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# Sleep during travel balances individual sleep needs

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**Travel is expected to have a deleterious effect on sleep, but an epidemiological-scale understanding of sleep changes associated with travel has been limited by a lack of large-scale data. Our global dataset of ~20,000 individuals and 3.17 million nights (~218,000 travel nights), while focused mainly on short, non-time-zone-crossing trips, reveals that travel has a balancing effect on sleep. Underslept individuals typically sleep more during travel than when at home, while individuals who average more than 7.5 hours of sleep at home typically sleep less when travelling. The difference in travel sleep quantity depends linearly on home sleep quantity and decreases as median sleep duration increases. On average, travel wake time advances to later hours on weekdays but earlier hours on weekends. Our study emphasizes the potential for consumer-grade wearable device data to explore how environment and behaviour affect sleep.**

Attaining sufficient sleep is critical to many aspects of human health[1–3]. Short and irregular sleep duration contributes to molecular, immune and neurological changes that play a role in disease development (for example, increasing the risk of obesity and cardiovascular diseases) and substantially affect mood, motor and cognitive performance[1,4–10]. Despite the importance of sleep to health, average sleep duration has continued to decrease among economically developed countries: for example, 30% of the US population slept on average less than six hours per night in 2013, compared with 3% in 1963[11–13].

Concurrently, travel has increased dramatically over the past two decades, with the number of air travellers nearly tripling[14]. There are good reasons to think that travelling negatively impacts sleep. Travel and new resting environments are known to influence sleep quantity and quality. The first-night effect was first documented in 1964, where sleep-initiation difficulty and prolonged sleep-onset latency were found to occur on the first night of sleep taking place in sleep laboratory[15,16]. Later, in 2016, Tamaki et al. showed that the first-night effect is a consequence of a single brain hemisphere displaying elevated alertness in new and unfamiliar environments. The hemisphere with reduced sleep depth showed more enhanced response to external stimuli during the resting period[17].

Travel fatigue and jet lag are conditions that can cause sleep complications when travelling[18–24]. Travel fatigue is associated with any long journey, regardless of the mode of transport, and is characterized by tiredness, disorientation and headaches, which usually last only for a day or so. But when flying across several time zones, there is the added effect of jet lag, with longer-lasting ramifications[18–21]. Jet lag is due to desynchronization of the body's internal clock and the new time zone one enters after long-distance longitudinal travel[22–24].

Jet lag is not limited to travel. Social jet lag is a measure used in sleep epidemiology to quantify the difference between weekend and weekday sleep timing, and if measured high, it is assumed to be occurring due to the constraints of early-morning work schedules on weekdays, which are often relieved on weekends[25,26]. Social demand can thus reduce sleep opportunity (the time available for sleep), and strict work cultures are known to impact sleep schedules as well[27–29]. Sleep duration also depends on individuals' sleep ability, which can be limited due to insomnia or other sleep disorders[30].

Most of the existing research to understand the effect of travel on sleep has focused on physiological and behavioural changes among professional athletes or subjective fatigue and alertness among aircrew staff, and has been carried out as small-scale studies (typically 10–30 study subjects)[18,31–38]. These studies have found no significant difference in sleep quantity and quality before and after short-haul air travel (without crossing of time zones)[32,39–42]. However, if journeys cross time zones, the outcome is different. Jet lag has been found to cause sleep issues in new time zones, including reduced sleep duration, more frequent and longer nighttime awakenings, delayed sleep onset after eastward travel, and advanced sleep offset after westward travel[22,39,43]. While multiple effects have been discussed, the quantitative changes in sleep due to travel have not been researched in an epidemiological context. Here we address this gap in the literature through a large and global dataset of sleep activity data recorded with wearable devices. The dataset consists of ~20,000 individuals residing in 121 countries with more than 3.17 million nights (~218,000 nights away from home), where ~81% of the trips are <1,000 km and 85% have no time zone crosses. The fact that only around 15% of the trips in our data set cross time zones and even fewer cross three or more time zones (6%) implies that our results are potentially less robust for longer trips that cross many time zones. For such trips, additional mechanisms may be at play.

Our work analyses the effects of travel and new resting environments on sleep behaviour. We find that sleep during travel tends to depend on sleep patterns at home; specifically, it serves a balancing function: people with shorter-than-average home-sleep duration tend to have longer nighttime sleep during travel, while those who have longer-than-average home-sleep duration tend to sleep less during travel.

## Results

**Measuring change in sleep duration due to travel.** In Fig. 1a, we present synthetic data to illustrate the complex patterns of sleep observed in our population. The data are highly realistic in that they retain all of the key statistical properties of the real sleep data. We use synthetic data to avoid revealing non-aggregated individual-level data, which may present a privacy risk. We use the median sleep duration, $M_{\mathrm{home}}$, to quantify the typical sleep duration at home. To evaluate behaviour when travelling, we estimate the average sleep duration for travel nights (denoted $\mu_{\mathrm{travel}}$). We define $\Delta_s = \mu_s - M_{\mathrm{home}}$ as the change in sleep duration relative to typical behaviour, where the state $s \in \{\mathrm{home}, \mathrm{travel}\}$. The variable $\Delta_s$ is estimated for each

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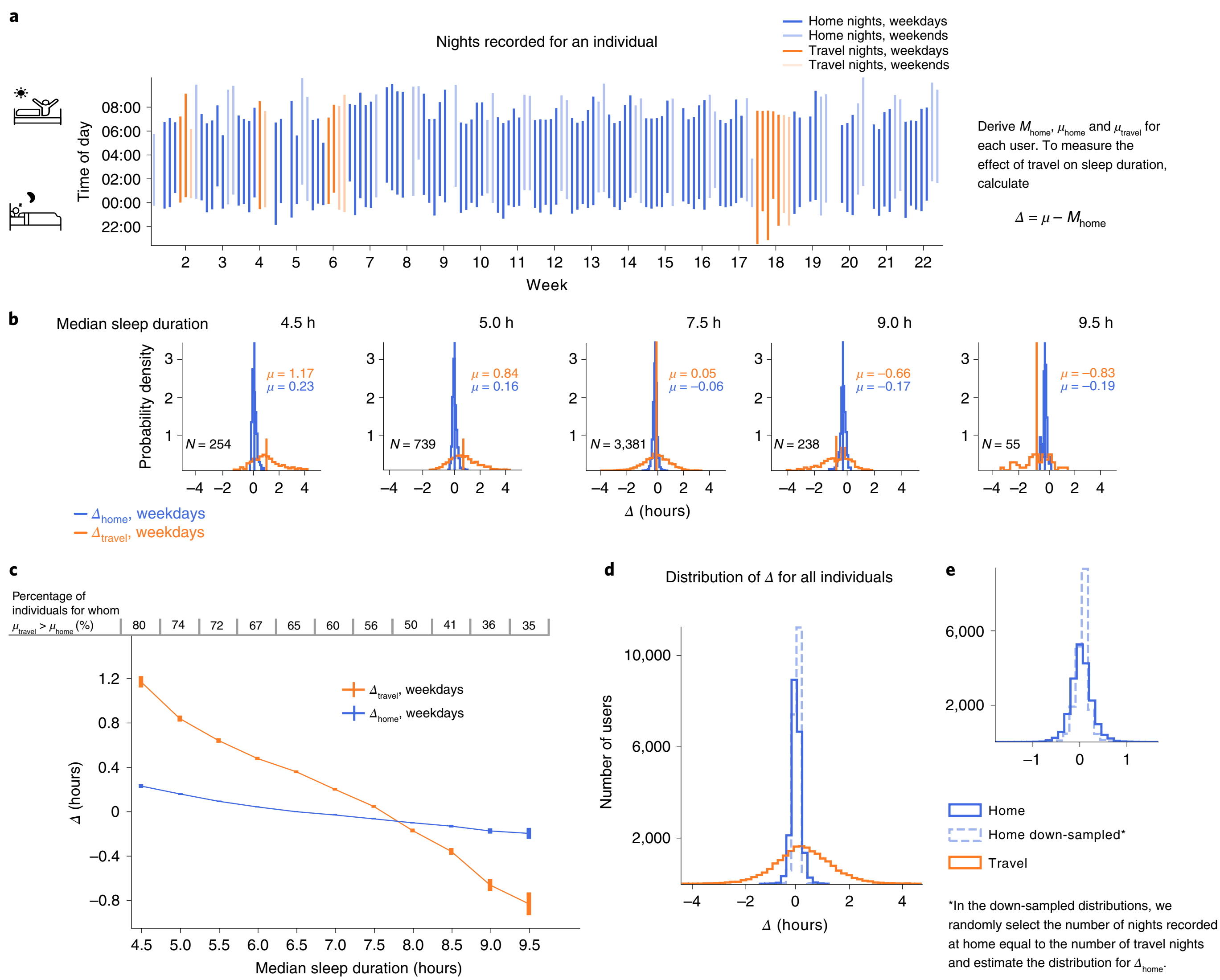


