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Sweet dreams are made of this: The co-benefit of a pedestrianisation policy in Paris on sleep

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Abstract

Road traffic is the primary source of air pollution in urban areas, as well as an important source of noise. It is increasingly regulated in Europe with noticeable positive effects on air quality and health outcomes. Co-benefits of traffic regulations, such as increased physical activity, are put forward to support the development of such policies. One co-benefit that has yet to be documented is sleep despite being a key determinant of health. We consider a flagship traffic policy in France, the *Paris Respire* campaign,[1] that was implemented in 2016 and intends to episodically reduce engine traffic related emissions across the city in targeted areas. We estimate its impact on sleep by relying on personalised sleep tracker data capturing individuals' sleep quantity and quality between 2015 and 2019 (N=938,386), and implementing a spatial and temporal difference-in-differences framework. The policy decreased daily vehicular traffic in target areas by 24.9% on average across the zones along with non-negligible temporal and geographical spillover effects decaying with distance. Controlling for these spillover effects, we estimate the impact of the policy increases the minutes of total sleep by 2.2% on the night following the application of the policy. We discuss the possible pathways of air pollution and noise pollution, with changes in traffic-related emissions likely being the driver of the effects of the policy. The policy implications are that, if the policy were to be uniformly enforced every weekend over a year, it would result in approximately 2 extra nights of 7-hour sleep inside a target zone. This study offers valuable insights for policymakers and urban planners seeking holistic approaches to improve urban well-being.

Keywords: air pollution, traffic, pedestrianisation, sleep, social impacts

JEL Codes: I19, I31, Q50, Q51, Q53

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[1]Literally *"Paris Breathes"*.

1 Introduction

Motorised transportation is one of the largest contributors of poor air quality, accounting for more than one-quarter of ambient air pollution in urban areas (Amato et al., 2014; Grange et al., 2017). Petrol and diesel vehicles release a wide spectrum of pollutants, principally carbon monoxide (CO), oxides of nitrogen (NO_X), and particulate matter (PM_{10}), prompting a growing interest among economists in understanding the negative consequences of urban road traffic on infant health (Currie & Walker, 2011; Beatty & Shimshack, 2014; C. Kang et al., 2024) and academic performance (Heissel et al., 2020; Austin et al., 2019) among others. These concerns have catalysed policy interventions ranging from direct user charges and standards (e.g. low emission zones) to traffic bans to reduce traffic-induced pollution (Davis, 2015; Wolff, 2014; ?, ?). Despite the considerable attention paid to air pollution effects, the relationship between traffic and population health remains the focus of analysis (e.g. Simeonova et al., 2019; Gehrsitz, 2017; Margaryan, 2021; Pestel & Wozny, 2021), with the indirect health and wider social impacts often being overlooked. As a result, the co-benefits of the traffic-related interventions are underestimated. With over 90% of the global population currently living in areas of poor air quality (World Health Organization, 2019), gaining further insight on its relationship with determinants of health, such as sleep, is crucial in further understanding and accounting for its wider societal and economic implications.

Sleep is a vital activity with a myriad of benefits, playing a pivotal role in maintaining health, bolstering productivity, enhancing cognitive function, and nurturing psychological well-being (Shrader & Gibson, 2018). Sleep deprivation, the state of insufficient sleep, has been linked with negative health and social outcomes, including elevated mortality risk (Cappuccio et al., 2010), engagement in risky behaviours (Smith, 2016; Venkatraman et al., 2007), and lower academic performance (Carrell et al., 2011). According to Hafner et al. (2017), the US loses the equivalent of around 1.2 million working days per year due to people not getting enough sleep, and insufficient sleep costs the UK economy £40 billion each year, equivalent to nearly 2% of its GDP (RAND, 2018). Some studies explore the role of environmental factors on sleep, such as ambient temperature (Minor et al., 2020), noise pollution (Muzet, 2007), and air quality (Liu et al. 2021). Given the ubiquity and necessity of sleep, and the value it adds to individuals' health and well-being, the welfare implications of any link between traffic and sleep in this setting are potentially enormous.

Motorised traffic could impact sleep mainly via two channels - air pollution and noise. Other channels include greater physical activity induced by the pedestrianisation of roads during certain hours. A large body of literature suggests that pollution exposure harms health and wellbeing, leading to preventable mortality and morbidity (see Chen et al. (2017); Currie et al. (2014) for an overview of the impact on a range of health outcomes), such as poor lung development (Gauderman et al., 2004), and obesity risks (Deschenes et al., 2020). These health and well-being effects widely impacts the economy, with consequences on productivity (Chang et al., 2016, 2019), crime (Bondy et al., 2020), cognitive performance (Ebenstein et al., 2016; Zhang et al., 2018; Lavy et al., 2014), and human capital formation (Austin et al., 2019; Currie et al., 2009). This creates large economic costs not only with increased hospitalisations (e.g. Janke, 2014; Moretti & Neidell, 2011; McCreanor et al., 2007) leading to increased healthcare spending (Barwick et al., 2018; Deryugina et al., 2019), but also through increased defensive medical spending (Deschênes et al., 2017), and losses in labour supply (Zivin & Neidell, 2018; Graff Zivin & Neidell, 2012). Air pollution potentially affects sleep quantity and quality through biological channels (e.g. through disturbances to distal airways or neural inflammation) and behavioural channels (e.g. reducing exercise and reducing exertion)

The *Paris Respire* policy, which was rolled out in 2016, offers a natural experiment through temporary pedestrianization regulations to study the relationship between traffic and sleep. We exploit variations in traffic that only apply to certain days and times, and specific areas of the city. Our paper also distinguished itself by using precise sleep data available at a large temporal scale across the city of Paris. In order to establish a causal relationship between traffic and sleep,we adopt a quasi-experimental approach, combined with advanced econometrics methods, to assess whether exogenous changes in traffic impact individual-level sleep quality and quantity in Paris, taking into account spatial and temporal spill-over. To the best of our knowledge, this study is the first to examine the impact of traffic on sleep and sleep deprivation. Identifying these effects is challenging due to numerous factors, which we aim to address in this paper. First, there are potential endogeneity problems caused by residential sorting. Traffic is not randomly assigned across locations. Individuals may sort into areas of better air quality depending on their income, health, or preference for noise or other factors (Chay & Greenstone, 2005; Moretti & Neidell, 2011). By not accounting for residential sorting, unobserved determinants of sleep may bias the estimation of the effect of pollution on sleep. Another challenge is that the effect of pollution on sleep might be highly dependent on individual avoidance behaviours. Avoidance behaviour occurs when individuals choose to reduce their exposure to air pollution, such as using air filtration systems, or being outdoors when air pollution is low (Neidell, 2009; Moretti & Neidell, 2011). This emphasises the need for an estimation technique that permits for the isolation of the effects on sleep using arguably exogenous changes in air quality.

Second, previous studies utilise sleep data collected from self-reported surveys or controlled laboratory settings, and thus, suffer from several limitations. For example, surveys are at risk of recall bias, are restricted in the detailed measurement of sleep, and often collected on a small sample. Similarly, short-term laboratory findings are not generalisable beyond the controlled environment. Recent systematic reviews (Liu, Wu, et al., 2020; Cao et al., 2021) emphasise the absence of a causal study and highlight links between diverse study methodologies and subjective air pollution and sleep measurements with uncertainty of a possible relationship between sleep and pollution. In attempts to move beyond the limited precision and/or temporal resolution of measures employed by previous studies, this paper draws on a unique and comprehensive sleep dataset consisting of over half a million geolocated daily sleep observations from over 2,000 people using sleep-activity mattresses across Paris between 2014 to 2019. These mattresses have pneumatic and sound sensors which enable the measurement of a user's respiratory rate, heart rate, body movements and snoring patterns. As a result, this sleep dataset offers detailed measurements comparable to laboratory studies through the identification of various indicators of sleep quality and quantity. Devices such as this mattress, and other commercial wearable devices, are becoming increasingly ubiquitous and provide observational studies with several empirical advantages over previous analyses[2] (Banks, 2020). The high frequency spatial and temporal reference information not only allows for merging with complementary datasets, but also enables for in-situ analyses to quantify any observed changes in sleep.

This paper's central task is to provide the first systematic documentation of the impacts of changes in air quality on sleep quality and quantity using a natural experiment. This is done through the exploration of the effects of the *Paris Respire* in two stages. First, we evaluate the effectiveness of the policy in reducing traffic, using road sensor data between 2014 and 2019. We leverage *Paris Respire* to assess changes in traffic flows, at hourly and daily levels, observed on roads in car-free zones with traffic observed outside of these areas across hours where the policy is operational and inactive. The nature of this policy gives rise to two potential spillover effects: (a) *Spatial* spillovers, and (b) *Temporal* spillovers. In the former case, it is plausible that the policy has indirect displacement effects of traffic, and air pollution, on neighbouring geographical units. Similarly, in the latter case, it is also plausible that individuals may change their travel patterns throughout the day to adjust for the temporary closure of these areas. In both instances, we identify that these (a) neighbouring areas, and (b) neighbouring hours may experience effects of the policy and, therefore, without providing specific consideration to them we risk failing to identify the counterfactual trend. Thus, we exploit the staggered and temporary introduction of *Paris Respire* across time and space in a spatial difference-in-differences (DD) framework that also accounts for both potential spillover effects (Butts, 2021).

