Inequality in behavioural heat adaptation: an empirical study with mobility data from the transport system in New York City, NY, USA

Annika Stechemesser, Leonie Wenz

Summary

Background Heat exposure, which can negatively affect human health and wellbeing, is heterogeneous within US cities. However, little is known about who can avoid heat stress by adjusting their everyday behaviour. We aimed to analyse the effect of ambient temperature on mobility, specifically subway (ie, the underground railway system) use, in New York City, NY, USA, during 2014–19.

Methods For this empirical study, subway use across New York City was measured with turnstile data from the New York City Metropolitan Transportation Authority between Jan 1, 2014, and Dec 31, 2019. Passenger numbers were then aggregated to the zip code tabulation area (ZCTA) level. Daily observational climate data were obtained from the US National Weather Service between Jan 1, 2014, and Dec 31, 2019. Socioeconomic data at the ZCTA level originated from the American Community Survey 2019. We extracted data on population age, ethnicity, commuting, employment, median household income, rent, and health-insurance coverage. We used a fixed-effects panel-regression model to assess the influence of temperature on subway use in New York City, which was the main outcome of our study.

Findings We obtained data for 438 subway stations across New York City. After data cleaning and preprocessing, the final aggregated data sample consisted of 238 508 instances of subway use in 1955 days across 6 years for 122 ZCTAs, with 168 days missing in the raw data and 67 days removed as outliers. The results of the fixed-effects panel-regression analysis showed a strong, non-linear effect of daily maximum temperature on subway use. Subway use was highest at 11·5°C and substantially decreased for temperatures that were colder and warmer than that, with reductions reaching 6·5% (95% CI 2·5–10·5) for the coldest temperature (ie, –6·5°C) and 10·5% (6·0–14·0) for the hottest temperature (ie, 34·5°C). Reductions differed between weekdays and weekends, when residents generally had more freedom to adjust their behaviour. Neighbourhoods that were at a socioeconomic disadvantage experienced smaller or no reductions in mobility in heat; mobility increased in neighbourhoods with beach access.

Interpretation Our study showed that temperature had a strong, non-linear effect on subway use, but the magnitude of the effect on subway use was heterogeneous across areas of the city on warm days. Weaker avoidance of heat stress correlated with less privilege, indicating compounding health risks. Everyday behavioural adaptation to heat is therefore an effect pathway that contributes to unequal heat effects and should be explored in future research.

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Potsdam Institute for Climate Impact Research, Potsdam, Germany (A Stechemesser MSc, L Wenz PhD)**; Institute of Physics, Potsdam University, Potsdam, Germany** (A Stechemesser)**; Mercator Research Institute on Global Commons and Climate Change, Berlin, Germany** (A Stechemesser, L Wenz)

Correspondence to: Dr Leonie Wenz, Potsdam Institute for Climate Impact Research, Potsdam 14473, Germany **leonie.wenz@pik-potdam.de**

or

Annika Stechemesser, Potsdam Institute for Climate Impact Research, Potsdam 14473, Germany **stechemesser@pik-potsdam.de**

Introduction

Anthropogenic climate change is causing temperatures to increase at unprecedented rates worldwide.[1] Multidisciplinary studies aiming to causally link changes in weather with changes in socioeconomic indicators have shown adverse effects of heat on human health and wellbeing, such as declining productivity,[2] reduced physical activity,[3] disrupted sleep,[3] adverse outcomes for mental health[3,4] and physical health,[3] and increased aggression.[5,6] The global heterogeneity in heat effects across regions is well documented; for example, inequality in the economic effects of climate change.[7,8] At the local level, there is evidence of unequal heat effects across different socioeconomic groups;[9–13] for example, differences in heat-island exposure between different ethnic groups.[14] Comparatively little is known about possible inequality in the capacity for everyday behavioural adaptation to avoid heat effects across different socioeconomic groups.

Because of the substantial number of adverse health outcomes that are caused by heat, one of the key recommendations of health specialists and public authorities is to avoid heat stress and take shelter on hot days,[15] which should coincide with a reduction in mobility in locations where the primary purpose is not heat mitigation.[16] However, whether and to what extent people follow these recommendations, and whether different socioeconomic groups have the same means to do so, remain unclear.

Research in context

Evidence before this study

We conducted a systematic search of PubMed using the search terms “climate change” AND “inequality” AND “mobility”, which returned 11 results, and using the search terms “heat stress” AND “public transport” AND “city”, which returned 19 results. We also used the search terms “heat stress” AND “inequality” AND “city”, which returned 14 results. As this systematic search of the evidence yielded a small number of results and most of the studies that we did find were not applicable to our context, we changed the approach and conducted a less formalised literature review on climate inequality. Multidisciplinary studies have shown adverse effects of heat stress on human health and wellbeing. The consequences of heat stress are heterogeneous at both global and local levels, ranging from unequal effects between high-income and low-income countries to within-city differences in heat-island exposure between different ethnic groups. However, local, everyday heat stress is not only determined by heat exposure, but also by the ability to avoid and adapt to heat stress (eg, by reducing mobility). In this study, we examined the effects of temperature on mobility in New York City (NY, USA) during 2014–19, before the COVID-19 pandemic, with a particular focus on potential socioeconomic and demographic disparities in the ability to adapt to heat.

Added value of this study

Due to the substantial negative health outcomes of heat stress, identifying groups who are particularly vulnerable to heat stress is crucial. In this study, we examined not only inequality of heat exposure but also inequality in the ability to adjust daily behaviour to avoid heat stress. Analysing mobility data from 438 subway (ie, the underground railway system) stations during 6 years across New York City’s diverse neighbourhoods allows for insights into authentic behavioural reactions to ambient temperature. We found that the extent to which subway use was reduced on hot days differed across neighbourhoods with lower mobility reductions in socioeconomically disadvantaged neighbourhoods, such as those with less health-insurance coverage, compared with more privileged areas. Across New York City, we found a non-linear effect of daily maximum temperature on subway-passenger volume, with highest ridership numbers in moderate weather, and near-linear reductions for cold and warm temperatures. Our results were also consistent for taxi use and bicycle use. These findings show that inequality does not only exist in heat exposure, but also in the ability to respond to heat.