**Fig. 1 | Sleep activity patterns and the relative change in sleep duration for travel nights. a**, For each individual ($N = 19,812$), we measure sleep onset, offset and duration for each recorded night. From these records, we derive three measurements: $M_{home}$, $\mu_{home}$ and $\mu_{travel}$. To measure the change in sleep duration due to travel, relative to typical behaviour at home, we derive a new measure, $\Delta_{travel} = \mu_{travel} - M_{home}$. The sleep data shown in **a** are synthetic, but with all key statistical properties preserved. We use synthetic data to illustrate the complexity of human sleep while ensuring that no non-aggregated individual-level data are displayed. **b**, The distributions of $\Delta_{travel}$ (orange) and $\Delta_{home}$ (blue) for groups with different median sleep durations. Individuals are grouped together by rounding their median to the nearest half-hour bin (referred to as *sleep groups*). **c**, The average $\Delta_{travel}$ for all sleep groups (median duration ranging from 4.5 to 9.5 hours) with error bars representing the s.e.m. **d**, The distributions of $\Delta_{home}$, $\Delta_{home\,DS}$ and $\Delta_{travel}$ for all individuals. **e**, A larger visual representation (a narrower range of the *x* axis) for the distributions of $\Delta_{home}$ and $\Delta_{home\,DS}$ in **d**. In **a**–**e**, dark orange represents $\Delta_{travel}$ on weekdays, light orange is $\Delta_{travel}$ on weekends, dark blue is $\Delta_{home}$ on weekdays, light blue is $\Delta_{home}$ on weekends and the dashed light blue lines represent $\Delta_{home\,DS}$.

individual in our sample. We explain the rationale for comparing mean with median for home and travel nights below.

**Sleep during travel depends linearly on sleep at home.** We first explore whether the change in sleep duration away from home depends on the typical sleep duration at home by plotting the distribution of $\Delta_s = \mu_s - M_{home}$ where $s \in \{\text{home, travel}\}$ for individuals with different median sleep durations. The results are shown in Fig. 1b, where individuals are grouped into sleep groups by rounding their median sleep duration to the nearest half-hour bin. The distributions are broad, but we see a clear trend that the average $\Delta_{travel}$ moves from positive to negative values as the median sleep duration increases. This implies that individuals who sleep little at home (duration ≤5.0 hours) tend sleep longer when they are away from home. On the opposite end of the spectrum, those who sleep longer at home (duration ≥9 hours) sleep less when they are away from home. To quantify this trend, we calculate the average $\Delta_{travel}$ for each sleep group (ranging from 4.5 to 9.5 hours), which reveals an approximately linear dependence of $\Delta_{travel}$ on typical sleep duration at home; the error bars in Fig. 1c show the s.e.m.

**Baseline effect for home nights.** In Fig. 1b,c, we also plot $\Delta_{home} = \mu_{home} - M_{home}$ (blue). This is to illustrate a baseline effect, which relates to the observed systematic change in sleep duration away from home. This baseline effect is a decreasing linear trend of $\Delta_{home}$ (blue line in Fig. 1c), which shows that there is a systematic difference between mean and median as a function of median sleep duration for nights at home.

Our hypothesis is that the slope of $\Delta_{\mathrm{home}}$ arises because of sleep–wake homeostasis, a physiological process that regulates sleep pressure. For example, a person who tends to sleep less than physiologically needed will build up sleep pressure from the last adequate sleep episode, which can be eliminated by a long nighttime sleep (a 'catch-up' night)[44,45]. These catch-up nights can result in a skewed distribution of sleep duration, with a disproportionately larger right tail—a positive skew (exemplified in Supplementary Fig. 12). Similarly, we expect a negative skew (a heavy left tail of the distribution) for individuals who tend to have longer nighttime sleep than they can sustain.

This behaviour is confirmed in Supplementary Fig. 12, which shows that 95% of individuals sleeping 4.5 hours at home have a longer average than median sleep duration, and on the opposite end of the spectrum, 93% of those sleeping 9.5 hours have a shorter average than median sleep duration. This could be why $\Delta_{\mathrm{home}}$ is positive for a median sleep duration of less than seven hours in Fig. 1c and negative for a median sleep duration longer than seven hours. The weak linear trend of $\Delta_{\mathrm{home}}$ and median sleep duration on Fig. 1c (which we believe is due to the process of sleep–wake homeostasis) explains our comparison of $\Delta_{\mathrm{travel}}$ with $\Delta_{\mathrm{home}}$ to obtain the absolute effect of travel on sleep.

**Robustness despite imbalanced travel and home sample sizes.** To directly compare $\Delta_{\mathrm{travel}}$ and $\Delta_{\mathrm{home}}$, we plot both distributions together in Fig. 1d. Visually, the two distributions are very different, with a much broader distribution for travel nights. To rule out the possibility that our results are due to this imbalance in sample sizes (for example, that the broad range of $\Delta_{\mathrm{travel}}$ is due to the lower sampling rate for travel nights), we perform an individual-level down-sampling of nights at home to balance our data sample. The distribution of down-sampled home values, $\Delta_{\mathrm{home\,DS}}$, (light-blue distribution), is shown in Fig. 1d,e. The down-sampled distribution is, in fact, slightly narrower than that of $\Delta_{\mathrm{home}}$ and remains quite different from the broad range of behaviour observed for the distribution of $\Delta_{\mathrm{travel}}$ (for a more detailed description, see 'Down-sampling nights at home' in the Supplementary Information).

