop FE. The top and bottom panels include income-PM2.5 and income-rain interactions. The middle and bottom panels include cooling-PM2.5 and cooling-rain interactions. From top to bottom panels, there are 17, 16, and 23 regressors (excluding 1100-1300 school stop FE). Standard errors, in parentheses, are clustered by date (two-way clusters by date and by school stop yield similar standard errors). ***Significant at 1%, **at 5%, *at 10%.

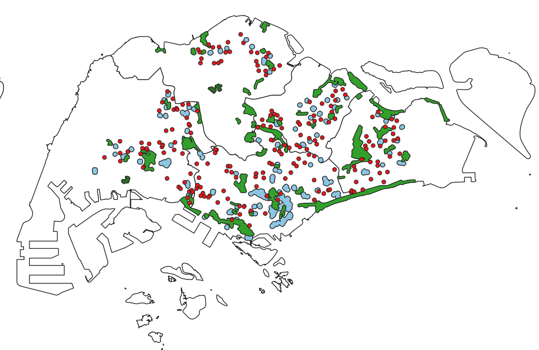
(a) Bus and rail stops



(b) Residential buildings

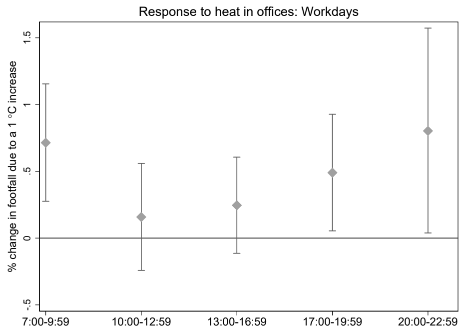


(c) Industrial areas (blue) and the CBD (yellow)

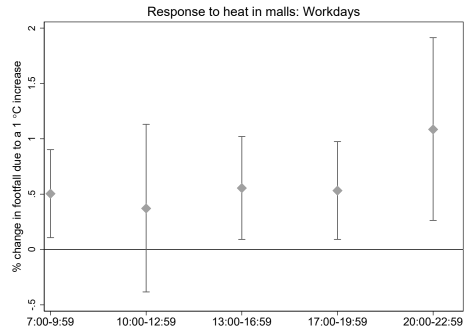


(d) Malls (light blue), schools (red), and parks (green)

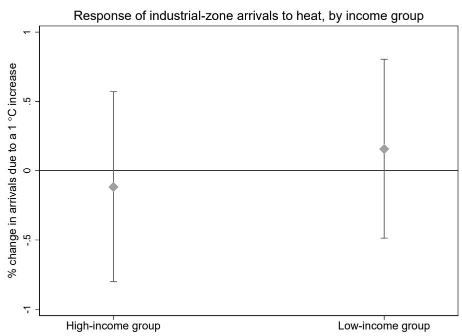
Figure 1: Maps showing (a) bus and rail stops, (b) residential buildings, (c) industrial areas and the Central Business District, and (d) malls, schools, and parks. Residences exclude dormitories that typically house low-income foreign workers; such purpose-built dormitories locate by industry or such workers ride employer-provided private transportation, rather than public transit, to work. We focus on middle/high schools because most children at this age ride public transit to school. Most stops that serve public parks also serve residences, which is why we do not use the commuter data to examine visits to public parks. Similarly, our analysis of industry commuting focuses on the nation's core industrial zone in the southwest, as this is not conflated by proximity to residences.



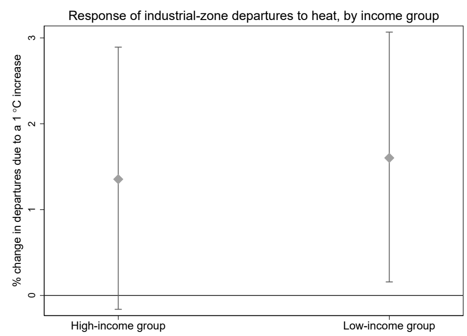
(a) Office towers, footfall, workdays



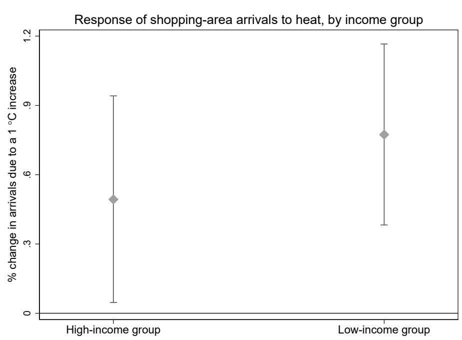
(b) Malls, footfall, workdays



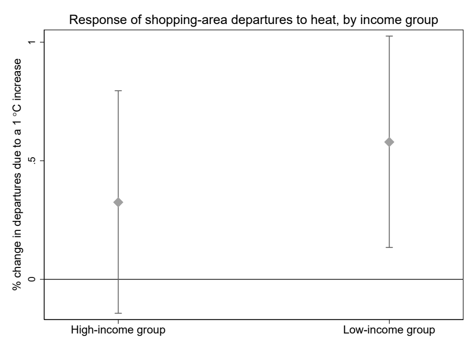
(c) Industry, bus/rail arrivals, workdays 6:00-9:59



(d) Industry, bus/rail depart., workdays 17:00-19:59



(e) Commercial, bus/rail arrivals, workdays 7:00-10:59



(f) Commercial, bus/rail depart., workdays 17:00 to 22:59

Figure 2: The impact of heat on workday indoor activities—and public transit to these activities—for different time intervals. Source: Regression specifications similar to those reported in Tables 1 and 2 (with narrower time intervals). The plots show 95% confidence intervals (CI) on the coefficient on the daily maximum heat index, β_{heat} (and, for panels c-f, on the sum of this coefficient and the interaction coefficient, $\beta_{heat} + \beta_{heat,lowIncome}$), converted from log points to a percent change.

Online Appendix

A Further details on data including sources

Footfall data locations and relevance. Based on the mobility of their subscribers, mobile phone company Starhub provided us with hourly footfall and bihourly (median) dwell time for 12 major agglomerations of activity (Figures A.1 and A.12). The three office towers are Capital Tower, Millenia Tower, and Republic Plaza. The five malls are AMK Hub, City Square Mall, IMM, Ngee Ann City, and VivoCity. The two open-access public parks are Botanic Gardens and East Coast Park. The two pay-for-entry commercial parks are Jurong Bird Park and Singapore Zoo.

StarHub claims to be able to separately count subscribers pinged at malls from those visiting neighbouring office towers. For example, malls Ngee Ann City and VivoCity have office towers nearby. In the data, footfall for Ngee Ann City and VivoCity refers to traffic at the malls. Similarly, office towers Capital Tower and Millenia Tower have malls nearby and footfall for Capital Tower and Millenia Tower in the data refers to people at the office complexes. StarHub's footfall product has commercial value, for example, to mall managers negotiating rental with tenants.

StarHub's subscribers accounted for one-third of the mobile phone market (StarHub, 2017). By 2016-17, Singapore already had a very high mobile phone penetration rate (IMD, 2020).

Individual-level commuter panel. In 2015-16, rides on public transit were overwhelmingly paid via farecards. The so-called EZ-Link card's popularity was due to its convenience and lower cost. To illustrate, a 5-km trip in 2020 cost an adult $0.83 via EZ-Link and $1.41 if paid by cash. No change was given on buses, so cash-paying riders paid more than the required fares if they did not carry the exact amount. Tap in-tap out with bank/credit cards was introduced only in 2019 (Awang, 2019).

We have travel information from 7.2 (resp., 7.3) million cards used in 2015 (resp., 2016). The number of cards exceeds Singapore's population of 5.6 million (DOS, 2017).[17] The difference is likely due to tourists who purchased EZ-Link cards during their visits. We note that 4.1 million cards were used in both year-on-year quarters, suggesting that most trips were made by residents who held on to their cards over extended periods.

Combining trip segments into trips. The trip segments reported in the commuter data need to be collapsed into trips, which is our focus. For example, if a person departs at stop A, transfers at stop B, and arrives at stop C, then there would be two observations in the raw data, one for each of the two segments, A to B and B to C, spaced within minutes of each other. To combine segments into trips, we assume that if the departure time of a segment is within 15 minutes of the arrival time of the previous segment, then the segments are part of the same trip (A to C in the example).

[17] This population comprises 3.4, 0.5, and 1.6 million citizens, permanent residents, and temporary residents (foreign workers of varying skill levels and students on longer-term visas), respectively.

Distribution of dwelling type by building. Singapore's income-segmented housing market consists of two broad types of dwellings, specifically apartments developed by a government agency and condominium apartments ("condos") and houses developed by private companies. Subsidies are offered on publicly developed apartments whereas condos are perceived as more premium, offering shared amenities such as a swimming pool. Like condos, land scarcity makes houses more expensive.

Building-level data come from the Housing and Development Board (apartment quantity and type), the Urban Redevelopment Authority (condos/houses), and the Singapore Land Authority (coordinates). For example, one residential building tower, identified by its unique postal code 180009 (and geographic coordinates), consists of 299 dwellings, 264 (88%) of which are 1-3 room apartments and the remainder are 4-room apartments. A second (higher-end) building, with postal code 109025, consists of 110 dwellings, all of which are condos. Across all residential buildings, dwellings total 1.4 million, distributed as 1.1 million apartments (across different sizes), 300,000 condos, and 75,000 houses. For perspective, 1-3 room apartments have floor space of 36-69 square meters.

Assigning commuters to income groups. For each of 4200 bus/rail stops situated within 400 meters of a residential building, we compute a weighted share of 1-3 room apartments among all dwellings in the 400-meter radius from the stop. We take as weights the inverse of the stop's distance to each residential building's street entrance (the closer a building is to a stop, the more likely a resident will use this stop vs. another stop). Continuing the above example, suppose that a stop is (i) 100 meters from building 180009 with its 299 dwellings, 264 of which are 1-3 room apartments, and (ii) 200 meters from building 109025 with its 110 condos. The 1-3 room apartment share is then 0.75, computed as $264 \times 100^{-1}/(299 \times 100^{-1} + 110 \times 200^{-1})$), and reflecting that this stop serves a relatively low-income residential population. This procedure yields a measure of the low-income share of the residential population served by each stop.

We now map cardholders to residential locations—and the socioeconomic distribution—and their trips to work, shopping, and school locations. We focus on a sample of residents who are active during daytime, adopting the following sampling procedure separately by quarter. For each date that a card is used, we save the card-date's "first departure" stop and "last arrival" stop subject to the restriction that either stop is within 400 meters of a residential building.[18] We then take the card's modal (i.e., most common) first-departure stop and modal last-arrival stop over travel dates in the quarter. To include the card by quarter in the sample of trips, we require (i) that either the modal first-departure stop or modal last-arrival stop are residential and one stop is within 600 meters of the other, and (ii) that the cardholder first departs from the modal first-departure stop (or any stop within 600 meters of this stop) at least eight times during the quarter. Table A.2 reports on a trip sample based on 3.2 million cards in 2015 and 2016 alike (and variants).

For each sampled card-quarter, we take the average low-income share of the residential population across the two "home" stops (modal first-departure and modal last-arrival stops). A "low-income residential neighbourhood" dummy takes the value 1 in the card-quarter if

[18]It is likely that the cardholder is departing from home earlier in the day and/or returning home later in the day. A first-departure stop and last-arrival stop (within date) both in an industrial area, e.g., a worker on a night shift, is not a focus of this sampling procedure. Because they tend not take public transit to work, low-income foreign workers housed in dormitories located nearby industry (rather than in residential buildings) are also not targeted by this procedure.

the low-income share lies in the upper quartile of the distribution over card-quarters in the sample and 0 otherwise. Figure A.3(a) shows the distribution of the low-income share; the 75th percentile is a low-income share of 0.40, interpreted as 1-3 room apartments accounting for 40% of the dwellings served by a card-quarter's home stops. For example, for a given card-quarter the two home stops are the stop in the above example, with a low-income share of 0.75, and another stop with a low-income share of 0.55, yielding an average of 0.65. This low-income share exceeds the 75th percentile (0.40) and so the low-income neighbourhood dummy is valued at 1 for all trips observed for that card-quarter.

Physical footprints of industry, malls, schools, and parks. The industrial zone was set aside in Singapore's 1980 Master Plan. None of the 430 stops located in the industrial zone (Figure 1(c)) are within 400 meters of a residential building or a mall.

We extract each mall's property line from openstreetmap.com. The 200-meter boundaries from the property lines often overlap across neighbouring malls (Figure 1(d)). After consolidating adjacent malls, we have 80 consolidated commercial areas and 680 stops within 200 meters of a commercial area.

Figure 1(d) also shows the locations of 200 middle/high schools, served by 1300 stops. As weights to average our surveyed school-specific space-cooling measure to the school-stop level (a stop may serve more than one school), we obtain school-level site areas from OneMap (and, where missing, URA Space).[19]

Singapore cultivates a "garden in a city" image, with about half of its land area covered by managed vegetation and young secondary forest, despite its high population density (Yee *et al.*, 2011; Tan *et al.*, 2013). Figure 1(d) further shows the location of public parks and commercial parks. We do not use the commuter data to study visits to public parks because 91% of the 383 stops that serve a public park also serve neighbouring residences.

Travel patterns by location type and income group. Figure A.5(a) to (d) (resp., (e) to (h)) plot the mean hourly industrial-zone (resp., mall) arrivals and departures, separately by income group. One-quarter of trips to and from industry pertain to low-income neighbourhood residents. For both income groups alike, arrivals and departures peak at 7:00 and 17:00, respectively, according with the notion that most of the industrial zone's travel is work related. Mall arrivals peak at 8:00, driven by workers at adjacent office towers, and again at 18:00, driven by leisure-seekers. Departures peak at 18:00, with volume one-third larger than the 18:00 arrival volume. This may be due to afternoon shoppers joining workers from adjacent offices in their journey home. Manufacturing workers start their workday earlier than workers in these commercial centres (and the general population of riders, in Figure A.2). To complement the office footfall analysis, Figure A.6 shows public transit to the Central Business District, with workday arrivals and departures peaking at 8:00 and 18:00, respectively.

Students commuting to schools. We restrict commuting to student cardholders through stops located within 400 meters of a school gate—and which are not home stops, i.e., the student is not commuting home. Besides focusing on student farecards, we focus on middle/high schools because the majority of their students ride public transit to school. Specifically, the 2012/13 Household Travel Survey (see below) indicates that 60% of

[19] When the reported site area combines a secondary school and a junior college that are co-located (see below), we distribute the site area among the co-located schools according to the number of years of instruction each offers, e.g., the secondary school's 4 years (67%) and the junior college's 2 years (33%).

secondary-school and 85% of junior-college students ride public transit to school. Thus, our commuter data captures most of these students' school travel. In contrast, in the younger age group one-half of students walk to a local primary school. For this reason, we did not examine commuting to primary school.

Middle/high school include (i) secondary schools, (ii) junior colleges, attended during the last two years of high school, (iii) "Millenia/Polytechnic Institutes," an alternative to junior colleges lasting three years for students considering a more technical vocation even if they subsequently stream into university, and (iv) "international schools," referring to a minority of schools that are private and are not run by the Ministry of Education. Examples for schools in groups (i) to (iv) are Xinmin Secondary School, Tampines Meridian Junior College, Ngee Ann Polytechnic, and Global Indian International School.

We identified 1416 bus/rail stops that serve 202 middle/high schools (establishments)—label these "school stops." To define a schoolday, we note that government-funded schools (which constitute the majority) follow a common holiday calendar, whereas private schools each choose a different calendar from that adopted by the public school system. Because the spatial unit in our regression analysis is a school stop, we drop the few school stops (75) that are situated nearby both a public and a private school(s), as we would otherwise have to contend with "partial" schooldays, e.g., days on which we would observe partial traffic to an open public school but not to its neighbouring private school on holiday. Our sample then comprises 1341 school stops serving 196 schools on 128 schooldays (1284 school stops remain when we restrict to stops through which we observe at least one student commuter over the entire sample period, suggesting the stop was active).

Air conditioning in schools. The National University of Singapore (NUS) admits students from across the city-state. In 2022, we surveyed 1508 NUS undergraduate students who were in middle/high school in 2014-2018, around the time of our commuter sample (men do 2-year national service before university). Through faculty listservs (e.g., Faculty of Engineering), we invited undergraduate students from across the university to complete the survey, and offered a "Lucky Draw" to boost participation. We implemented a short survey on Qualtrics to collect data on the experienced *use* (rather than installation) of air conditioning in the "classrooms in which instruction took place." The typical respondent provided two measures, between 0 and 100%, one for their middle school and another for their high school. We also collected air conditioner prevalence for private schools, from which NUS also admits. In all, we collected 2900 responses across 180 schools. We will publish the survey instrument and data collected.

We explain by way of example how we aggregate the surveyed school-level air conditioning usage to each school stop, specifying as weights the size of the schools that each stop serves (if the stop serves more than one school, and about half do). Say a stop serves (1) one small school, size 1, with 70% cooling according to the actual experience of its recent alumni, and (2) another large school, size 2, with 50% cooling. We then calculate the contemporaneous air conditioning measure for that school stop as $(0.7 \times 1 + 0.5 \times 2)/(1 + 2) = 0.56$. In the example, the weighting reflects the fact that the larger, less space-cooled school (2) accounts for more students flowing through the stop than the small, more-cooled school (1): 56% of the classroom instruction experienced by the stop's student users had space cooling around the time of our commuter data (2015-2016). To weigh across schools sharing a stop, we use the land area occupied by each school's buildings (because we were not able to obtain student enrolment by school). The number of survey responses offers an alternative proxy for school size.

Why are schools among the last indoor environments without widespread space cooling? Prime Minister (and parent) Goh Chok Tong voiced a common belief among parents that if their children study in harsher conditions they will grow more resilient. In a speech in 2002, he asked whether Singaporean children had “too comfortable a life” partially due to widespread air conditioning—“(they) sleep in air-conditioned rooms...travel in...air-conditioned buses and MRT”—and whether this would hinder their ability to “take hardship, accept setbacks, and pull themselves up after a fall” (MOI, 2002).

Ambient environment. We obtained one-hour ambient air temperature, relative humidity, rainfall, and wind speed measurements recorded at consistently operating weather stations maintained or compiled by the National Environmental Agency (NEA), the NUS Department of Geography, and the Iowa State University Environmental Mesonet. The NEA also reports one-hour ambient PM2.5 concentrations (particulate matter up to 2.5 μm in diameter), for each of five areas of Singapore. Publicly available one-hour PM2.5 data are averages across monitoring stations within each of the five areas.

We average one-hour readings across weather stations (or PM2.5 areas) for (i) temperature: Jun-Aug 2016 & 2017 with 11 stations, Oct-Dec 2015 with 4 stations, Oct-Dec 2016 with 20 stations; (ii) rainfall: Jun-Aug 2016 & 2017 with 13 stations, Oct-Dec 2015 & 2016 with 10 stations; (iii) relative humidity and wind speed: 4 stations; and (iv) PM2.5: 5 areas of Singapore.

By taking the mean across weather stations' one-hour readings, we average out the idiosyncrasies associated with each station's microenvironment (e.g., a station in the built-up urban area yet atop a high-rise building), and because people are mobile. Our source of environmental variation is thus temporal.

Figure 3 in Anderson *et al.* (2013) describes the algorithm that combines the one-hour mean air temperature and one-hour relative humidity readings into a one-hour heat index. This heat index is adopted by the US National Weather Service (NWS, 1990, 2020). OSHA (2016) assigns a “moderate” risk of heat-related illness when the heat index is in the 91-103 °F range and notes that the risk is higher “before workers have had a chance to adapt to warm weather.”

Singapore's tropical climate exhibits mild seasonality. For example, the daily maximum heat index in the summer June-August footfall sample is only 0.5 °C higher than in the October-December commuter sample.

Our analysis controls for air quality particularly in view of a severe pollution episode during the commuter sample month of October 2015, which was caused by land fires in neighbouring countries upwind (Koplitz *et al.*, 2016; Rosales-Rueda and Triyana, 2019; Salvo, 2018, 2020). Despite the poor air, workplaces and schools did not close (MOM, 2015).

Urban heat island and built-up areas vs. parks. Roth (2007) asserts that “vegetation (can) be an effective means to reduce heat storage uptake during daytime and hence has the potential to effectively mitigate the nocturnal heat island” (p.1859). Using our data to illustrate urbanisation's very local effect, July-August one-hour air temperatures[20] recorded

[20]Singapore's climate is mildly warmer, drier, and less windy during the southwest monsoon from June to September relative to the northeast monsoon from December to early March. Roth (2007) notes that the urban heat island in the tropics is more intense in the dry season.

at the Tai Seng weather station near the built-up Central Business District exceed that at the Choa Chu Kang South station in the less developed Kranji reservoir area by 0.84 °C on average. The temperature difference grows during the night, as the built-up Tai Seng (the "urban island") releases heat stored during the day, recording 1.42 °C higher on average that Choa Chu Kang South at 5:00.

The urban climate literature provides support for an amenity value of urban parks. In a meta-analysis of 16 studies on urban parks and green areas across different climates, Bowler *et al.* (2010) find a cooling effect during the day of about 1 °C relative to non-green sites, with the cooling differential increasing at night. Han *et al.* (2022) et al. find "large, mitigating effects of urban forestry on urban heat and substantial energy savings."

Arnberger *et al.* (2017) use stated-behaviour experiments to document visits to urban parks as a heat-coping strategy among the elderly living in heat islands of Vienna. They conjecture that "having small apartments may be an added reason to decide to go out" (p.110).

The Viennese apartment setting resembles housing in land-scarce Singapore, where apartments account for 95% of dwellings. Surveying 1600 visitors of all ages in Singapore's Botanic Gardens, Chow *et al.* (2016) find that "despite the discomfort sensations and preferences, a large majority of survey respondents felt comfortable/very comfortable at all sites in both monsoon periods" (p.74).

In a review of the urban heat exposure literature, focusing on physiology and building technology, Nazarian and Lee (2020) write: "Little is known about the real-time thermal discomfort and strain people experience as they go about their daily lives" (p.2).

Other economic data.

Student-level daily attendance and annual test scores at a private school. United World College of Southeast Asia (UWCSEA) is a large private school that caters mainly to families who are in Singapore over the long term and across a wide array of nationalities including Singaporeans. Enrolment is about 6000 per year, across two campuses, Dover and East, both offering K2 to Grade 12.

In December 2016, we obtained daily individual-level attendance for all schooldays between August 2011 and November 2016 for the East campus and August 2012 to November 2016 for the Dover campus. In all, our sample comprises 3.9 million student-schoolday observations, with 9067 students enrolled at some point over 947 schooldays. We further observe a student's age, campus of study, number of siblings enrolled at the school, and the date on which the student first enrolled in the school.

Whereas our regression specification includes student FE (see empirical model (4) below), some students switched campus or their number of siblings varied during their enrolment at the school, so we control for these individual time-varying potential shocks to attendance. We combine the attendance records with daily environmental conditions. We also control for schooldays shortly before and after holidays because, for example, international families may travel early out of the country during the last days of term.

Our second UWCSEA panel dataset, obtained in 2022, includes performance in standardized age-specific tests taken annually by students in Grades 3 to 10 in the years 2015 to 2020. On varying schooldays in January or February, the school administered four International Schools Assessment (ISA) tests in (i) mathematical literacy, (ii) narrative/reflective writing, (iii) reading, and (iv) exposition/argument writing as part of the school curriculum. The

ISA is designed by the Australian Council for Educational Research and follows the OECD's Programme for International Student Assessment (PISA). Tests (i) and (ii) were taken on a first day of testing and tests (iii) and (iv) were taken on a second day of testing, subsequent to (and often the day after) the first day of testing. Instead of the student's age, here we observe the student's grade, i.e., Grade 3 to 10. We also observe the student's campus of study.