Implications of all the available evidence

Disparities in mobility reduction in heat across neighbourhoods showed differences in the ability of residents to behaviourally adjust to heat within the same city. Contextualising our results with socioeconomic indicators showed that some neighbourhoods already had an increased heat burden—despite probably being responsible for fewer greenhouse-gas emissions than high-income areas—and experienced compounding heat and health risks from the lack of mobility reduction. With heat extremes continuing to increase due to anthropogenic climate change, we identified both disparities in mobility behaviour in heat and compounding heat risks as novel heat effects that increase the climate gap.

Mobility behaviour is particularly interesting because it provides insights into unprompted, behavioural reactions to ambient temperature in everyday life. We focused on New York City because cities are especially vulnerable to heat due to the heat-island effect and dense populations.[14,17] Furthermore, New York City is one of the ten most unequal cities in the USA in both income and wage inequality,[18] making it suitable for assessing hyperlocal, disparate heat effects and mitigation abilities. Finally, New York City has the most public-transport use in the USA[19] and has one of the largest public-transportation systems in the world.[20] Average weekday-ridership totals in the New York City subway exceeded 5·5 million passengers before the COVID-19 pandemic.[21] However, New York City subway stations have a severe heat problem. The US Regional Plan Association found that subway stations are frequently up to 6°C hotter than above ground.[22] Because of these hot conditions, newspaper articles referred to a so-called subterranean heatwave.[23] Although the subway trains themselves have air conditioning, full air conditioning in the subway-station system is structurally impossible; cost estimates for installing chiller plants as an alternative are approximately US$4·8 billion.[23]

Consequently, subway use in hot weather exposes passengers in New York City to heat stress. Medical literature has shown that even relatively brief waiting times in hot, humid, and busy subway stations can have heat-induced health consequences.[24] These consequences are especially severe for vulnerable groups in the population who might have reduced thermoregulatory capacities, such as people older than 65 years or people with chronic disease or disability.[25] Furthermore, frequent delays in the subway system cause long waiting times in overheated stations. In 2017, only 63% of New York City subway trains were on time, with the on-time performance reducing by more than 30% since 2012.[26] The most common reason for delays is overcrowding of stations.[26] As well as time spent in the subway system itself, walking to the subway station in hot weather also contributes to heat exposure. Furthermore, subway use is also an indicator of activity outdoors and in other contexts where people are exposed to heat, which might increase heat stress.

In this study, we aimed to analyse the effect of temperature on mobility, specifically subway (ie, the underground railway system) use, in New York City, NY, USA, during 2014–19, before the COVID-19 pandemic, with a focus on potential socioeconomic disparities in the ability to adapt to and mitigate heat. We aimed to assess whether and to what extent which residents in New York City adjusted their mobility behaviour in response to heat. By exploring socioeconomic disparity regarding both the effects of heat extremes and behavioural responses to cope with these extremes, we contribute to the literature on climate justice.

Methods

Data sources and preprocessing

For the primary analysis of this empirical study, we analysed data on subway use, climate, various socio-economic indicators, and general heat exposure in New York City, NY, USA. We used fixed-effects panel-regression techniques, a segmentation algorithm, and pair-wise Spearman correlations. As control data, we used these data but also included data on tourism and beach access (appendix pp 15–17, 24). In our secondary analyses, we also analysed data on taxi use and bicycle use to examine possible differences between public and individual forms of transport (appendix pp 25–27).

All data used in this study are publicly available from official sources; therefore, the study did not require ethics approval.

Outcomes

The main outcome of our study was the heterogeneous influence of temperature on subway use in New York City.

Subway-use data

Subway use across New York City was measured with turnstile data from the New York City Metropolitan Transportation Authority[27] between Jan 1, 2014, and Dec 31, 2019, purposefully excluding the years during and after the COVID-19 pandemic, which disrupted transport worldwide.[28] Each turnstile collects the cumulative entries to and exits from its subway station and records them multiple times a day. Unrealistically high turnstile data (ie, >60 000 entries and exits per day) were deemed to be faulty and therefore removed. As different turnstiles collect data at different timepoints and meaningfully interpreting the difference between entries and exits is not possible, we aggregated the data to the total passenger volume per day and station (or station complex, which is a large station with multiple entries and exits). The passenger volume per day approximates the patterns in which people experienced the weather. Passenger numbers were then aggregated to the zip code tabulation area (ZCTA; a statistical unit that approximates postcodes) level with the geolocation of each station and a plausible maximum walking distance of 1 km was assumed (appendix p 18). We conducted an outlier-detection analysis on the aggregated data to reduce bias from weather-independent events that affect subway use, such as large-scale traffic disturbances (appendix pp 4, 11–14).

Climate data

The climate data used in this study originated from the US National Weather Service.[29] We used daily observational data from the national weather station located in Central Park (New York City, NY, USA) that had been collected between Jan 1, 2014, and Dec 31, 2019. We also conducted a robustness check using the Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate data from Oregon State University (Corvallis, OR, USA), which were collected between Jan 1, 2014, and Dec 31, 2019, and provide climate data on a 4 km×4 km grid after interpolating weather-station data under consideration of the local topography (appendix pp 41–43).

For **PRISM climate data** see https://prism.oregonstate.edu/

Socioeconomic and heat-exposure data

See **Online** for appendix

Socioeconomic data at the ZCTA level originated from the American Community Survey 2019, which was conducted between Jan 1 and Dec 31, 2019. We extracted data on population age, ethnicity, commuting, employment, median household income, rent, and health-insurance coverage.

Heat-vulnerability data were obtained via the Heat Vulnerability Index for New York City,[30] a neighbourhood-level heat indicator considering local temperature, coverage of air conditioning, green space, and poverty rates, collected between 2000 and 2011 (specific collection dates were not available). Furthermore, we approximated local heat exposure by including ZCTA-level coverage of air conditioning from the New York City Housing and Vacancy Survey in 2017,[31] conducted between Jan 1 and May 31, 2017 and measured as the proportion of households with functioning air conditioning.

We also used data from the 2015 New York City Tree Census,[32] conducted between May 1, 2015, and Oct 31, 2016, which reports the location of more than 650 000 trees across New York City to compute the ZCTA-level tree count as an approximation of green space in the local area.