Figure 1 only shows behaviour on weekdays since we follow the convention of sleep research and analyse weekdays and weekends separately. In the next section, we include data from weekends to understand the effect of travel on weekend nights.

**Social jet lag impacts the change in sleep during travel.** Social jet lag was conceptualized by Wittman et al. and quantifies the difference between "biological time preferences" and time of work and other social demands. Stated more plainly, social jet lag measures the difference between weekday (workdays) and weekend (work-free days) sleep behaviour ('Calculation of social jetlag' in the Supplementary Information)[25]. In Fig. 2a, we show how social jet lag is distributed across our sample. Most individuals (80%) have some amount of social jet lag ranging from 9 to 98 minutes. Figure 2b shows that social jet lag depends on sleep duration and that individuals with high values of social jet lag typically sleep little on weekdays (four to five hours) and a lot on weekends (nine to ten hours). This large quantitative difference is usually attributed to the constraints of an early work schedule on weekdays, causing substantial sleep deprivation on weekdays and sleep compensations during weekends[25,26]. In Fig. 2c, we plot the distribution of $\Delta_{\mathrm{travel}}$ for weekdays (dark orange) and weekends (light orange) for groups of individuals with different ranges of social jet lag (defined by percentiles). We observe a larger effect of travel on sleep duration for individuals with high values of social jet lag, and individuals in the top tenth percentile (>99 minutes) gain on average 45 minutes of sleep when nights take place away from home on weekdays but lose 32 minutes of sleep on weekends.

**Effects of travel on weekend nights.** Next we examine how sleep duration changes for travel nights on weekends and compare it with the patterns observed previously for weekday nights (Fig. 1). Figure 2d shows the distributions of $\Delta_{\mathrm{travel}}$ on weekdays (dark orange) and weekends (light orange) organized by sleep groups, where the grey horizontal lines represent the distribution median and quartiles. Figure 2e illustrates the averages of $\Delta_{\mathrm{travel}}$ by sleep groups with the s.e.m. The relationship between $\Delta_{\mathrm{travel}}$ and typical sleep duration on weekends is effectively the same as on weekdays: the change in sleep duration during travel decreases as the sleep duration at home increases. However, the relative change is slightly larger in the positive direction (the line is pushed further up on $y$ axis) on weekdays than on weekends when observing the distribution averages and quartiles in Fig. 2d,e. A possible explanation for these differences is that people are often constrained by time and alarm clocks on weekdays and consequently sleep less than they might need; therefore, there is more opportunity to gain sleep. An opposite effect is expected for weekends, when there is more opportunity to lose sleep[25,26].

**Sleep onset shows a similar behaviour to duration.** So far we have studied sleep duration for travel nights, but sleep duration is derived from two variables: bedtime (sleep onset) and wake-up time (sleep offset). We now investigate whether the effect of travel extends to sleep onset and offset. To explore this question, we use the same methodology as above. We thus calculate $\Delta_{\mathrm{onset,travel}} = \mu_{\mathrm{onset,travel}} - M_{\mathrm{onset,home}}$ and $\Delta_{\mathrm{offset,travel}}$. These quantities are then aggregated into averages by user groups, defined by percentiles (10th, 25th, 50th, 75th and 90th) of the distribution of median sleep duration (see Fig. 3a for weekdays and Fig. 3f for weekends). The average $\Delta_{\mathrm{onset,travel}}$ (blue) and $\Delta_{\mathrm{offset,travel}}$ (yellow) are shown with the s.e.m. for weekdays in Fig. 3b and weekends in Fig. 3g. We find that the change in sleep onset depends on the duration of home sleep: those who sleep less than 6.2 hours on weekdays (the bottom 25th percentile) go to bed earlier on weekday travel nights. For those sleeping 7.5 hours or less (the bottom 50th percentile), the travel sleep onset on weekends is advanced to earlier hours. The dependence of $\Delta_{\mathrm{onset,travel}}$ on typical sleep duration is approximately linear, and sleep onset advances from earlier to later hours (relative to typical behaviour at home) as typical home sleep duration increases.

**Sleep offset shows the opposite behaviour on travel nights.** Wake-up time during travel tends to be later for all individuals on weekdays but earlier on weekends (yellow curves in Fig. 3b,g). The individuals in the bottom tenth percentile on weekdays and the top tenth percentile on weekends change their behaviour the most relative to typical hours at home, waking up $33 \pm 2$ minutes later on weekdays and $45 \pm 2$ minutes earlier on weekends when nights take place away from home. The top tenth percentile on weekdays and the bottom tenth percentile on weekends change their behaviour the least (with shifts of $7 \pm 1$ and $8 \pm 2$ minutes in wake-up time on weekdays and weekends, respectively). The middle group (10th–90th percentiles in the distribution of median sleep duration) exhibit more homogeneity on weekdays, where wake-up hours on weekdays are 22–29 minutes later, whereas the range is broader on weekends and there is a slight linear dependence with typical sleep duration at home (with wake-up time occurring 18–36 minutes earlier than at home). A possible explanation for the difference in the change in sleep timing (onset and offset) due to travel between weekends and weekdays is the fact that sleep patterns tend to be shifted to earlier hours than is natural to individuals on weekdays due to morning work schedules[25,26]. This constraint seems to extend to the relative change in sleep timing away from home, since bed and wake-up times are almost always shifted to later hours for most groups on weekdays and earlier hours on weekends.