The second stage of this paper focuses on estimating how the consequent changes in traffic impact individuals' sleep outcomes. To identify this effect, using the above-mentioned spatial DD approach, we compare sleep observations from users in car-free zones against users outside of these zones, across days where the policy was and was not in operation whilst accounting for potential spillover effects. We estimate a daily time-series Poisson-regression model that includes day of week, month, year, and individual fixed effects. The range of time fixed effects non-parametrically absorb seasonal and temporal trends in pollution and sleep. The individual fixed effects capture

[2] There is increasing research suggesting that information from such devices ("wearables") can accurately detect sleep (S. G. Kang et al., 2017; Zinkhan et al., 2014)

observed and unobserved factors unique to each user, such as income, health status, mattress-use and behavioural patterns, to the extent they do not vary over time. We also include extensive controls for weather to capture time-varying environmental factors. The remaining variation associated with the policy is likely to be independent from the numerous behavioural and environmental factors that affect sleep.

The first set of results indicates that although hourly traffic and congestion reduce in certain areas in response to *Paris Respire*, it is displaced to areas that do not implement the policy. Nonetheless, the overall daily effects of the policy observes significant decreases in traffic volumes and congestion. The second set of results confirm that, accounting for unusual sleep patterns, changes in air-quality associated with traffic-changes induced by *Pairs Respire* lead to improvements in sleep quality and quantity. We find no evidence of changes in sleep latency or fragmentation. Taken together, the evidence points to a pattern of fairly wide effects of *Pars Respire*, such that the population treated within the policy is not the only one that benefits.

The last part of the paper discusses the selection of the regulated zones and the potential mechanisms between traffic and sleep. The idea of zones restricted to traffic was suggested by the Mairie of Paris in 2003 but was only implemented gradually across Paris starting in 2016. While the overall objective of the policy was to reduce noise and pollution, it is unclear how the different zones were identified. We compare the noise in the various zones and their adjacent areas and found no evidence of systematic bias. We also see only less than 1.5% movers between treated and control zones over our 6 years of data. In terms of the mechanisms that explain our results, we cannot determine whether traffic affects sleep via noise, air pollution, or both. However, using the limited data available on pollution and noise, and based on the correlations between traffic, air pollution, and noise, and considering that the policy is active only during the day, we argue that the effect is likely driven by improvements in air quality during daytime hours.
This paper proceeds as follows. The subsequent section (Section 2) describes background information on air pollution and traffic, and provides details of the policy leveraged, *Paris Respire*. This is then followed by a detailed overview of the different datasets used (Section 3). Section 4 details the empirical strategy. In Section 5, we present our results that describe the impacts of *Paris Respire* on traffic and sleep. Section 6 outlines results from robustness and sensitivity checks. We conclude in Section 7.

2 Institutional and Environmental Background

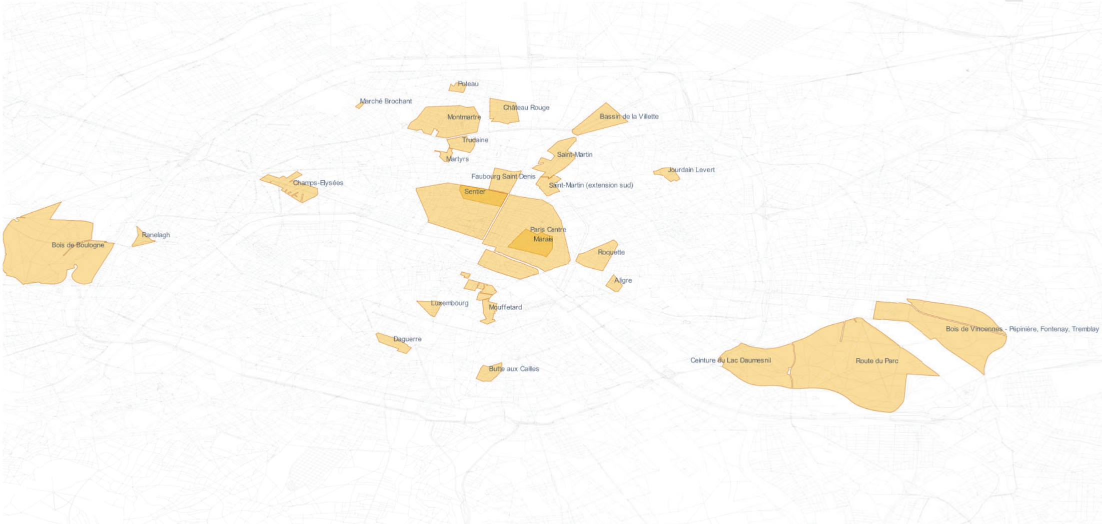
Paris is a city with a long history of poor air quality and systemic breaches of the European limit value for nitrogen dioxide (NO_2) (Font et al., 2019b; Petit et al., 2017; Bessagnet et al., 2005), although the ambiant air quality had greatly improved by the start of the campaign with all the European limit value for NO_2 being met by the start of the campaign (Font et al., 2019a).
As part of the Mayor of Paris' campaign in 2014, a greener and environmentally friendly transformation was lauded. One of her air pollution policies was the introduction of a temporary car-free policy, *Paris Respire*, recognising the impact of traffic and congestion on air quality as a source of large concern. The participating areas were announced and the policy was introduced in 2016. *Paris Respire* involves the reduction of the number of cars in the city by restricting certain districts (henceforth *target zones*) to motorised traffic on Saturdays, Sundays, and/or public holidays during selective hours of a day (henceforth *policy hours*), generally between 10am and 6pm. We refer to a day where the policy is introduced, for any length of time, as *policy day*. The pedestrianisation process affects roads across 26 districts. These districts are highlighted in Figure 1. The majority of the districts affected are located in central Paris, and range from the touristic districts of Champs-Élysées and Montmartre, to the dining and entertainment locale of Mouffetard. The closure, depending on the district, is implemented over the summer or throughout the year over certain days and/or hours of the week. There are exceptions to the prohibitions on vehicular traffics. Taxis, buses, and delivery vehicles are allowed limited access to these areas provided that they do not exceed a maximum speed of 20 kilometres per hour (kmph). During these closures, the areas also remain accessible to residents with authorised vehicles. There is unlimited access to those who are walking, cycling, or skating. Table 1 outlines the implementation details for each target zone.

Table 1: The implementation details of *Paris Respire* across Paris for each target zone

Target Zone	When?	Policy Days	Winter Policy Hours	Summer Dates	Summer Policy Hours	Authorised Vehicles
Montmartre	All Year	Sundays & Public Holidays	11:00-18:00	3 Apr - 28 Aug	11:00-19:00	Residents, Taxis & Disabled
Ranelagh	Summer	Sundays & Public Holidays		24 Jul - 21 Aug	10:00-18:00	Residents, Taxis, Disabled & Deliveries
Marais	All Year	Sundays	10:00-18:00	3 Apr - 25 Sep	10:00-19:30	Residents & Taxis
Trudaine	All Year	Sundays & Public Holidays	14:00-18:00	5 Jun - 25 Sep	14:00-19:00	Residents & Taxis
Bois de Boulogne	All Year	Saturdays, Sundays & Public Holidays	09:00-18:00			None
Bassin de la Villette	All Year	Sundays & Public Holidays	14:00-18:00	1 Apr - 30 Sep	14:00-20:00	Residents, Taxis, Disabled & Deliveries
Champs-Elysées	First Sunday of the Month	First Sunday of the Month	10:00-18:00			Residents & Taxis
Butte aux Cailles	Summer	Sundays & Public Holidays		1 Apr - 30 Sep	10:00-20:00	Residents, Taxis, Disabled & Deliveries
Poteau	All Year	Sundays	10:00-14:00			Residents & Taxis
Bois de Vincennes	All Year	Sundays & Public Holidays	09:00-18:00	3 Apr - 25 Sep	09:00-20:00	None
Martyrs	All Year	Saturdays & Sundays	10:00-20:00			Residents, Taxis, Disabled & Deliveries
Faubourg Saint Denis	All Year	Sundays & Public Holidays	10:00-18:00	From 23 Jun	10:00-20:00	Residents, Taxis & Disabled
Aligre	All Year	Sundays	10:00-14:00			Residents, Taxis & Disabled
Sentier	All Year	Sundays & Public Holidays	10:00-18:00	3 Apr - 25 Sep	10:00-19:00	Residents & Taxis
Saint-Martin (south)	Summer	Sundays & Public Holidays		24 Jul - 21 Aug	10:00-20:00	Residents & Taxis
Luxembourg	Summer	Sundays & Public Holidays		3 Apr - 27 Nov	10:00-18:00	Residents & Taxis
Roquette	Summer	Sundays & Public Holidays		24 Jul - 21 Aug	10:00-20:00	Residents, Taxis, Disabled & Deliveries
Saint-Martin	All Year	Sundays & Public Holidays	10:00-18:00	3 Apr - 25 Sep	10:00-20:00	Residents & Taxis
Daguerre	All Year	Sundays & Public Holidays	10:00-18:00			Residents, Taxis, Disabled & Deliveries
Ceinture du Lac Daumesnil	All Year	Sundays & Public Holidays	09:00-18:00	3 Apr - 30 Sep	09:00-20:00	None
Paris Centre	First Sunday of the Month	First Sunday of the Month	10:00-18:00			Residents
Mouffetard	All Year	Sundays & Public Holidays	10:00-18:00			Residents
Route du Parc	All Year	Sundays & Public Holidays	09:00-18:00	1 Apr - 30 Sep	09:00-20:00	None
Marché Brochant	All Year	Sundays	10:00-13:00			Residents
Château Rouge	All Year	Saturdays	11:00-19:00			Residents, Taxis & Disabled
Jourdain Levert	All Year	Sundays & Public Holidays	10:00-18:00	1 Apr - 30 Sep	10:00-20:00	Residents, Taxis, Disabled & Deliveries