Tests were administered on different dates across the Dover and East campuses, thus generating some variation in environmental conditions—6 years $\times$ 2 campuses/year $\times$ 2 testing dates/campus/year = 24 testing dates in all. This limited variation contrasts with the preceding school attendance sample with up to 947 schooldays in all. Within a campus and year, there is no variation in testing dates across grades. For example, in 2017, 1900 students in Grades 3-10 in the Dover campus took tests (i) and (ii) on February 13 and tests (iii) and (iv) on February 14; that same year, 1500 students in Grades 3-10 in the East campus took tests (i) and (ii) on February 21 and tests (iii) and (iv) on February 22. In the sample, domain-specific tests have mean scores of (i) 545 in mathematical literacy (across 14,896 maths tests taken over the years by 6004 students), (ii) 532 in narrative/reflective writing, (iii) 507 in reading, and (iv) 557 in exposition/argument writing.

Large-scale Household Travel Surveys. The Land Transport Authority (LTA) "conducts a large-scale island-wide travel survey... every four to five years... across all residential areas... cover(ing) how respondents go to work, send their children to school, and which shopping centres they frequent... (and) which transport modes are used" (LTA, 2022). The focus is on the busier workdays, outside weekends and public holidays.

We use the individual-level one-day travel diaries collected in the 2012/13 and 2016/17 waves, spanning June 25, 2012 to May 30, 2013 and August 19, 2016 to June 20, 2017, with 23,861 and 40,303 respondent-date observations, respectively. For the 2016/17 wave, the LTA introduced a new phone-based app for respondents to record—beyond a first day—their travel patterns for up to seven days. Judging from the data, participation in the 2016/17 multiday extension was partial and so we focus on the one-day travel diary—just like in the 2012/13 data.[21]

Similar to our analysis of the commuter sample, we drop 5073 respondent-dates whose first trip on the day does not start from their home, for example, a respondent works night shifts and is not active during daytime. We declare that we did not analyse that subsample so our decision to exclude it does not select on whatever travel patterns its subpopulation displays.

Our final sample consists of 59,091 respondent-dates (a single workday per respondent), 137,144 respondent-trips, and 415 workdays over the two collection years combined. We observe all trips, if any, that a respondent makes in a day, including trip-level start and end times and locations, travel modes, and main purpose, e.g., work, shopping, education. Because we observe travel modes other than public transit, including car/taxi and walking/cycling, and the purpose of travel, these data complement the commuter sample. Thus we observe where and how respondents travel, and how long they stay in their destination.

We focus on two types of activity (i) work and (ii) shopping/dining, which we label shopping hereafter. Few trips are recorded to neighbourhood parks including green spaces in

[21] 2016/17 respondents with $T > 1$ might select on individual characteristics such as being more digitally savvy, more organized, or less busy. So we use single (the first) one-day entries for all respondents.

one's township, perhaps because respondents do not perceive these very local trips as travel away from home. As such, very local trips on foot may be understated. Results based on time away from home should be interpreted with this caveat in mind.

The 2012/13 (but not 2016/17) dataset further reports the postal code of each trip's destination. This identifies the exact building. There are 4288 work destinations and 868 shopping destinations across 11,650 and 4055 work and shopping trips. We downloaded postal-code lists of major (i) office towers from officefinder.com.sg and (ii) malls from Wikipedia and imputed full air conditioning for these destinations. These major locations comprise 326 and 170 work and shopping destinations (8% and 20% of the work and shopping destinations in the data) and 2816 work and 1789 shopping trips (25% and 44% of the work and shopping trips in the data).

We shared the remaining list of building-level destinations (e.g., postal code 529203 work, postal code 079011 shopping) with a team of research assistants—all three knowledgeable of Singapore. The assistants were tasked with assessing a probability that each building offered space cooling to its work occupants and, separately where applicable, to its shopping visitors. A key online tool the assistants used was Google Street View. From building pictures they recorded any evidence of space cooling, such as visible air-conditioning parts (e.g., condensers, window units, chillers), window types (closed or some open), and so on.

The assistants were able to assess probabilities for the vast majority of destinations. A minority of destinations could not be located in the online maps, e.g., a building had been demolished since 2012 or the postal code contained a typo. Research assistants were not given the travel dates nor ambient environmental conditions associated with trips to destination buildings they were investigating.

From the Household Travel Surveys, we also learn that workers travel on average for 2.5 hours per workday, of which 1.5 hours are inside air-conditioned cabins (in-vehicle time is recorded). Singapore's modern transit system may differ in this sense from that in other rich urban areas such as London's Underground (Ampofo *et al.*, 2004). Beyond in-vehicle time, on opening Singapore's first air-conditioned bus interchange in 2002, minister Yeo Cheow Tong stated that it would "enable passengers to move smoothly from their buses or MRT (rail) to the HDB (housing) Centre or the shops in the surrounding area" (MOT, 2002).

Retail activity. We examine whether heat affects economic behavior using the Singapore Department of Statistics' monthly volume indices for 18 retail sectors. Six sectors relate more directly to food and beverage (F&B): (1) Supermarkets; (2) Food and Alcohol; (3) Restaurants; (4) Fast Food Outlets; (5) Cafes, Food Courts, Pubs and Other Eating Places; and (6) Food Caterers. Whereas the first two of these F&B sectors sell to shoppers for subsequent preparation and consumption,[22] the other four F&B sectors are eateries targeting diners, i.e., "services that refer to the sales of prepared food and drinks for in-premises consumption or on a take-away basis." Unfortunately, these data exclude hawker centres (personal correspondence with SingStat), a popular type of food court, which, like schools, remain one of the last bastions in Singapore without widespread space cooling.

Singaporeans often eat meals outside the home. A Health Promotion Board survey in 2010 found that nearly 35% of dinners were eaten at dining venues (restaurants, food courts,

[22]The Department of Statistics defines Food and Alcohol as "referring to retail stores which sell food & beverages that are generally not meant for immediate consumption within their premises."

etc.) and that over 45% of the resident population dines outside the home at least six times a week (HPB, 2013).

The other 12 retail sectors are less directly related to F&B: (7) Department Stores; (8) Mini-Marts and Convenience Stores; (9) Motor Vehicles; (10) Petrol Service Stations; (11) Cosmetics, Toiletries and Medical Goods; (12) Wearing Apparel and Footwear; (13) Furniture and Household Equipment; (14) Recreational Goods; (15) Watches and Jewellery; (16) Computer and Telecommunications Equipment; (17) Optical Goods and Books; and (18) Others.

The sample period—for which 16 retail sectors have complete series—is January 1997 to December 2020, with 288 monthly observations in each series. Two sectors have series starting later in the sample period, Department Stores, with 156 observations, and Food Caterers, with 192 observations. The retail sales panel thus consists of $16 \times 288 + 156 + 192 = 4956$ sector-month observations. Our regression specification includes the one-month means of (i) the daily maximum heat index, (ii) rainfall (total each hour), (iii) wind speed (one-hour means), and (iv) the daily pollution index (24-hour conditions reported at 16:00 daily).

We control for pollution using the NEA's Pollution Standards Index because PM2.5 records begin only in 2009. PM2.5 was included in the pollution index only in April 2014. Because PM2.5 is the key determinant of Singapore's pollution index (Salvo, 2018), we include the pollution index as two separate series, one series for months prior to April 2014 (and zero-valued thereafter) and another series for months staring in April 2014 (and zero-valued before the major change in the index's composition). Indeed, the pollution index exhibits a jump in April 2014, when PM2.5 was included in its formula.

B Further analysis of economic activity

B.1 Further analysis of the two main datasets

Sensitivity analysis of the main findings. Table A.8 reports on a nonlinear specification, finding evidence of convexity in the heat-footfall relationship. Table A.9 considers a lagged structure. We do not find evidence of "harvesting," i.e., a hot day does not bring forward activity that would have happened the next day anyway. Instead, effects appear to accumulate (because heat is serially correlated, the table also reports overall cumulative effects).

On 4% of days in the footfall and commuter samples, calculation of the heat index yields a maximal daily value before 6:00, due in part to relative humidity that tends to be high during the night-time compared with daytime hours. Figure A.14 shows estimates when we specify as our key regressor the "daytime" maximum heat index, with daytime hours defined between 6:00 and 22:00, rather than taking the maximum heat index over the 24 hours in a day.

Figures A.15 to A.17 report on regressions that specify alternative measures of thermal discomfort to the US National Weather Service heat index: (i) apparent temperature (Steadman, 1994; ABM, 2010), which considers wind speed in its definition on top of air temperature and relative humidity; (ii) the Humidex index (Masterson and Richardson, 1979; Buzan *et al.*, 2014); and (iii) the temperature-humidity discomfort index (Chow *et al.*, 2016).

The figures provide more details on the alternative measures of heat stress and compare their realizations with that of the heat index we adopt in our main specification.

Figures A.18 to A.22 provide further sensitivity analysis to dropping controls in the regression specification (PM2.5, rainfall, wind speed); dropping from the estimation sample the one-quarter of dates with more rainy afternoons; specifying less granular month-of-year fixed effects and year fixed effects instead of year-by-month (month-of-sample) fixed effects as in our main specification; and taking hourly footfall instead of log hourly footfall as the dependent variable.

As further alternatives to the daily maximum heat index, Figures A.23 and A.24 show results when we specify the concurrent one-hour heat index or the heat index lagged by one hour, respectively. Figure A.25 shows estimates when we specify as our key regressor the "morning maximum" heat index, with morning hours defined between 0:00 and 10:00.

The results reported in Figures A.26 to A.28 are based on alternative resident commuter samples from the baseline requirement that a "cardholder first departs from the modal first-departure stop (or any stop within 600 meters of this stop) at least eight times during the quarter" (Table A.2).

Footfall at two large public parks. Tables 1 and A.7 and Figure A.11 show increased footfall at large outdoor public parks on hotter days, particularly outside of the typical daytime work (or school) shift particularly, in the late afternoon and early evening. Positive estimates through the day suggest results are not limited to people switching from the hotter to the relatively cooler hours of the day.

We interpret the finding as indicating that on hotter days open-access urban parks such as the Botanic Gardens and East Coast Park are increasingly attractive destinations on the basis of environmental amenities they offer, such as vegetation canopy and less heat-storing concrete.

We apply our +0.6% and +0.9% estimates of park footfall on workdays and non-workdays (Table 1, columns 4 and 5) to annual visitorship of 7 and 4 million at East Coast Park and Botanic Gardens (NPB, 2022), using our footfall sample to distribute this visitor density over workdays and non-workdays. Every unseasonable +1 °C attracts +1400 visitors to these two parks per week (five workdays and two non-workdays).

This calculation is conservative in that it ignores the many other parks including smaller neighbourhood ones (Yu and Hien, 2006) and areas of managed vegetation. Assuming each of 5.6 million residents visits an urban green space once every fortnight (no official data are available), every unseasonable +1 °C week attracts +10,000 visitors.

Commercial-park activity in the two main datasets. Figure A.11 and Table A.7 show no significant impact of heat on footfall in commercial parks—Jurong Bird Park and the Singapore Zoo. Similarly, Table A.10 shows statistically insignificant estimates of heat on public transit to and from these commercial parks.

It may be that the composition of visitors differs between these pay-for-entry parks and the public parks, e.g., the former has a larger share of tourists (MTI, 2019) (captured by footfall if they carry StarHub phone cards), or that visitors' flexibility to reschedule varies. If anything, it would appear from the point estimates for the different time intervals shown in Figure A.11 that commercial-parks visitors may shift their visits to earlier in the day to avoid the afternoon heat, though estimates are not significantly different from zero. Moreover, both commercial parks close to visitors at 18:00 (Figure A.1(d)), recalling that the heat-induced increase in public-park attendance is largest in the evening (Figure A.11).

Foreign worker visits to public parks in the commuter sample. We find some evidence that commuting between stops serving low-income foreign worker dormitories and Jurong Central Park increases on hotter days (Figure A.30). This public park is relatively close to some of the larger dormitories and workers are known to congregate there on their days off.

Overall public transit (including non-residents). We analyse public transit ridership aggregated to the citywide level, irrespective of the nature of travel, e.g., a resident's work or recreation, a tourist's activity. The evidence presented in Figure A.9 suggests that heat induces a reallocation of travel within the workday, away from the early afternoon and toward the typically cooler morning and evening. Given our finding that heat increases footfall in indoor spaces and outdoor public parks, the evidence is also consistent with increased travel by car/taxi.

Rain and daily activity. We briefly discuss estimates on rain. We estimate some significantly negative effects of rain on footfall in parks, particularly on non-workdays. Rain does not impact footfall in offices and malls. We estimate significantly negative effects of rain on public transit in the industrial zone and in commercial areas, perhaps because of substitution to car travel, including taxi and ride-hailing. However, this adverse effect of rain tends to shrink toward zero for low-income groups, with low-income commuters seeming to manage despite the rain. We do not obtain significant impacts of rain on student attendance at schools. We interpret the evidence as consistent with tropical—and thus showery—Singapore having covered its main footpaths, e.g., linking bus/rail stops to commercial and residential buildings, to attract commuters to public transit. This provides further evidence of adaptation to the current climate, and note that Singapore's climate going forward is forecast to become wetter (NCCS, 2022).

B.2 Individual-level panel models

We estimate individual FE models of school attendance and test scores at a large private school:

$$f_{it} = W_t\beta + X_{it}\gamma + \alpha_i + \alpha_t + \epsilon_{it}, \tag{4}$$

where f_{it} denotes the particular outcome for student i on date t (attendance or test score), X_{it} are time-varying individual characteristics (e.g., student age bins one-year wide) with associated parameter vector γ, and α_i are individual FE.

We also implement individual FE regressions to examine time at a location or away from home. Here, individual i is a cardholder. Tables A.11 and A.12 examine individual-level panels that are conditional on commuters taking public transit to and from workplaces or malls, or to leave and return home. A 1 °C rise in the daily maximum heat index is associated with increased daily durations at the industrial zone, at the Central Business District, or away from home of 0.3%, 0.6%, and 0.3%, respectively.

Table A.15 below, based instead on Household Travel Surveys that include travel on all modes, confirms that on hotter days, people are more likely to go out and to a commercial area, significantly so among low-income groups.

B.3 Attendance and test scores at a large private school

We examine individual-level daily attendance records between 2012 and 2016 at UWCSEA. With climate control across its buildings, this school provides a high-adaptation benchmark and in this sense complements the main analysis. Figure A.31 shows the heat-attendance relationship in the raw data. Table A.13 shows that heat has a precisely estimated zero impact on student attendance at this school. In column 3, a 1 °C rise in the daily maximum heat index has a 0.00 effect (s.e. 0.03) on student attendance. With sample mean attendance of 95.64 every 100 schooldays, this is a 0.00/95.64 impact. Including environmental conditions over the preceding three calendar days does not change the result. We note that for this school, heat does not *raise* attendance, as we estimated to be the case for air-conditioned establishments in Singapore's wider population of schools. This may partly be due to the school's ample resources, including resourceful parents who may be more willing to run the air conditioner at home if the child is absent on hot days (Liu and Salvo, 2018).

We now turn to standardized test scores between 2015 and 2020 at the same school—a second individual-level panel with only 24 schooldays of testing (and environmental variation) compared with 947 schooldays of attendance in the first panel. In our preferred specification, where besides year FE we include time trends that vary across test-takers in Grades 3-10, heat has no significant effect on test outcomes (Table A.14, column 4).[23] Our results differ from Graff Zivin *et al.* (2018) who find that ambient temperatures starting at 26 °C (79 °F) impair child performance—in a setting with less adaptation than ours.

B.4 Large-scale household travel surveys

Figure A.32 is based on 24,000 one-day travel diaries spanning workdays from June 2012 to May 2013 from the Household Travel Survey. That year, the LTA collected the postal code for each trip's destination. The purpose of each trip was also recorded. Recall that this enabled our research assistants to assess a probability that each destination-building offered air conditioning to its users. The assessed probability can be interpreted as the share of space in the building with cooling, separately for workers and for shoppers. Overall, air-conditioned destinations are prevalent in the samples, with 75% of work trips and 59% of shopping trips destined for buildings that have at least an 80% space-cooling share.

We then split the sample of trips into those occurring on days with above- vs. below-median heat. We alternatively consider the median of (i) the daily maximum heat index over days in 2012/13 or (ii) the deseasoned daily maximum heat index. The plots show that, relative to cooler days, the distribution of trips over the destination building cooling share significantly shifts to the right on hotter days.[24] Specifically, buildings with at least an 80% cooling share account for 60% of shopping destinations on days with above-median heat compared with 53% of shopping Similarly, the distribution of work destinations shifts in the direction of more space cooling on hotter vs. cooler days. Because most workplaces are fixed, we interpret the evidence as consistent with hotter days being associated with

[23] Linear time trends account for any grade-specific inflation in test scores, e.g., Grade 3 tests becoming "easier" over time. The year FE imply that identifying variation is across testing dates within a year. We reject adverse effects of magnitude greater than $(0.73 - 1.96 \times 1.58)/1070 = -0.2\%$ of the mean score.

[24] In terms of travel mode, shopping trips to less cooled buildings have a greater share of walking/cycling, those to more cooled buildings have a greater share of motorized travel. Plausibly, heat induces a shift in the composition of retail sales, away from local shops/eateries ("mom and pops") towards malls.

greater attendance among workers with space-cooled workplaces relative to workers without air conditioning.

Table A.15 uses the combined sample of respondent-dates in the 2012/13 and 2016/17 Household Travel Survey to examine the impact of a day's heat on the likelihood that a respondent that day (i) leaves home, goes to work (if a worker), goes to a shopping destination, and (ii) travels in a mode not covered in our commuter sample, i.e., car/taxi, walk/cycle. We also examine (iii) the time associated with these activities.

The evidence is consistent with that in the footfall and commuter samples. Compared with cooler weather, on unseasonably hot days people are more likely to go out and end up in a shopping area, significantly so among low-income respondents—see the note on the joint significance of $\beta_{heat} + \beta_{heat,lowIncome}$ in the table's caption.[25] Relative to cooler days, low-income respondents on hotter days tend to spend more time away from home and more time on shopping/dining trips. Estimates of a day's heat on the likelihood of workers going to work and the time spent working are insignificant in this sample, possibly because respondents include workers with less cooling in the workplace (recall Figure A.32).

B.5 Retail activity

Table A.16 shows economically and statistically insignificant effects of heat in a monthly panel of sales quantity indices for 18 retail sectors (1997-2020). This non-significance result is robust to restricting the sample to the six F&B sectors and examining for heterogeneous effects according to the type of F&B sector, specifically eateries (sales of prepared food for immediate consumption as in restaurants) vs. non-eateries (supermarkets' sales of food typically for subsequent preparation). We do not detect differences in retail activity—including food retail—in unseasonably hotter vs. cooler months.

B.6 Back-of-the-envelope of expanded space cooling in tropical Jakarta

We were not able to find studies of the relationship between heat and mortality for the rapidly developing megacity of Jakarta, or even for Indonesia. So we take estimated heat-related excess mortality in Southeast Asia for the "current" period of 2010-2019 from Gasparrini *et al.* (2017), specifically a 95% CI of 0.5 to 3.6%.[26] Applying this 95% CI of heat-related excess mortality to Jakarta's entire population of 10.2 million, of which 66,800 die each year (WHO, 2023), yields 330 to 2400 heat deaths annually. Here we focus on Jakarta's elderly subpopulation (persons aged 65 and above) of 380,000, of which 26,400 die each year (WHO, 2023). We were not able to find age-specific heat-related excess mortality, so we conservatively take that for the overall population. This yields 130 to 950 heat-induced deaths among the elderly each year.

To value the health damage from heat exposure in Jakarta, we follow Viscusi and Masterman (2017) and adjust a measure of the value of a statistical life (VSL) for the US to that

[25] Similar to the commuter sample, low-income status is 1 if more than 40% of dwellings in the respondent's residential building, which we observe, are 1-3 room apartments, and 0 otherwise.

[26] See their Table S1 showing Southeast Asia as the region with the highest heat-related excess mortality among nine regions of the world—both due to climate and to human development conditions.

in low-income Jakarta based on relative incomes:

$$VSL_{Jakarta} = VSL_{US} \times \left(\frac{Y_{Jakarta}}{Y_{US}}\right). \tag{5}$$

Viscusi and Masterman use $VSL_{US} = \$9.6$ million and $Y_{US} = \$56,620$ (2015 GNI per capita), which along with $Y_{Jakarta} = \$8975$ (2019 GDP per capita at market exchange rates, per Statistics Indonesia (2023)), yields $VSL_{Jakarta} = \$1.5$ million. If we do not adjust the VSL according to age, the value of preventing heat-induced elderly mortality in Jakarta is \$0.20 to \$1.4 billion each year. Aldy and Viscusi (2007) discuss why VSL may differ with age (e.g., lower life expectancy, higher incomes) and we note that a “senior discount,” while controversial, may be about 20 to 37% (i.e., one-fifth to almost two-fifths less).

Only to fix ideas, we weigh the above benefit calculation against the cost of technologies that would move developing Jakarta’s heat-induced health damage to that inflicted on rich Singapore, for which we are not able to reject zero (Tables A.17 and A.18). We crudely assume that adaptation takes the form of providing space-cooled centres to host vulnerable seniors, which we take to be the number of elderly Jakartans times the fraction without air conditioning at home: $380,000 \times (1 - 0.3) = 266,000$. Importantly, our cost calculation focused on heat shelters (Friedman, 2022; Meko and Grullon Paz, 2022) ignores the many human systems such as education and medical services that accompany investments in built infrastructure and evolve as a city grows richer.

There are no guidelines for occupancy density of cooling space that we are aware of. Instead, we follow recommendations in Section 502 of the International Code Council’s Standard for the Design and Construction of Storm Shelters (ICC, 2020), specifically a minimum of 5 square feet (sq ft) per person for tornado community storm shelters and 20 sq ft per person for hurricane community storm shelters. The difference in recommendations is due to the difference in expected shelter duration: 2 hours for a tornado and 24 hours for a hurricane.

Since cooling centres typically operate only during the day, we lean towards the tornado recommendation and use 10 sq ft (0.93 square meter) per person, which results in a required space of $266,000 \times 0.93 = 247,000$ sqm. The average rental rate of mall space in Jakarta, inclusive of electricity and air conditioning, at the end of 2019 was \$694 per sqm per year (Cushman and Wakefield, 2019). The annual cost of renting 247,000 sqm inclusive of energy consumption is \$0.17 billion. Assuming one care staff per 30 elderly visitors, each care staff valued at the median annual salary for nurses in Jakarta of \$7000, adds a wage bill of \$0.06 billion. Assuming the year-round operation of these cooling centres (270 kWh per sqm per year, per JICA (2009)), adding the climate damage from coal-fired electricity (0.96 kg of CO2 per kWh) valued at a social cost of carbon dioxide of \$185 per ton of CO2 (Rennert *et al.*, 2022) takes the annual cost of abating heat-induced deaths to \$0.25 billion.