Finally, we approximated the mean walking distance to the nearest subway station for each ZCTA (appendix p 18) and obtained data from the Supplementary Nutrition Assistance Program, which provides food assistance to people living in New York who need it.[33]

Empirical model

We used a fixed-effects panel-regression model to assess the influence of temperature on subway use in New York City. Our principal explanatory variable was daily maximum temperature as peaks in temperature are likely to capture the heat experience during the day and potential heat stress better than, for example, the mean temperature. Robustness checks that were based on daily mean temperature provided similar results (appendix pp 38, 42). We used a semiparametric approach and binned the temperature variable into 1°C bins to allow for non-linear temperature effects without requiring the specification of a functional form. A dummy variable was introduced for each 1°C bin where

$$B_i(T_d) = \begin{cases} 1 \text{ if } T_d \in \text{Bin}_i \\ 0 \text{ else.} \end{cases}$$

We only considered bins higher than –7°C and lower than 35°C as there were too few days (ie, <4) with a temperature less than –7°C or more than 35°C. In the primary analysis, the omitted temperature bin was 11–12°C, which was the temperature range in which subway use was highest. The method requires the omission of a bin and all parameters are computed with respect to this bin. This method is standard for this approach. For robustness, we also considered 3°C bins (appendix p 26).

The dependent variable $r_{n,d}$ was the radius-weighted passenger volume in ZCTA at day d. The natural logarithm was applied to the dependent variable $r_{n,d}$ to address the skewness of the ridership distribution. After the log transformation, the ridership distribution approximately conforms to normality (appendix p 14). We controlled for daily precipitation P_d, windspeed W_d, and snow depth S_d using data from the Central Park weather station because these factors can influence public-transport availability and thermal comfort. As the passenger volume differed considerably between weekdays, a weekday dummy D_d was included. To account for changes in mobility due to holidays, we used the holiday calendar of the New York Stock Exchange[34] and included a dummy variable H_d to indicate whether a day was a holiday or not. Furthermore, to account for the unequal effects of tourism across ZCTAs and months of the year, we included a tourism and visitor control ($V_{n,d}$), which approximated the general attractiveness of a ZCTA to tourists under consideration of monthly fluctuations in visitor numbers (appendix pp 15–17).

To flexibly approximate time trends that operated on a lower frequency than the daily level, such as expansions of the subway trains, stations, or systems, we used Chebyshev polynomials up to order j=0,...,5. The zero and first-order Chebyshev polynomials were defined as

$$Ch_0=1 \text{ and } Ch_1(d)=d,$$

where d represented the day. All higher-order polynomials were defined recursively

$$Ch_{j(d)}=2dCh_{j-1}(d) - Ch_{j-2}(d), j \geq 2.$$

Motivated by research published in 2020 that showed that bus routes leading to public beaches in Berlin, Germany, were frequented more often in hot weather than other routes,[16] we also used a beach dummy b_n to indicate whether a ZCTA had beach access (appendix p 24). Lastly, we included ZCTA fixed-effects μ_n and year fixed-effects η_d to reduce omitted variable bias from time-invariant differences between ZCTAs and location-invariant differences between years.

Overall, the model reads as

$$\log(r_{n,d}) = \sum_{i=0}^{N} \alpha_i B_i(T_d) + \beta P_d + \gamma S_d + \delta W_d + \zeta H_d + \theta D_d + \kappa V_{n,d} + \sum_{j=0}^{5} \lambda_j Ch_{n,j}(d) + \xi b_n + \mu_n + \eta_d + \varepsilon_{n,d}; \quad (1)$$

where N corresponds to the number of bins and $\varepsilon_{n,d}$ corresponds to the error term. Errors were clustered two ways by ZCTA and by day to account for possible correlations between observations. The coefficient of interest α_i captures the temperature effect in bin Bin_i. The same model was used to analyse the taxi and bicycle data to enable a comparison with individual forms of transport, with daily taxi rides for each taxi zone and daily bicycle rentals for each ZCTA as dependent variables (appendix pp 25–27). Bicycle-sharing data were obtained from Citi Bike (New York City, NY, USA) and taxi data were obtained from The New York City Taxi and Limousine Commission (New York City, NY, USA).

Parametrisation of the mobility–temperature response

We parametrised the mobility–temperature response using two different approaches. First, we applied an iterative-segmentation algorithm that was developed by Muggeo[35,36] to determine natural breaking points in the response and to fit linear functions between them. Specifically, the algorithm relied on a linear formulation of the problem in this study

$$\alpha_i \sim B_{i_{mid}}$$

where

$$B_{i_{mid}}$$

describes the midpoint of the i-th temperature bin. The algorithm requires the input of starting conditions (ie, the values for each breaking point that are specified by the user, from which the algorithm will then be optimised) for each breaking point and then proceeds to automatically detect suitable breaking points in the data. In the estimation process, linear models are iteratively fitted. For each iteration, the breaking-point values are updated on the basis of an estimated difference-in-slope parameter. The algorithm converges when the gap between the fitted straight lines is small. The standard error of the estimated breakpoint is obtained via the Delta method. The final breaking points estimated are interpreted as approximations of natural thresholds at which the nature of the relationship between temperature and subway use changes.

As an alternative to the piecewise linear parametrisation, we fitted a quadratic function to the results of the panel regression. We also conducted a robustness test in which we fitted a quadratic model directly to the raw data (appendix p 31). Compared with the binned regression approach, however, the quadratic fit had the disadvantage that the function was symmetrical, which the hot and cold temperature responses were not necessarily. Furthermore, data coverage differed between cold and hot temperatures. Estimating a binned model was therefore more precise.

ZCTA-level regressions for the mobility–heat response

As we are particularly interested in the response to heat and possible differences therein across ZCTAs, we conducted an additional analysis at the ZCTA level, in which we only considered days with a daily maximum temperature of 19·5°C or higher. This cutoff was informed by the high breaking point of the piecewise-linear analysis; robustness checks were conducted with alternative cutoffs (ie, 17°C and 23°C; appendix pp 26–27). We conducted separate linear-regression analyses for each ZCTA that was included in the analysis. As in the general-panel model, we used daily radius-weighted total subway use as the dependent variable and daily maximum temperature as the independent variable. Controls were included for the other climate variables and for weekdays and holidays. The model thus reads

$$\log(r_d) = \nu T_d + \beta P_d + \gamma S_d + \delta W_d + \zeta H_d + \theta D_d + \kappa V_{n,d} + \sum_{j=0}^{5} \lambda_j Ch_j(d) + \eta_d + \varepsilon_d; \quad (2)$$

where ν is the coefficient of interest for the respective ZCTA, describing its mobility–heat response. Errors were clustered by year.