Motorised traffic can be a source of air and noise pollution. Road transport accounts for a large proportion of primary emissions, contributing up to 73% of nitrogen oxides (NO_x) (Airparif, 2016), while noise pollution from traffic appears to be concentrated around the roads (see Map XXX in Appendix, Section A.3).
changes in traffic represent a unique proxy for changes in air quality. Figure 4 illustrates the high correlations between traffic, measured as the number of vehicles, and the daily average of NO_X and NO_2 concentrations over the study period. As expected, traffic is highly correlated with concentrations in Paris.

Figure 1: A map of Paris, France. Areas in yellow highlight all target zones that are part of the *Paris Respire* pedestrianisation campaign. A full outline of the implementation can be found in Table 1.



3 Data

The main datasets in this analysis consist of information on (a) hourly and daily road traffic, and (b) individual daily sleep measurements. The structural characteristics and traffic information are obtained from the *Comptage Routier* database provided by OpenParis[3] (Direction de la Voirie et des déplacements, 2019a) from 1 March 2014 to 31 March 2019. The information on geolocated individual-level sleep characteristics is provided as proprietary data from the *Sleep Tracking Mat* developed by health electronics company, Withings, from 16 October 2014 to 22 March 2019. Both datasets are merged with meteorological data from MeteoFrance (MeteoFrance, 2020), using daily weather measurements averaged across all meteorological monitoring stations, and air pollution data from AirParif (Airparif, 2020), using inverse distance weighting.

Target zones from the policy are provided as polygon vectors in the *Sectures Paris Respire* dataset[4] (Direction de la Voirie et des déplacements, 2019b). This geographical information is overlaid on both traffic and sleep datasets to identify observations that fall inside and outside the target zone. All spatial matching is conducted using qGIS 3.10.2 (QGIS.org, 2021).

Below, the emphasis is on describing the data on road traffic and sleep outcomes as these are the main variables of interest. Table 2 outlines summary statistics for all aspects of our analysis, and is further discussed below.

[3]Any rights in individual contents of the database are licensed under the Database Contents License (OpenData, n.d.).

[4]This dataset identifies the polygon vector of each zone under the scheme, and further outlines its detailed implementation and operation (i.e. the hours of operation, the days of implementation, etc.)

3.1 Road Traffic Data

The traffic aspects are captured by fixed measurement sensors across the roads of Paris. Each road is composed of various arcs represented by each sensor (henceforth referred to as *road sensor*). This dataset contains hourly traffic measurements, such as traffic count and occupancy rate, recorded by 3,320 sensors, providing 75,598,882 observations over our study period. This dataset reports (1) traffic count (number of vehicles), and (2) occupancy rate. The occupancy rate, measured in percent, captures the flow of traffic and is provided as the percentage of the time, over an hour, that the measuring road sensor is blocked by a vehicle. Therefore, we utilise this to build a measure for estimated congestion as a fluidity-adjusted count of traffic. This is calculated by multiplying the occupancy rate with the traffic count to obtain a weighted indicator of traffic. To ensure our dataset only comprises working segments of each road, we use the *Travaux perturbants la circulation* database (Direction de la Voirie et des déplacements, 2019c) to identify roadworks and traffic disruptions during our period of interest on qGIS. This dataset is further collapsed at the daily level to obtain daily mean traffic measurements at each road sensor (N=642,192).

Panel A of Table 2 outlines summary statistics for measures of traffic and shows that, on average, the hourly traffic count is 559 vehicles (SD 562) per road sensor and the daily traffic count is 472 vehicles (SD 354) per road sensor. Figure 2 illustrates the intersection between road sensors and target zones. Further descriptives, by policy variables, can be found in Appendix B Table 10.

Figure 2: A map of Paris, France. Thick lines represent roads which traffic is monitored. Orange represents roads and zones in the target zones as part of the *Paris Respire* pedestrianisation campaign. Brown lines represent road sensors that are not targeted by the policy.

3.2 Environmental Data

Meteorological data are available for 10 irregularly-spaced stations across Paris. This dataset (N=18,850) includes daily measurements of temperature, precipitation, and relative humidity over the period of our study. Panel C of Table 2 outlines summary statistics for weather across Paris.

Two main sources of pollution are considered in relation to traffic: air and noise. Air pollution measurements are recorded across 54 irregularly-spaced monitoring stations at an hourly level across Paris, among one only falls into a regulated zone. We use hourly measurements of NO_2, NO_x,

$PM_{2.5}$, and PM_{10} (N=3,387,168). This dataset is further collapsed at the daily level to obtain daily average pollution measurements at each monitoring site (N=141,132). Panel B of Table 2 outlines summary statistics for measures of the four pollutants.

Noise pollution comes two different sources: an air pollution map at the XXX resolution from Paris respire, and directly from monitoring stations that cover the post- and pre-policy periods. The map, available in Appendix, is the latest noise map of air pollution concentrations in Paris. We use it to compare air pollution pollution levels in the regulated zones versus their boundaries. Hourly noise levels come directly from the noise pollution monitors from Bruit Paris.[5] Only six stations are permanent and provide noise data for our period of analysis, among which only one falls into a regulated zone. Their locations is diplayed in a map in Appendix...

Table 2: Sample Descriptive Statistics. Panel A summarises all traffic characteristics across road sensors at the hourly and daily level. The variables presented in Panel B refer to the measurements of air pollution concentrations at all monitoring stations across the city. The weather variables shown in Panel C are measured across all monitoring stations across the city. Panels D and E summarise the sleep dataset, including user information and general sleep behaviours.

	Mean	SD	Min	Max	N
A. Traffic Characteristics					
Hourly Vehicles	559.34	562.32	0	33272	75,653,520
Hourly Congestion	52.27	112.94	0	33272	63,792,896
Daily Mean Vehicles	472.28	354.27	0.50	1588	642,192
Daily Mean Congestion	33.07	44	0	219.99	540,900
B. Pollution Characteristics (in μgm^{-3}**)**					
Daily Mean NO_2	39.25	12.39	12.76	116.10	1,857
Daily Mean NO_X	91.79	45.08	24.74	618.47	1,857
Daily Mean $PM_{2.5}$	14.01	9.02	3.56	91.00	1,857
Daily Mean PM_{10}	25.03	11.48	6.23	119.76	1,857
C. Weather Characteristics					
Daily Precipitation (in mm)	1.73	4.14	0.00	55.67	1,885
Daily Mean Temperature (in $^\circ C$)	12.39	6.34	-4.73	30.27	1,885
Daily Relative Humidity (in $\%$)	72.83	11.20	39.00	97.00	1,885
D. User Characteristics					
Age (in years)	39.45	11.31	19.00	94.00	511,309
Body Mass Index (BMI)	24.75	4.60	11.32	49.50	493,791
Height (in cm)	175.20	8.58	110.00	200.00	494,714
Weight (in kg)	76.33	16.76	40.00	198.00	493,922
E. Sleep Characteristics					
Duration in bed (in mins)	492.91	78.50	193.00	779.00	511,309
Total sleep time (in mins)	415.54	85.13	0.00	759.00	511,309
Duration in deep sleep (in mins)	121.40	43.56	1.00	557.00	509,784
Duration in light sleep (in mins)	213.44	55.85	1.00	597.00	511,277
Duration in REM sleep (in mins)	82.71	28.01	1.00	346.00	501,059
Duration spent awake overall (in mins)	62.50	51.30	0.00	600.00	511,038
Sleep onset latency (in mins)	20.52	24.48	0.00	403.00	511,309
Sleep offset latency (in mins)	15.72	19.06	0.00	523.00	505,594
Sleep efficiency	0.84	0.12	0.00	1.00	511,309
Night efficiency	0.08	0.39	0.00	133.00	495,266

[5] https://rumeur.bruitparif.fr

3.3 Sleep Data

We utilise sleep information from 2,365 users of Withings' mattress (N=852,063). Each user's sleep observation is geo-coded through the connection between their mattress and a mobile application, thereby providing the location of the sleep episode. This dataset consists of additional information on user characteristics (e.g. age, sex, height, and weight) of each individual.