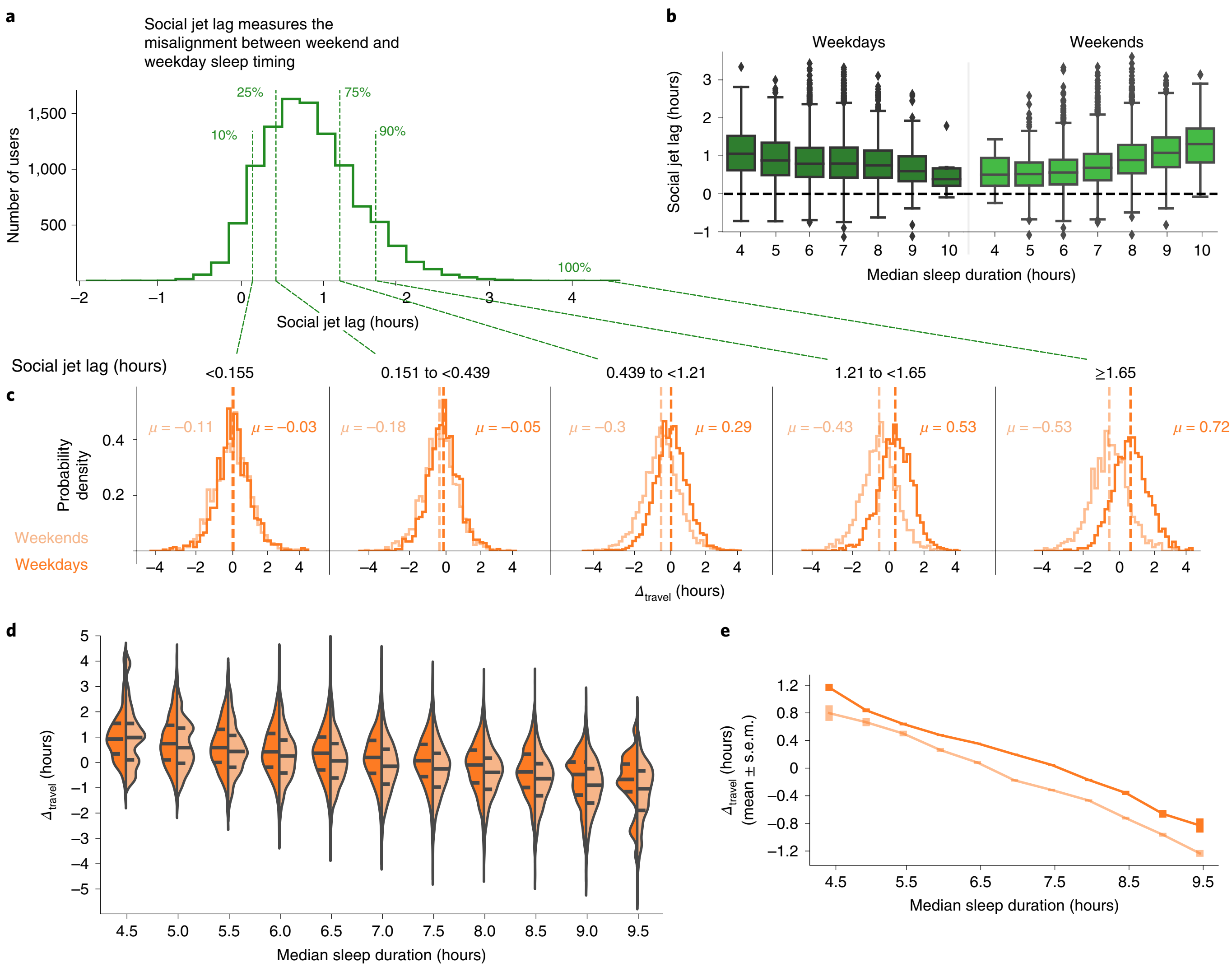


**Fig. 2 | Disproportionate effect of travel on individuals with high social jet lag and the connection between weekends and weekdays. a**, Definition of social jet lag and distribution of social jet lag across the sample. The dotted green lines mark the 10th, 25th, 75th and 90th percentiles of the distribution of social jet lag. **b**, Box plots of social jet lag for individuals with different sleep durations. The horizontal lines represent the median, the box limits correspond to the upper and lower quartiles, the whiskers define 1.5 times the interquartile range and the points are outliers. Dark green represents social jet lag plotted for groups with different median sleep durations on weekdays, and light green represents social jet lag for groups with different median sleep durations on weekends. **c**, Distribution of $\Delta_{travel}$ on weekdays (dark orange) and weekends (light orange) for groups of individuals with different ranges of social jet lag (defined by the 10th, 25th, 75th and 90th percentiles). **d**, The distributions of $\Delta_{travel}$ for groups with different median sleep durations by day type—weekends (lighter orange) and weekdays (darker orange). The grey horizontal lines mark the quartiles of the distributions. **e**, The average $\Delta_{travel}$ plotted with the s.e.m. by sleep groups (half-hour bins for median sleep duration) on weekdays (dark orange) and weekends (light orange). The sample sizes are $N = 19{,}812$ for weekdays and $N = 13{,}515$ for weekends.

**Mixed-effects models for robustness checks and demographics.** Our dataset contains males and females, covers a wide range of ages and originates from individuals across the world, and sleep behaviour has been shown to depend on these demographic indicators[26,46–52]. In the analysis above, we ignore this heterogeneity and explore sleep behaviour during travel averaged across our entire population. To understand the effects of the underlying heterogeneity on our results, we now explore the relationship between the change in sleep duration on travel nights ($\Delta_{travel}$) and typical sleep duration at home ($M_{home}$) using mixed-effects models.

Specifically, we analyse the effects of the following demographic covariates: generation (millennial, Gen X or baby boomer), gender (male or female), region of residence (East or West, represented as Asia or North America and Europe) and BMI category (normal weight, overweight or obese). All of these categories are defined formally in the Supplementary Information ('Data coverage & demographics'). We implement a model with a three-way interaction term between home (true or false), every demographic variable and median duration centred on the mean (the model is defined formally in 'Controlling for demographic heterogeneity with mixed effects model' in the Supplementary Information).

Our mixed-effects model confirms the large difference between the rate of decrease for $\Delta$ at home and this rate away from home. The decline is $0.4 \pm 0.008$ hours ($24 \pm 0.5$ minutes) larger when travelling than at home (for an hour increment in typical sleep duration) on weekdays and $0.35 \pm 0.01$ hours ($20 \pm 1$ minutes) larger on weekends (Supplementary Tables 12 and 13, fixed effect dur_C:homeFalse).

The region of residence is the most influential covariate in terms of level of significance and effect size on both weekends and weekdays. The difference between East and West is smaller in terms of