Assessing effects on weekdays and weekends

To assess differences between weekdays and weekends at the ZCTA level, we interacted daily maximum temperature with a weekday–weekend dummy. The linear interaction model, isolating daily maximum temperatures of 19·5°C or higher, reads as

$$\log(r_d) = \nu_1 T_d + \nu_2 T_d{*}D_d + \theta D_d + \beta P_d + \gamma S_d + \delta W_d + \zeta H_d + \kappa V_{n,d} + \sum_{j=0}^{5} \lambda_j Ch_{n,j}(\mathrm{d}) + \eta_d + \varepsilon_d. \quad (3)$$

Correlations between ZCTA-level mobility–heat response and socioeconomic indicators

To assess possible explanations for disparate heat effects on mobility across ZCTAs, we computed pairwise Spearman correlations between the mobility–heat coefficients ν and different socioeconomic indicators for each ZCTA. We did not include ZCTAs with beach access in this analysis as their mobility patterns structurally differed from the rest of the city. The Spearman correlations assessed the strength and direction of the correlations (ie, positive or negative). As a large negative ν would correspond to a strong reduction of subway use and, therefore, a protective mobility–heat response (ie, a favourable outcome in heat), a negative Spearman correlation would indicate that the socioeconomic indicator is high if the subway reduction is large. For example, a negative correlation between subway use in heat and median household income would mean that high median income was associated with a large reduction in subway use.

Furthermore, we conducted simple linear regressions between the mobility–heat coefficients and socioeconomic indicators (appendix pp 38–39). Conducting sequential time-series regressions to assess localised temperature effects on ridership and then correlating the local mobility heat with socioeconomic and heat-exposure indicators was more flexible and easier than an interaction-based panel approach, as we did not have to make a priori specifications about the relationship between the mobility–heat responses of different ZCTAs and socioeconomic indicators.

Role of the funding source

The funders had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

Results

Overall, we obtained data for 438 subway stations across New York City, NY, USA, between Jan 1, 2014, and Dec 31, 2019. After data cleaning and pre-processing, the final aggregated data sample consisted of 238 508 instances of subway use in 1955 days across 6 years for 122 ZCTAs, with 168 days missing in the raw data and 67 days removed as outliers. 4726 (<1%) of 9 673 625 unrealistically high turnstile instances were removed before aggregation to the daily level.

The results of the binned fixed-effects panel-regression analysis showed a strong, non-linear effect of daily maximum temperature on subway use (figure 1). Subway use was highest in the 11·5°C bin and substantially decreased for temperatures that were colder and warmer than that, with reductions reaching 6·5% (95% CI 2·5–10·5) for the coldest temperature bin (ie, –6·5°C) and 10·5% (6·0–14·0) for the hottest temperature bin (ie, 34·5°C; appendix p 28). We conducted robustness checks with Chebyshev polynomials up to order three and seven, which provided similar results (appendix p 31).

Fitting a piecewise linear function provided three segments supporting our finding that there was an overall non-linear temperature effect on subway use across New York City (figure 1), with subway use increasing moderately for temperatures between 0·5°C and 19·5°C (slope of 0·03, 95% CI –0·08 to 0·13). For temperatures colder than 0·5°C, ridership increased strongly as the temperature got closer to 0·5°C (0·8, 0·26 to 1·3). For

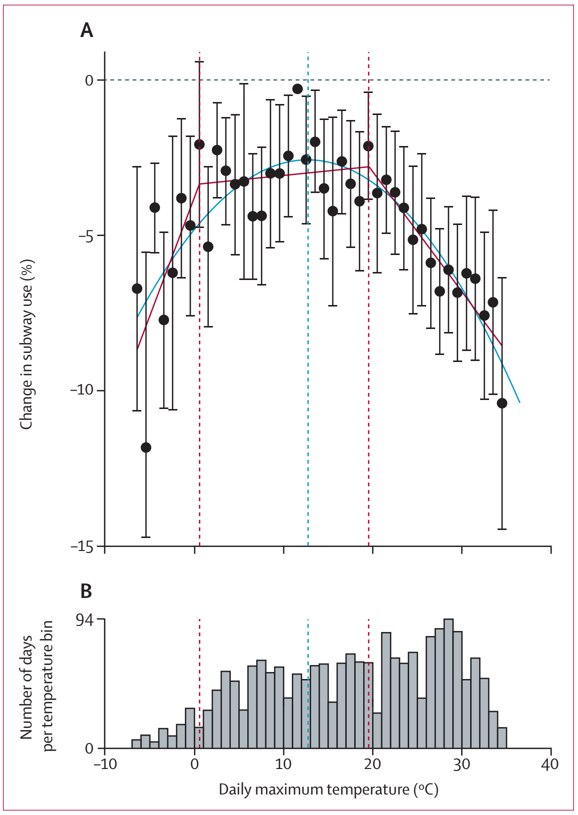

***Figure 1:* Non-linear effects of daily maximum temperature on subway use in New York City, NY, USA and the number of days in each temperature bin during the observation period (2014–19)**

(A) Non-linear effects of daily maximum temperature on subway use in New York City, NY, USA. Black dots show the coefficients of the binned fixed-effects panel-regression model estimating the effect of daily maximum temperature on the percentage change in subway use in New York City for each 1°C temperature bin. The percentage change in subway use is relative to the 11·5°C bin. Error bars denote 95% CIs. Errors are clustered two-way for zip code tabulation areas and for days. Red lines show a segmented model fitted to the binned results; blue lines show a quadratic polynomial fit. Vertical red dotted lines indicate the breaking points of the segmented line (ie, 0·5°C and 19·5°C); vertical blue dotted lines indicate the maximum of the quadratic polynomial (ie, 12·7°C). (B) The number of days in each temperature bin during the observation period (2014–19).

temperatures warmer than 19·5°C, there were strong decreases in ridership (–0·4, –0·56 to –0·23). Robustness tests showed that our results were not sensitive to the specific choice of starting conditions (appendix pp 34–36). As an alternative, we fitted a quadratic function to the results of the binned model (figure 1). The maximum of the quadratic, which can be interpreted as separating the hot and cold responses, was at 12·7°C. Fitting a quadratic model to the raw data also provided parameters that were statistically significant (appendix p 33). Results from a robustness check with PRISM climate data were consistent with the main findings (appendix pp 41–43).