Table A.1: Summary statistics in the footfall and commuter samples (including school AC)

	No. obs.	Mean	Std. dev.	Min.	Max.
	June to August of 2016 and 2017				
Heat index, daily maximum (°C)	3128	35.81	1.83	30.68	39.70
Air temperature, daily maximum (°C)	3128	30.80	1.22	27.27	33.12
Air temperature, one-hour mean (°C)	3122	29.06	1.71	23.59	33.12
Relative humidity, one-hour mean (%)	3128	73.80	9.45	45.52	98.82
PM2.5, one-hour mean (μg/m^3)	3128	14.32	8.88	2.80	172.60
Rainfall, one-hour sum (mm)	3128	0.25	1.22	0.00	17.93
Wind speed, one-hour mean (m/s)	3128	2.60	1.17	0.18	6.40
Footfall in office towers (three locations)	6144	994.99	560.70	44	2210
Footfall in shopping malls (five)	14,720	1930.52	1531.19	30	10,534
Footfall in public parks (two)	5888	9021.53	3373.83	2170	24,035
Footfall in commercial parks (two)	3680	494.26	277.72	30	1900
Median dwell time (minutes, 12 locations)	15,032	116.69	144.62	10	667
	October to December of 2015 and 2016				
Heat index, daily maximum (°C)	3128	35.34	1.67	29.51	39.22
Air temperature, daily maximum (°C)	3128	31.03	1.30	26.67	33.22
Air temperature, one-hour mean (°C)	3128	28.57	2.01	22.83	33.22
Relative humidity, one-hour mean (%)	3128	74.19	11.45	42.75	98.90
PM2.5, one-hour mean (μg/m^3)	3128	23.03	26.74	2.60	210.20
Rainfall, one-hour sum (mm)	3128	0.34	1.45	0.00	22.90
Wind speed, one-hour mean (m/s)	3128	2.38	1.13	0.07	7.17
Arrivals to the industrial zone	4352	680.45	1389.41	5	6810
Departures from the industrial zone	4352	583.10	858.32	6	4495
Arrivals at commercial areas (80 locations)	471,040	446.32	1530.41	0	36,541
Departures from commercial areas	471,040	434.35	1559.38	0	36,154
Student arrivals at school stops (1284)	236,256	54.28	143.31	0	4098
Student departures from school stops	236,256	53.67	139.48	0	3587
Air conditioning in classrooms (%)	2932	49.14	35.88	0	100

Notes: The sample periods are June to August of 2016 and 2017 (footfall sample, at the top) and October to December of 2015 and 2016 (commuter sample, at the bottom). An observation is a (i) date-hour pair for environmental variables, (ii) location-date-hour triple for footfall (...-bihour for dwell time), (iii) date-hour-income group triple for industrial-zone arrivals/departures, (iv) location-date-hour-income group tuple for commercial-area arrivals/departures, (v) school stop-schoolday pair for student arrivals/departures, or (vi) survey respondent-school for air conditioning prevalence. Environmental statistics are for 6:00-22:59 on all days (except for the daily maximum heat index and air temperature in which the maximum is taken over the 24 hours in a day). Footfall/commuter statistics for (i) office towers are for 7:00-22:59 on workdays, (ii) the industrial zone are for 6:00-22:59 on workdays, (iii) commercial parks are for 9:00-18:59 on all days, and (iv) public parks and shopping locations are for 7:00-22:59 on all days. Commuting is observed for the southwest industrial zone, each of 80 consolidated commercial areas, and 1284 school stops. Sources: NEA (temperature in 2016 & 2017, rainfall, PM2.5), NUS Geography & Iowa State University Environmental Mesonet (temperature in 2015, relative humidity, wind speed), StarHub (footfall), LTA (commuter flows), NUS student survey (air conditioning in schools).

Table A.2: Second main dataset: Preparing the sample of trips by resident commuters who are active during daytime hours

	Cards in 2015	Cards in 2016
Cards in the raw data	7,216,805	7,336,058
Drop card(-quarter)s:		
(a) only w/ days w/ non-residential first-departure & last-arrival stops	-49,970	-56,552
(b) w/ non-residential modal first-departure stop & modal last-arrival stop	-122,142	-129,341
(c) w/ modal first-departure stop and modal last-arrival stop not nearby (600m)	-2,413,021	-2,469,937
(d) w/ < 8 first departures from the modal first-departure stop (or nearby stops)	-1,408,070	-1,446,316
Cards in the sample of trips (baseline analysis)	3,223,602	3,233,912
75th percentile of the low-income share over 6,457,514 card-quarters: 0.401		
Sensitivity analysis 1		
Drop card(-quarter)s:		
(d-1) w/ < 6 first departures from the modal first-departure stop (or nearby stops)	-1,134,566	-1,171,021
Cards in the sample of trips (sensitivity analysis 1)	3,497,106	3,509,207
75th percentile of the low-income share over 7,006,313 card-quarters: 0.399		
Sensitivity analysis 2		
Drop card(-quarter)s:		
(d-2) w/ < 10 first departures from the modal first-departure stop (or nearby stops)	-1,625,830	-1,662,655
Cards in the sample of trips (sensitivity analysis 2)	3,005,842	3,017,573
75th percentile of the low-income share over 6,023,415 card-quarters: 0.403		
Sensitivity analysis 3		
Drop card(-quarter)s:		
(d-3) w/ < 8 last arrivals at the modal last-arrival stop (or nearby stops)	-1,409,115	-1,447,384
Cards in the sample of trips (sensitivity analysis 3)	3,222,557	3,232,844
75th percentile of the low-income share over 6,455,401 card-quarters: 0.401		

Notes: The raw data comprise the trip segments of all individual bus and rail trips made throughout Singapore in two quarters, October-December 2015 and October-December 2016, that were paid with an EZ-Link card, Singapore's public transit farecard. As explained in the text, we collapse trip segments into trips (see Figure A.2 summarizing all trips in the raw data). Each card has its unique identifier; we observe trips in both year-on-year quarters for 4,059,426 cards. We conduct the sampling procedure separately by quarter. To map trips in the commuter data to the industrial zone, commercial areas, and the Central Business District, by income group, we focus on a sample of residents who are active during daytime, typically departing from home prior to returning home within a day, i.e., the card-quarter's modal first-departure-in-day stop and modal last-arrival-in-day stop are in a same residential area. This residential area allows us to assign a (likely) income group to each card-quarter, based on the neighbourhood's composition of dwelling types (share of 1-3 room apartments among all dwellings in proximity to a card-quarter's home stops). In three robustness tests (Figures A.26 to A.28), we vary the commuting frequency threshold (d) from the baseline "cardholder first departs from the modal first-departure stop (or any stop within 600 meters of this stop) at least eight times during the quarter".

Table A.3: The impact of heat on public-transit arrivals or departures over all time intervals

	Industrial zone Workdays 6:00-22:59		Commercial areas Workdays 7:00-22:59		Commercial areas Non-workdays 10:00-22:59	
	Arrivals	Departures	Arrivals	Departures	Arrivals	Departures
Log hourly arrivals or departures	(1)	(2)	(3)	(4)	(5)	(6)
Effects across both income groups						
Daily max. heat index (1 °C)	0.0017	0.0067**	0.0010	0.0025***	-0.0030	-0.0032
	(0.0026)	(0.0034)	(0.0011)	(0.0009)	(0.0026)	(0.0030)
Number of regressors	35	35	113	113	102	102
Effects by income group						
Daily max. heat index (1 °C)	0.0006	0.0057*	-0.0002	0.0012	-0.0063**	-0.0069**
	(0.0028)	(0.0035)	(0.0011)	(0.0011)	(0.0029)	(0.0032)
Low-income group × max. heat	0.0023***	0.0019**	0.0024**	0.0025***	0.0066***	0.0075***
	(0.0008)	(0.0009)	(0.0011)	(0.0009)	(0.0022)	(0.0016)
Overall heat on low-income	0.0028	0.0077**	0.0022*	0.0037***	0.0003	0.0006
	(0.0025)	(0.0033)	(0.0013)	(0.0010)	(0.0027)	(0.0031)
Number of regressors	38	38	116	116	105	105
R-squared	0.9934	0.9877	0.9032	0.9266	0.9302	0.9309
Number of observations	4352	4352	324,786	324,511	115,525	115,933
Mean of dep. var. levels (1000s)	0.6804	0.5831	0.4579	0.4472	0.4569	0.4918

Notes: This table shows results for 12 OLS regressions across two panels. It follows Table 2 exactly except that the dependent variable is the log hourly number of arrivals or departures, and not the sum of arrivals and departures. An observation is a date-hour-income group triple in columns 1-2 or a location-date-hour-income group tuple in columns 3-6. All regressions control for concurrent PM2.5, rainfall, wind speed, hour-of-day FE, day-type FE, year-month FE, and a low-income-group dummy. Columns 3-6 further include location FE. Results are similar in the top panel if we collapse the data across both income groups. Given relatively modest commuting at selected times, we specify the average hourly arrivals or departures within quarter-of-sample as regression weights (specific to the location type and workdays/non-workdays). Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.4: Heat, student income, school cooling, and attendance, by arrivals or departures

Log daily student arrivals or departures at stops nearby schools	Student arrivals		Student departures	
	Arrivals (1)	Arrivals+1 (2)	Depart (3)	Depart+1 (4)
By student income group				
Daily max. heat index (1 °C)	0.0063	0.0040	0.0052	0.0016
	(0.0071)	(0.0063)	(0.0078)	(0.0067)
Low-income group × max. heat	0.0038	0.0055	-0.0006	0.0045
	(0.0025)	(0.0045)	(0.0036)	(0.0044)
Overall heat on low-income	0.0101	0.0095	0.0047	0.0062
	(0.0073)	(0.0067)	(0.0088)	(0.0076)
No. of obs. (stop-schoolday-income)	157,718	185,422	156,393	185,422
Mean of dependent var. in levels	43.2584	37.7951	43.8798	38.0101
By school cooling				
Daily max. heat index (1 °C)	0.0010	0.0011	-0.0002	-0.0023
	(0.0109)	(0.0101)	(0.0119)	(0.0112)
School cooling × max. heat	0.0268**	0.0247*	0.0177	0.0223*
	(0.0124)	(0.0129)	(0.0119)	(0.0126)
Overall heat with full cooling	0.0278***	0.0258***	0.0175*	0.0200**
	(0.0096)	(0.0095)	(0.0091)	(0.0092)
No. of obs. (stop-schoolday)	75,043	79,301	74,299	79,301
Mean of dependent var. in levels	79.4985	75.2299	81.5305	76.3879
By student income and school cooling				
Daily max. heat index (1 °C)	0.0017	0.0025	0.0027	0.0007
	(0.0105)	(0.0098)	(0.0112)	(0.0104)
Low-income group × max. heat	0.0003	-0.0009	-0.0033	-0.0021
	(0.0025)	(0.0034)	(0.0035)	(0.0031)
School cooling × max. heat	0.0165	0.0122	0.0094	0.0088
	(0.0112)	(0.0110)	(0.0110)	(0.0107)
Low-income group × cooling × heat	0.0086***	0.0123***	0.0066***	0.0112***
	(0.0006)	(0.0005)	(0.0005)	(0.0005)
No. of obs. (stop-schoolday-income)	136,985	158,602	135,942	158,602
Mean of dependent var. in levels	43.5508	38.6149	44.5604	39.1938

Notes: This table shows results for 12 OLS regressions across three panels. It follows Table 3 exactly except that the dependent variable is the log daily number of student arrivals or departures, and not the sum of arrivals and departures. In columns 2 and 4, we add 1 before taking logs to account for a minority (∼5%) of zero-valued observations. Standard errors, in parentheses, are clustered by date (two-way clusters by date and by school stop yield similar standard errors). ***Significant at 1%, **at 5%, *at 10%.

Table A.5: Heat and indoor activity on workdays, by time interval

	Work			Work/leisure	Leisure
Log hourly footfall					
	Offices 7:00-9:59 (1)	Malls 7:00-9:59 (2)	Offices 17:00-19:59 (3)	Malls 17:00-19:59 (4)	Malls 20:00-22:59 (5)
Daily max. heat index (1 °C)	0.0071***	0.0050**	0.0049**	0.0053**	0.0108***
	(0.0022)	(0.0020)	(0.0022)	(0.0022)	(0.0042)
PM2.5 (10 μg/m^3)	-0.0013	0.0040	0.0016	-0.0007	0.0068
	(0.0046)	(0.0054)	(0.0043)	(0.0057)	(0.0065)
Rainfall (1 mm)	-0.0012	-0.0020	-0.0022	-0.0028	0.0010
	(0.0038)	(0.0017)	(0.0041)	(0.0026)	(0.0113)
Number of observations	1152	1920	1152	1920	1920
Number of regressors	22	24	22	24	24
R-squared	0.9716	0.8640	0.8709	0.9267	0.9372
Mean of dep. var. in levels (1000s)	0.6965	0.4579	1.0155	2.5225	1.6283
Log hourly public transit					
	Industrial zone Arrivals 6:00-9:59 (6)	Commercial area Arrivals 7:00-10:59 (7)	Industrial zone Departures 17:00-19:59 (8)	Commercial area Departures 17:00-19:59 (9)	Commercial area Departures 20:00-22:59 (10)
Daily max. heat index (1 °C)	-0.0012	0.0049**	0.0134*	0.0051	0.0011
	(0.0035)	(0.0023)	(0.0077)	(0.0037)	(0.0017)
Low-income group × max. heat	0.0027***	0.0028*	0.0024*	0.0020	0.0024**
	(0.0010)	(0.0014)	(0.0014)	(0.0013)	(0.0012)
PM2.5 (10 μg/m^3)	-0.0165	-0.0060	-0.0032	-0.0017	-0.0020**
	(0.0109)	(0.0040)	(0.0021)	(0.0012)	(0.0009)
Low-income group × PM2.5	0.0021***	0.0001	0.0008	0.0008	0.0003
	(0.0007)	(0.0013)	(0.0006)	(0.0011)	(0.0011)
Rainfall (1 mm)	-0.0076***	-0.0034	-0.0075***	-0.0048***	-0.0067***
	(0.0022)	(0.0022)	(0.0027)	(0.0014)	(0.0021)
Low-income group × rainfall	0.0070***	0.0038**	-0.0012*	0.0019	-0.0048
	(0.0020)	(0.0017)	(0.0007)	(0.0022)	(0.0041)
Number of observations	1024	81,544	768	61,277	61,074
Number of regressors	25	104	24	103	103
R-squared	0.9819	0.9293	0.9823	0.9561	0.9484
Mean of dep. var. in levels (1000s)	2.5255	0.6331	1.9405	0.8641	0.5665

Notes: This table shows results for 10 OLS regressions. An observation is a location-date-hour triple in columns 1-5, a date-hour-income group triple in columns 6 and 8, or a location-date-hour-income group tuple in columns 7 and 9-10, on workdays during the indicated time interval. In columns 1-5, the dependent variable is the log hourly footfall at an office tower (3 locations) or a mall (5 locations). In columns 6-10, the dependent variable is the log hourly number of bus/rail arrivals or departures in the industrial zone (a single aggregated location) or in a commercial area (80 locations). All regressions control for concurrent wind speed, hour-of-day FE, day-type FE, and year-month FE. As day-type FE, separate indicators denote: Monday, ..., Friday when the public school system is in session; Monday, ..., Friday during vacations; Saturday; and Sunday/public holiday. We further include location FE in columns 1-5, 7, and 9-10, and a low-income-group dummy in columns 6-10. The joint impact of heat and its interaction with the low-income dummy is significant at the 1% level in column 7, at 5% in columns 8 and 10, at 10% in column 9, and not significant in column 6. Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.6: Heat and indoor activity on non-workdays, by time interval

Log hourly footfall in malls	10:00-12:59 (1)	13:00-16:59 (2)	17:00-19:59 (3)	20:00-22:59 (4)
Daily max. heat index (1 °C)	0.0051	0.0047	0.0066**	0.0104**
	(0.0038)	(0.0034)	(0.0030)	(0.0045)
PM2.5 (10 μg/m^3)	0.0046	-0.0046	-0.0079	-0.0001
	(0.0043)	(0.0091)	(0.0078)	(0.0072)
Number of observations	840	1120	840	840
Number of regressors	16	17	16	15
R-squared	0.9492	0.9452	0.9348	0.9203
Mean of dep. var. in levels (1000s)	1.9347	3.3752	3.4573	2.0798
Log hourly public transit in commercial areas	Arrivals 10:00-12:59 (5)	Arrivals 13:00-16:59 (6)	Departures 17:00-19:59 (7)	Departures 20:00-22:59 (8)
Daily max. heat index (1 °C)	-0.0023	-0.0069**	-0.0095**	-0.0059*
	(0.0038)	(0.0030)	(0.0045)	(0.0035)
Low-income group × max. heat	0.0072**	0.0064***	0.0065***	0.0072***
	(0.0032)	(0.0022)	(0.0021)	(0.0025)
PM2.5 (10 μg/m^3)	-0.0016	-0.0010	-0.0018	0.0007
	(0.0023)	(0.0012)	(0.0022)	(0.0029)
Low-income group × PM2.5	-0.0000	-0.0028***	-0.0023**	0.0012
	(0.0011)	(0.0008)	(0.0009)	(0.0019)
Rainfall (1 mm)	-0.0125	-0.0065***	-0.0087***	0.0218
	(0.0097)	(0.0014)	(0.0018)	(0.0137)
Low-income group × rainfall	-0.0020	0.0018	0.0041***	-0.0041
	(0.0073)	(0.0020)	(0.0006)	(0.0155)
Number of observations	26,778	35,675	26,795	26,728
Number of regressors	95	96	95	95
R-squared	0.9389	0.9454	0.9491	0.9465
Mean of dep. var. in levels (1000s)	0.5451	0.5489	0.6113	0.5495

Notes: This table shows results for 8 OLS regressions. An observation is a location-date-hour triple in columns 1-4 and a location-date-hour-income group tuple in columns 5-8, on weekends and public holidays during the indicated time interval. In columns 1-4, the dependent variable is the log hourly footfall at a mall (5 locations). In columns 5-8, the dependent variable is the log hourly number of bus/rail arrivals or departures in a commercial area (80 locations). All regressions control for concurrent wind speed, hour-of-day FE, day-type FE, year-month FE, and location FE. We further include a low-income-group dummy in columns 5-8. Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.7: Heat and outdoor activity on workdays and non-workdays, by time interval

	Public parks			Commercial parks	
	7:00-9:59	17:00-19:59	20:00-22:59	9:00-12:59	13:00-18:59
Log hourly footfall, workdays	(1)	(2)	(3)	(4)	(5)
Daily max. heat index (1 °C)	0.0058**	0.0081***	0.0119***	0.0063	-0.0008
	(0.0026)	(0.0030)	(0.0029)	(0.0045)	(0.0041)
PM2.5 (10 μg/m^3)	0.0122*	-0.0010	0.0045	0.0022	-0.0066*
	(0.0069)	(0.0080)	(0.0080)	(0.0061)	(0.0040)
Rainfall (1 mm)	-0.0016	-0.0018	0.0059	-0.0006	-0.0041**
	(0.0023)	(0.0031)	(0.0064)	(0.0017)	(0.0020)
Number of observations	768	768	768	1024	1536
Number of regressors	21	21	21	22	24
R-squared	0.9000	0.9152	0.9642	0.7449	0.8784
Mean of dep. var. in levels (1000s)	6.8969	9.6591	7.2087	0.4493	0.4602
Log hourly footfall, non-workdays	(6)	(7)	(8)	(9)	(10)
Daily max. heat index (1 °C)	0.0077	0.0116**	0.0157***	0.0039	-0.0085
	(0.0049)	(0.0057)	(0.0054)	(0.0083)	(0.0070)
PM2.5 (10 μg/m^3)	0.0029	-0.0319**	-0.0246**	-0.0115	-0.0208
	(0.0086)	(0.0130)	(0.0102)	(0.0146)	(0.0256)
Rainfall (1 mm)	-0.0031	-0.0167*	-0.0109	-0.0037	-0.0159**
	(0.0064)	(0.0088)	(0.0111)	(0.0106)	(0.0068)
Number of observations	336	336	336	448	672
Number of regressors	13	13	13	14	16
R-squared	0.9175	0.9337	0.9579	0.8585	0.9551
Mean of dep. var. in levels (1000s)	5.9010	11.9646	8.4200	0.5510	0.6027
Log hourly footfall, all days	(11)	(12)	(13)	(14)	(15)
Daily max. heat index (1 °C)	0.0067***	0.0095***	0.0132***	0.0055	-0.0036
	(0.0025)	(0.0027)	(0.0026)	(0.0041)	(0.0035)
PM2.5 (10 μg/m^3)	0.0111*	-0.0072	-0.0033	0.0001	-0.0092
	(0.0059)	(0.0069)	(0.0059)	(0.0051)	(0.0062)
Rainfall (1 mm)	-0.0036	-0.0087***	0.0024	-0.0006	-0.0066***
	(0.0030)	(0.0034)	(0.0066)	(0.0020)	(0.0024)
Number of observations	1104	1104	1104	1472	2208
Number of regressors	23	23	23	24	26
R-squared	0.8802	0.9015	0.9531	0.5758	0.7941
Mean of dep. var. in levels (1000s)	6.5938	10.3608	7.5774	0.4803	0.5036

Notes: This table shows results for 15 OLS regressions. An observation is a park-date-hour triple, on workdays (columns 1-5), non-workdays (columns 6-10), or in a pooled sample of workdays and non-workdays (columns 11-15), during the indicated time interval. The dependent variable is the log hourly footfall at a park (2 public parks in the first three columns or 2 commercial parks in the last two columns). All regressions control for concurrent wind speed, hour-of-day FE, day-type FE, year-month FE, and location FE. Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.8: Heat and footfall over all time intervals: A nonlinear heat specification

	Offices	Malls		Public parks		Commercial parks	
	Workdays 7:00-19:59	Workdays 7:00-22:59	Non-workdays 7:00-22:59	Workdays 7:00-22:59	Non-workdays 7:00-22:59	Workdays 7:00-18:59	Non-workdays 7:00-18:59
Log hourly footfall	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Daily max. heat index $\in$ [34.5,37.5)	-0.0017	0.0113	0.0006	0.0059	-0.0006	0.0010	0.0050
°C (*sample density: 64%*)	(0.0076)	(0.0097)	(0.0187)	(0.0111)	(0.0305)	(0.0163)	(0.0275)
Daily max. heat index $\geq$ 37.5 °C	0.0276***	0.0266**	0.0669**	0.0142	0.0928**	-0.0067	0.0453
(*sample density: 16%*)	(0.0095)	(0.0126)	(0.0267)	(0.0156)	(0.0365)	(0.0196)	(0.0377)
PM2.5 (10 μg/m^3)	-0.0001	-0.0004	0.0006	-0.0003	-0.0179**	0.0004	-0.0137
	(0.0018)	(0.0030)	(0.0055)	(0.0039)	(0.0072)	(0.0059)	(0.0157)
Rainfall (1 mm)	0.0008	-0.0001	0.0048	-0.0012	-0.0050**	-0.0039**	-0.0134**
	(0.0008)	(0.0014)	(0.0043)	(0.0013)	(0.0025)	(0.0018)	(0.0057)
Number of observations	4992	10,240	4480	4096	1792	3072	1344
Number of regressors	33	38	30	35	27	31	23
R-squared	0.9520	0.9346	0.9501	0.8696	0.9245	0.7459	0.8088
Mean of dep. var. levels (1000s)	1.1700	1.7621	2.3154	8.7401	9.6649	0.4045	0.5018

Notes: This table shows results for 7 OLS regressions. It follows Table 1 exactly except that it replaces the linear daily maximum heat variable with three daily maximum heat bins of width as indicated; the reference bin is daily max. heat index $\leq$ 34.5 °C, with sample density of 20%. Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.9: Heat and footfall over all time intervals: A lagged-heat specification

	Offices	Malls		Public parks	
Log hourly footfall	Workdays 7:00-19:59	Workdays 7:00-22:59	Non-workdays 7:00-22:59	Workdays 7:00-22:59	Non-workdays 7:00-22:59
Concurrent and prior day's heat	(1)	(2)	(3)	(4)	(5)
Daily max. heat index (1 °C)	0.0035*	0.0039*	0.0045*	0.0046	0.0078
	(0.0019)	(0.0022)	(0.0026)	(0.0030)	(0.0047)
One-day lagged heat index (1 °C)	0.0023	0.0038	0.0037	0.0046	0.0014
	(0.0019)	(0.0023)	(0.0028)	(0.0030)	(0.0050)
Overall heat today and yesterday	0.0058***	0.0077**	0.0082**	0.0091**	0.0092
	(0.0021)	(0.0030)	(0.0039)	(0.0037)	(0.0060)
PM2.5 (10 μg/m^3)	0.0001	-0.0010	-0.0003	-0.0006	-0.0200**
	(0.0019)	(0.0029)	(0.0060)	(0.0035)	(0.0077)
Rainfall (1 mm)	0.0007	-0.0002	0.0041	-0.0009	-0.0061**
	(0.0009)	(0.0014)	(0.0043)	(0.0013)	(0.0029)
Number of observations	4914	10,080	4480	4032	1792
Number of regressors	33	38	30	35	27
R-squared	0.9517	0.9346	0.9498	0.8702	0.9204
Mean of dep. var. levels (1000s)	1.1692	1.7623	2.3154	8.7441	9.6649
Concurrent and prior two days' heat	(6)	(7)	(8)	(9)	(10)
Daily max. heat index (1 °C)	0.0027	0.0037*	0.0044	0.0035	0.0068
	(0.0019)	(0.0022)	(0.0027)	(0.0029)	(0.0048)
One-day lagged heat index (1 °C)	0.0014	0.0030	0.0036	0.0036	0.0002
	(0.0020)	(0.0023)	(0.0027)	(0.0032)	(0.0050)
Two-day lagged heat index (1 °C)	0.0039**	0.0024	0.0003	0.0052*	0.0038
	(0.0016)	(0.0026)	(0.0026)	(0.0031)	(0.0054)
Overall heat today and past two days	0.0080***	0.0091***	0.0083*	0.0123***	0.0108*
	(0.0023)	(0.0037)	(0.0043)	(0.0043)	(0.0064)
PM2.5 (10 μg/m^3)	0.0005	-0.0010	-0.0002	-0.0001	-0.0195**
	(0.0018)	(0.0030)	(0.0061)	(0.0035)	(0.0082)
Rainfall (1 mm)	0.0014	0.0001	0.0041	-0.0001	-0.0060**
	(0.0009)	(0.0015)	(0.0043)	(0.0013)	(0.0028)
Number of observations	4836	9920	4480	3968	1792
Number of regressors	34	39	31	36	28
R-squared	0.9518	0.9345	0.9498	0.8704	0.9205
Mean of dep. var. levels (1000s)	1.1687	1.7604	2.3154	8.7417	9.6649