Time filtering of data/Data processing and criteria

To reduce the risk of including sleep observations from those suffering from insomnia, observations from shift workers, or any other possible problems, outliers from the sleep data are removed by applying inclusion filters to sleep duration, onset, and offset. We adopt inclusion criteria, applied in Jonasdottir et al. (2021), for minimum and maximum allowable sleep duration used in prior global observational sleep studies (3 hours<duration<13 hours) (Roenneberg et al., 2012). Sleep entries are further filtered based on local timing onset and offset times. We apply the following sleep timing filters, which removes all sleep observations with onset or offset times greater than one and a half standard deviations away from the sample average computed separately for weekdays and weekends:

- 21:31 ONSET WEEKDAYS 02:40
- 06:05 OFFSET WEEKDAYS 10:21
- 21:42 ONSET WEEKENDS 03:20
- 06:27 OFFSET WEEKENDS 11:33

To ensure that sleep estimates are representative of typical sleeping behaviour and that individuals spend time in the area that their mat is located, we further require all participants to have a minimum threshold of sleep observations (Jonasdottir et al., 2021), a minimum period of 4 weeks (with at least 1 weekday and weekend night per week that amount to a minimum 8 nights per user), and be adults over 19 years of age.

We choose to apply the same criteria as Jonasdottir et al. (2021) as they are the strictest, leaving a final sample size of 543,432 observations from 2,158 users for analysis. The inclusion criteria resulted in an attrition of 8.7% of users. Of all users, 72% are male, with an average age of 39.45 (SD 11.3). Panel D of Table 2 outlines the general characteristics of all users. We also run sensitivity analysis using time filters adopted by Roenneberg et al. (2012), and Walch et al. (2016).

Sleep Characteristics

The Withings' mattress records sleep activity through the presence of pneumatic and sound sensors, and has been shown to correlate to laboratory sleep polysomnography (PSG) results (Rosa et al., 2019). This provides an average respiratory rate, average heart rate, and the number of times an individual wakes up in a single sleep episode. Each sleep episode is detailed by the duration (in minutes) a user spends in the following states:

- In bed
- Total sleep time (TST)
- In rapid eye movement (REM) sleep
- In stages 1 and 2 of non-rapid eye movement (non-REM) sleep (light sleep)
- In stage 3 of non-rapid eye movement (non-REM) sleep (deep sleep)
- Total wake time (Wakefulness)
- Awake at night (Wake after sleep onset; WASO)
- To fall asleep (Sleep onset latency)

- To wake up (Sleep offset latency)

The duration of sleep and its different phases can be used to construct several measures of quantity and quality of sleep. Summary statistics for all sleep variables are outlined in Panel E of Table 2. The average duration spent in bed, over the course of our sample, was 506.4 minutes (SD 80.4). This is equivalent to approximately eight hours per user per night. In this time, users spent an average of 404.7 minutes (SD 85.9) asleep (approximately 6.7 hours).

Total sleep time (TST) is the total amount of sleep from the time a user falls asleep until they wake up. This includes all stages of sleep, including non-REM to REM sleep. A low TST may suggest that a user slept for an insufficient period of time, whilst a long TST suggests prior sleep deprivation. Sleep fragmentation, through recurrent awakenings or low duration quantities in sleep stages, may result in non-restorative sleep even when normal TSTs are achieved. Therefore, it is important to adopt a multi-faceted approach to assess sleep changes.

Sleep onset latency is the duration of the time between when the user is in bed until they fall asleep. Likewise, *sleep offset latency* is the duration between a user waking up and getting out of bed.

Sleep fragmentation is assessed through measures of wakefulness. *Total wake time* is the amount of wake time during the total recording time in minutes after the sleep onset. This gives a general estimation for overall quality of sleep. We further consider *wake after sleep onset (WASO)*, which refers to periods of wakefulness occurring after defined sleep onset and, thus, a better reflection of sleep fragmentation than total wake time.

The detailed assessment of sleep quality requires two approaches. We first glean insights to sleep quality by assessing sleep quantity in certain sleep phases (e.g. in REM and non-REM sleep). Non-REM sleep is considered a direct measure of daytime alertness and the subjective refreshing quality of sleep. *Light sleep* is the changeover between states of wakefulness and sleep, and is an estimate of the degree of sleep fragmentation. This is the phase in which body maintenance occurs (e.g. regulation of metabolism regulates) (Shrivastava et al., 2014). Deep sleep sees slower heart rates and breaking, with the body relaxing and contributing to restfulness. During this phase, our bodies secrete growth hormones associated with cellular rebuilding and repair (Shrivastava et al., 2014). Finally, *REM sleep* is typically the dream state in which the brain is very active. It is important for emotion regulation and memory - where peak protein synthesis occurs at the cellular level (Shrivastava et al., 2014). Secondly, we calculate two additional variables to directly assess sleep quality: *Sleep efficiency* and *Night efficiency*. Sleep efficiency is the ratio between the time one spends asleep to the time one spends in bed. A value of 1 relates to a night where an individual falls asleep as soon as they go to bed. Sleep efficiency gives an overall sense of how well the patient slept, but it does not distinguish frequent, brief episodes of wakefulness. A low sleep efficiency could result from long sleep latency and long sleep offset to time in bed, with otherwise normal quantity and quality of sleep in between. Night efficiency is the ratio between the time one spends awake at night to the time one spends asleep. A value of 0 relates to a night where an individual does not wake up at any point at night, suggesting low wakefulness.

Appendix B Table 11 further outlines the key summary statistics for sleep variables across observations by policy variables. Appendix C Figure 8 illustrates the spread of users inside and outside of target zones.

4 Identification Strategy

Our aim is to estimate the causal impact of the introduction of *Paris Respire* on sleep via improvements in air quality. Thus, there are two primary empirical objectives: (1) to assess whether *Paris Respire* is effective at reducing traffic and, by extension, traffic-related emissions, and if it is, (2) to assess the impact of this change on outcomes of nocturnal sleep. The staggered and temporary introduction of pedestrianisation across districts in Paris presents a quasi-experimental design. This motivates our primary identification strategy, which deploys a reduced-form specification exploiting policy-induced variations in air pollution in a difference-in-differences approach. Since we exploit a policy defined by geographic boundaries, we choose to extend the classical DD framework to account for the spatial nature of the policy. Butts (2021) demonstrates that the traditional DD approach produces biased estimates when treatment effects crosses over borders.

Our treatment units (target zones) are districts that are part of the *Paris Respire* campaign. However, due to the spatial nature of the policy, it is plausible that there are indirect effects on neighbouring areas around target zones, and general equilibrium effects across the city. Non-target districts, otherwise considered control units, that are close to target zones, may experience effects of the policy and, therefore, would fail to identify the counterfactual trend as traditional control units because their outcomes are affected by treatment (Butts, 2021). Additionally, changes in treated units' outcomes would not only reflect the effect of their own treatment status, but also the effect from the treatment status of neighbouring units. This geographical displacement of outcomes is referred to as *spatial* spillovers. As one example, traffic and congestion may not have reduced overall but be displaced to the boundaries of each target zone. Similarly, in attempts to avoid target zones, vehicles may take alternative routes which reduce the traffic around the boundaries of each target zone. These localised spillover effects are, thus, important causal effects themselves and prompt a semi-parametric estimation strategy using a set of distance bins from target zones in 1km increments (e.g. being 0km, 0-1km, 1-2km, or >2km from a target zone).

Although the empirical models are nested in the above framework, we separately elaborate on empirical strategies for each equation to uncover reduced form estimates because (a) the data do not fully overlap as nocturnal sleep outcomes are measured at a daily level, while changes in traffic are observed at an hourly level, and (b) omitted variable bias unique to each model requires different controls.