Subsequently, we conducted neighbourhood-level analyses to account for potential heterogeneity in the mobility response to warm weather. The iterative-segmentation algorithm in the panel regression showed that a linear approximation captured the warm response relatively well (R^2 0·87). Therefore, we conducted individual linear regressions for each ZCTA that was included in the analysis for days of 19·5°C or warmer, which provided a single coefficient that described the temperature-induced change in subway use in warm weather per °C. Results showed large differences between ZCTAs in the effects of warm temperatures on subway use. In 116 (95%) of 122 ZCTAs, temperatures of 19·5°C or warmer reduced subway use, with a reduction of up to 11·8 % (95% CI 10·3–13·4) on a day with a daily maximum temperature of 30°C compared with 19·5°C (figure 2A). ZCTAs across New York City that had beach access (appendix p 24) displayed structurally different mobility–heat responses (figure 2B), with mobility increases of up to 70·5% (60·6–80·1) on a day with a daily maximum temperature of 30°C compared with 19·5°C. Of the ZCTAs displaying mobility reductions in heat, these reductions were generally largest in southwest Brooklyn and Manhattan, in particular on the Upper East Side and Upper West Side, and smallest in Queens and the Bronx (appendix p 24). These disparities also persisted on particularly hot days (ie, >30°C) on which the temperature effects on subway use were even stronger than for a warm response starting at 19·5°C (appendix p 36).

At weekends, people have fewer work or school obligations in the USA than on weekdays.[37] Accordingly, results from ZCTA-level weekday–weekend interaction models showed different patterns for weekday and weekend reductions in subway use in warm weather (ie, ≥19·5°C; figure 3). At weekends, mobility reductions in dense areas, such as central Manhattan, were up to 10 percentage points stronger than on weekdays (figure 3) when the weather was warm, suggesting that people avoid these areas when given the choice to do so. By contrast, the mobility increases near beaches were stronger at weekends than on weekdays (figure 3), implying that residents used public transport as a heat-mitigation strategy.

After establishing differences in the mobility–heat response across ZCTAs, we assessed whether these differences could be explained by socioeconomic and environmental characteristics related to heat exposure, demographic characteristics, ethnicity, and commuting (figure 4). For all variables except commuting, we used coefficients for the weekend response, in which some people were more flexible in adjusting their mobility behaviour than on weekdays. Via pairwise Spearman correlations, we found that a high proportion of people employed in heat-vulnerable industries (eg, agriculture; construction; transportation; or utilities such as electric power, water supply, or sewage removal) had low weekend subway-use reductions in warm weather (Spearman correlation 0·59, 95% CI 0·46 to 0·70). ZCTAs with a long walk to the subway also had low weekend subway-use reductions in warm weather (0·12, –0·01 to 0·30). Furthermore, the New York City Heat Vulnerability Index was generally high for ZCTAs in which we found low

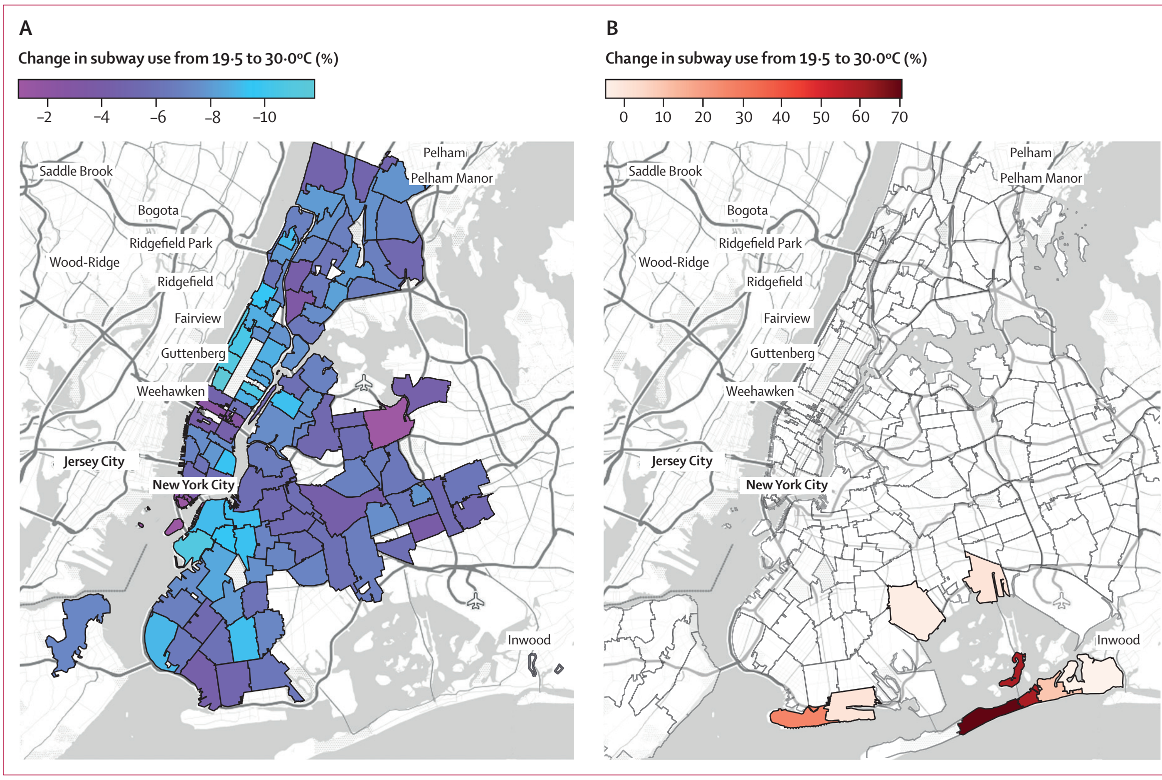

***Figure 2:* Heat effects on subway use across ZCTAs in New York City, NY, USA**

(A) Different colours indicate ZCTA-level mobility–heat responses to daily maximum temperatures of 30·0°C compared with 19·5°C, obtained by running separate linear regressions for each ZCTA. Excluding ZCTAs with access to a beach, the effect of heat is generally negative, with the largest mobility reductions occurring in Manhattan and southwest Brooklyn and the smallest reductions in Queens and the Bronx (appendix p 24). (B) The effect of temperature on mobility is positive for ZCTAs with beach access and for ZCTAs that are surrounded by water. The base map tiles used are by Stamen Design CC BY 3.0 Map data © OpenStreetMap contributors. ZCTA=zip code tabulation area.

weekend mobility reductions in response to warm weather. When considering the coverage of air conditioning separately, we found that ZCTAs with low air conditioning also had low subway-use reductions in warm weather (–0·34, –0·5 to –0·17). ZCTAs with more trees had low subway-use reductions in warm weather (0·28, 0·10 to 0·44).