Notes: This table shows results for 10 OLS regressions. It follows Table 1 exactly except that it includes the daily maximum heat index on the previous day in columns 1-5 and the daily maximum heat index on the previous two days in columns 6-10. We also report overall cumulative effects, given serial correlation in heat: the pairwise correlation coefficient between the daily maximum heat index and the daily maximum heat index lagged one day (resp., two days) is 0.42 (resp., 0.37). Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.10: Heat and commuter traffic at bus stops serving commercial parks (all days)

	5 bus stops		3 bus stops (excl. more industrial)	
	Arrivals at commercial park stops 9:00-12:59	Departures from commercial park stops 14:00-19:59	Arrivals at commercial park stops 9:00-12:59	Departures from commercial park stops 14:00-19:59
Log hourly bus arrivals or departures	(1)	(2)	(3)	(4)
Daily max. heat index (1 °C)	-0.0091	-0.0050	-0.0079	-0.0034
	(0.0098)	(0.0066)	(0.0104)	(0.0073)
Low-income group × max. heat	-0.0075	-0.0058	-0.0040	-0.0081
	(0.0088)	(0.0050)	(0.0091)	(0.0064)
PM2.5 (10 μg/m^3)	-0.0063	-0.0014	-0.0054	0.0007
	(0.0076)	(0.0042)	(0.0076)	(0.0044)
Low-income group × PM2.5	0.0046	-0.0006	0.0001	-0.0028
	(0.0067)	(0.0033)	(0.0070)	(0.0032)
Rainfall (1 mm)	-0.0300***	0.0017	-0.0293***	0.0052
	(0.0085)	(0.0063)	(0.0083)	(0.0060)
Low-income group × rainfall	-0.0330*	-0.0041	-0.0267*	-0.0072
	(0.0171)	(0.0049)	(0.0156)	(0.0051)
Number of observations	2924	4416	2914	4401
Number of regressors	28	30	28	30
R-squared	0.7895	0.7873	0.8059	0.8001
Mean of dep. var. in levels (1000s)	0.0380	0.0428	0.0374	0.0395

Notes: This table shows results for 4 OLS regressions. An observation is a location-date-hour-income group tuple, including workdays and non-workdays, during the indicated time interval (based on Figure A.10). The dependent variable is the log hourly number of arrivals at or departures from bus stops serving two commercial-park locations: the Jurong Bird Park, comprising up to four stops (stops 21301, 21309, 22011, 22019), and the Singapore Zoo, comprising one stop (48131 at the Zoo gate). Columns 1-2 consider all four stops by the Bird Park, whereas columns 3-4 exclude the two more industrial stops, 21301 and 21309, on the transversal Jurong Pier Road that runs along the Park's east side and likely serve industrial workers too. All regressions control for concurrent wind speed, hour-of-day FE, day-type FE, year-month FE, location FE, and a low-income-group dummy. Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.11: Heat and duration in the industrial zone and in the Central Business District

	Duration observed conditional on public transit to and from the...					
	...Industrial zone		...Central Business District			
	Minutes	Log(Minutes)	Minutes		Log(Minutes)	
	Workday (1)	Workday (2)	Workday (3)	Non-workday (4)	Workday (5)	Non-workday (6)
Daily max. heat index	1.6922*	0.0034*	2.2530**	0.5866	0.0055**	0.0028
(1 °C)	(0.8727)	(0.0019)	(1.1357)	(0.5054)	(0.0026)	(0.0021)
Low-income group	-0.0135	0.0003	0.0798***	-0.0093	0.0002**	-0.0000
× max. heat	(0.0791)	(0.0003)	(0.0284)	(0.0352)	(0.0001)	(0.0001)
Daily mean PM2.5	-0.2886	-0.0007	-0.4705*	0.0168	-0.0010	0.0007
(10 μg/m^3)	(0.2441)	(0.0006)	(0.2803)	(0.2018)	(0.0007)	(0.0008)
Low-income group	-0.1533	-0.0006	-0.1532**	0.1993***	-0.0006***	0.0005
× PM2.5	(0.1287)	(0.0004)	(0.0753)	(0.0680)	(0.0002)	(0.0004)
Daily mean rainfall	-1.5318	-0.0031	-3.3131	0.0481	-0.0075	-0.0032
(1 mm/h)	(1.5234)	(0.0034)	(2.4206)	(2.2961)	(0.0059)	(0.0095)
Low-income group	0.4363	0.0013	0.7544	0.0428	0.0014	0.0027
× rainfall	(0.4039)	(0.0011)	(0.4771)	(0.5119)	(0.0013)	(0.0024)
Number of obs.	1,785,153	1,785,153	21,971,208	5,966,222	21,971,208	5,966,222
No. of regr. (excl. FE)	20	20	20	12	20	12
Cardholder FE	Yes	Yes	Yes	Yes	Yes	Yes
	(86,822)	(86,822)	(1,687,189)	(1,066,545)	(1,687,189)	(1,066,545)
Mean of dep. var. (levels)	561.1630	561.1630	443.5021	285.4774	443.5021	285.4774

Notes: This table shows results for 6 fixed effects regressions. An observation is a cardholder-date, on workdays or non-workdays as indicated. The dependent variable is the time elapsed (or the log of the time elapsed) between a cardholder's arrival at the indicated location—industrial zone or Central Business District (CBD)—and their departure from the same location later on the same day. While this duration measure is at the individual rather than aggregate level, a limitation is that it is observed conditional on the cardholder riding public transit to and from the location, that is, for both legs of the journey. As such, it ignores the positive extensive margin of heat (Table 2 and Figure A.7). All regressions control for daily mean wind speed, day-type FE, and year-month FE. The low-income-group dummy is subsumed in the individual FE. Standard errors, in parentheses, are two-way clustered by cardholder and by date. ***Significant at 1%, **at 5%, *at 10%.

A workday sample mean of 561 minutes (9.4 hours daily) in the industrial zone is (i) comparable to "average weekly paid hours worked per employee" reported for 2016 by MOM (2017) of 48.9 hours for manufacturing (9.8 hours daily) and (ii) somewhat higher than the mean time at work of 444/0.868 = 512 minutes (8.5 hours daily) among workers who went to work on workdays in the Household Travel Survey (Table A.15).

A workday sample mean of 444 minutes (7.4 hours daily) in the CBD is somewhat lower than the average weekly paid hours worked per employee reported by MOM (2017) of 41.1 hours for financial & insurance services (8.2 hours daily). This is consistent with some commuters to the CBD being visitors to the downtown attractions or for business meetings in the CBD, rather than CBD workers.

Table A.12: Heat, time spent in malls, and time away from home

	Duration observed conditional on public transit on both ends of a journey for... ...Time spent in malls (minutes)					...Time away from home (minutes)			
	Adults		Students		Seniors	Adults		Seniors	
	Workdays (1)	Non-workdays (2)	Schooldays (3)	Non-Schooldays (4)	All days (5)	Workdays (6)	Non-workdays (7)	Workdays (8)	Non-workdays (9)
Daily max. heat index (1 °C)	1.0984*	0.2001	0.0057	0.8695***	0.2780	1.7358**	0.2555	0.6257**	-0.2253
	(0.5718)	(0.4041)	(0.6970)	(0.2443)	(0.1754)	(0.8074)	(0.6059)	(0.3016)	(0.4337)
Low-income group × max. heat	0.0294	-0.0565	-0.1737	0.0746	0.0774	-0.1331	-0.1644	0.1465*	0.4781***
	(0.0605)	(0.0898)	(0.2645)	(0.1163)	(0.0673)	(0.0963)	(0.1578)	(0.0850)	(0.1835)
Daily mean PM2.5 (10 μg/m^3)	-0.2785*	0.1367	-0.4711	-0.2899	-0.0067	-0.4959**	-0.3781*	-0.3808***	-0.6679***
	(0.1602)	(0.1816)	(0.3145)	(0.2433)	(0.0075)	(0.1981)	(0.2165)	(0.1297)	(0.1406)
Low-income group × PM2.5	0.0437	0.1451***	0.0834	0.2814***	0.0049	-0.1037**	0.0381	-0.0188	0.2332***
	(0.0535)	(0.0399)	(0.1027)	(0.0800)	(0.0048)	(0.0448)	(0.0473)	(0.0485)	(0.0678)
Daily mean rainfall (1 mm/h)	-1.5503	0.5902	-0.9390	-1.0041	0.3554**	-1.9150	0.3707	-1.5018**	-1.4171
	(1.1956)	(2.6197)	(1.3812)	(1.1013)	(0.1776)	(1.5028)	(3.5361)	(0.6762)	(1.9094)
Low-income group × rainfall	0.5233**	0.3953	-0.5492	0.3995	-0.0018	0.1859	0.0559	0.1824	-0.2443
	(0.2112)	(0.2537)	(0.6112)	(0.3355)	(0.0081)	(0.3526)	(0.4894)	(0.2425)	(0.6431)
Number of obs.	75,993,685	29,634,573	4,139,046	6,849,007	16,682,901	71,830,295	18,946,703	11,924,317	3,965,184
No. of regr. (excl. FE)	20	12	13	17	22	20	12	20	12
Cardholder FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(3,493,028)	(3,049,994)	(354,425)	(411,262)	(502,967)	(3,411,119)	(2,448,414)	(480,828)	(377,640)
Mean dep. var. (levels)	352.4123	266.7208	203.1768	214.6738	223.6018	610.3250	471.1970	465.5607	400.8523

Notes: This table shows results for 9 fixed effects regressions. An observation is a cardholder-date of a specific card type and day type, as indicated. In columns 1-5, the dependent variable is the time spent in malls, defined as the time elapsed between a cardholder's arrival at a commercial area and subsequent departure from that area later on the same day. If there are multiple such mall visits by a cardholder in a day, we sum the duration of stays. When the cardholder lives near a commercial area, we exclude commuting through mall stops that double as his/her home stops, because the cardholder may be commuting home. We define a schoolday based on the public school calendar, ignoring that a minority of schools are private and follow their separate calendar. We caution that cardholder-dates without trips that arrive at and depart from a mall on public transit are dropped from the estimation sample when in reality the mall duration for many of these dropped cardholder-dates may be zero valued, i.e., the cardholder did not visit malls on that day. In columns 6-9, the dependent variable is the time elapsed between an individual resident's first departure from one of his/her home stops to his/her final return to a home stop that same date. We caution that cardholder-dates without trips departing from and returning home on public transit are dropped from the estimation sample when in reality the time away from home for many of these dropped cardholder-dates may be zero valued, i.e., the cardholder did not leave home that day. All regressions control for daily mean wind speed, day-type FE, and year-month FE. The low-income-group dummy is subsumed in the individual FE. Standard errors, in parentheses, are two-way clustered by cardholder and by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.13: Heat and school attendance at a large private school

Student attendance: Outcome is 100 if the enrolled student is present on the school day, and 0 otherwise	(1)	Control PM2.5 (Aug 2012 on) (2)	Control rain and wind (3)	Control mean W_{t-1} to W_{t-3} (4)	Control morning rain (5)	Flexible max. heat bins (6)
Daily max. heat index (1 °C)	0.01	0.01	0.00	0.00	0.00	
(*sample range: 26.0 to 38.5* °C)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	
Daily max. heat index: Mean past 3 calendar days (1 °C)				0.04		
				(0.04)		
Daily max. heat index ∈ [31.5,33.5)						-0.13
°C (*sample density: 33%*)						(0.11)
Daily max. heat index ∈ [33.5,35.5)						-0.14
°C (*sample density: 46%*)						(0.13)
Daily max. heat index ≥ 35.5 °C						-0.04
(*sample density: 12%*)						(0.17)
Daily mean PM2.5 (10 μg/m^3)		-0.06**	-0.05*	-0.05	-0.05*	-0.05*
(*sample range: 6 to 157* μg/m^3)		(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
PM2.5: Mean past 3 calendar days (10 μg/m^3)				-0.01		
				(0.05)		
Daily mean rainfall (1 mm/h)			-0.02	-0.02		-0.03
(*sample range: 0 to 4.9* mm/h)			(0.04)	(0.04)		(0.04)
Rainfall: Mean past 3 calendar days (1 mm/h)				0.07		
				(0.08)		
Morning rain, 6:00-8:00 (1 mm/h)					-0.04***	
(*sample range: 0 to 25.5* mm/h)					(0.01)	
Wind speed			Yes	Yes	Yes	Yes
Wind speed: Mean past 3 days				Yes		
Number of observations	3,857,189	3,590,288	3,590,288	3,585,629	3,590,288	3,590,288
No. of regressors (excl. FE)	103	93	95	99	95	97
Student FE	Yes (9067)	Yes (8913)	Yes (8913)	Yes (8913)	Yes (8913)	Yes (8913)
Mean of dependent variable	95.68	95.64	95.64	95.64	95.64	95.64

Notes: This table shows results for 6 fixed effects regressions. An observation is an enrolled student-schoolday in the period August 2011 to November 2016 for the East campus and August 2012 to November 2016 for the Dover campus. The dependent variable is 100 (%) if the student is present on the schoolday and 0 otherwise. There are 947 schooldays in the sample. Besides student FE, all specifications include day-type FE (day-of-week dummies, dummies for different days surrounding vacations, breaks and public holidays), year-month FE, student age bins (one-year wide), a campus dummy (may vary within student), dummies for the number of siblings enrolled at the school (may vary within student), and an indicator for the student's first year of enrolment (which may coincide with the student's first year in Singapore). Column 2 adds a control for daily mean PM2.5, which is missing prior to August 2012. Column 3 adds controls for daily mean rainfall and wind speed. Column 4 adds controls for the means over the three preceding calendar days of daily maximum heat, daily mean PM2.5, daily mean rainfall, and daily mean wind speed. Because classes at this school all start at 8:00, column 5 replaces daily mean rainfall with morning mean rainfall (6:00 to 8:00). Column 6 repeats the specification of column 3 but replaces the linear daily maximum heat variable with three daily maximum heat bins of width as indicated; the reference bin is daily max. heat index ≤ 31.5 °C, with sample density of 10%. Standard errors, in parentheses, are clustered by date (two-way clusters by date and by student yield very similar standard errors). ***Significant at 1%, **at 5%, *at 10%.

Table A.14: Heat and student test scores at a large private school

Standardized score on the day's test	(1)	(2)	(3)	(4)	(5)
Daily max. heat index (1 °C)	4.90***	3.09*	3.03*	0.73	4.22***
(*sample range: 31.9 to 38.3* °C)	(1.66)	(1.66)	(1.77)	(1.58)	(1.07)
PM2.5 (10 μg/m^3)			8.07	10.77*	8.67
(*sample range: 10.1 to 24.7* μg/m^3)			(9.98)	(6.15)	(5.75)
Daily mean rainfall (1 mm/h)			-0.25	5.25	-0.18
(*sample range: 0 to 1.7* mm/h)			(2.90)	(3.73)	(2.65)
Year FE		Yes	Yes	Yes	
Grade-specific linear time trends				Yes	Yes
Number of observations	29,544	29,544	29,544	29,544	29,544
No. of regressors (excl. FE)	10	15	18	26	21
Student FE	Yes (6004)	Yes (6004)	Yes (6004)	Yes (6004)	Yes (6004)
Mean of dependent variable	1070.41	1070.41	1070.41	1070.41	1070.41

Notes: This table shows results for 5 fixed effects regressions. An observation is a student-date for which an International Schools Assessment (ISA) test was administered between 2015 and 2020, specifically, two dates per campus (Dover and East) for each of the six years, and thus $2 \times 2 \times 6 = 24$ testing dates in all—and always in January or February, thus fixing seasonality. The dependent variable is a student's test score on a date, i.e., the sum of maths and narrative writing scores on a first day of testing or the sum of reading and exposition writing scores on a second day of testing. Besides student FE, all specifications include a day-type dummy (maths and narrative writing tested on a first day vs. reading/exposition writing tested on a second day), a campus dummy, and grade FE (Grades 3 to 10). Column 2 adds year FE. Column 3 adds controls for daily mean PM2.5, rainfall, and wind speed. Column 4 adds grade-specific linear time trends to account for, e.g., any grade-specific inflation in test scores. Standard errors, in parentheses, are clustered by date (two-way clusters by date and by student yield very similar standard errors). ***Significant at 1%, **at 5%, *at 10%.

Table A.15: Heat and economic activity: Evidence from one-day travel diaries

	Binary dependent variable (Yes=100, No=0)					Dependent variable is a workday's minutes...			
	Left home (1)	Went to Work (2)	Shopped/ dined (3)	Traveled by car/taxi (4)	Walked/ cycled (5)	Away from home (6)	At work (7)	Shopping/ dining (8)	On other activities (9)
Daily max. heat index (1 °C)	0.1766	-0.0212	0.0335	0.2639	-0.1628	1.0188	0.5169	0.2383	-0.1527
	(0.1539)	(0.1531)	(0.1869)	(0.1971)	(0.1658)	(1.0443)	(1.3362)	(0.2302)	(0.3214)
Low-income group × max. heat	0.3430	0.0610	0.7584**	-0.5002**	0.1425	1.7405	-1.2061	0.5021	0.3488
	(0.2258)	(0.2311)	(0.3022)	(0.2513)	(0.2656)	(1.7216)	(1.6801)	(0.3727)	(0.4747)
PM2.5 (10 μg/m^3)	-0.0172	0.0470	-0.0966*	-0.1043*	0.0137	-0.3916	0.2376	-0.1169*	-0.0030
	(0.0492)	(0.0454)	(0.0535)	(0.0622)	(0.0490)	(0.3711)	(0.4135)	(0.0619)	(0.0756)
Low-income group × PM2.5	-0.0249	0.0742	-0.0319	0.1642**	0.0011	0.6369	0.4237	-0.0646	-0.0003
	(0.0534)	(0.0793)	(0.0781)	(0.0808)	(0.0755)	(0.4273)	(0.5838)	(0.0909)	(0.1476)
Rainfall (1 mm)	-0.0398	-0.0004	-0.0152	0.0404	-0.0247	-0.1081	-0.0912	0.0094	-0.0069
	(0.0255)	(0.0214)	(0.0260)	(0.0345)	(0.0268)	(0.1291)	(0.2166)	(0.0342)	(0.0433)
Low-income group × Rainfall	-0.0295	0.0012	0.0162	-0.0336	-0.0215	0.2034	-0.2091	-0.0047	0.0832
	(0.0385)	(0.0359)	(0.0449)	(0.0456)	(0.0476)	(0.2768)	(0.2772)	(0.0531)	(0.0738)
Number of observations	59,091	28,717	59,091	59,091	59,091	51,329	27,495	58,252	56,871
Number of regressors	39	39	39	39	39	39	39	39	39
Mean of dep. variable in levels	82.7893	86.8127	24.2033	25.9955	17.7337	473.5654	444.3602	22.1706	27.6394

Notes: This table shows results for 9 OLS regressions. An observation is a respondent-workday (a single workday per respondent) in the two Household Travel Survey waves from June 25, 2012 to May 30, 2013 and August 19, 2016 to June 20, 2017. There are 415 workdays in the combined sample. In columns 2 and 7 we restrict estimation to respondents whose work status is employed, self-employed, or volunteer worker (Singapore's labour force participation is 68%, and the full sample includes elderly and children outside the labour force); for clarity, 87% of workers went to work on the surveyed workday. In columns 1-5, the dependent variable is 100 (%) if the respondent left home, travelled to work, travelled to shop/dine, travelled in a car (including taxi), or walked/cycled to a destination on the day, and 0 otherwise. In columns 6-9, the dependent variable is the time (in minutes) in the indicated activity (0 minute if no trip for that purpose was reported). There are fewer observations in columns 6 and 8-9 than in column 1, and in column 7 than in column 2, due to one-way trips in the records. All regressions control for daily mean wind speed, day-type FE, year-month FE, and a low-income-group dummy; similar to the commuter sample, low-income is 1 if more than 40% of dwellings in the respondent's residential building are 1-3 room apartments, and 0 otherwise. The joint impact of heat and its interaction with low-income is significant at the 1% level in column 3, at 5% in columns 1 and 8, at 10% in column 6, and insignificant in columns 2, 4-5, 7, and 9. Standard errors, in parentheses, are clustered by date. ***Significant at 1%, **at 5%, *at 10%.