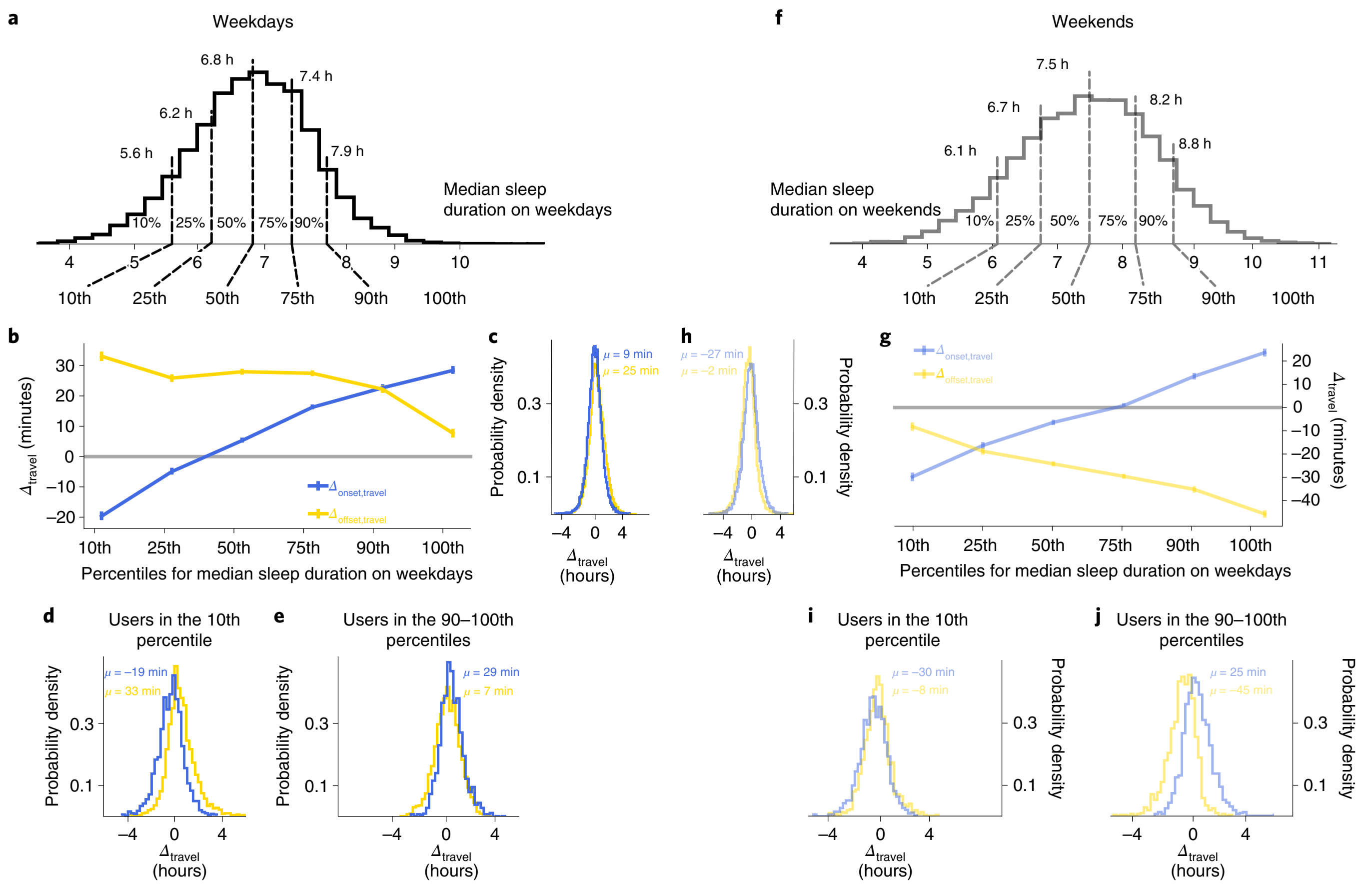


**Fig. 3 | Change in sleep onset and offset on travel nights. a**,**f**, The distributions of median sleep duration on weekdays (black line in **a**) and weekends (grey line in **f**) with the 10th, 25th, 50th, 75th and 90th percentiles marked with dashed lines (black (**a**) and grey (**f**) on weekdays and weekends, respectively). **b**,**g**, The change in sleep onset and offset relative to typical home sleep (the blue lines are $\Delta_{onset,travel}$, and the yellow lines are $\Delta_{offset,travel}$; darker colours represent weekdays, and lighter colours represent weekends) aggregated into averages (with s.e.m.) by user groups defined by the percentiles of sleep duration illustrated in **a** and **f**. **c**,**h**, The distributions of $\Delta_{onset,travel}$ (blue lines, darker for weekdays and lighter for weekends) and $\Delta_{offset,travel}$ (yellow lines, darker for weekdays and lighter for weekends) for all individuals in the sample. **d**,**i**, The distributions of $\Delta_{onset,travel}$ (blue lines, darker for weekdays and lighter for weekends) and $\Delta_{offset,travel}$ (yellow lines, darker for weekdays and lighter for weekends) for individuals with the lowest sleep duration on weekdays (**d**) and weekends (**i**) (bottom 10th percentile). **e**,**j**, The distributions of $\Delta_{onset,travel}$ (blue lines, darker for weekdays and lighter for weekends) and $\Delta_{offset,travel}$ (yellow lines, darker for weekdays and lighter for weekends) for individuals with the highest sleep duration on weekdays (**e**) and weekends (**j**) (90–100th percentiles). The sample sizes are $N = 19{,}812$ for weekdays and $N = 13{,}515$ for weekends.

the rate of decrease of $\Delta_{travel}$ (0.015-hour more negative decline for eastern residence on weekends but none on weekdays) but much greater when considering the intercept, which is $0.59 \pm 0.008$ hours ($35 \pm 1$ minutes) higher for individuals in the West on weekdays and $0.46 \pm 0.01$ hours ($28 \pm 1$ minutes) higher on weekends (see the fixed effects dur_C:east_westeast and homeFalse:east_westeast in Supplementary Tables 12 and 13). Gender has a significant effect on $\Delta_{travel}$ on weekdays, where women tend to gain more sleep during travel nights than men (the intercept is $0.12 \pm 0.08$ hours higher for women; see the fixed effect homeFalse:genderFEMALE in Supplementary Table 12). Furthermore, individuals in the obese BMI category lose more sleep during travel (on average $0.14 \pm 0.01$ and $0.12 \pm 0.02$ hours on weekday and weekend nights, respectively; see the fixed effect homeFalse:bmi_cat3 in Supplementary Table 12) than those in the other weight groups. To provide an overview of these results, we list the model estimates of $\Delta_s$ where $s \in \{\text{home, travel}\}$ for different median sleep durations (4.5, 7.0 and 9.5 hours) and by the most important covariates in Table 1 (also visualized in Supplementary Figs. 13 and 14).

**Mixed-effects model including time zones, distance and direction.** One possible hypothesis is that our results may be impacted by time zone changes, distance travelled and/or direction of the journey (eastward or westward travel). To investigate this question, we again employ a mixed-effects model, but now including only travel nights. We define new covariates for time zone changes (absolute difference relative to home 0, >0 to 1, >1 to 3, >3 to 6 and >6 hours) and the direction of the journey (eastward or westward) and include a continuous variable for distance travelled. In Supplementary Fig. 5, we illustrate the distribution of distance travelled and find that it is approximately log-normal. Furthermore, we support our choice of boundaries for time zone changes in the Supplementary Information ('The effect of time zone changes, direction of travel and distance'). We note that 81% the nights are less than 1,000 km away from home, 85% of trips do not include a time zone change and only ~7% include a time zone change of more than one hour.

The mixed-effects model uses the following covariates: median sleep duration and log(distance) (in km) centred on the population average, time zone changes, direction of the journey and the demographic variables used before. The model is defined with two-way interaction terms between (1) all demographic covariates and median sleep duration, (2) time zone changes and direction of travel, and (3) log(distance) and median sleep duration. The model