4.1 Selection into Treatment

As with all natural experiments, there are possible selection biases that should be considered. First, if mattress users have a preference, or a dislike of the policy, they may move ahead of the policy implementation. The overall policy was suggested years before its implementation, and we cannot exclude the possibility that certain users moved outside of Paris. However, the zones were gradually announced and introduced, suggesting fewer opportunities to move across regulated zones. In our dataset, less than 1.5% of the users moved between treated vs untreated zones between 2015 and 2016.[6] Because the treatment is staggered and temporary, we do not exclude these users, and are not concerned that self-selection into treatment could bias our estimates.
Second, it is possible that policymakers selected the zones based on their noise or pollution levels. In the results section, we analyze air and noise pollution data to address this concern.

[6] Among the movers across treatment group, 62.5% moved from a regulated zone, to an unregulated zone.

4.2 Impact on Traffic

We first investigate how effective *Paris Respire* is in reducing traffic in the following Poisson regression[7]:

$$\begin{aligned} log(Y_{sh}) = \alpha + \beta PolicyHour_{sh} + \sum_{d=2}^{4} \beta_d (MinDistanceBin_{sdh} \times PolicyHour_h) \\ + \gamma PolicyDay_{st} + \sum_{d=2}^{4} \gamma_{dt} (MinDistanceBin_{sdt} \times PolicyDay_t) \\ + \tau MeanTemperature_t + \rho MeanPrecipitation_t \\ + \zeta AnnualCarFreeDay + S_t + \theta_{Sensor} + \epsilon_{sh} \end{aligned} \quad (1)$$

where Y_{sh} represents traffic across road sensor s on hour h. Traffic is measured as (1) a count of the number of vehicles, and (2) a fluidity-adjusted count of the number of vehicles across sensor s.

$PolicyHour_{sh}$ equals to 1 if sensor s falls inside a target zone during in policy hour h. The parameter of interest is β, which assesses the change in traffic in target zones.[8] $PolicyHour_h$ equals to 1 if *Paris Respire* is active somewhere in Paris in hour h. Whilst $MinDistanceBin_{sdh}$ are four mutually exclusive indicator bins which equal to 1 if the sensor (s) falls into a predefined distance bin d, where $d = 1, 2, 3, 4$, during policy hour h, and zero otherwise. These distances are in 1km increments that capture the minimum distance between sensor s and the nearest target zone during the policy hour (illustrated in Figure 3). The interaction term, $PolicyHour_h \times MinDistanceBin_{sdh}$, allows us to semi-parametrically identify the effect of non-additive spatial spillovers associated with the policy as we move away from the target zone.[9] Its inclusion removes any bias from the zone effect (i.e. the direct effect estimate) without imposing any assumptions by estimating the average spillover effects on treated and control units (Butts, 2021).

As the pedestrianisation is only operational over selected hours on certain days, observed traffic at times before or after policy hours may also experience effects of the policy and negate them from behaving as "true" control units similar to the spatial spillover effects discussed previously. Thus, we include $PolicyDay_{st}$ to capture any potential temporal spillover effects on the day of the policy. $PolicyDay_{st}$ equals to 1 if sensor s falls inside a target zone on day t when the policy is active at any hour of the day, and zero otherwise. These temporal effects may be associated with changes in individuals' travel patterns throughout the day to adjust for the temporary closure of these areas. For example, individuals may choose to use their vehicles in hours outside of the closure, displacing traffic to other time periods of the day. Individuals may also decide to avoid motorised transport

[7]While Poisson models are more commonly applied in the health sciences literature to describe relative risk, they are increasingly being adopted in economics due to their flexibility with non-linearity. Traditional approaches in the economic literature have involved transforming the non-negative outcome variable (e.g. using logs or inverse hyperbolic sine), which commits to a nonlinear relationship and attempts to recast a multiplicative model as an additive one. Additionally, any transformation suggesting nonnormality of the data, particularly skewness, can indicate a nonlinear effect. In a linear regression, the mean of the dependent variable depends linearly on the independent variables, with the assumption that the data is assumed to be normally distributed around the population regression line (Wooldridge, 2010; Cameron & Trivedi, 2010). A Poisson model, a generalised linear model (GLM) with a log link, extends linear regression by introducing (a) a link function that establishes a curve that characterises the mean of the dependent variable as a function of the independent variables, and (b) a distribution that specifies how the values of the dependent variable are dispersed around the mean given by the curve (Wooldridge, 1999; Cameron & Trivedi, 2010). Specifically, it produces consistent estimates for the exponential model regardless of the distribution of the error term and can even be used for noncount data (Wooldridge, 1999; Cameron & Trivedi, 2010; Silva & Tenreyro, 2006; Wooldridge, 2010). Ciani and Fisher (2019) further argues that it is preferable to estimate such an exponential model by Poisson Quasi Maximum Likelihood (QMLE) as it relaxes the requirement of statistical independence of the error term. Thus, it circumvents the risk of confounding distributional and mean changes often seen with running ordinary least squares (OLS) on a log-linearised model (Wooldridge, 1999). In short, instead of fitting a straight line, a Poisson regression fits an exponential curve. In our case, an exponential curve providing relative effects is both theoretically and empirically more appealing and produces more realistic practical recommendations.

[8]The exponentiated coefficients from a Poisson regression model are interpreted as Incidence Rate Ratios (IRR). This provides a relative measure, a rate ratio, of the number of occurrences in the presence of an event compared to the number of occurrences in the absence of an event. A value of 1 indicates that the ratio of events are equal, and thus suggests no changes. Any deviation above and below this value can be interpreted as a percentage change.

[9]The term, $PolicyHour_{sh}$, is equivalent to the collective interaction term, $PolicyHour_h \times MinDistanceBin_{sh1}$, where $d = 1$ for road sensors inside a target zone.

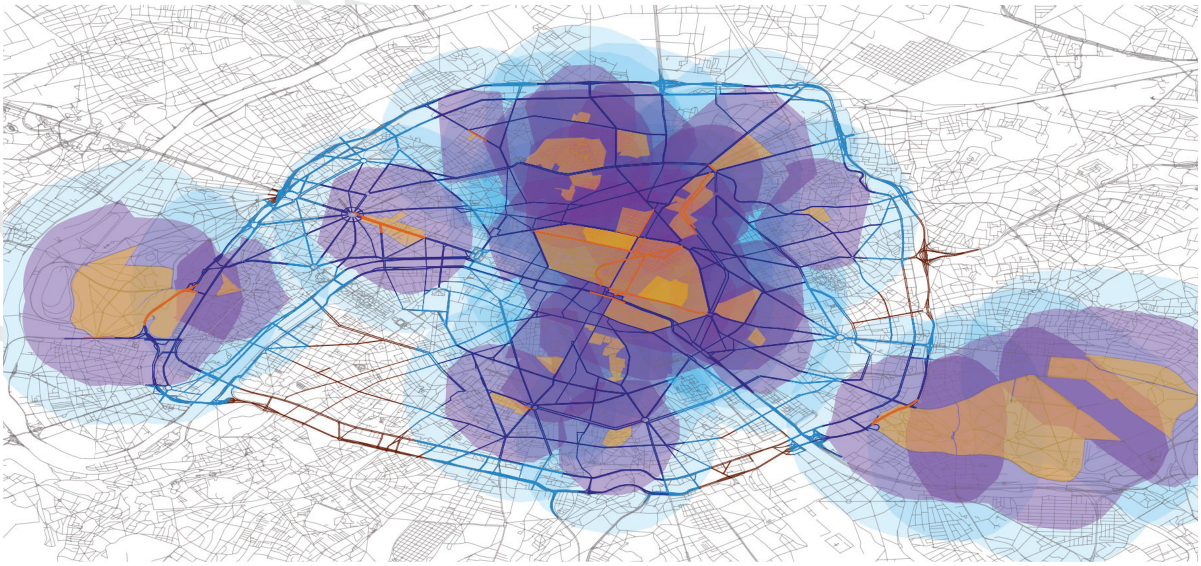
altogether.

$PolicyDay_t$ equals to 1 if *Paris Respire* is operational anywhere in Paris on day t, and zero otherwise. $MinDistanceBin_{sdt}$ are two mutually exclusive indicator bins which equal to 1 if the sensor, s, falls into predefined distance bins as defined previously during policy day t, and zero otherwise. Therefore, the interaction term, $MinDistanceBin_{sdt} \times PolicyDay_t$, is included to estimate the spatial decay associated with any temporal treatment effects.