Regarding demographic indicators, strong mobility reductions were correlated with increased median household income (Spearman correlation –0·43, 95% CI –0·57 to –0·27), increased rent (–0·36, –0·52 to –0·19), and an increased number of people older than 65 years (–0·61, –0·72 to –0·48). A large proportion of households using the Supplementary Nutrition Assistance Program (0·47, 0·31 to 0·60), without health insurance (0·45, 0·29 to 0·58), or that included people who were unemployed (0·36, 0·19 to 0·58) were correlated with weak subway-use reductions in warm weather. Furthermore, ZCTAs that had a large proportion of White residents also had large weekend subway-use reductions in warm weather (–0·55, –0·67 to –0·41). By contrast, ZCTAs with high proportions of Black (0·34, 0·15 to 0·49), Hispanic (0·35, 0·17 to 0·50), or American Indian and Alaska Native residents (0·14, –0·04 to 0·32) had smaller subway-use reductions in warm weather.

The analysis of commuting patterns showed that correlations between weekday mobility reductions in warm weather and socioeconomic indicators were generally weaker (appendix p 37). Bus (Spearman correlation –0·25, 95% CI –0·42 to –0·08), car (–0·10, –0·38 to 0·09), and bicycle (–0·05, –0·23 to 0·13) commutes were correlated with a large weekday subway-use reduction in warm weather. A dependence on the subway (0·22, 0·04 to 0·39) or walking (0·54, 0·39 to 0·66) for the commute was associated with small reduction in weekday subway use. People who commuted primarily by ferry or worked from home had no correlation with changes in subway use.

Overall, we found that communities that were already at a socioeconomic disadvantage and, therefore, had a higher heat vulnerability also had a lower mobility reduction compared with advantaged neighbourhoods, contributing further to the heat exposure and resulting in compounding heat risk.

We found non-linear temperature effects on the number of taxi trips that were similar to the results for subway use (appendix p 27). Temperatures led to decreases in taxi use of up to 3·5% (95% CI –10·5 to 3·6) on cold days (ie, –6·5°C) and up to 6% (–0·8 to 11·5) on warm days (ie, 34·5°C). Fitting a quadratic function to the results

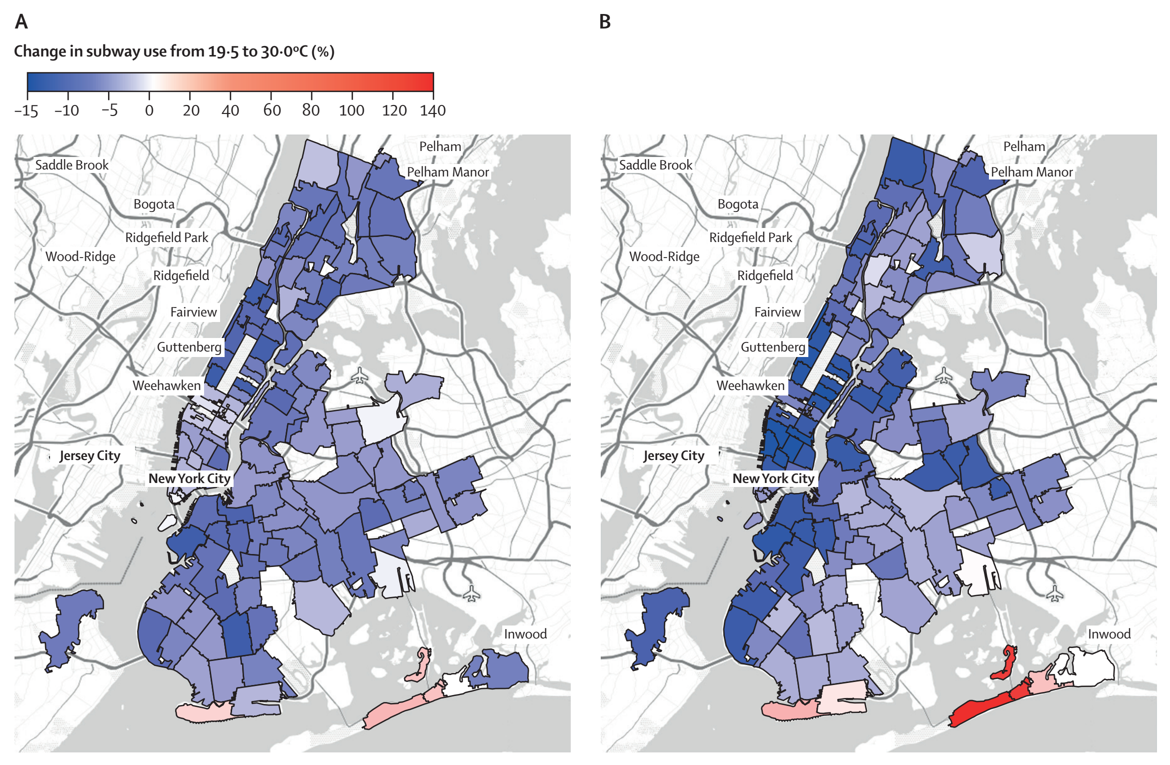

Figure 3: **ZCTA-level heat effects on subway use on weekdays and weekends in New York City, NY, USA**
(A) Linear interaction model measuring ZCTA-level effects of daily maximum temperature on subway use on warm days (ie, ≥19·5°C) that are weekdays. (B) Linear interaction model measuring ZCTA-level effects of daily maximum temperature on subway use on warm days (ie, ≥19·5°C) that are at weekends. The base map tiles used are by Stamen Design CC BY 3.0 Map data © OpenStreetMap contributors. ZCTA=zip code tabulation area.

provided a maximum of 10°C, a difference of 2·7°C compared with the maximum of the subway analysis. Applying the binned fixed-effects panel-regression model to the bicycle-sharing data were similar, with reductions in warm weather reaching up to 32% (–58·7 to –5·4) for days with a temperature of more than 32°C. Bicycle use peaked at 24·5°C and decreased for temperatures warmer than that. Here, the effect size is large, probably due to substantially less data.