Table A.16: The impact of heat on retail sales volume

Log of the monthly sectoral index	All 18 sectors including F&B (1)	6 Food & Beverage sectors No heterogeneity (2)	With heterogeneity (3)
One-month mean of daily max. heat index (1 °C)	-0.0008 (0.0017)	0.0016 (0.0025)	-0.0104 (0.0147)
Eateries dummy × max. heat			0.0188 (0.0188)
One-month mean of pollution index × Pre April 2014 dummy (range 24 to 84 points)	0.0002 (0.0002)	0.0002 (0.004)	-0.0050 (0.0034)
Eateries dummy × pollution index pre April 2014			0.0082* (0.0049)
One-month mean of pollution index × Post April 2014 dummy (range 37 to 113 points)	0.0003 (0.0002)	0.0003** (0.0002)	-0.0025** (0.0010)
Eateries dummy × pollution index post April 2014			0.0042*** (0.0006)
One-month mean of rainfall (1 mm/h)	-0.0707*** (0.0219)	0.0031 (0.0334)	-0.0209 (0.0408)
Eateries dummy × rainfall			0.0385 (0.0276)
Number of observations	4956	1632	1632
Number of regressors (excl. sector FE)	39	39	43
Sector FE	Yes (18)	Yes (6)	Yes (6)

Notes: This table shows results for 3 OLS regressions. An observation is a retail sector-month. The dependent variable is the log of the monthly index (2014 = 100, by sector) of chained volume for the sample period January 1997 to December 2020. See the Appendix for a list of the 18 retail sectors; two sectors (Department Stores and Food Caterers) have partial availability. All regressions control for one-month mean of wind speed, month FE, and year FE. We control for pollution using the NEA's Pollution Standards Index because PM2.5 records begin only in 2009. As explained in the Appendix, our pollution covariates (the pollution index interacted with a pre-April 2014 dummy and the pollution index interacted with a post-April 2014 dummy) account for a major change in the pollution index's composition on April 1, 2014. Column 1 includes all 18 retail sectors. Columns 2-3 restrict the estimation sample to the 6 Food & Beverage (F&B) sectors. In column 3, we include interact a subset of environmental conditions (heat, pollution, rainfall) and a dummy equal to 1 for the F&B sectors comprising eateries (services that refer to the sales of prepared food and drinks for in-premises consumption, e.g., Restaurants) and 0 for the non-eateries sectors (retail stores not meant for immediate consumption within their premises, e.g., Supermarkets). The eateries dummy is subsumed in the sector FE. Robust standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

Table A.17: The impact of heat on health polyclinic visits and disease incidence

Panel 1(a): Weekly polyclinic visits (in log.) with concurrent heat and PM2.5

	Upper respiratory infection	Diarrhoea	Conjunctivitis	Chickenpox	Sum of 4 categories
1-week mean of daily max. heat index (1 °C)	-0.010***	0.002	-0.010**	-0.019**	-0.008***
	(0.004)	(0.003)	(0.005)	(0.008)	(0.003)
1-week mean of PM2.5 (10 μg/m^3)	0.010***	-0.021***	0.018***	0.000	0.006**
	(0.003)	(0.002)	(0.004)	(0.006)	(0.003)
Observations	383	383	383	383	383
R-squared	0.676	0.841	0.416	0.478	0.718
Number of regressors	25	25	25	25	25
Mean dep. var. in levels (visits/week)	19,381.81	3633.43	621.67	100.38	23,737.29

Panel 1(b): Weekly polyclinic visits (in log.) with concurrent heat and PM2.5, and their lags

	Upper respiratory infection	Diarrhoea	Conjunctivitis	Chickenpox	Sum of 4 categories
Sum of concurrent 1-week mean of daily max. heat index (1 °C) and 1-week lag	-0.020***	0.004	-0.019***	-0.027***	-0.016***
	(0.005)	(0.003)	(0.006)	(0.010)	(0.004)
Sum of concurrent 1-week mean of PM2.5 (10 μg/m^3) and 1-week lag	0.010**	-0.025***	0.018***	-0.003	0.005
	(0.004)	(0.003)	(0.005)	(0.007)	(0.004)
Observations	382	382	382	382	382
R-squared	0.690	0.844	0.425	0.485	0.730

Panel 2(a): Weekly incidence (in log.) with concurrent heat and PM2.5

	Hand-foot-and-mouth disease	Dengue	Salmonella	Sum of all 21 diseases reported
1-week mean of daily max. heat index (1 °C)	0.003	0.067***	0.031***	0.017
	(0.013)	(0.020)	(0.010)	(0.012)
1-week mean of PM2.5 (10 μg/m^3)	-0.028**	0.042***	-0.003	-0.000
	(0.012)	(0.009)	(0.007)	(0.007)
Observations	383	383	379	383
R-squared	0.886	0.807	0.213	0.709
Number of regressors	25	25	25	25
Mean dep. var. in levels (cases/week)	546.78	230.87	36.78	836.16

Panel 2(b): Weekly incidence (in log.) with concurrent heat and PM2.5, and their lags

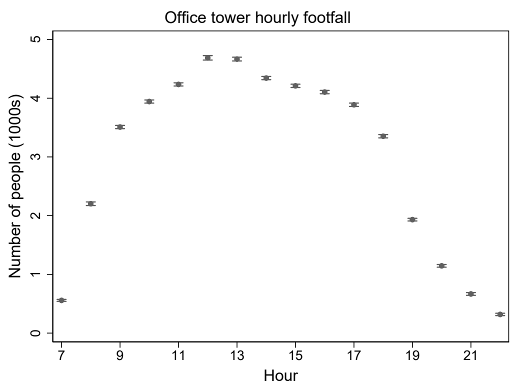
	Hand-foot-and mouth disease	Dengue	Salmonella	Sum of all 21 diseases reported
Sum of concurrent 1-week mean of daily max. heat index (1 °C) and 1-week lag	0.002	0.114***	0.049***	0.026*
	(0.015)	(0.024)	(0.015)	(0.014)
Sum of concurrent 1-week mean of PM2.5 (10 μg/m^3) and 1-week lag	-0.043***	0.045***	-0.006	-0.004
	(0.010)	(0.010)	(0.010)	(0.008)
Observations	382	382	378	382
R-squared	0.888	0.815	0.221	0.710

Notes: This table shows results for 18 OLS regressions. An observation is an epidemiological week, starting on a Sunday and ending the subsequent Saturday. The sample period spans (the week ending) September 1, 2012 to December 28, 2019 (constrained by PM2.5 availability). In panel 1, the dependent variable is log weekly polyclinic visits by disease type or their sum (only four categories are reported). In panel 2, the dependent variable is log weekly incidence by disease type (among the three more prevalent) or the sum of all 21 continuously reported diseases. In each panel, the first set of regressions (a) includes concurrent heat and PM2.5 whereas the second set of regressions (b) additionally includes one-week heat and PM2.5 lags (and we report the sum of the coefficient estimates of the variable and its lag). The key regressor of interest, one-week mean of the daily maximum heat index, exhibits a range of 30.4 to 40.6 °C. All regressions control for concurrent wind speed, share of day type (Sundays/public holidays, school vacations), month FE (based on the last day of the week), and year FE. The data are from Singapore's Ministry of Health. Robust standard errors are in parentheses. ***Significant at 1%, **at 5%, *at 10%.

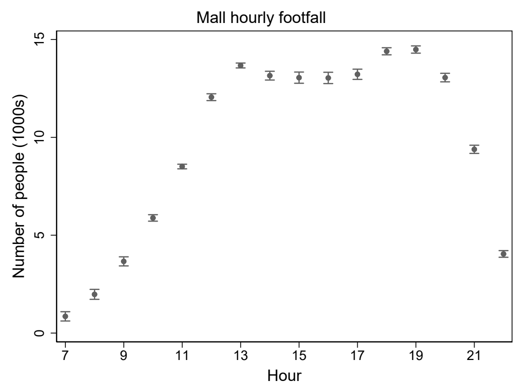
Table A.18: The impact of heat on all-cause mortality and infant mortality

	Log deaths	Log infant deaths
1-month mean of daily max. heat index (1 °C)	0.011	0.003
	(0.008)	(0.091)
1-month mean of PM2.5 (10 μg/m^3)	0.002	0.024
	(0.005)	(0.056)
1-month rainfall (mm)	0.002	-0.013
	(0.003)	(0.031)
Observations	88	88
R-squared	0.770	0.268
Number of regressors	25	25
Mean of dep. var. in levels (deaths/month)	1680.78	7.47

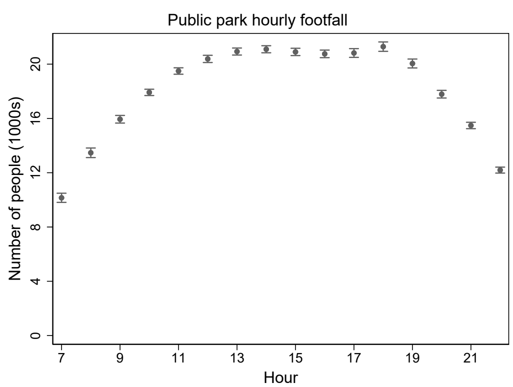
Notes: This table shows results for 2 OLS regressions. An observation is a calendar month. The sample period spans September 2012 to December 2019 (constrained by PM2.5 availability). The dependent variable is log monthly deaths or log monthly infant deaths. The key regressor of interest, one-month mean of the daily maximum heat index, exhibits a range of 32.1 to 39.7 °C. Regressions control for concurrent rainfall and wind speed, share of day type (Sundays/public holidays, school vacations), month FE, and year FE. The data are from Singapore's Registry of Births and Deaths. Robust standard errors are in parentheses.



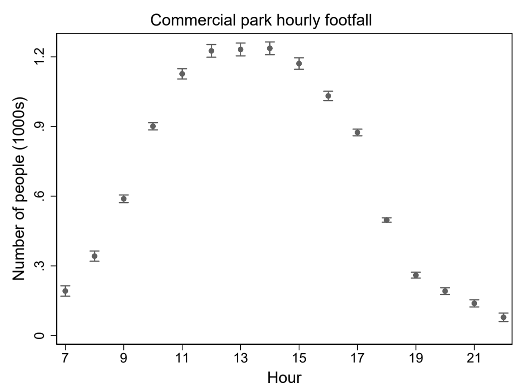
(a) Office towers



(b) Malls

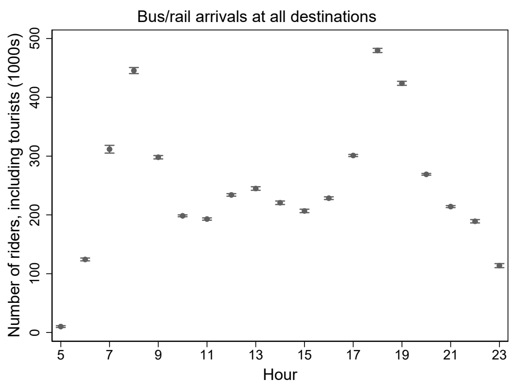


(c) Public parks

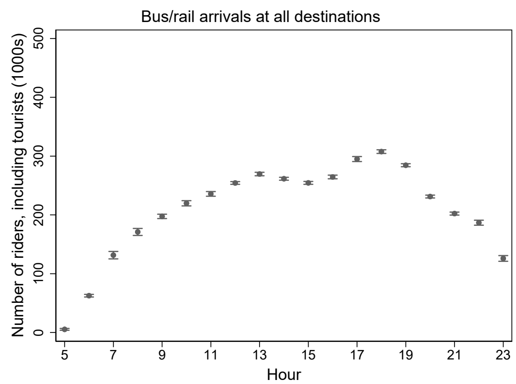


(d) Commercial parks

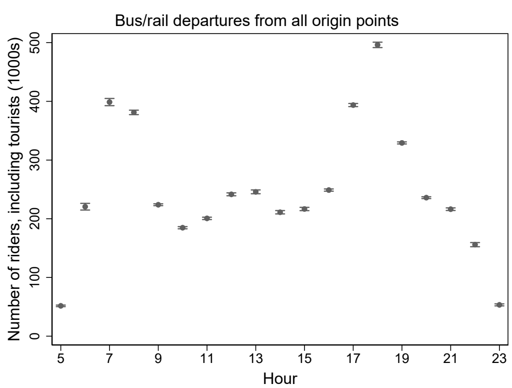
Figure A.1: Footfall's diurnal cycle, by location type. We generate separate time series by summing footfall within location type, i.e., (a) across three office towers, (b) across five malls, (c) across two public parks, and (d) across two commercial parks. An observation in these time series is a date-hour (within location type). Taking each time series, we regress footfall on hour fixed effects (FE), day-type FE, and year-month FE, and plot 95% CI for the hour-by-hour predictions (holding other covariates at their observed values). The office tower footfall regression restricts the sample to workdays. The sample period is June to August of 2016 and 2017.



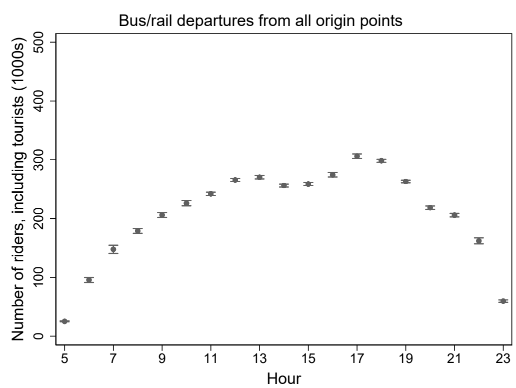
(a) All arrivals, workdays



(b) All arrivals, non-workdays

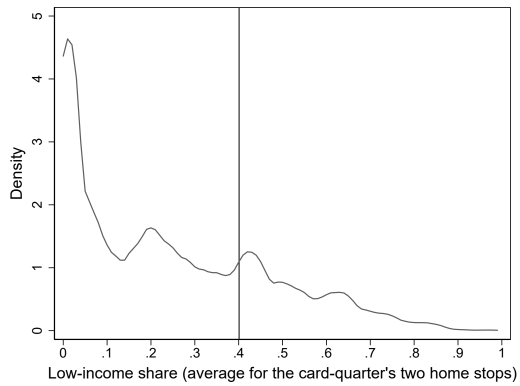


(c) All departures, workdays

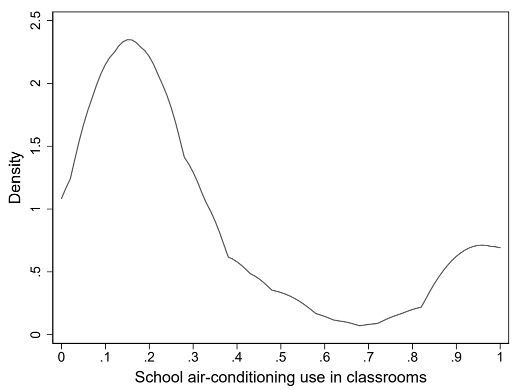


(d) All departures, non-workdays

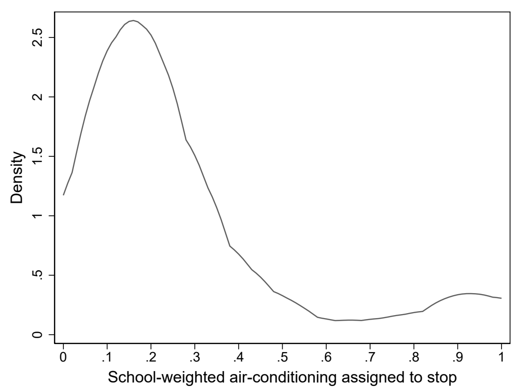
Figure A.2: Bus/rail arrivals at any destination point and departures from any origin point on public transit, separately for workdays and non-workdays. Here we do not restrict trips to cardholders with a likely residential location but consider all travel linked to a transit farecard (see Table A.2 describing the raw data with 7.2 million cards used in 2015 and 7.3 million in 2016). This includes trips by tourists who purchased transit farecards during their visits. We generate separate time series by summing arrivals or departures across Singapore within date-hour (by workdays vs. non-workdays). Taking each time series, we regress the number of riders on hour FE, day-type FE, and year-month FE, and plot 95% CI for the hour-by-hour predictions. Day-type FE indicate that there is more commuting on Friday than on Monday, on Saturday than on Sunday/public holiday, and when schools are in session than when schools are on vacation.



(a) Low-income share, distribution over commuters

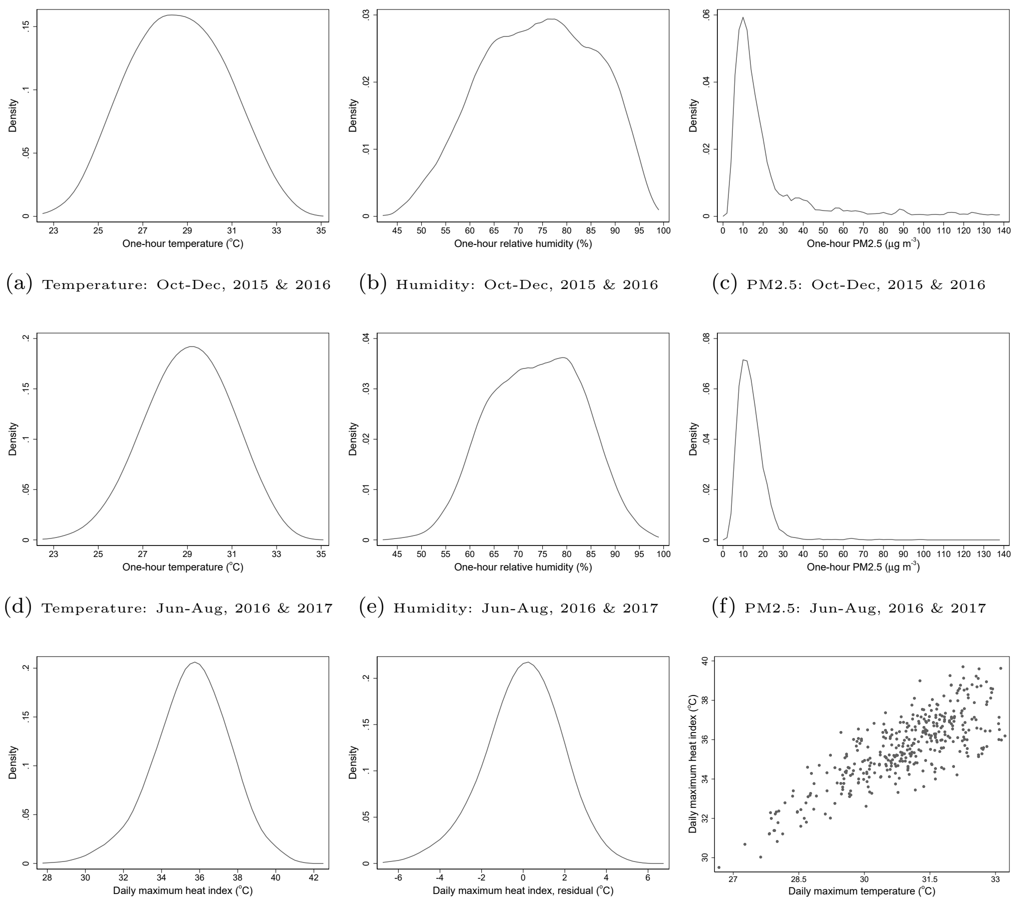


(b) Air-conditioner use, distribution over schools



(c) Air-conditioner use, distribution over school stops

Figure A.3: Heterogeneity measures used to analyse the commuter data. (a) Distribution of the low-income share across resident commuters who are active during daytime hours (1=all dwellings in the neighbourhood are 1-3 room apartments). An observation is a card-quarter pair (Table A.2 reporting 3.2 million cards in Oct-Dec 2015 and 3.2 million cards in Oct-Dec 2016). The sampling procedure finds each card's (1) modal first-departure stop and (2) modal last-arrival stop over travel dates in the quarter, each stop described by the low-income share of the residential population it serves. A card-quarter's low-income share is then the average low-income share for these two "home" stops. The 75th percentile across card-quarters in the sample is 0.40, marked in the figure. We assign the one-quarter of card-quarters on the right-hand side of the vertical line to the low-income group. Table A.2 shows that this 75th percentile is not sensitive to how we define resident commuters. (b,c) Distribution of air conditioning in "classrooms in which instruction took place" across (b) 176 middle/high schools (1=fully air conditioned, median over multiple survey responses for the same school) and (c) 1163 bus/rail stops that serve these schools (1=all schools served by the stop are fully air conditioned). The distribution across stops (and regression estimates) are similar if instead of land area we use the number of survey responses as school weights.

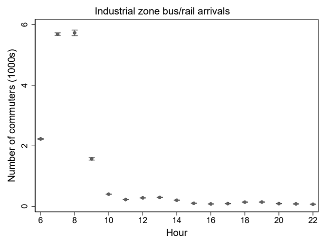


(a) Temperature: Oct-Dec, 2015 & 2016 (b) Humidity: Oct-Dec, 2015 & 2016 (c) PM2.5: Oct-Dec, 2015 & 2016

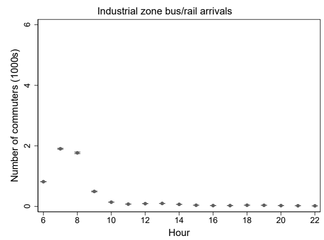
(d) Temperature: Jun-Aug, 2016 & 2017 (e) Humidity: Jun-Aug, 2016 & 2017 (f) PM2.5: Jun-Aug, 2016 & 2017

(g) Max. heat: Both periods (h) Max. heat residuals: Both periods (i) Heat vs. temperature: Both periods

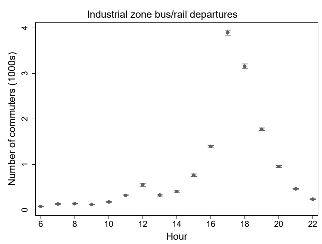
Figure A.4: Environmental conditions in our commuter (first row) and footfall (second row) samples: (a) and (d) show one-hour air temperature (°C), (b) and (e) one-hour relative humidity (%), (c) and (f) one-hour PM2.5 (μg/m^3). An observation in (a) to (f) is a date-hour pair in the indicated sample restricted to hours of most economic activity (6:00-22:59). An observation in (g) to (i) is a date in our two samples. From the one-hour temperature and one-hour relative humidity we compute the one-hour heat index and, in (g), show the daily maximum heat index (°C, maximum taken over the 24 hours within a date). Daily maximum heat index residuals in (h) partial out year-month means to account for the mild seasonality observed in the tropics and year-to-year variation; substantial variation in the daily maximum heat remains. (i) compares the daily maximum heat index (°C) to the daily maximum temperature (°C, maximum taken over the 24 hours within a date); the latter does not account for humid conditions.



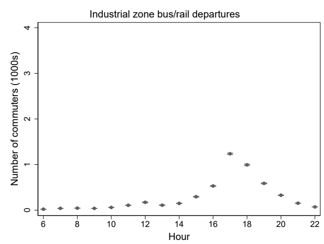
(a) Industry arrivals, high income



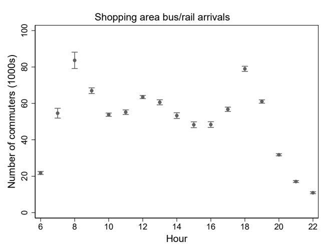
(b) Industry arrivals, low income



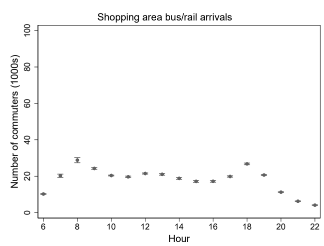
(c) Industry departures, high income



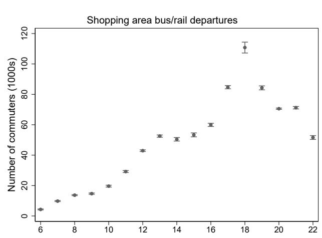
(d) Industry departures, low income



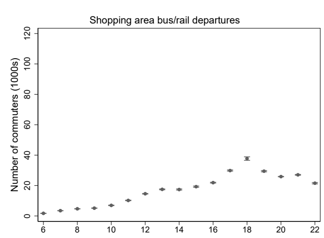
(e) Shopping arrivals, high income



(f) Shopping arrivals, low income

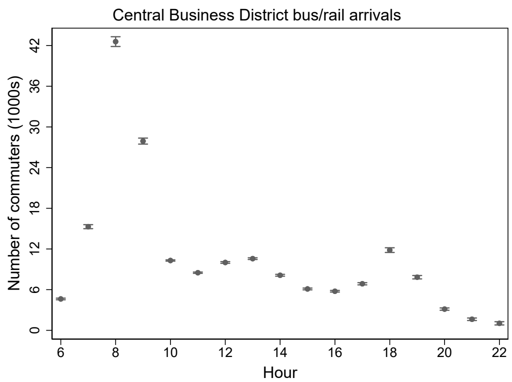


(g) Shopping departures, high income

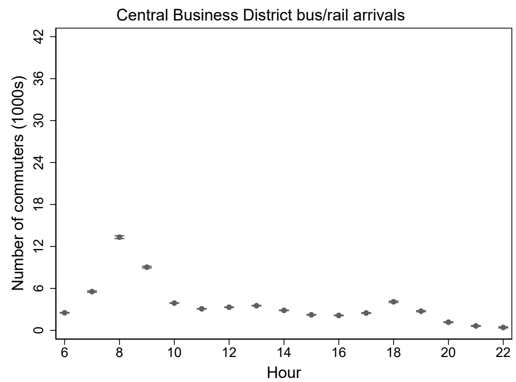


(h) Shopping departures, low income

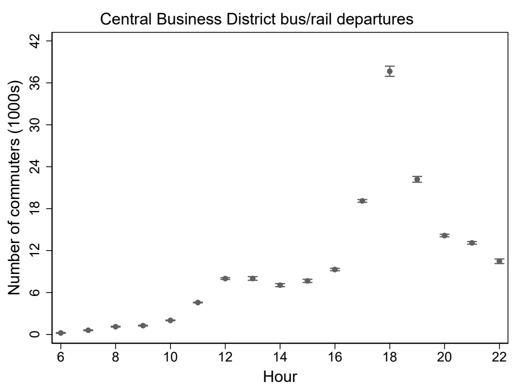
Figure A.5: Bus/rail arrivals to and departures from: (a) to (d) the industrial zone, and (e) to (h) 80 consolidated commercial areas across Singapore and their adjacent office towers, by income group (in the resident trip sample). We generate separate time series by summing arrivals or departures within location type, i.e., industrial zone or across commercial areas (and income group). An observation in these time series is a date-hour (within location type and income group). Taking each time series, we regress the number of commuters on hour FE, day-type FE, and year-month FE, and plot 95% CI for the hour-by-hour predictions. The industry commuter regressions restrict the sample to workdays.