**Table 1 | Estimates of $\Delta_s$ from mixed-effects models for different sleep groups (individuals are grouped together by rounding individual median sleep duration to the nearest half-hour bin) for the most important demographic groups (in terms of significance and effect size from the model results)**

| Median sleep duration (hours) | 4.5 | 7.0 | 9.5 | 4.5 | 7.0 | 9.5 |
|---|---|---|---|---|---|---|
| | | Weekday travel | | | Weekday home | |
| $\Delta_s$ for men in the West (hours) | $1.64 \pm 0.017$ | $0.452 \pm 0.010$ | $-0.741 \pm 0.038$ | $0.167 \pm 0.076$ | $-0.015 \pm 0.00070$ | $-0.198 \pm 0.009$ |
| $\Delta_s$ for men in the East (hours) | $1.07 \pm 0.013$ | $-0.159 \pm 0.022$ | $-1.39 \pm 0.057$ | $0.181 \pm 0.012$ | $-0.039 \pm 0.0041$ | $-0.259 \pm 0.020$ |
| $\Delta_s$ for women in the West (hours) | $1.81 \pm 0.029$ | $0.564 \pm 0.020$ | $-0.685 \pm 0.07$ | $0.167 \pm 0.076$ | $-0.015 \pm 0.00070$ | $-0.198 \pm 0.009$ |
| $\Delta_s$ for women in the East (hours) | $1.24 \pm 0.025$ | $-0.0469 \pm 0.032$ | $-1.33 \pm 0.089$ | $0.181 \pm 0.012$ | $-0.039 \pm 0.0041$ | $-0.259 \pm 0.020$ |
| | | Weekend travel | | | Weekend home | |
| $\Delta_s$ for men in the West (hours) | $1.25 \pm 0.052$ | $0.158 \pm 0.041$ | $-0.937 \pm 0.044$ | $0.216 \pm 0.0095$ | $-0.00276 \pm 0.0025$ | $-0.222 \pm 0.015$ |
| $\Delta_s$ for men in the East (hours) | $1.02 \pm 0.079$ | $-0.266 \pm 0.0037$ | $-1.55 \pm 0.087$ | $0.216 \pm 0.0095$ | $-0.00276 \pm 0.0025$ | $-0.222 \pm 0.015$ |

is defined explicitly in the section 'The effect of time zone changes, direction of travel and distance' in the Supplementary Information.

**Small effect of time zones and distance travelled.** At first we notice that when controlling for distance travelled, time zone changes, direction of the journey and demographic heterogeneity, the relative change in sleep due to travel is still highly dependent on typical home sleep. The rate of decrease of $\Delta_{\text{travel}}$ is ~$0.5 \pm 0.02$ hours for an hour increment of home sleep (Supplementary Tables 15 and 16, fixed effect dur_C). That is approximately the same effect measured in the model that also included home nights (from now on referred to as model A) and can be obtained by adding the fixed effects dur_C and dur_C:homeFalse in Supplementary Tables 12 and 13. The effects of the demographic covariates are also measured similarly in terms of significance and effect sizes as in model A.

Distance is a significant effect for both weekday and weekend travel nights: a 1% increase in distance on weekdays results in a 0.17-hour increase in $\Delta_{\text{travel}}$ on weekdays and a 0.039-hour increase on weekends (Supplementary Tables 15 and 16, fixed effect log_distance_c). Time zone changes also influence $\Delta_{\text{travel}}$. Individuals are likelier to lose sleep if there are time zone changes during their trips, and the sleep loss is larger as time zone changes increase in magnitude. For example, the average decrease is 0.14, 0.17, 0.28 and 0.43 hours for time zone changes of 0 to 1, >1 to 3, >3 to 6 and >6 hours, respectively (Supplementary Table 15, fixed effects tz_diff_cat1, tz_diff_cat>1-3, tz_diff_cat>3-6 and tz_diff_cat>6). Furthermore, our modelling suggests that people are likelier to lose sleep during eastward travel than westward, an effect that is higher on weekdays than on weekends.

In interpreting these results, the reader should note that our data are more sparse in the case of time zone changes, as only ~7% of travel nights, or roughly 15,000, include a time zone change of more than one hour. For this reason, and to ensure that aggregating time zone changes into categories for the covariate in the model does not influence the results, we also explore time zones without aggregation; this does not change our findings ('Model B1: time zone changes as covariate without aggregation' in the Supplementary Information).

**Results are robust when varying the number of travel nights.** An important parameter in our analysis is how many travel nights an individual must have to be included in our dataset. Here we explore whether our results depend on the minimum number of travel days. We examine the estimates of fixed effects while the inclusion criterion changes, ranging from a minimum of 2 to 12 travel days per individual. For this purpose, we use a simplified version of the model defined in the section 'Robustness in terms of varying number of minimum travel days per individual' in the Supplementary Information. This analysis shows that our estimates of fixed effects persist but in some instances become slightly smaller in magnitude. In some cases, the estimated effects fall just outside the range of the standard error of the mean for the full dataset (Supplementary Tables 19 and 20). However, the differences with respect to the full dataset are small, and overall we confirm our findings. For example, the difference between the slope for home nights and that for travel nights is −0.397 to −0.389 (estimate ± s.e.m.) for the full dataset but −0.379 to −0.366 with a minimum of 12 travel days (for weekdays). This difference is larger on weekends: −0.387 to −0.374 for 2 travel days (full dataset) but −0.342 to −0.317 for 12 travel days. The larger deviation for users with a higher threshold of minimum number of travel days on weekends might be due to fewer data points (there are five weekdays versus two weekend days per week) and more variability of sleep on weekends, which could be exacerbating the difference[52]. Overall, the same results are found when the number of travel days required per individual is increased, with some indications of a slight change in magnitude.

## Discussion

Drawing on a dataset of 3.17 million nights with a subset of ~218,000 travel nights (where ~81% of the trips are <1,000 km and 85% have no time zone crosses) for approximately 20,000 individuals, we observe a systematic change in sleep duration and timing (onset and offset) on travel nights, relative to typical at-home behaviour. The change in sleep duration due to travel depends linearly on the typical sleep quantity at home and decreases as median sleep duration increases—a pattern identified for both weekdays and weekends. Our main finding is that sleep during travel tends to have a balancing effect. Underslept individuals tend to sleep more when travelling than at home, while individuals whose overall nighttime sleep is long tend to sleep less when away from home. The change in sleep onset and offset on travel nights supports the observed changes in sleep duration. Wake-up time is on average advanced to later hours on weekdays compared with typical nights at home, but to earlier hours on weekends. The change in sleep onset on travel nights is linearly dependent on typical sleep duration at home and is advanced to later hours as median sleep duration increases. Distance has a larger effect on travel sleep on weekdays than on weekends, and individuals are likelier to lose sleep if there are time zone changes when they are travelling; this loss grows larger as time zone changes increase in magnitude.

The observed dependence of the change in sleep duration on travel nights on typical sleep duration at home is found on both weekdays and weekends, but individuals are slightly more inclined to gain sleep on weekdays than on weekends. This latter finding is probably associated with constraints due to social demands (work, school and so on) and is further supported by the fact that individuals who have high social jet lag are disproportionately affected by travel[25,26]. Our results show that, on average, wake-up time is shifted to later hours during travel nights on weekdays but to earlier hours on weekends, while the change in bedtime on travel nights is linearly dependent on median sleep duration at home. This highlights the fact that wake-up time is a more controllable factor, since individuals can set an alarm to wake up at a specific hour but cannot necessarily fall asleep at a predefined time. A previous study indicated related results, where individuals seemed to catch longer nighttime sleep on weekends by shifting their bedtime marginally more than their wake-up time[52].