Discussion

In this empirical study of mobility data from the transport system in New York City, NY, USA, we found that temperature had a strong, near-linear effect on subway use. Effects in warm weather (ie, ≥19·5°C) differed between ZCTAs and between weekends and weekdays. At the weekend, we contend that people generally had more choice of activity than on weekdays. Therefore, mobility responses at the weekend, which were generally stronger than on weekdays, were likely to capture neighbourhood-level disparities in heat adaptation more accurately. Correlations between the ZCTA-level weekend mobility–heat response and environmental and socioeconomic indicators, as well as correlations with the weekday response and commuting patterns, showed disparities in heat mitigation between different socioeconomic groups within the same city. At the weekend, weak mobility reductions in hot weather were associated with factors such as reduced median household income, a large proportion of households using the Supplementary Nutrition Assistance Program, a large proportion of residents who were not White, a large proportion of residents working in industries that are particularly vulnerable to heat, and reduced access to air conditioning.

Our results can be plausibly explained by three different underlying mechanisms that all diminish the ability to mitigate heat by reducing mobility: job restrictions, budgetary constraints, and local thermal discomfort. First, jobs with low income are less likely to allow remote work[38] and they might require frequent work at the weekend; people might even have more than one job to earn enough money to financially support themselves and continue to use the subway to commute. Often, these jobs also have high heat exposure (eg, construction, agriculture, and transport or utilities) and therefore contribute to heat burden. Second, reduced income also means a reduced budget to leave New York City and go on holiday when the weather is hot. Therefore, subway use might be high in neighbourhoods where people have strong budgetary constraints. Finally, residents might choose to leave their neighbourhood on hot days because of local thermal discomfort in their home and

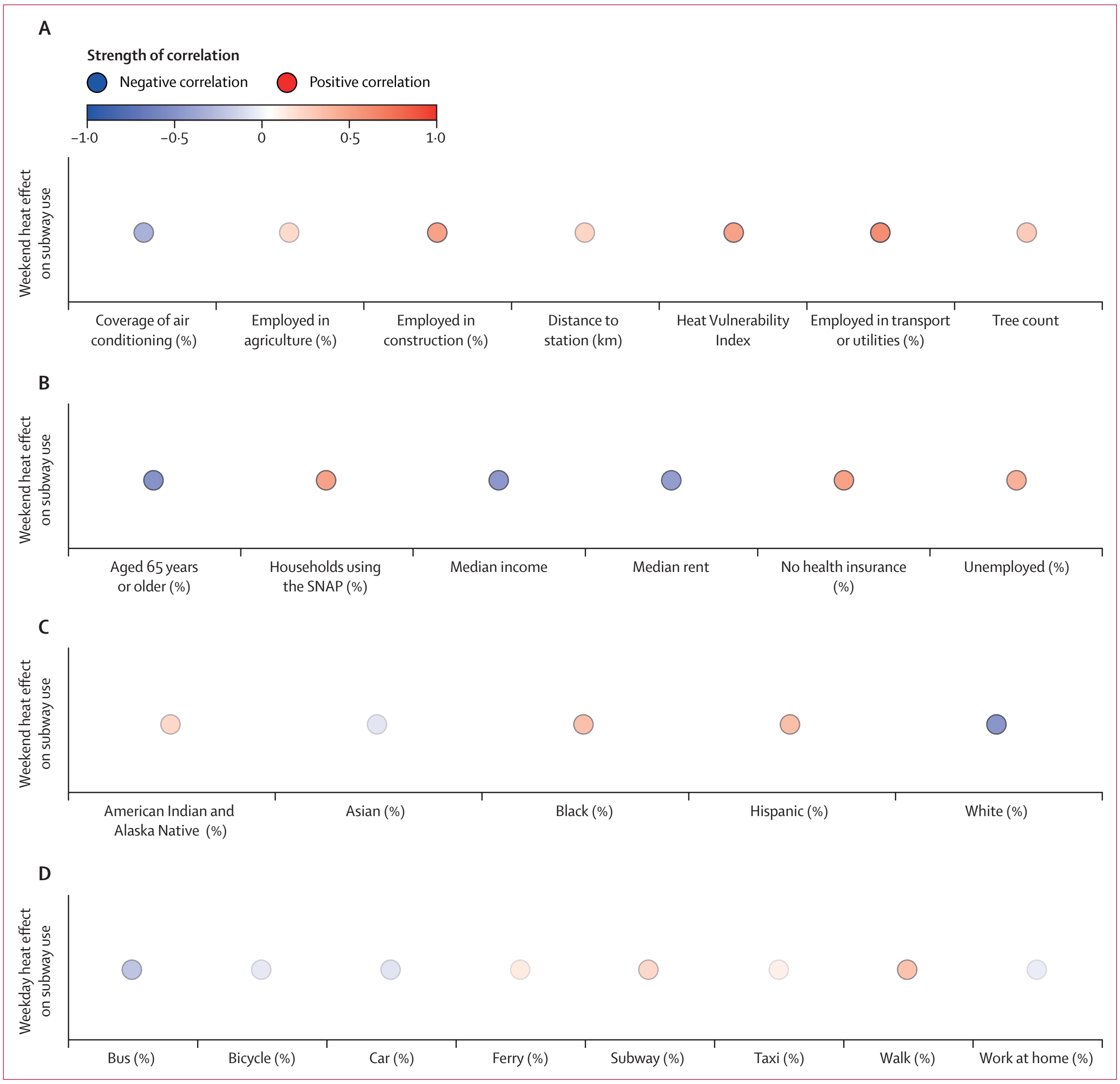

***Figure 4:* Correlations between ZCTA-level mobility–heat response and environmental and socioeconomic indicators**
(A) ZCTA heat exposure. (B) Demographic characteristics. (C) Ethnicity. (D) Commuting. The colour of the circles denotes whether a socioeconomic indicator correlates negatively (blue) or positively (red) with the ZCTA-level effect of heat on transport use. The transparency of the circles denotes the strength of the Spearman correlation. SNAP=Supplementary Nutrition Assistance Program. ZCTA=zip code tabulation area.

neighbourhood, which might be caused by, for example, no air conditioning or dense housing. Our results suggest that people in heat-exposed neighbourhoods use public transport as their heat-mitigation strategy, having to trade off between the discomfort of travelling (eg, walking to the station and waiting there) and their overall thermal comfort. ZCTAs with increased tree cover had smaller reductions in mobility than ZCTAs with reduced tree cover and ZCTAs with beach access showed strong increases in transportation. This finding supports previous work by Nissen and colleagues[16] in Berlin, Germany, who found that bus routes leading to a lake were busier on summer days than other routes decreased. In the subway in New York City there is probably a trade-off: unpleasant heat exposure in stations to then enjoy comfortable temperatures by the beach compared with in the local ZCTA. The strength of the trade-off is also dependent on the journey length and the characteristics of the local ZCTA, again indicating within-city differences in the ability to mitigate heat stress.