Furthermore, to account for potential confounders, we control for a set of road sensor and seasonality fixed effects. Seasonality is particularly important for our analysis as traffic and vehicle use can vary seasonally. S_t is a vector of seasonal effects controlling for cyclical variation (including day of week, month, year, school holiday and bank holiday fixed effects). The vector can be expanded as $S_t = \sum_{DoW=2}^{7} \mu_{DoW} DayOfWeek_{DoW} + \sum_{m=2}^{12} \nu_m Month_m + \sum_{y=2}^{5} \xi_y Year_y + \rho_v Holiday_v$. This approach is attractive because it is does not impose any assumption on how temporal effects impact traffic, does not constrain the model to a specific functional form, and reduces the risk of specification errors. Additionally, as seasonality is measured at a relatively fine scale, the flexibility inherited from such granular fixed effects also accounts for traffic changes that are driven by behavioural changes. For example, a day during summer holidays may be different from a typical day during the winter in a behavioural sense similar to how traffic may behave differently between a day during the week and over the a weekend. Road sensor fixed effects (θ_{Sensor}) controls for potential non-time varying differences in roads that can confound the main effect, such as road size and connectivity.

$MeanTemperature_t$ represents the mean temperature in Celsius on day t. $MeanPrecipitation_t$ represents the mean precipitation on day t. $AnnualCarFreeDay$ equals one if day t is Paris' Annual Car Free Day, an annual campaign where all roads in the city are pedestrianised. Finally, ϵ_{sh} represents the standard idiosyncratic disturbance term.

Figure 3: A map of Paris, France. Thick lines represent roads which traffic is monitored. Orange represents roads and zones in the target zones as part of the *Paris Respire* pedestrianisation campaign. Purple represents roads and zones up to 1km from a target zone. Blue represents roads and zones between 1km and 2km from a target zone. Brown lines represent road sensors that are not targeted by the policy.



Whilst an hourly analysis is specifically insightful to the efficacy of the policy, for our purposes, we also estimate the average daily effect of *Paris Respire* on traffic, and traffic-related emissions, using the following equation:

$$
\begin{aligned}
log(Y_{st}) = \alpha + \beta PolicyDay_{st} + \sum_{d=2}^{4} \beta_d(MinDistanceBin_{sdt} \times PolicyDay_t) \\
+ \tau MeanTemperature_t + \rho MeanPrecipitation_t \\
+ \zeta AnnualCarFreeDay + S_t + \theta_{Sensor} + \epsilon_{st} \quad (2)
\end{aligned}
$$

where Y_{st} represents traffic across road sensor s on day t. $PolicyDay_{st}$, $MinDistanceBin_{sdt}$, S_t, θ_{Sensor}, $AnnualCarFreeDay$, $MeanTemperature_t$, $MeanPrecipitation_t$, and ϵ_{st} enter the model as defined previously (Eq. 1).

In this instance, the parameter of interest is β, the coefficient on the indicator variable $PolicyDay_{st}$, which assesses the average treatment effect of the policy on traffic inside a target zone.

In all specifications, we use distance bins of 1km increments as our preferred specification. Sensitivity tests are also conducted using a different distance increments. Additionally, we use robust standard errors clustered at the sensor-day of week level to account for heteroskedasticity and allow for arbitrary within-group and serial correlations at the road and day of the week level. We cluster over individual road sensors as they represent the unit of analysis and as we observe several observations per sensor per day. As the two-way strategy is theoretically and empirically more conservative, it remains our preferred approach in the main identification.

4.3 Impact on Sleep

To assess the impact of any policy-induced variations in air quality, associated with traffic changes, on daily sleep outcomes, we estimate the following Poisson regression equation that parallels Eq. 2:

$$
\begin{aligned}
log(Y_{it}) = \alpha + \beta PolicyDay_{it} + \sum_{d=2}^{4} \beta_d(MinDistanceBin_{idt} \times PolicyDay_t) \\
+ \tau MeanTemperature_t + \rho MeanPrecipitation_t + \eta MeanHumidity_t \\
+ \zeta AnnualCarFreeDay + S_t + \theta_{User} + \epsilon_{it} \quad (3)
\end{aligned}
$$

where Y_{it} represents the *number of minutes* user i spends in a sleep phase on day t. Sleep outcomes considered include sleep quantity (i.e. the duration spent in bed, and the duration of overall sleep), and sleep quality (i.e. the durations spent in deep sleep, in light sleep, in REM sleep, awake at night, to fall asleep, and to wake up).

$PolicyDay_{it}$ equals one if user i falls inside a target zone on day, t, when the policy is active at any hour of the day. The parameter of interest is β, the coefficient on the indicator variable $PolicyDay_{it}$, which assesses the change in sleep quantity in target zones.

Akin to Eq. 2, $MinDistanceBin_{idt}$ are indicator bins which equal to 1 if a user (i) falls into a predefined distance bin d, where $d = 1, 2, 3, 4$, during policy day t, and zero otherwise. These distances are in 1km increments that capture the distance between user u and the nearest target zone. $PolicyDay_t$ is defined as above. Thus, as discussed above, the interaction term, $PolicyDay_t \times MinDistanceBin_{idt}$, allows us to semi-parametrically identify treatment effects as we move away from the target zone.

We further control for a set of user and seasonality fixed effects. S_t remains a vector of seasonal effects controlling for cyclical variation (including day of week, month, year, school holiday, and bank holiday fixed effects). This model benefits from the same advantages of using a flexible approach as mentioned previously. The range of time fixed effects non-parametrically absorb seasonal and temporal trends in pollution and sleep. The user fixed effects (θ_{User}) capture observed and unobserved factors unique to each user, such as income, health status, mattress use, and behavioural patterns, to the extent they do not vary over time.

Recent literature has identified relationships between weather and sleep outcomes, beyond those associated with seasonality (e.g. Minor et al., 2020; Mattingly et al., 2021; Mullins & White, 2019; Obradovich et al., 2017). Therefore, additional controls are included to account for weather-related changes to sleep. $MeanTemperature_t$ and $MeanPrecipitation_t$ are introduced as defined previously. $MeanHumidity_t$ represents the mean relative humidity, k on day t.

Again, $AnnualCarFreeDay$ equals one if day t is Paris' Annual Car Free Day. Finally, ϵ_{it} represents the standard idiosyncratic disturbance term.

We run a linear regression akin to specification Eq. 3 to estimate effects on non-count measures of sleep (see Appendix D). In all specifications, we use robust standard errors clustered at the user-day of week level to account for heteroskedasticity and allow for arbitrary within-group and serial correlations at the user and day of the week level. We cluster over individual users as they represent the unit of analysis.

4.4 Traffic, Air Pollution and Noise

A reduction in traffic is expected to reduce air and noise pollution. In an ideal setting, we would use direct daily and noise pollution exposures that capture the high spatio-temporality of each pollutant. However, the network of monitoring stations spread across Paris are sparse and do not capture the spatial differences of pollution across the areas under the policy. The use of a sparse network risks introducing measurement error, through the inaccurately accounting for regional characteristics which affect noise and air pollution dispersion.

Using limited data on air and noise pollution, we examine correlations between traffic, air, and noise pollution to understand to what extent traffic might affect either aspect, or both. Looking at the design of the policy, we also argue that the traffic bans do not affect noise levels at night but could have residual effects on air quality during nighttime. An element of this policy is introducing a speed restriction of 20 kilometres (km) per hour (about 12.4 miles per hour). Studies have shown that aerodynamic noise from vehicles are only present at speeds over 20 miles per hour (Nelson & Phillips, 1998; Sandberg, 2001; Rasmussen & Donavan, 2009; Frost & Ison, 2007). This, coupled with the policy only being operational during the day, allows us to mitigate any concerns of the potential impact any changes in noise and light pollution may have on nocturnal sleep — enabling the isolation of air pollution as our main channel of interest. Due to the association between traffic and traffic-related air pollution, it is plausible that any effects observed are largely derived due to changes in air pollution.

5 Results

5.1 Zones Characteristics

5.2 Policy Impact on Traffic

Table 3 outlines the results of the impact of *Paris Respire* on traffic outcomes, at an hourly level. The number of vehicles per road sensor during a policy hour decrease by 55.1% in a target zone to a statistically significant level ($p<0.001$). This reduction is also observed during non-policy hours on a policy day, albeit at a smaller decrease of 30.1% ($p<0.001$). A parallel relationship is also present when considering impacts on congestion, with a decrease of 61.5% during a policy hour ($p<0.001$) and 56.3% during non-policy hours ($p<0.001$) on a policy day. Despite these reductions, there was an increase in traffic outside of the target zones during policy hours. During these hours, traffic increases by 54.0% ($p<0.001$) and congestion increases by 134.4% ($p<0.001$) across roads up to

1km away from a target zone. This increases slightly to 65.0% (p<0.001) and 161.2% (p<0.001), respectively, across roads between 1 to 2 km away from a target zone. Finally, traffic increases by 37.6% (p<0.001) and congestion increases by 79.6% (p<0.001) across roads over 2km away from a target zone. Although this provides evidence of negative spatial spillover policy effects, our results suggest that there was a decrease in traffic and congestion in non-policy hours. During this time, traffic falls by 33.1% (roads between 0-1km), 38.4% (roads between 1-2km), and 35.3% (roads >2km), while congestion falls by 63.0% (roads between 0-1km), 67.4% (roads between 1-2km), and 62.1% (roads >2km). All findings are statistically significant (p<0.001).