We observe different effects of travel on sleep depending on demographic variables, where the most significant and influential factor is region of residence—a variable that identifies whether an individual lives in the East (Asia) or in the West (North America and Europe). Those residing in the East are more inclined to lose sleep when travelling, whereas those in the West tend to gain sleep. The differences between eastern and western residence are lower on weekends; this observation might be due to the fact that work schedules can be stricter in Asian countries and possibly regulate sleep behaviour more strongly there[53]. We also speculate that the difference may be related to the baseline for at-home behaviour. Individuals in the East sleep less on average than those in the West—6.4 versus 7.1 hours on weekdays and 6.9 versus 7.8 hours on weekends—a pattern also identified in other studies[48–51].

The overall dependence of $\Delta_{\text{travel}}$ on typical sleep duration remains when controlling for time zone changes, distance travelled and direction of the journey (eastward or westward travel). Distance and time zone changes have an effect on travel sleep, where individuals tend to gain sleep with increasing travel distance, but lose sleep if there are time zone changes during their trips, an effect that grows larger as time zone changes increase in magnitude. Furthermore, we find that people tend to lose more sleep during eastward than westward travel, which is consistent with previous work[22,43].

We now discuss the limitations of our analyses. First, there are relatively few nights recorded away from home (~7% out of 3.18 million nights). We require individuals to have at least two travel nights to be included in our sample, but that sampling rate might not reflect the full range of behaviour for an individual. To mitigate this limitation, we analyse the effect of travel with panel data analysis using hierarchical linear modelling, which uses all data points simultaneously to examine the effect of covariates while controlling for individual baseline behaviour and characteristics. We also perform down-sampling for nights recorded at home (to be equal to the number of travel days), which demonstrates that the large distinction between the distribution of $\Delta$ at home and the distribution away from home persists with the same sampling rate. Most importantly, our results remain the same when changing the inclusion criterion from 2 to 12 travel days while comparing estimates of fixed effects. Second, approximately 81% of travel nights occur less than 1,000 km away from home, and 85% of trips include no time zone changes. Our sample is thus biased towards relatively short-distance travel and unlikely to provide a full picture of the effects of jet lag. Third, we do not control for national holidays in our analysis, since it was not possible to find reliable global data regarding these days. To gain some understanding of the role of holidays, we considered travel in the days between Christmas and New Year's (26–30 December) for the countries that celebrate these holidays (residence in the West) and found the same pattern as in the main results ('Travel during official holidays' in the Supplementary Information). Fourth, our sample of individuals may not be representative of the wider population due to potential unobserved factors also associated with wearable device ownership[54]. Fifth, we note that the wristbands have not been publicly validated using the gold standard of polysomnography as recommended in the Sleep Research Society Workshop on wearable devices for the measurement of sleep[55]. However, we find that our dataset converges with country-level sleep measures from separate large-scale datasets, demonstrates consistency over the period of observation and replicates age-related sleep trends from previously published self-report studies, including changes in sleep duration and timing[52]. The devices have also been internally validated by the manufacturer.

Due to the nature of the data collection, we cannot know whether individuals are travelling to entirely new destinations (as they may have visited any location outside the data collection window), and we do not know whether trips are for the purpose of business or leisure. These limitations may impact our understanding of the first-night effect, since participants' familiarity with each destination is uncertain, and more generally since holidays often imply different sleep schedules from workdays[16,17]. We hope that these unknowns can be considered in future studies.

The effect of travel on sleep behaviour has not been studied for a cohort of this size before, and most of the research has aimed to understand the effect of travel on sleep to optimize athletic performance or to apprehend fatigue among aircrews.[18,31–38,56]. Interestingly, one of these studies identified a related pattern—travel was negatively correlated with sleep duration on weekdays among kite surfers ($N=94$)[56]. Generally, travel is believed to have deleterious effects on sleep, but our study reveals that travel seems to have a more complex impact on the sleep of travellers, with a high likelihood of respite for underslept individuals, while the deleterious effects are reserved for those who tend to be well rested[18–24].

## Methods

**Data collection.** The dataset was collected from 2015 to 2019 via Sony SmartBands (SmartBand Talk (SWR30) and SmartBand 2 (SWR12)) designed to track physical activity and sleep behaviour. When first connecting the wristband to their smartphone, individuals receive visual instructions on how and where (wrist) to place the device, and they are advised to wear it on their dominant side. Users provided informed consent for their data to be processed. All data processing was carried out in accordance with the European Union's General Data Protection Regulation 2016/679 and the regulations set out by the Danish Data Protection Agency. The General Data Protection Regulation describes regulations for data protection and privacy in the European Union and the European Economic Area; it also addresses the transfer of personal data outside the European Union and European Economic Area. The wristbands use proprietary, internally validated algorithms based on movement registered by an internal accelerometer to estimate sleeping and waking states in one-minute intervals. The one-minute sleep states are used to infer sleep onset, offset and duration for each night. Nighttime awakening or sleep fragmentation is also accounted for and quantified as wake after sleep onset. The measurements produced by the wristbands exhibit a high degree of face validity and converge with estimates of age-related changes from the literature ('Comparison of country-level statistics to external large-scale data sets' in the Supplementary Information)[52]. By using these wristbands, we follow a growing trend of utilizing commercial devices in sleep research to study sleep behaviour in naturalistic settings at large scales[52,57–62].

The individuals are anonymous and self-report their age, gender, height and weight. The location data originate from GPS traces; these are not collected at a fixed sampling rate, but estimates are updated when there is a change in the motion state of the device (if the accelerometer registers a change).

**Data preprocessing.** We removed outliers to reduce the risk of including sleep observations from those suffering from insomnia, artificially shortened night observations due to individuals ceasing wristband use in the middle of the resting period, observations from night-shift workers or any other possible data errors. The details of this process are described step-by-step in the Supplementary Information ('Data pre-processing').

We transformed the raw location data to stop locations using the infostop algorithm[63], converting traces to stops, each with an ID, start time and end time. We discarded sleep observations without associated stop locations. We defined a person's sleep location as the stop location with a start time closest to the sleep onset. To ensure consistency, we only accepted locations where sleep begins and an individual does not leave the location until after the sleep has ended. We expected people to sleep at home for the majority of the time and therefore used sleep location to infer home location. The location where most nights take place is defined as an individual's home location. We removed individuals from the dataset if their percentage of nights at home was lower than 70%. We used this threshold to ensure that we selected individuals with a fixed home location and retained approximately 80% of the individuals by applying this selection criterion. Henceforth, we refer to nights that take place at least 20 km away from home as travel nights.

We used the median sleep duration to quantify the typical sleep duration (for nights recorded at home). For the median to be representative of an individual's typical behaviour, we required all participants to have a minimum of ten nights recorded at home; in this, we treated weekends and weekdays separately. In the Supplementary Information ('Filtering & inclusion criteria'), we provide evidence that ten nights is a reasonable threshold.

As we wish to understand the quantitative effect of travel on sleep duration and timing, we also required individuals to have a minimum number of nights recorded away from home. We set this minimum to two travel days (by day type; weekdays and weekends). Again, we justified this choice using robustness checks ('Results') and down-sampling home nights, as shown in the Supplementary Information ('Down-sampling nights at home'). Note that we separated the analyses by day type (weekend versus weekday), and individuals may be included in the analysis for a single day type or both.