Overall, the observed ZCTA-level disparities in mobility behaviour in heat and the strong positive correlations between reduction of mobility and socioeconomic factors suggest that being able to adjust mobility behaviour is a privilege that coincides with other privileges. The increased heat exposure coincides with conditions that are also likely to reduce the ability to deal with the health outcomes of heat, for example reduced access to health insurance. The New York City Heat Vulnerability Index, which currently does not consider mobility, is high in areas where the reduction in subway use is low in warm weather. We found unequal heat effects on mobility across New York City with compounding risks in ZCTAs that already have an increased heat burden and are probably responsible for fewer greenhouse-gas emissions than higher-income ZCTAs.[39] Therefore, we have added to literature showing unequal effects of climate change either across or within countries and cities[7–12,14,40] by highlighting disparities in mobility behaviour in heat and compounding heat risks in New York City as a new effect pathway.

Furthermore, our study contributes to literature on weather effects on transport by reconciling previous, conflicting results that have shown either increases or decreases in mobility with warm temperatures.[16,41,42] By using a semiparametric approach that allowed the modelling of cold and hot responses simultaneously, we showed that subway use increases when going from cold to moderate temperatures and strongly decreases thereafter. Our analyses of taxi and bicycle data showed similar temperature effects. Our results suggest that the heat tolerance for bicycle use is higher than for taxi or subway use, probably because bicycle use happens outside. Therefore, assuming that there are some substitution effects between subway use and bicycle use in moderately warm weather (ie, 19·5–24·5°C) is plausible. However, once a crucial heat threshold (ie, 24·5°C) was crossed, bicycle use also declined. Overall, the robustness of our results across multiple transport types (eg, public and individual) suggested a common effect of temperature on mobility.

Use of high-resolution subway data allowed us to assess not only the overall effects of temperature on ridership, but also to compare ZCTAs. Furthermore, despite the generally high quality and high time resolution of the turnstile data, 168 days were missing from our dataset and we had to remove another 67 days because the data were faulty or represented outliers. Moreover, our knowledge of non-temperature-related factors affecting the subway system, such as construction activities or system failures, was not exhaustive. Although our outlier-filtering methods probably addressed most of these factors, some non-structural biases might have persisted. Another limitation of our study was that individual trips were not possible to distinguish, as the data only provided entry totals and exit totals for each station. Consequently, conducting a comprehensive assessment of the overall heat exposure during a journey was challenging due to the absence of information regarding exact origin and destination points. Although the data did not allow us to quantify the effects for individuals, we found evidence for such patterns in the aggregated data (eg, increased mobility near beaches). Furthermore, we do not know the exact length of time of a trip as the data were aggregated to the daily level. This is a limitation as spatiotemporal patterns, which might give additional insights into adaptation mechanisms over the course of a day (eg, moving necessary trips to cool morning or evening hours), remain elusive. Similarly, the mobility response might have varied depending on whether there was a single hot day or several hot days consecutively. Explicitly analysing the effect of heatwaves will be, therefore, a promising topic for future research. Finally, socioeconomic and environmental indicator data were aggregated at the ZCTA level and were not perfectly homogeneous. Therefore, the analysis at the ZCTA level does not necessarily reflect the individual lived realities of the diverse residents. Instead, our results should be interpreted as an indicator for the entire ZCTA.

With rapid, anthropogenic climate change, temperatures are predicted to increase and heatwaves will become more frequent and intense.[1] New York City is striving to implement a Green New Deal to prepare for the challenges ahead.[43] Fighting local inequality is high on the agenda, and healthy lives and efficient mobility are explicitly named as action points. Our results highlight the inequalities that remain and offer entry points for policy to alleviate these differences. We highlight not only the unequal effects of heat within a single US city, but also unequal possibilities to mitigate heat stress via behavioural adaptation. As a fundamental part of everyday life that is, at the same time, susceptible to heat stress, mobility should be considered as a factor that widens the climate change adaptation gap between societal groups. Unaddressed, this disparity can exacerbate unequal health effects from heat.

Contributors

AS and LW designed the study, analysed the results, and revised the manuscript. AS processed the climate and mobility data, conducted the analyses, and wrote the manuscript. LW contributed to the writing of the manuscript.

Declaration of interests

We declare no competing interests.

Data sharing

New York City Metropolitan Transportation Authority turnstile data are available from https://data.ny.gov/Transportation/MTA-Subway-Hourly-Ridership-Beginning-February-202/wujg-7c2s. Zip code tabulation area (ZCTA) shapefiles for aggregation are available from https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html. Weather-station data are available via the US National Oceanic and Atmospheric Administration from https://www.ncdc.noaa.gov/cdo-web/datasets/GHCND/stations/GHCND:USW00094728/detail. Socioeconomic data at the ZCTA level via the American Community Survey are available from https://www.census.gov/programs-surveys/acs. The New York Points of Interests are available from https://data.cityofnewyork.us/City-Government/Points-Of-Interest/rxuy-2muj. The report containing per-month hotel occupancy data is available from https://assets.simpleviewinc.com/simpleview/image/upload/v1/clients/newyorkcity/FYI_Hotel_reports_March_2020_9afc1fca-79c1-47a9-8a21-fdefa3c4ffcb.pdf. The 2015 New York City Street Tree Census is available from https://data.cityofnewyork.us/Environment/2015-Street-Tree-Census-Tree-Data/uvpi-gqnh. Data on coverage of air conditioning and the New York City Heat Vulnerability Index are available via the New York City Environment and Health Data Portal from https://a816-dohbesp.nyc.gov/IndicatorPublic/beta/data-explorer/climate/?id=2141#display=summary. Citi Bike data are available from https://citibikenyc.com/system-data. Data on yellow-cab use are available via the New York City Taxi and Limousine Commission from https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page. Additional information on each data source and a visualisation of the data use in a flowchart are provided in the appendix (pp 3–8). Code scripts will be made available in Zenodo. No other documents will be available.

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