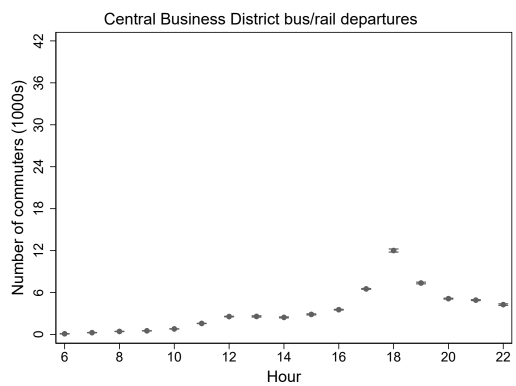
(a) CBD arrivals, high income



(b) CBD arrivals, low income

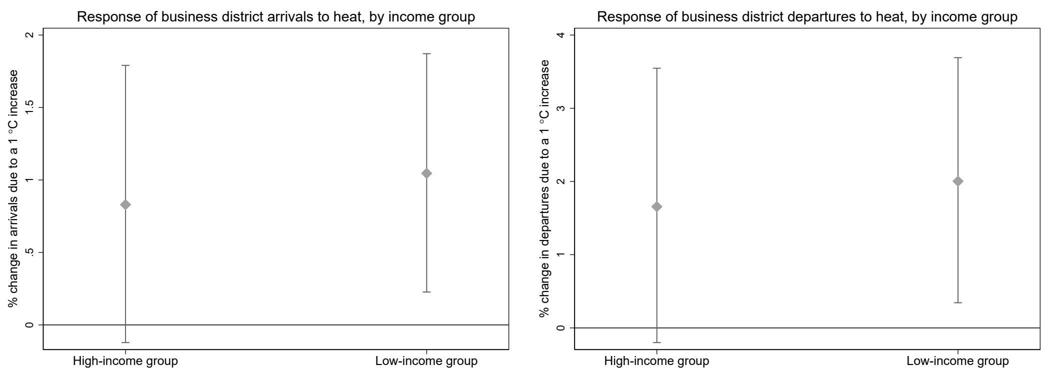


(c) CBD departures, high income



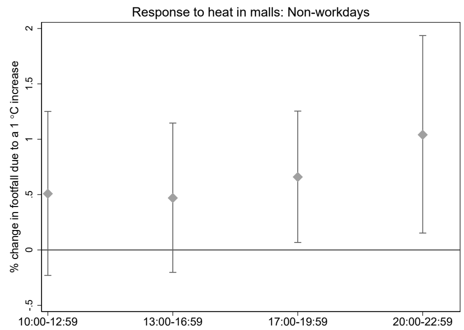
(d) CBD departures, low income

Figure A.6: Bus/rail arrivals to and departures from the Central Business District (CBD) on workdays, by income group (in the resident trip sample; less than 1% of card-quarters reside in the CDB and here we drop these trips). We generate separate time series by summing arrivals or departures across the 76 bus stops and 9 rail stations in the “downtown core” area. An observation in these time series is a date-hour (within income group). Taking each time series, we regress the number of commuters on hour FE, day-type FE, and year-month FE, and plot 95% CI for the hour-by-hour predictions.

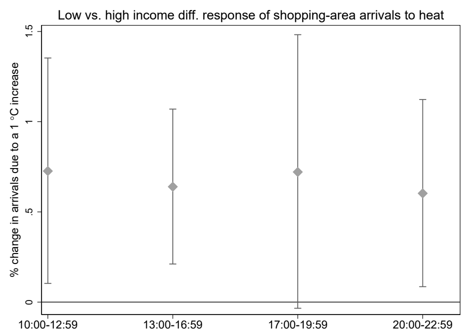


(a) CBD, bus/rail arrivals, workdays 7:00-9:59 (b) CBD, bus/rail depart., workdays 17:00-19:59

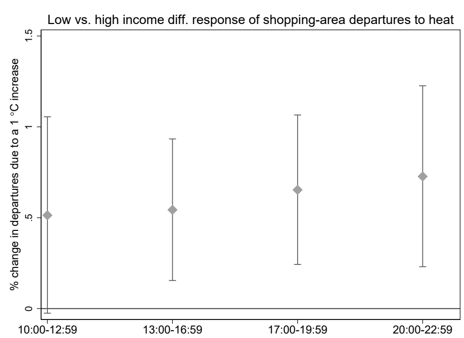
Figure A.7: The impact of heat on public transit to and from the Central Business District (CBD) on workdays. Panel a shows impacts, by income group, on arrivals during the morning peak, i.e., the 7:00-9:59 time interval. Panel b shows impacts on departures during the evening peak, i.e., the 17:00-19:59 time interval. Source: Regression specifications similar to those reported in Table 2, in which the dependent variable is the log hourly number of bus/rail arrivals or departures in the "downtown core" area, and an observation is a date-hour-income group on workdays during the indicated time interval. The plots show 95% CI on the coefficient on the daily maximum heat index, β_{heat}, and on the sum of this coefficient and the interaction coefficient, $\beta_{heat} + \beta_{heat,lowIncome}$, converted from log points to a percent change.



(a) Malls, footfall, non-workdays

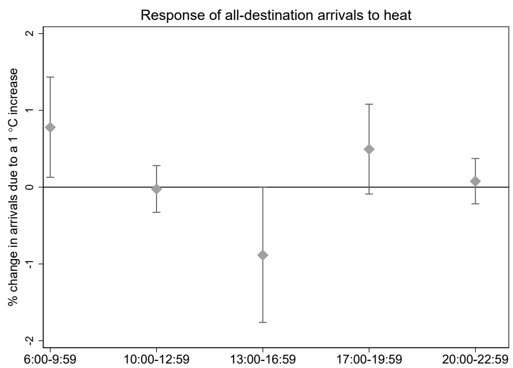


(b) Commercial areas, bus/rail arrivals, non-workdays

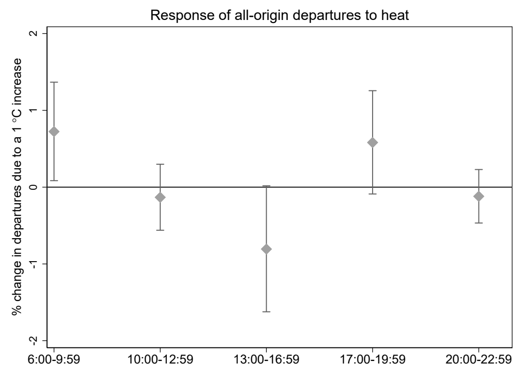


(c) Commercial areas, bus/rail departures, non-workdays

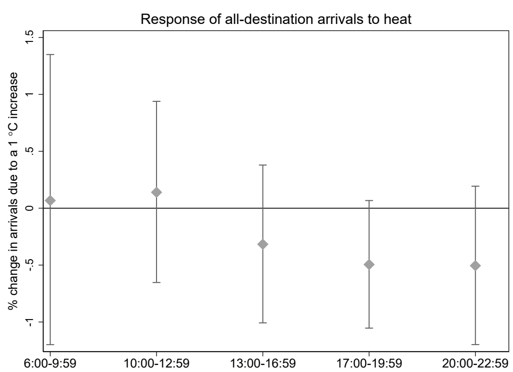
Figure A.8: The impact of heat on indoor activities—and public transit to these activities—during weekends and public holidays, for different time intervals. Source: Regression specifications reported in Table A.6. The plots show 95% CI, converted from log points to a percent change. Panels b and c show the differential public transport demand response to heat by low-income neighbourhood residents relative to the high-income group, i.e., 95% CI on the coefficient $\beta_{heat,lowIncome}$ as reported in Table A.6 (converted to a percent change).



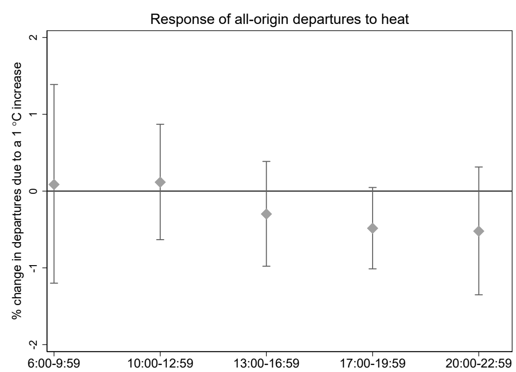
(a) All areas, bus/rail arrivals, workdays



(b) All areas, bus/rail departures, workdays

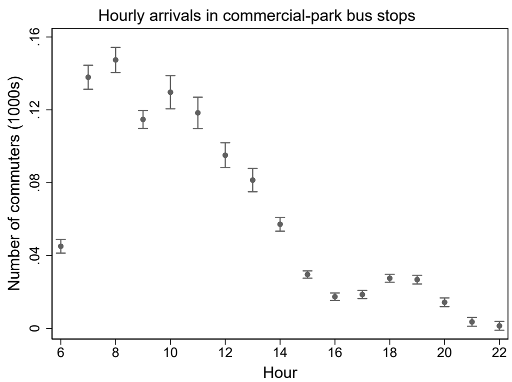


(c) All areas, bus/rail arrivals, non-workdays

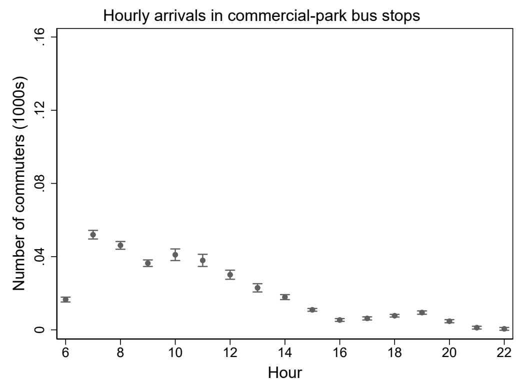


(d) All areas, bus/rail departures, non-workdays

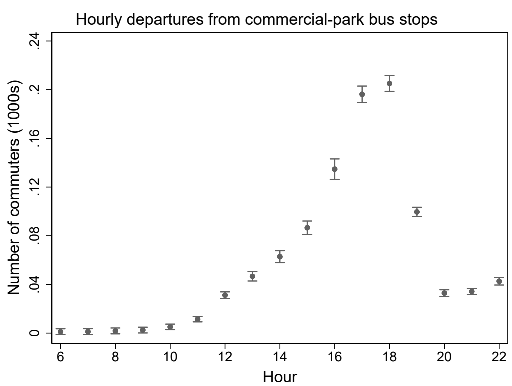
Figure A.9: The impact of heat on public transit ridership at the citywide level, for different time intervals. The top panels show estimates based on workday observations and the bottom panels show non-workdays. Source: Regression specifications similar to those reported in Table 2 implemented on date-hour level time series of arrivals aggregated over all destination points (left panels) or departures aggregated over all origin points (right panels). Here we do not restrict trips to cardholders with a likely residential location but consider all travel linked to a transit farecard (see Table A.2 describing the raw data with 7.2 million cards used in 2015 and 7.3 million in 2016). This includes trips by tourists who purchased transit farecards during their visits. See Figure A.2 summarizing all trips in the raw data. The plots show 95% CI on the coefficient on the daily maximum heat index, converted from log points to a percent change.



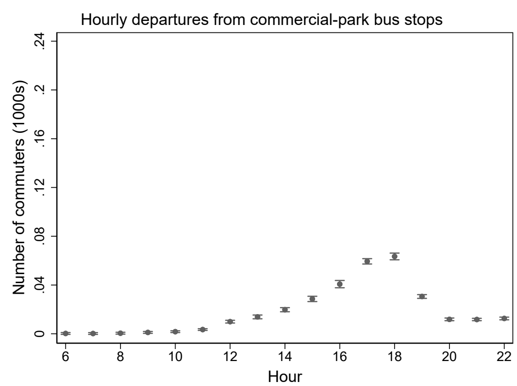
(a) Commercial-park arrivals, high income



(b) Commercial-park arrivals, low income

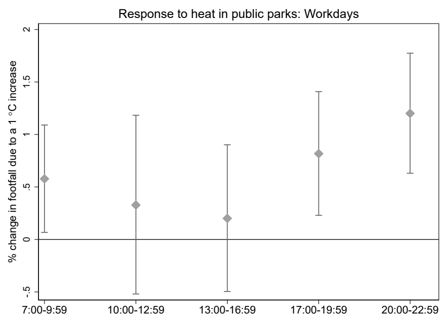


(c) Commercial-park departures, high income

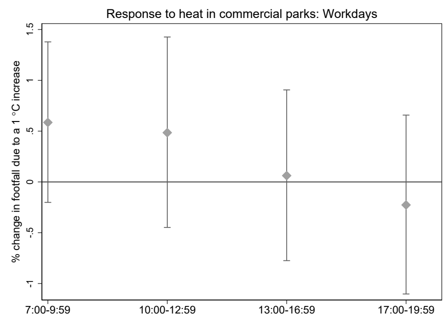


(d) Commercial-park departures, low income

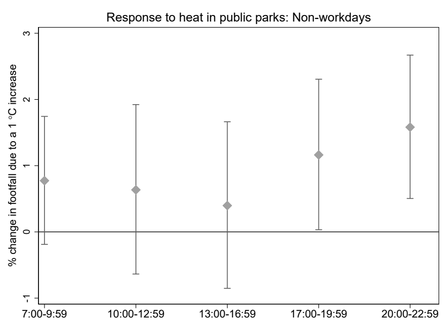
Figure A.10: Arrivals to and departures from bus stops serving commercial parks, by income group (in the resident trip sample). We generate separate time series by summing arrivals or departures across five stops serving the Jurong Bird Park (and surrounding industry) and the Singapore Zoo (in an isolated area). An observation in these time series is a date-hour (within income group). Taking each time series, we regress the number of commuters on hour FE, day-type FE, and year-month FE, and plot 95% CI for the hour-by-hour predictions. Neither location was served by rail. Compared with open-access public parks, these commercial venues are expensive to visit and attract a large share of tourists who often arrive by private tour bus or taxi (not observed in the commuter data). In panels a and b, arrivals before 9:00 are concentrated in the two more industrial bus stops nearby the Bird Park; arrivals peak at 10:00 in a subsample that excludes these two stops (21301 and 21309). The slight increase in arrivals around 17:00 is likely due to the Night Safari, a relatively small operation that is adjacent to the Singapore Zoo.



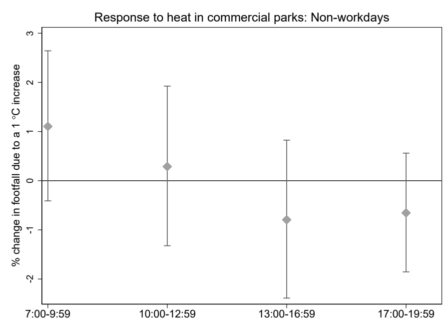
(a) Public parks, footfall, workdays



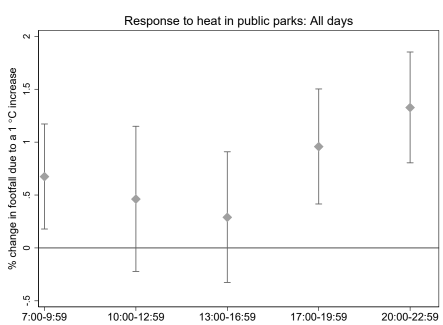
(b) Commercial parks, footfall, workdays



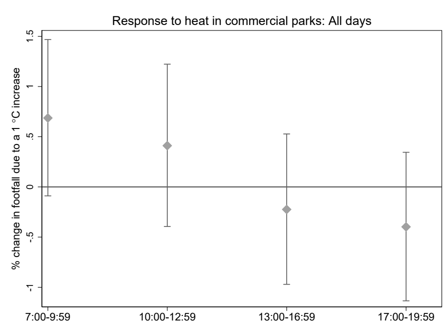
(c) Public parks, footfall, non-workdays



(d) Commercial parks, footfall, non-workdays

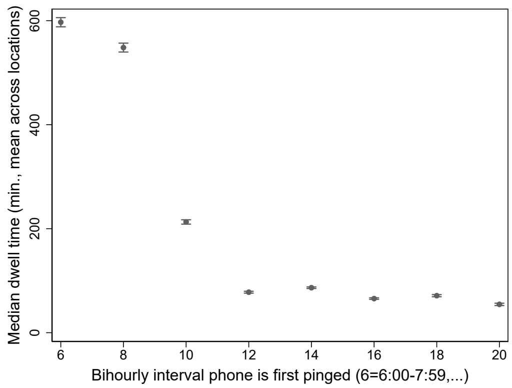


(e) Public parks, footfall, all days

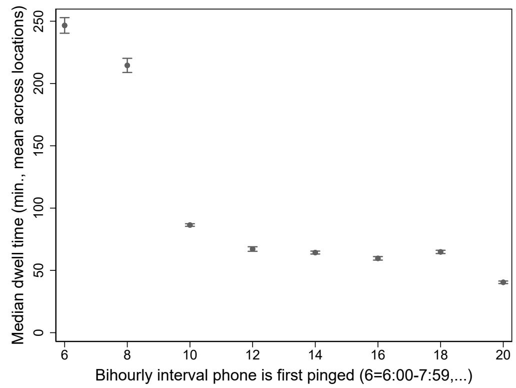


(f) Commercial parks, footfall, all days

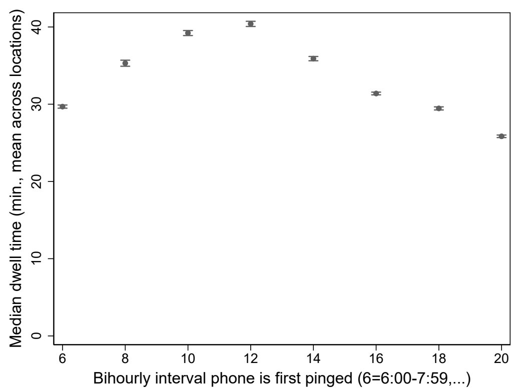
Figure A.11: The impact of heat on outdoor leisure-related activities, for different time intervals. The top panels show estimates based on workday observations, middle panels show non-workdays, and the bottom panels are based on a pooled sample of workdays and non-workdays. The Jurong Bird Park and the Singapore Zoo close in the evening so the right panels use a sample with hourly observations no later than 19:00. Source: Regression specifications similar to those reported in Table 1 (with narrower time intervals). The plots show 95% CI, converted from log points to a percent change.



(a) Office towers, median dwell time

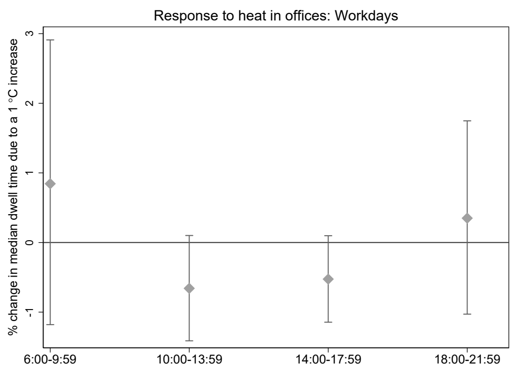


(b) Malls, median dwell time

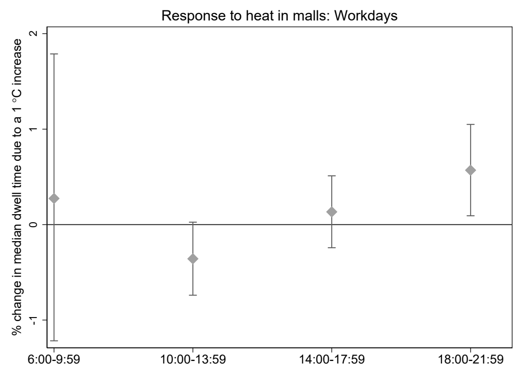


(c) Public parks, median dwell time

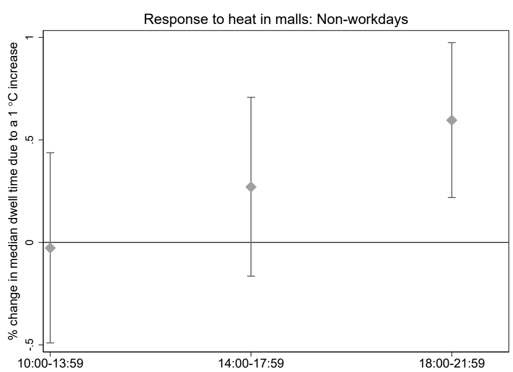
Figure A.12: Dwell time's diurnal cycle, by location type. The dwell time complements the footfall measure described in Figure A.1. It captures the length of time, in minutes, that a phone remains in a location, pinging a triangulation of cell phone towers. The initial ping determines the bihourly interval in which it contributes to the data. Pinged phones with dwell time less than 5 minutes are excluded, as these may reflect passing foot traffic. For each location, date, bihour triple (e.g., City Square Mall, 6/1/2016, 18:00-19:59), we observe the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution of dwell time for phones first pinged at the location-date-bihour. We generate separate time series by taking the mean across locations of the median dwell time for each date-bihour pair. An observation in these time series is a date-bihour (within location type). Taking each time series, we regress (the mean of the median) dwell time on bihour FE, day-type FE, and year-month FE, and plot 95% CI for the bihour-by-bihour predictions (holding other covariates at their observed values). The office tower dwell time regression restricts the sample to workdays. The sample period is June to August of 2016 and 2017.



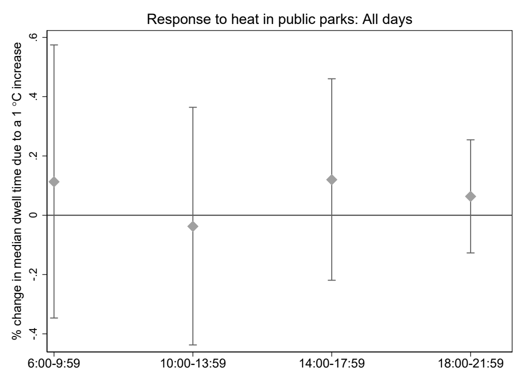
(a) Office towers, dwell time, workdays



(b) Malls, dwell time, workdays

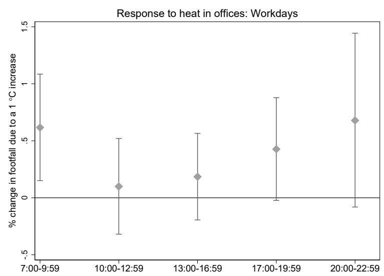


(c) Malls, dwell time, non-workdays

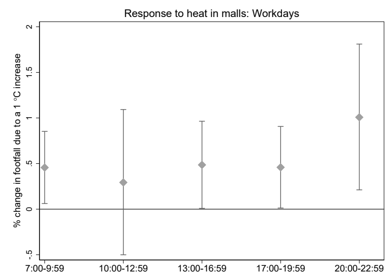


(d) Public parks, dwell time, all days

Figure A.13: The impact of heat on dwell time in offices, malls, and parks, as described in Figure A.12, for different time intervals at which persons carrying phones enter a location. Source: Regression specifications similar to those reported in Table 1 except that the dependent variable is the log of median dwell time and an observation is a location-date-bihour triple (with the estimation sample based on narrower time intervals, as indicated). The plots show 95% CI on the coefficient on the daily maximum heat index, converted from log points to a percent change. We verified that results based on the 25th or 75th, rather than 50th, percentile of the dwell time distribution are similar.