After the preprocessing, the final dataset used for the analyses consisted of 2.4 million weekday nights (6.0% travel nights) from 19,812 individuals and 0.77 million weekend nights (9.4% travel nights) from 13,515 individuals. There are 10,823 individuals included in both the weekend and weekday analyses. About 81% of the trips are <1,000 km away from home, and ~85% of the travel nights have no time zone changes. An in-depth exploration of how individuals are distributed by demographics and data coverage is presented in the Supplementary Information ('Data coverage & demographics').

**Data modelling.** To support our main findings, we employed a mixed-effects model—a panel data analysis with a hierarchical linear model where the relationship between the change in sleep duration away from home (relative to regular behaviour) and typical sleep duration at home is explored[64].

The mixed-effects model enabled us to retain the hierarchical structure of the data—repeated measurements within an individual. Initially, $\Delta$ was estimated as a single measurement per individual ($\Delta = \mu - M_{\mathrm{home}}$, where $\mu$ is the average sleep duration on travel nights and $M_{\mathrm{home}}$ is the median sleep duration at home, both estimated separately for weekday and weekend nights), but in the mixed-effects models, we estimated it for every recorded night for each individual, defined as

$$\Delta_{i,j} = \mathrm{duration}_{i,j} - M_j, \qquad (1)$$

where $i = 1, \ldots, N$ and $j = 1, \ldots, K$, where $N$ is the total number of nights for individual $j$, $K$ is the total number of individuals and $M_j$ is the median sleep duration (either on weekdays or on weekends) for individual $j$. We note that the dependent variable ($\mathbf{y}$) in the mixed-effects model is $\Delta_{i,j}$, and the model is specified in matrix form as

$$\mathbf{y} = X\boldsymbol{\beta} + Z\mathbf{u} + \boldsymbol{\epsilon}, \quad \text{with} \quad \mathbf{u} \sim N_q(0, G) \quad \text{and} \quad \boldsymbol{\epsilon} \sim N_n(0, R), \qquad (2)$$

where $\boldsymbol{\beta}$ represents the fixed-effects parameters, $\mathbf{u}$ represents the random effects, $X$ is the $n \times p$ design matrix for the fixed-effects parameters and $Z$ is the $n \times q$ design matrix describing the random effects. The term $\boldsymbol{\varepsilon}$ is a vector representing the measurements errors, $R$ is the covariance matrix for the $\boldsymbol{\varepsilon}$ and $G$ the covariance matrix for the random effects ($\mathbf{u}$). The dependent variable is $\Delta_{i,j}$, and the fixed-effects parameters are the demographic variables (gender, generation, BMI category and region of residence) and home. The independent variable is median sleep duration (continuous), and we control for individual baseline behaviour since each individual has a random effect (intercept).

We analysed the dataset using R version 3.5.1 and the lmerTest package. We used the lmer function to fit the dataset and applied Satterthwaite's degrees of freedom method to estimate the $P$ values for the significance of the fixed effects[65–67]. The model was reduced by removing insignificant fixed effects (one at a time) with the drop1 function, which uses $F$-tests (one-sided) for its estimates. We centred the median sleep duration around its sample mean to help improve interpretability and prevent multicollinearity.

**Reporting Summary.** Further information on research design is available in the Nature Research Reporting Summary linked to this article.

## Data availability

The raw data are not publicly available to preserve individuals' privacy (according to the privacy policy for the wearable devices). Aggregated and anonymized data supporting the key findings in the paper are available from Figshare (https://doi.org/10.6084/m9.figshare.17207231); researchers interested in single-night data resolution may contact the corresponding authors regarding full data access.

## Code availability

The code used to generate the results of this paper is available for download on GitHub (https://github.com/siggasvala/Travel-and-sleep).

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## Author contributions

S.S.J., S.L. and J.B. designed the research. S.S.J. preprocessed the data, performed the data analysis and created the figures. S.S.J., S.L. and J.B. analysed the results and wrote the paper.

## Competing interests

The authors declare no competing interests.

## Additional information

**Supplementary information** The online version contains supplementary material available at https://doi.org/10.1038/s41562-022-01291-0.

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| ☐ | ☒ | Estimates of effect sizes (e.g. Cohen's $d$, Pearson's $r$), indicating how they were calculated |

*Our web collection on statistics for biologists contains articles on many of the points above.*

## Software and code

Policy information about availability of computer code

| | |
|---|---|
| Data collection | The data was collected with wearable devices; SmartBand (SmartBand Talk [SWR30] and SmartBand 2 [SWR12]). |
| Data analysis | Pyspark 2.3.0<br>Python 3.6.3<br>R 3.5.1 |

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Raw data are not publicly available to preserve users' privacy (stated in the Privacy Policy of the wearable devices). Aggregated and anonymized data supporting the findings of this study are available from the corresponding authors upon request. Figure 1A contains raw data-points from the data-set.

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# Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

| | |
|---|---|
| Study description | The study uses hierarchical, cross-sectional, quantitative and observational data, where 1-level mixed effects models were implemented for analysis. The data-set was collected via wristbands designed to track physical activity and sleep behavior. |
| Research sample | The sampled population is large scale (approximately 19000 users) and global (from 95 distinct countries) with wearable device owners. There are certain geographic regions more dominant than others, but we do control for that in our analysis. Users range from age 19-69 and 1/3 are women. The data-set offers unique methodological advantages; scale, longitudinal coverage, and ecologically valid observations. However, it is not strategically sampled and wearable device users may not be representative of the wider population due to potential unobserved factors associated with wearable device ownership. |
| Sampling strategy | The data is observational therefore no sampling strategy applied. However it provides an outlook on a large cross-section of the entire population, considering number of users, number of countries they reside in, as well individuals are at all stage of adult life and both genders. |
| Data collection | The data was collected with wearable devices; SmartBand (SmartBand Talk [SWR30] and SmartBand 2 [SWR12].<br>SONY has asked not to be named in the papers, and we are asked not to disclose device models of the wearable devices. |
| Timing | October 2015 - May 2019. |
| Data exclusions | There are approximately 15 million nights in the full data-set without any inclusions criteria. A large part of the data excluded to explore the effect of travel on sleep, but that is due to the fact that many users do not have nights recorded away from home. The data exclusion process is described concisely in the SI. |
| Non-participation | 0 |
| Randomization | Users are allocated into groups by quantitative measures such how long they typically sleep. They are also grouped by demographic variables such as country of residence, age and gender. |

# Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

## Materials & experimental systems

| n/a | Involved in the study |
|---|---|
| ☒ | ☐ Antibodies |
| ☒ | ☐ Eukaryotic cell lines |
| ☒ | ☐ Palaeontology and archaeology |
| ☒ | ☐ Animals and other organisms |
| ☒ | ☐ Human research participants |
| ☒ | ☐ Clinical data |
| ☒ | ☐ Dual use research of concern |

## Methods

| n/a | Involved in the study |
|---|---|
| ☒ | ☐ ChIP-seq |
| ☒ | ☐ Flow cytometry |
| ☒ | ☐ MRI-based neuroimaging |