Table 3: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on traffic outcomes, per road sensor. Traffic outcomes include (1) Traffic Count, the hourly number of vehicles per road sensor, and (2) Congestion, an hourly fluidity-adjusted count of vehicles per road sensor. Regression results correspond to Eq. 1.

	Traffic Count	Congestion
PolicyHour, β (in target zone)	0.449***	0.385***
	(0.084)	(0.089)
PolicyHour x Distance 0-1km	1.540***	2.344***
	(0.0089)	(0.036)
PolicyHour x Distance 1-2km	1.650***	2.612***
	(0.011)	(0.049)
PolicyHour x Distance >2km	1.376***	1.796***
	(0.011)	(0.036)
PolicyDay, β (in target zone)	0.699***	0.437***
	(0.017)	(0.018)
PolicyDay x Distance 0-1km	0.669***	0.370***
	(0.0033)	(0.0057)
PolicyDay x Distance 1-2km	0.616***	0.326***
	(0.0042)	(0.0066)
PolicyDay x Distance >2km	0.647***	0.379***
	(0.0048)	(0.0092)
Annual Car Free Day	0.879***	0.773***
	(0.0047)	(0.012)
Mean Precipitation	0.999***	1.001***
	(0.000037)	(0.000095)
Mean Temperature	1.003***	1.004***
	(0.000047)	(0.00011)
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
Road Sensor FE	Yes	Yes
pseudo R^2	0.569	0.504
N	75,624,141	6,3757,304

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 shows the average daily impact of the policy on traffic. A day with pedestrianisation sees a 24.7% decrease in the daily average count of vehicles per road in the target zone (p<0.001). These treatment effects typically decay over distance, and while there are smaller reductions compared to the target zones, we observe a greater gain outside of the immediate roads, with the number of vehicles decreasing by 15.4% (p<0.001), 19.7% (p<0.001), and 21.6% (p<0.001) for roads with distances 0-1km, 1-2km, and >2km from a target zone, respectively. Similar results are found when considering the effects on daily congestion. Daily average congestion also falls by 42.8% (p<0.001) in target zones on a policy day. We find further evidence of displacement effects, where there is a decrease in congestion in the surrounding areas by 33.2% (roads between 0-1km), 38.7% (roads between 1-2km), and 42.0% (roads >2km). We find all effect estimates to be statistically significant (p<0.001).

Table 4: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on traffic outcomes, per road sensor. Traffic outcomes include (1) Traffic Count, the daily average number of vehicles per road sensor, and (2) Congestion, a fluidity-adjusted count of daily average vehicles per road sensor. Regression results correspond to Eq. 2.

	Traffic Count	Congestion
PolicyDay, β (in target zone)	0.753***	0.572***
	(0.025)	(0.038)
PolicyDay x Distance 0-1km	0.846***	0.668***
	(0.0094)	(0.018)
PolicyDay x Distance 1-2km	0.803***	0.613***
	(0.0092)	(0.018)
PolicyDay x Distance >2km	0.784***	0.580***
	(0.0099)	(0.018)
Annual Car Free Day	0.910***	0.873**
	(0.018)	(0.043)
Mean Precipitation	1.000	1.002***
	(0.00017)	(0.00037)
Mean Temperature	1.003***	1.003***
	(0.00022)	(0.00046)
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
Sensor FE	Yes	Yes
pseudo R^2	0.429	0.355
N	642,178	540,891

Robust S.E. clustered by Road Sensor x Day of Week in parentheses
Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 Policy Impact on Sleep

We find that the decrease in daily traffic, and by extension policy-induced reduction in air quality, results in changes in sleep quantity, and by extension, sleep quality across certain sleep phases (Table 5). In general, with regard to sleep quantity, we observe that users in a target zone experience a 2% (p<0.001) and 2.2% (p<0.001) increase in the number of minutes spent in bed and asleep overall. This indicates that users gain sleep quantity on the night of a policy day. This gain is also observed across distance, at an increasing rate. Users that slept up to 1km away from a target zone benefit from a 2.5% (p<0.001) and 2.6% (p<0.001) increase in duration spent in bed and overall sleep, respectively. Users between 1-2km away from a target zone gain 3.0% (p<0.001) and

3.1% (p<0.001) in duration spent in bed and overall sleep, respectively (p<0.001). This increases slightly for users over 2km away to 2.4% (p<0.001) and 2.5% (p<0.001).

Table 5: Incidence Rate Ratios (IRR) of the effect of *Paris Respire*-induced changes in air quality on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with duration in bed, total sleep, deep sleep, REM sleep, and light sleep as sleep outcomes.

	In Bed	Total Sleep Time	Deep Sleep	REM Sleep	Light Sleep
PolicyDay, β (in target zone)	1.020***	1.022***	1.021**	1.030**	1.022***
	(0.0048)	(0.0056)	(0.0083)	(0.0092)	(0.0063)
PolicyDay x Distance 0-1km	1.025***	1.026***	1.028***	1.034***	1.028***
	(0.0034)	(0.0042)	(0.0066)	(0.0075)	(0.0048)
PolicyDay x Distance 1-2km	1.030***	1.031***	1.034***	1.041***	1.028***
	(0.0043)	(0.0051)	(0.0077)	(0.0087)	(0.0057)
PolicyDay x Distance >2km	1.024***	1.025***	1.026**	1.031**	1.028***
	(0.0049)	(0.0061)	(0.0086)	(0.0096)	(0.0075)
Annual Car Free Day	0.986**	0.986*	0.980*	0.991	0.988
	(0.0049)	(0.0062)	(0.0093)	(0.011)	(0.0079)
Mean Temperature	0.999***	0.998***	0.997***	0.998***	0.999***
	(0.000057)	(0.000072)	(0.00011)	(0.00013)	(0.000086)
Mean Humidity	1.000**	1.000**	1.001***	1.000	1.000***
	(0.000022)	(0.000027)	(0.000044)	(0.000048)	(0.000034)
Mean Precipitation	1.000	0.998	1.000	1.001	0.999
	(0.0011)	(0.0014)	(0.0022)	(0.0025)	(0.0017)
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
pseudo R^2	0.156	0.219	0.301	0.154	0.268
N	510,901	510,901	509,374	500,648	510,869

Robust S.E. clustered by User x Day of Week in parentheses
Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our assessment of non-duration based sleep quality indicators suggests that there are no statistically significant changes associated (Table 6). We assess other phases of sleep, associated with sleep latency and sleep fragmentation, in Table 7. Results document statistically non-significant findings, suggesting that treatment effects do not translate to changes in users' sleep fragmentation and latency.

Taking average values for overall duration spent asleep and assuming 52 weeks per year, we calculate the annual sleep effects implied by our estimates. If mean daily sleep per user is 415.54 minutes per night, an increase of 2.2% results is a gain of 9.14 minutes. Over the year, assuming the policy is only implemented over the weekend, each user gains an additional 15.8 hours of sleep (equivalent to 2.26 nights of 7-hours sleep).

5.4 Traffic, Air and Noise Pollution

Table 6: The effect of *Paris Respire* on sleep quality measurements per user per day. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes.

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.000667	0.00572
	(0.0029)	(0.0061)
PolicyDay x Distance 0-1km	0.000553	0.00327
	(0.0023)	(0.0051)
PolicyDay x Distance 1-2km	0.000906	0.0118
	(0.0027)	(0.0085)
PolicyDay x Distance >2km	0.000457	0.00311
	(0.0031)	(0.0056)
Annual Car Free Day	-0.00119	0.00371
	(0.0039)	(0.0057)
Mean Temperature	-0.000615***	0.000855***
	(0.000046)	(0.00015)
Mean Humidity	0.0000153	-0.000141**
	(0.000017)	(0.000054)
Mean Precipitation	-0.00182*	0.00423*
	(0.00088)	(0.0021)
Constant	0.851***	0.0796***
	(0.0014)	(0.0040)
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.337	0.052
N	510,901	494,887

Robust S.E. clustered by User x Day of Week in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes.

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.982	0.966	1.003	1.048
	(0.029)	(0.029)	(0.019)	(0.035)
PolicyDay x Distance 0-1km	0.994	1.013	1.020	1.039
	(0.024)	(0.025)	(0.016)	(0.029)
PolicyDay x Distance 1-2km	0.979	1.018	1.013	1.034
	(0.027)	(0.028)	(0.019)	(0.033)
PolicyDay x Distance >2km	1.007	1.010	1.028	1.066
	(0.033)	(0.033)	(0.021)	(0.037)
Annual Car Free Day	0.948	0.933^{*}	0.984	1.044
	(0.036)	(0.032)	(0.022)	(0.042)
Mean Temperature	0.998^{***}	1.000	1.002^{***}	1.006^{***}
	(0.00046)	(0.00045)	(0.00029)	(0.00053)
Mean Humidity	1.000	1.000	0.999^{***}	0.998^{***}
	(0.00017)	(0.00017)	(0.00011)	(0.00020)
Mean Precipitation	1.010	1.005	1.024^{***}	1.027^{**}
	(0.0090)	(0.0085)	(0.0055)	(0.0100)
Day of Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes
pseudo R^2	0.239	0.230	0.331	0.268
N	504,886	510,884	510,630	494,894

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Explore noise and air pollution pathways

A reduction in traffic can improve air quality as well as reduce noise. We explore the strength of these two possible patways.