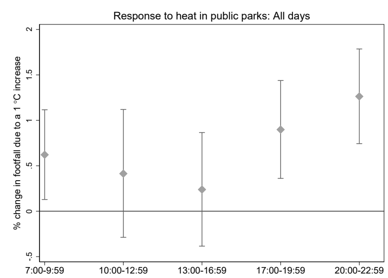


(a) Office towers, footfall, workdays

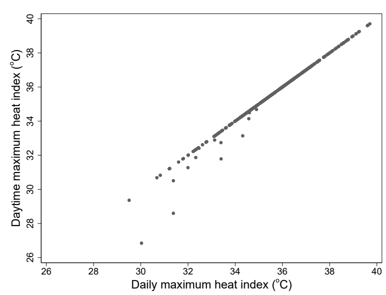


(b) Malls, footfall, workdays

(c) Malls, footfall, non-workdays

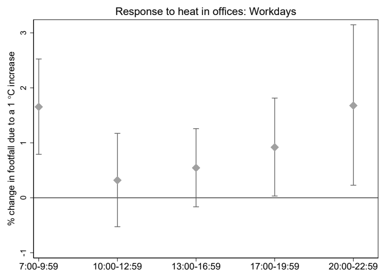


(d) Public parks, footfall, all days

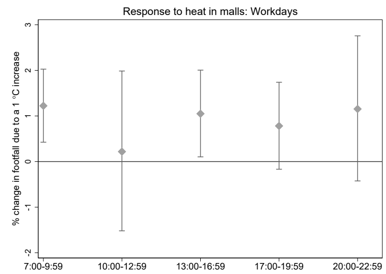


(e) Daytime max vs. daily 24-hour max heat

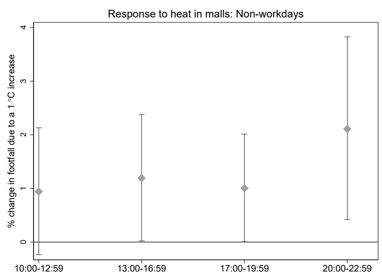
Figure A.14: Sensitivity analysis: Thermal discomfort. Instead of the maximum heat index over the 24 hours in a day, we specify the "daytime" maximum heat index, with daytime hours defined between 6:00 and 22:00. In Singapore, relative humidity rises over the afternoon and night and falls during the morning (sample means are 86% at 6:00 and 66% at 14:00). Due to the high humidity after midnight, for 4% of days the heat index is maximal before 6:00 (otherwise heat usually peaks between 12:00 and 15:00). Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daytime maximum heat index, converted from log points to a percent change. The bottom panel plots the daytime (6:00-22:00) maximum heat index (this sensitivity analysis) against the 24-hour daily maximum heat index (main specification) for days in our sample.



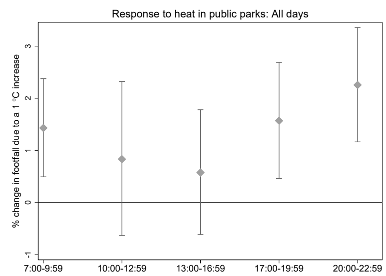
(a) Office towers, footfall, workdays



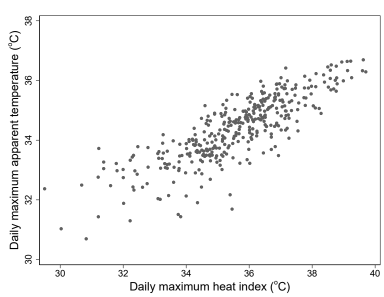
(b) Malls, footfall, workdays



(c) Malls, footfall, non-workdays

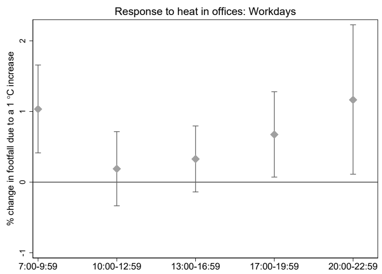


(d) Public parks, footfall, all days



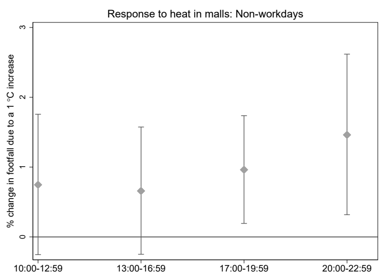
(e) Apparent temperature vs. heat index

Figure A.15: Sensitivity analysis: Thermal discomfort. Instead of the daily maximum heat index, we specify the daily maximum "apparent temperature." Apparent temperature increases in temperature and relative humidity and decreases in wind speed (Steadman, 1994; ABM, 2010). In Singapore, wind tends to be higher in the afternoon relative to the morning and night. We compute the one-hour apparent temperature from one-hour air temperature, relative humidity, and wind speed, and take the maximum apparent temperature value over the 24 hours of each day. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum apparent temperature, converted from log points to a percent change. We control for wind speed in the footfall regression equation but findings are similar if we drop this regressor. The bottom panel plots the daily maximum apparent temperature (this sensitivity analysis) against the daily maximum heat index (main specification) for days in our sample.

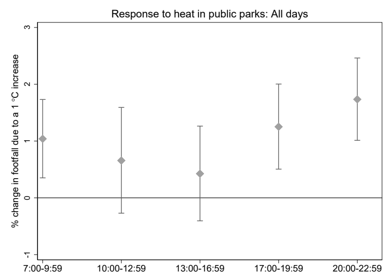


(a) Office towers, footfall, workdays

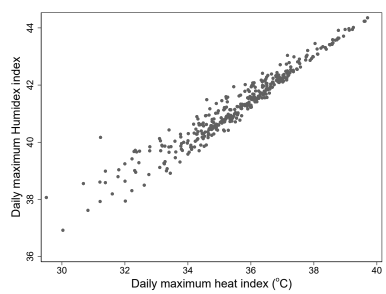
(b) Malls, footfall, workdays



(c) Malls, footfall, non-workdays

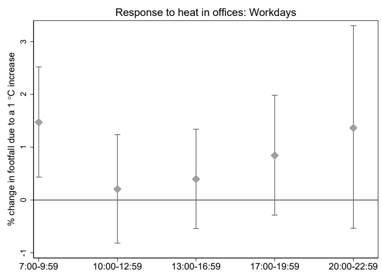


(d) Public parks, footfall, all days

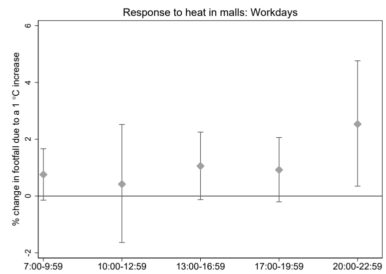


(e) Humidex index vs. heat index

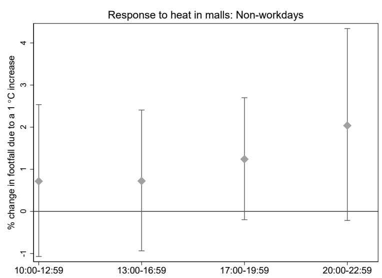
Figure A.16: Sensitivity analysis: Thermal discomfort. Instead of the daily maximum heat index, we specify the daily maximum "Humidex" index. Like the heat index, Humidex is a function of temperature and relative humidity (Masterson and Richardson, 1979; Buzan *et al.*, 2014). We compute the one-hour Humidex from one-hour air temperature and relative humidity, and take the maximum humidex value over the 24 hours of each day. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum Humidex, converted from log points to a percent change. The bottom panel plots the daily maximum Humidex (this sensitivity analysis) against the daily maximum heat index (main specification) for days in our sample.



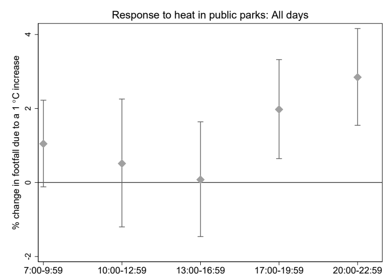
(a) Office towers, footfall, workdays



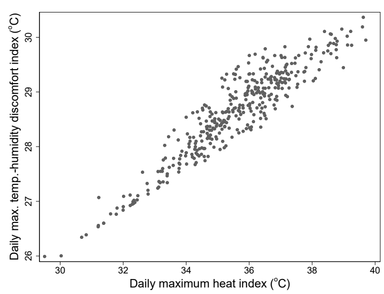
(b) Malls, footfall, workdays



(c) Malls, footfall, non-workdays

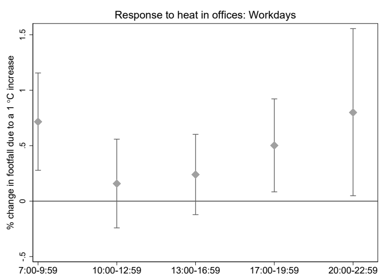


(d) Public parks, footfall, all days

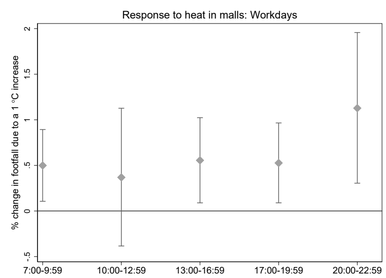


(e) Temp.-humidity index (THI) vs. heat index

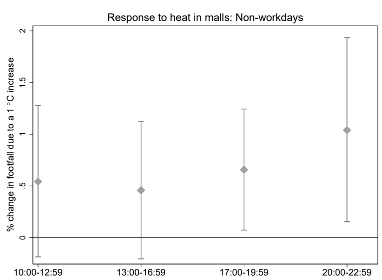
Figure A.17: Sensitivity analysis: Thermal discomfort. Instead of the daily maximum heat index, we specify the daily maximum "temperature-humidity discomfort index" (THI) (Chow *et al.*, 2016). We compute the one-hour THI from one-hour air temperature and relative humidity, and take the maximum THI value over the 24 hours of each day. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum THI, converted from log points to a percent change. The bottom panel plots the daily maximum THI (this sensitivity analysis) against the daily maximum heat index (main specification) for days in our sample.



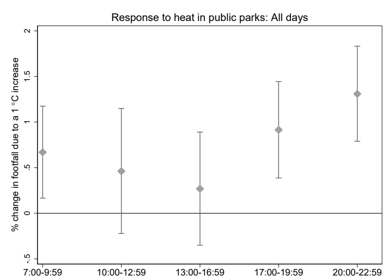
(a) Office towers, footfall, workdays



(b) Malls, footfall, workdays

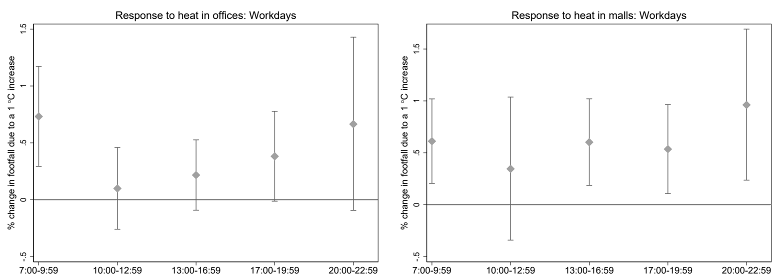


(c) Malls, footfall, non-workdays

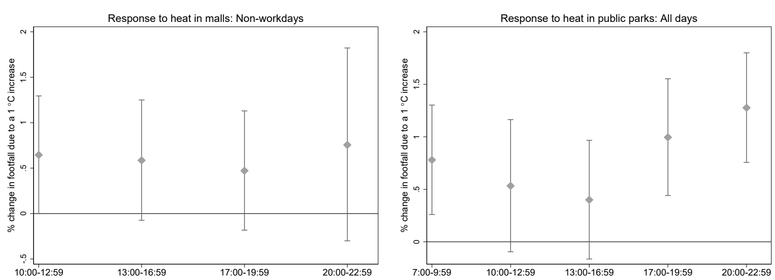


(d) Public parks, footfall, all days

Figure A.18: Sensitivity analysis: Air quality control. We drop concurrent PM2.5 as a covariate in the regression specification. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum heat index, converted from log points to a percent change.

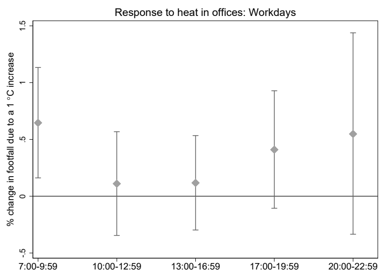


(a) Office towers, footfall, workdays (b) Malls, footfall, workdays

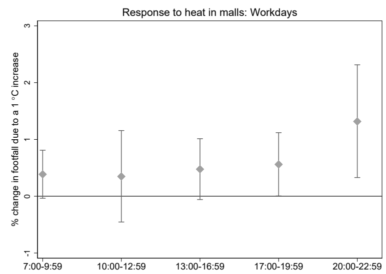


(c) Malls, footfall, non-workdays (d) Public parks, footfall, all days

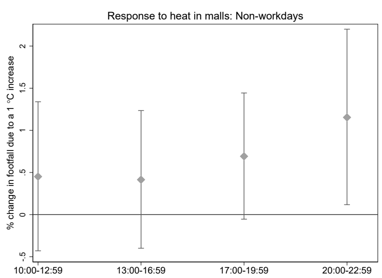
Figure A.19: Sensitivity analysis: Weather controls. We drop concurrent rainfall and wind speed as covariates in the regression specification. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum heat index, converted from log points to a percent change.



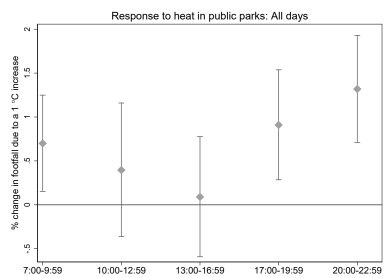
(a) Office towers, footfall, workdays



(b) Malls, footfall, workdays

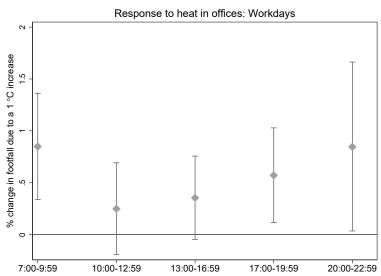


(c) Malls, footfall, non-workdays

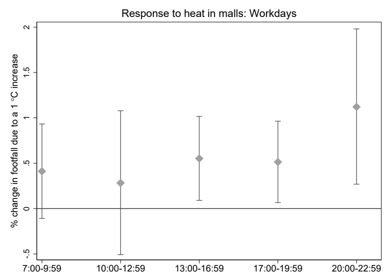


(d) Public parks, footfall, all days

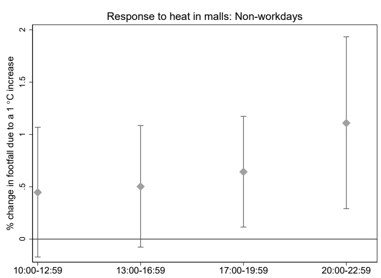
Figure A.20: Sensitivity analysis: Rainy afternoons. We drop from the estimation sample the one-quarter of dates with more rainy afternoons, defined as mean afternoon (12:00 to 16:00) rainfall of at least 0.35 mm/h (the 75th percentile of mean afternoon rainfall over all days in the sample). The objective is to check whether days with rainy afternoons are directly influencing our findings, e.g., if a rainy afternoon lowers a day's maximum heat and this directly keeps people at home instead of going to the mall or the park in the evening. (We still control for concurrent rainfall in the regression specification.) Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum heat index, converted from log points to a percent change.



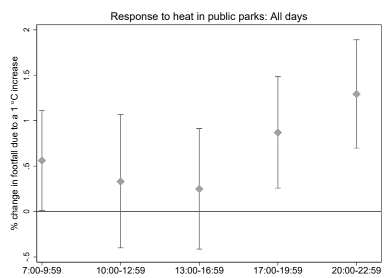
(a) Office towers, footfall, workdays



(b) Malls, footfall, workdays

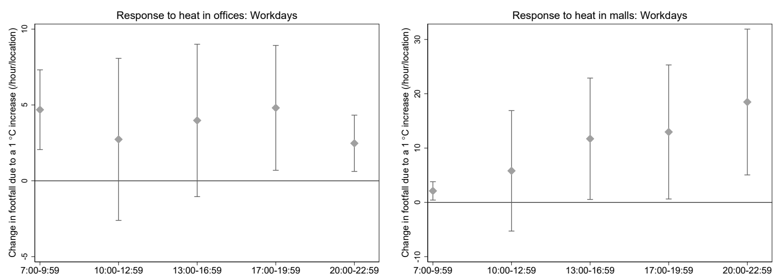


(c) Malls, footfall, non-workdays

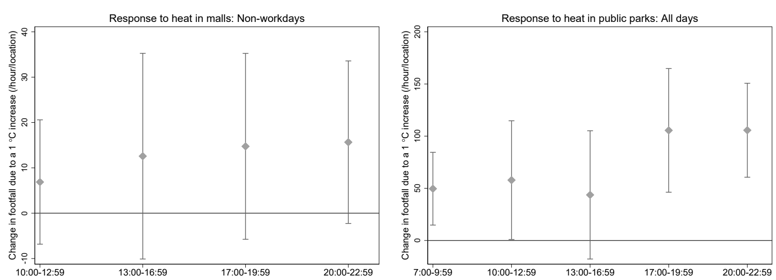


(d) Public parks, footfall, all days

Figure A.21: Sensitivity analysis: Seasonality control. Instead of year-month (month-of-sample) fixed effects (FE), we specify month FE and year FE in the regression specification. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum heat index, converted from log points to a percent change.

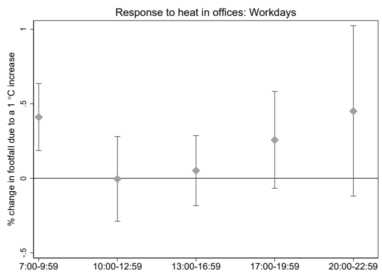


(a) Office towers, footfall, workdays (b) Malls, footfall, workdays

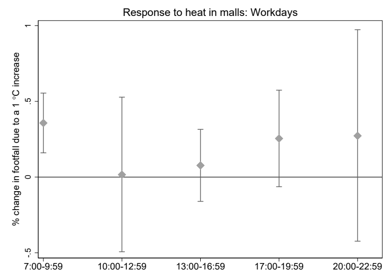


(c) Malls, footfall, non-workdays (d) Public parks, footfall, all days

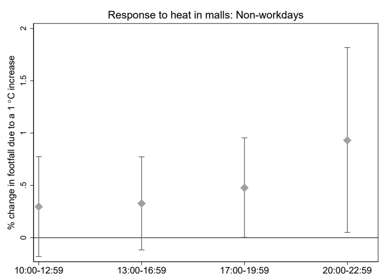
Figure A.22: Sensitivity analysis: Functional form for activity. Instead of log hourly footfall, we specify the dependent variable as hourly footfall in the regression specification. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the daily maximum heat index, in persons/hour/location per +1 °C.



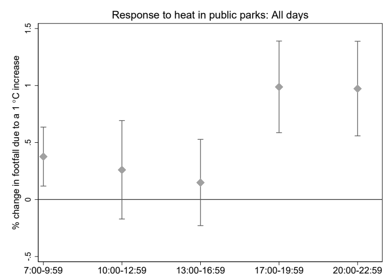
(a) Office towers, footfall, workdays



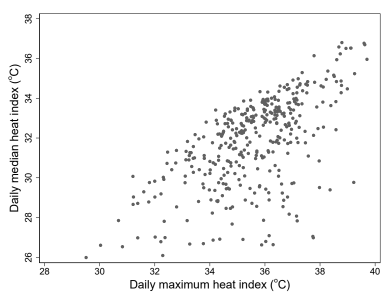
(b) Malls, footfall, workdays



(c) Malls, footfall, non-workdays

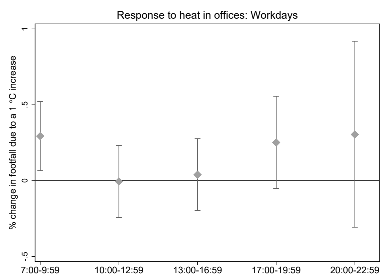


(d) Public parks, footfall, all days

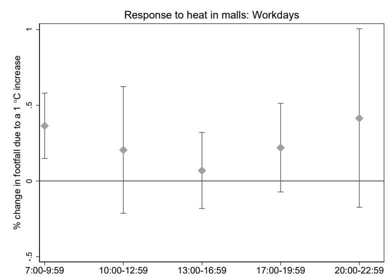


(e) Daily median vs. maximum heat index

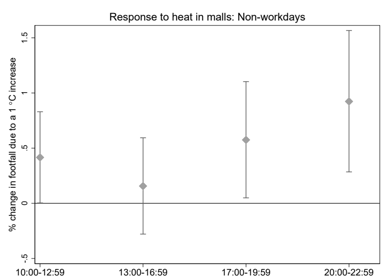
Figure A.23: Sensitivity analysis: Instead of the daily maximum heat index, we specify the concurrent one-hour heat index. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the one-hour heat index, converted from log points to a percent change. The bottom panel plots a day's median heat index against its maximum heat index, both measures taken over 24 one-hour realizations in a day. For days in our sample, the pairwise correlation coefficient of the two measures is 0.61. There is little density at low realizations of the median and high realizations of the maximum, in the bottom right corner of the scatter. Most of the density lies along a positive gradient that is downward shifted from the diagonal.



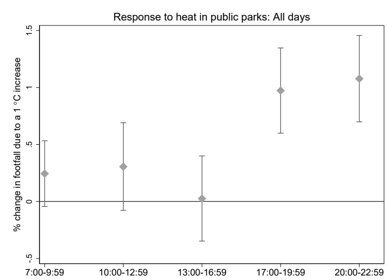
(a) Office towers, footfall, workdays



(b) Malls, footfall, workdays

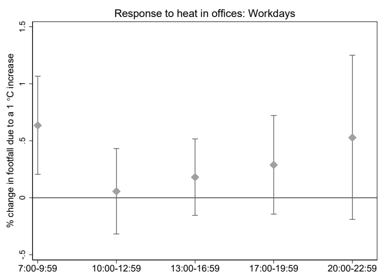


(c) Malls, footfall, non-workdays

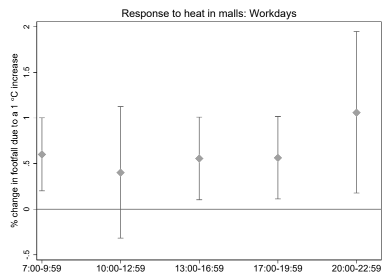


(d) Public parks, footfall, all days

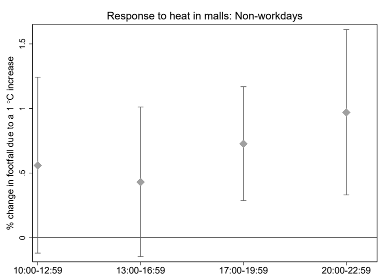
Figure A.24: Sensitivity analysis: Instead of the daily maximum heat index, we specify the one-hour heat index lagged by 1 hour, e.g., heat during the hour starting at 7:00 to explain footfall over the hour starting at 8:00. We also specify one-hour lags for the PM2.5, rainfall, and wind speed controls. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the prior hour's heat index, converted from log points to a percent change.



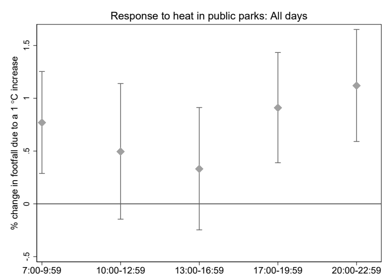
(a) Office towers, footfall, workdays



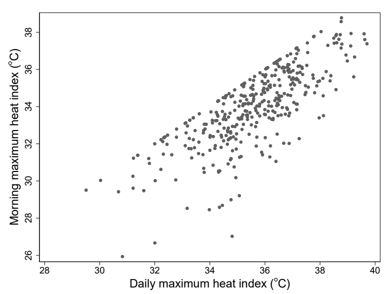
(b) Malls, footfall, workdays



(c) Malls, footfall, non-workdays

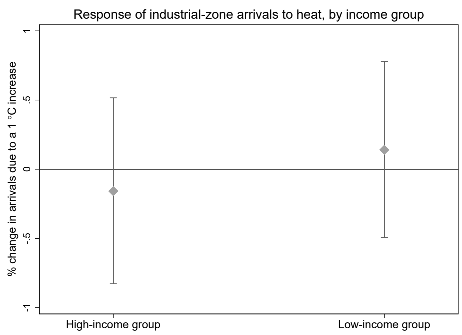


(d) Public parks, footfall, all days

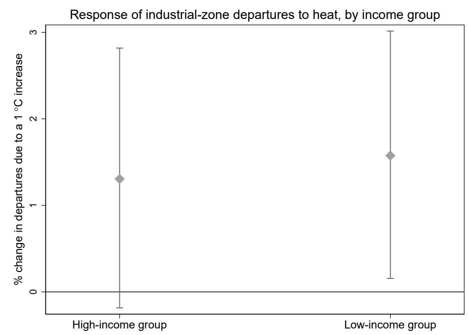


(e) Morning max vs. 24-hour max heat index

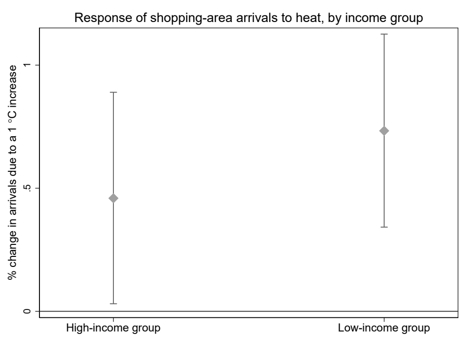
Figure A.25: Sensitivity analysis: Instead of the maximum heat index over the 24 hours in a day, we specify the "morning maximum" heat index, defining morning as 0:00 to 10:00. Compare panels a and b to Figure 2(a,b). Compare panel c to Figure A.8(a). Compare panel d to Figure A.11(e). The plots show 95% CI on the coefficient on the early-morning maximum heat index, converted from log points to a percent change. The bottom panel plots this early-morning maximum against the 24-hour maximum heat index (main specification) for days in our sample. For days in our sample, the pairwise correlation coefficient of the two measures is 0.77. There is little density at low realizations of the early-morning maximum and high realizations of the 24-hour maximum, in the bottom right corner of the scatter. Most of the density lies along a positive gradient that is downward shifted from the diagonal. Days with high heat peaks tend to exhibit hot mornings, i.e., hot mornings signal hot days.



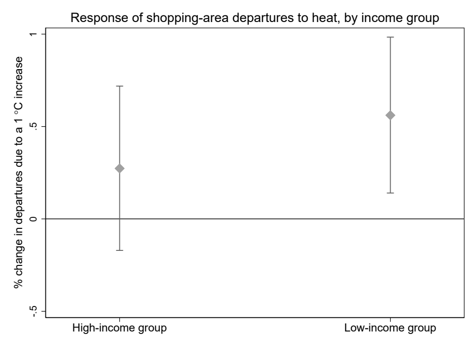
(a) Industry, bus/rail arrivals, workdays 6:00-9:59



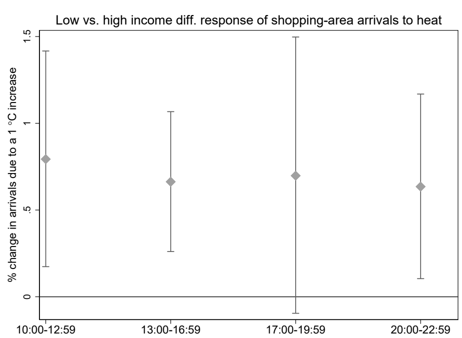
(b) Industry, bus/rail depart., workdays 17:00-19:59



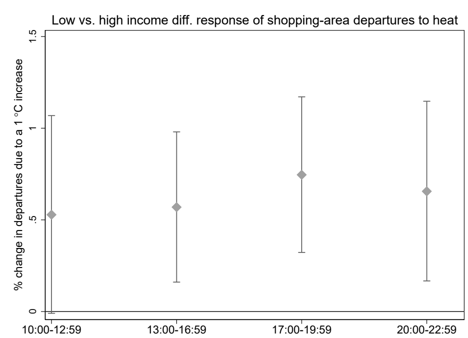
(c) Shopping, bus/rail arrivals, workdays 7:00-10:59



(d) Shopping, bus/rail depart., workdays 17:00 to 22:59

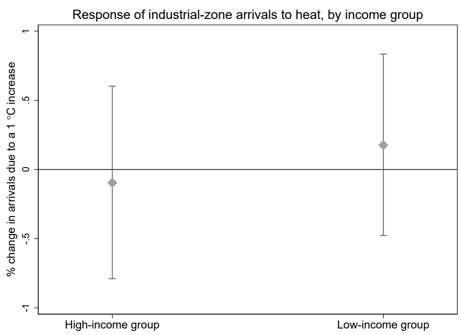


(e) Shopping, bus/rail arrivals, non-workdays

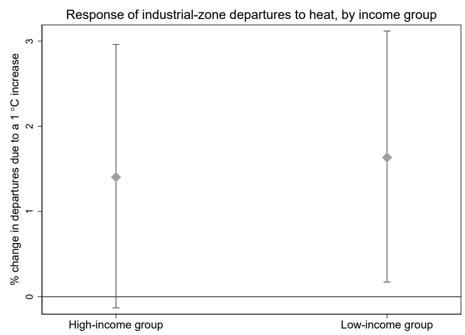


(f) Shopping, bus/rail departures, non-workdays

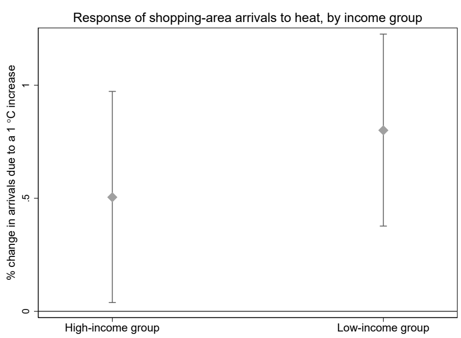
Figure A.26: Sensitivity analysis: Varying the sample of trips by residents who are active during daytime hours. Here we define a resident commuter as a "cardholder who first departs from the modal first-departure stop (or any stop within 600 meters of this stop) at least six times during the quarter"—rather than eight times. See sensitivity analysis 1 in Table A.2 (3.5m cards in 2015 and 2016 alike). Compare panels a to d to Figure 2(c-f). Compare panels e and f to Figure A.8(b,c). The plots show 95% CI.



(a) Industry, bus/rail arrivals, workdays 6:00-9:59

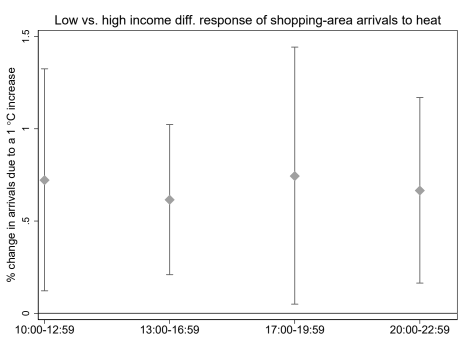


(b) Industry, bus/rail depart., workdays 17:00-19:59

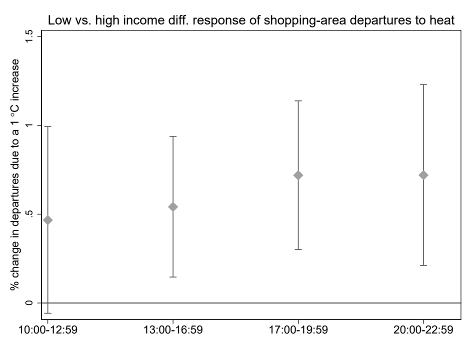


(c) Shopping, bus/rail arrivals, workdays 7:00-10:59

(d) Shopping, bus/rail depart., workdays 17:00 to 22:59

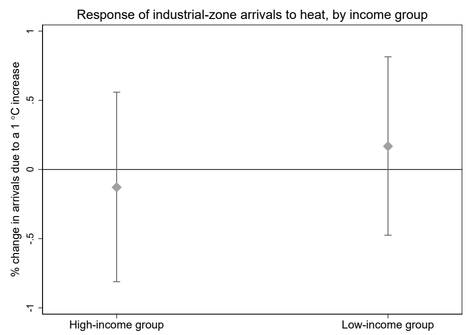


(e) Shopping, bus/rail arrivals, non-workdays

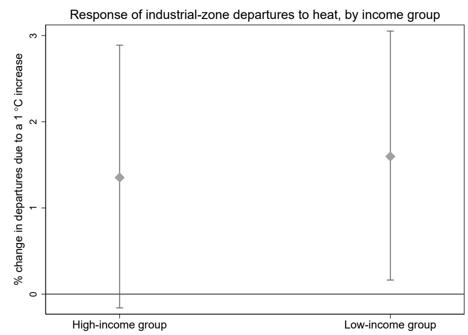


(f) Shopping, bus/rail departures, non-workdays

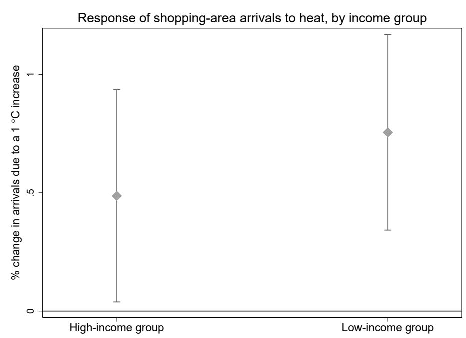
Figure A.27: Sensitivity analysis: Varying the sample of trips by residents who are active during daytime hours. Here we define a resident commuter as a "cardholder who first departs from the modal first-departure stop (or any stop within 600 meters of this stop) at least 10 times during the quarter"—rather than eight times. See sensitivity analysis 2 in Table A.2 (3.0m cards in 2015 and 2016 alike). Compare panels a to d to Figure 2(c-f). Compare panels e and f to Figure A.8(b,c). The plots show 95% CI.



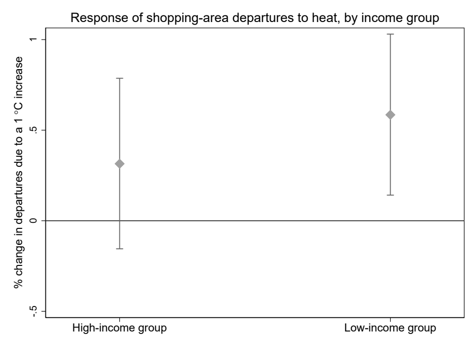
(a) Industry, bus/rail arrivals, workdays 6:00-9:59



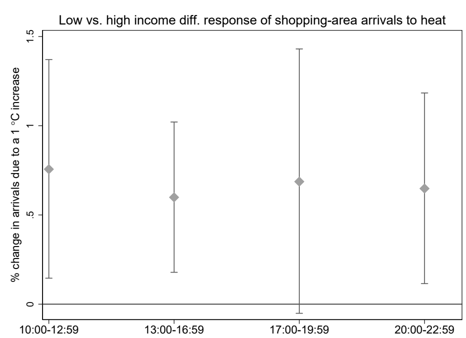
(b) Industry, bus/rail depart., workdays 17:00-19:59



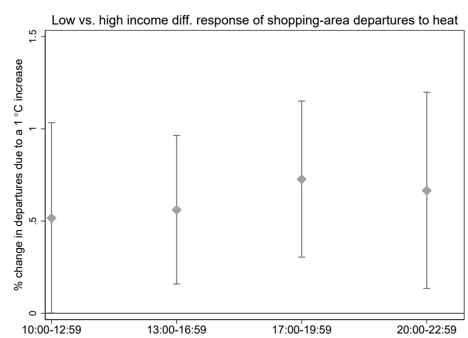
(c) Shopping, bus/rail arrivals, workdays 7:00-10:59



(d) Shopping, bus/rail depart., workdays 17:00 to 22:59

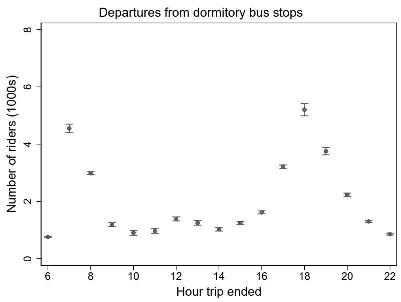


(e) Shopping, bus/rail arrivals, non-workdays

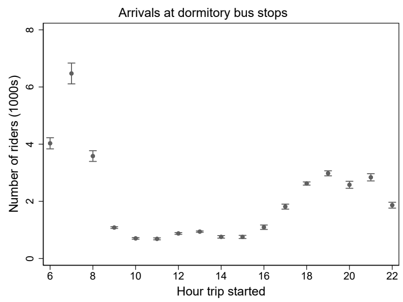


(f) Shopping, bus/rail departures, non-workdays

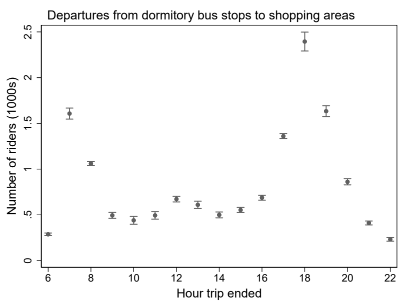
Figure A.28: Sensitivity analysis: Varying the sample of trips by residents who are active during daytime hours. Here we define a resident commuter as a cardholder who *last arrives* at the modal last-arrival stop—rather than first departs from the modal first-departure stop—(or any stop within 600 meters of this stop) at least eight times during the quarter. See sensitivity analysis 3 in Table A.2 (3.2m cards in 2015 and 2016 alike). Compare panels a to d to Figure 2(c-f) Compare panels e and f to Figure A.8(b,c). The plots show 95% CI.



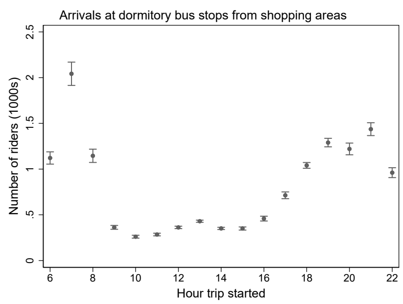
(a) Dorm stop departures



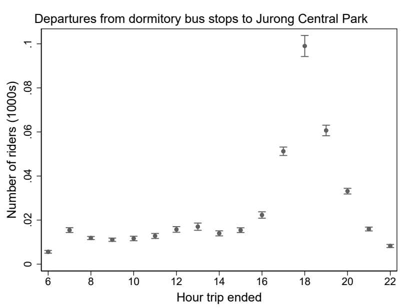
(b) Dorm stop arrivals



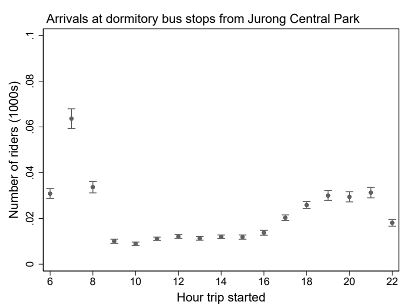
(c) Dorm stop departures to commercial areas



(d) Dorm stop arrivals from commercial areas

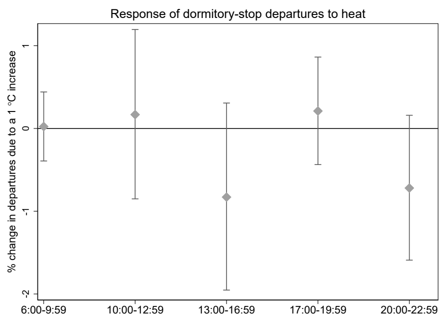


(e) Dorm stop departures to Jurong Central Park

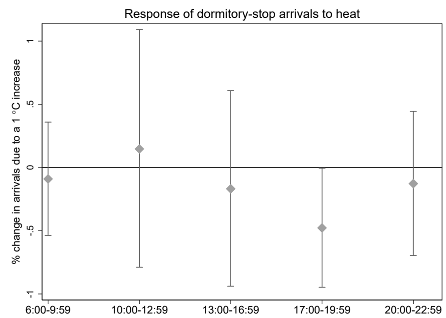


(f) Dorm stop arrivals from Jurong Central Park

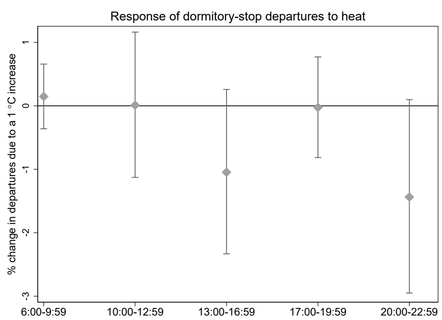
Figure A.29: Departures from and arrivals at bus stops serving foreign worker dormitories. Here we pool the sample across all days because low-income foreign workers do not follow the typical weekly business calendar. We generate separate time series by summing arrivals or departures over 153 bus stops located within 600 meters of a dorm (and not nearby residential buildings or malls). No dorm was served by rail. The top panels consider departures from dorms to any destination point (resp., arrivals at dorms from any origin point) on public transit. The middle panels restrict departures from dorms to (resp., arrivals at dorms from) commercial areas. The bottom panels restrict departures from dorms to (resp., arrivals at dorms from) Jurong Central Park—a public park that is popular among foreign workers. Taking each time series, we regress the number of riders on hour FE, day-type FE, and year-month FE, and plot 95% CI for the hour-by-hour predictions.



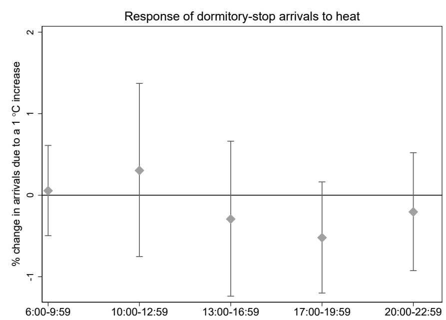
(a) Dorm stop departures



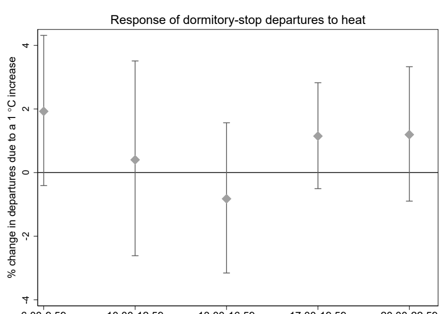
(b) Dorm stop arrivals



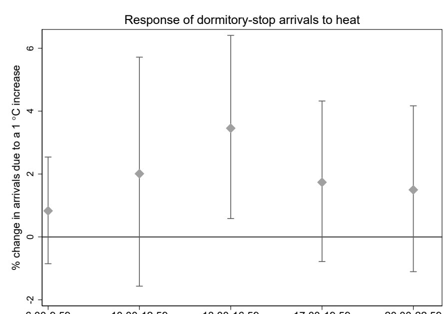
(c) Dorm stop departures to commercial areas



(d) Dorm stop arrivals from commercial areas

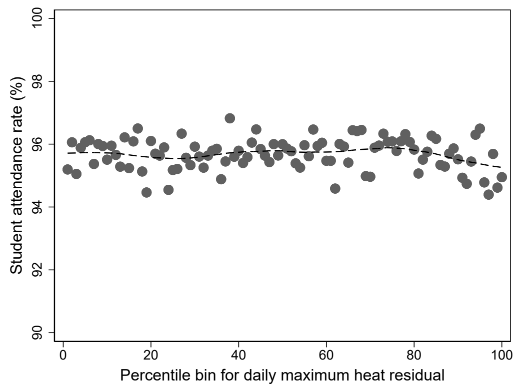


(e) Dorm stop departures to Jurong Central Park

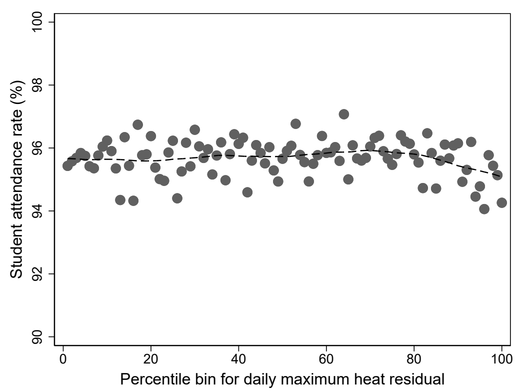


(f) Dorm stop arrivals from Jurong Central Park

Figure A.30: The impact of heat on departures from and arrivals at bus stops serving foreign worker dormitories, for different time intervals (Figure A.29 summarizes these trips). Source: Regression specifications similar to those reported in Table 2 implemented on date-hour level time series of log hourly number of departures (left panels) or log hourly number of arrivals (right panels) aggregated over 153 bus stops located within 600 meters of a dorm. The plots show 95% CI on the coefficient on the daily maximum heat index, converted from log points to a percent change.

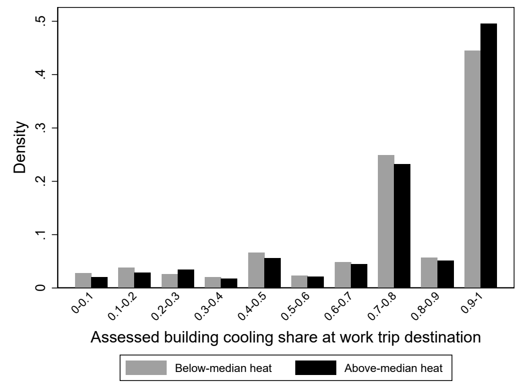


(a) Deseasoned heat

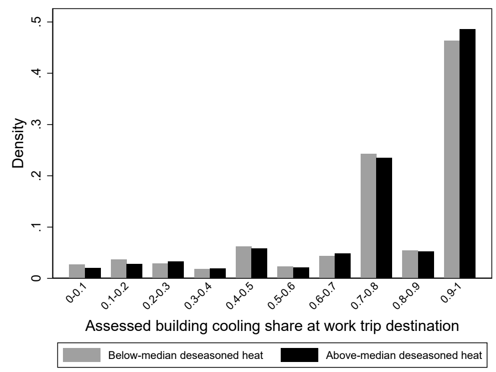


(b) Deseasoned heat net of year means

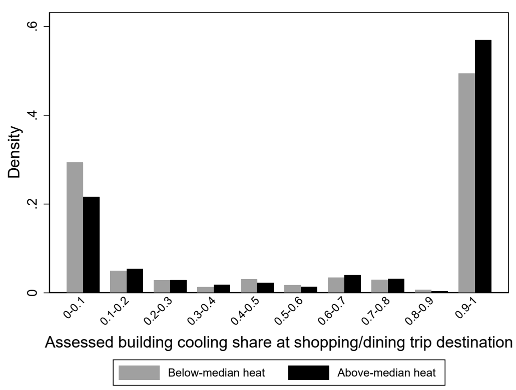
Figure A.31: The ambient heat-student attendance relationship at a large private school with extensive climate control. We take the daily maximum heat index recorded for each of the 947 schooldays in the 2011-2016 UWCSEA student-level daily attendance panel and partial out (top panel) month fixed effects or (bottom panel) year-month fixed effects to account for mild tropical seasonality and year-to-year changes. We then take percentiles of the distribution of heat residuals and plot the mean attendance rate (%) across enrolled students and schooldays in each percentile bin. In each panel, we fit a kernel-weighted local polynomial smoothing curve.



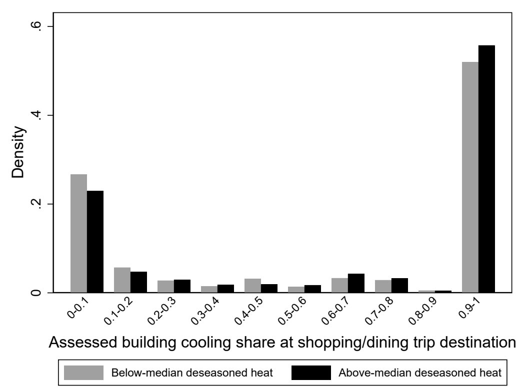
(a) Work on days above vs. below median heat



(b) Work on days above vs. below median deseasoned heat



(c) Shopping on days above vs. below median heat



(d) Shopping on days above vs. below median deseasoned heat

Figure A.32: Distribution of (a,b) 11,164 work trips and (c,d) 3955 shopping trips over the destination building's cooling share, in the 2012/13 Household Travel Survey. An observation is a respondent-trip on workdays between June 25, 2012 and May 30, 2013. Our research assistants—who were not given access to travel dates—were able to assess a space-cooling share for 3871 work destinations and 822 shopping destinations, accounting for 90% and 95% of total work and shopping destinations in the raw data. In the left panels, we split the "trip over destination's cooling share" distributions according to whether the trip happened on days with above vs. below median heat (the median applied in-sample, i.e., to the vector of daily maximum heat index realizations between June 2012 and May 2013). In the right panels, we split the distributions according to whether the trip happened on days with above vs. below median heat after removing month means from the daily maximum heat index realizations. Kolmogorov-Smirnov tests of equality (above- vs. below-median heat) reject at the 1% level of significance in panels a, c, and d and has p-value 0.13 for b, maybe because work attendance responds less to heat within month than across months, e.g., workers in less air-conditioned workplaces choose holidays in July.