6.1 Traffic and Noise

Since 2016, the City of Paris measures noise with permanent and temporary noise stations.[10]

7 Discussion

In this paper, we study the impact of the implementation of *Pairs Respire*, a temporary pedestrianisation policy in Paris in targeted zones, on traffic and sleep in Paris over the period from 2014 to 2019. We show that the policy reduces the levels of overall traffic and congestion at a daily level. We subsequently provide evidence that sleep is sensitive to these changes.

Our results confirm that *Paris Respire* is an effective policy instrument to reduce the levels of traffic and congestion during its implementation, within the targeted zones, by over 50%. However, there is evidence of spatial displacement of traffic and congestion during policy hours. This is echoed by findings of Sleiman (2021), who reports an increase in the occupancy rate and probability of congestion associated with the pedestrianisation of the Parisian riverbank. Despite this, we demonstrate that the average daily effect of the policy appears to be an overall decrease in traffic and congestion by approximately 20% across all areas. This strongly suggests that these improvements are associated with lower air quality standards. We further show that these improvements in air quality translate into significant positive, albeit small, impacts on sleep, in terms of sleep quantity and quality. However, we do not find evidence of possible impacts on other elements of sleep, such as sleep fragmentation and latency. Nonetheless, small changes can lead to large impacts — World Economic Forum (2019) estimates that a gain of one hour of sleep, moving from six to seven hours a night, could add \$226.4 billion to the US economy, \$75.7 billion to the Japanese economy, \$34.1 billion to the German economy, and \$29.9 billion to the UK economy. We further extrapolate our findings to estimate that we could gain an additional 2.3 days of 7-hours total sleep time each year, if the policy were to be implemented every weekend. Using estimates from Shrader and Gibson (2018), this is associated with a 0.95% in weekly earnings and translates to USD 744 in gains in annual income per individual.

Ultimately, we present reduced form estimates that look at the impact of *Paris Respire*. We show that *Paris Respire* impacts traffic and sleep outcomes across the city. While we believe that the main channel is pollution, observed changes could also be associated with other behavioural responses that influence sleep. It could be argued that our identified changes in traffic influences sleep through three potential channels: air, light, and noise pollution. While noise and light pollution have negative contemporaneous effects on sleep (Muzet, 2007; Liu, Ghastine, et al., 2020), the operational hours of *Paris Respire* are restricted to the day and the policy enforces strict speed limits which would translate into reduced road noise. Therefore, users' nighttime exposure to light and noise remains consistent with non-policy days and any variations accounted by the DD framework and series of fixed effects. While we are unable to measure the direct impact of air pollution on sleep, our results are consistent with both the impacts of traffic changes on air pollution (e.g. Malina & Scheffler, 2015; Wolff, 2014; Grange et al., 2017), and the impacts of air pollution on health (e.g. Currie et al., 2014). As we also demonstrate that traffic in Paris is highly correlated with traffic-related emissions, we strongly speculate that these changes in individual-level sleep are associated to changes in air quality.

We acknowledge two main caveats of our analysis. First, while the data on sleep episodes used in this paper allow to precisely identify the residential locations of users, we are unable to estimate precise air pollution exposure at these locations. This is due to the sparsity of the city's pollution monitoring network within the city, and also the absence of additional information on each users' movement and activity patterns during the day. As air pollution varies temporally and spatially, we are unable to assign precise exposure levels at the same spatial and temporal granularity of the sleep data without making large assumptions that introduces errors into our analysis. Our approach leverages an exogenous change that is beneficial in identifying a causal relationship, but prevents us from identifying the dose-response relationship between air pollution and sleep. We encourage future research to (a) identify potential inflexion points of pollution-sleep impacts to support targeted policy approaches, and (b) further unravel the potential routes in which pollution influences sleep.

Second, the access and adoption of sleep mattresses is not geographically or demographically uniform. Our dataset contains more people who are middle-aged and male, with a selection of users who may be experiencing sleep issues (although sleep filtering would have removed abnormal observations) or personally invested in their quality of sleep. The ownership of these devices may also be associated with unobserved demographic factors, such as higher socioeconomic status or physiological curiosity, possibly reducing the accuracy of our estimates. Thus, the magnitude of our effect estimates are likely conservative.

Despite these caveats, our results of the impact of this policy on traffic and sleep have implications to support environmental policies for policy makers and future research. Improvements in air quality also garner gains in sleep. A continued evaluation of the relationship between sleep and air pollution is required to ensure that interventions for air pollution, often designed for direct health gains, are also optimised for gains in other social outcomes. Future research is needed to investigate equitable policy, planning, and design innovations that alleviate the stress of increased air pollution.

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A Data Summary

A.1 Environmental data

A.1.1 Air pollution data

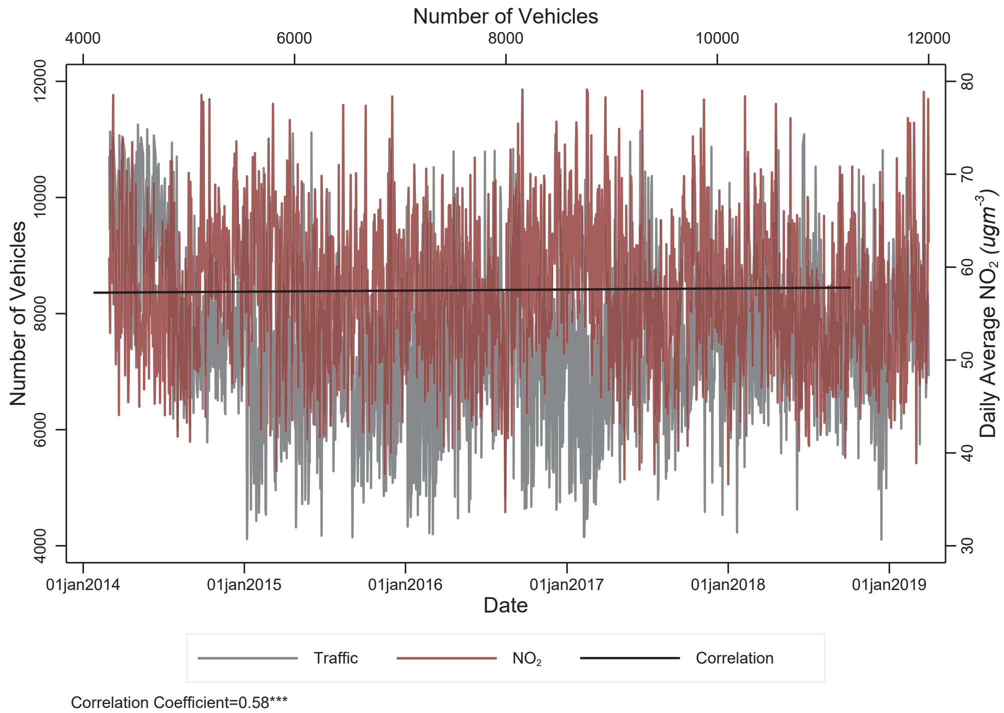
A.1.2 Noise pollution data

	Day				Night			
Zone ID	**Inside**		**Rings**		**Inside**		**Outside**	
			500m	**1km**			**500m**	**1km**
1	38.05	<	41.47	45.36	39.80	<	41.43	43.08
2	35.49	<	38.36	40.46	39.10	<	41.11	41.30
3	42.61	<	45.59	46.00	43.97	>	42.59	42.30
4	39.89	<<	44.61	43.52	41.82		41.85	42.16
5	43.56	<	49.98	49.19	42.63		42.45	40.92
6	43.79		44.15	43.82	43.76	>	42.55	42.22
7	43.42	<	45.21	45.03	39.72	<	41.38	41.72
8	42.54	<<	52.42	56.32	33.45	<<	42.33	45.56
9	40.82		41.23	40.80	40.95		41.17	41.31
10	45.68	<<	52.39	49.74	36.54	<<	41.75	41.87
11	56.72	>>	50.42	50.00	47.43	>	42.70	42.47
12	48.62		48.01	47.41	43.00	>	41.74	41.81
13	43.70	>	42.37	45.20	42.03		42.77	42.74
14	47.34	<	48.45	49.71	41.16	<	42.81	42.92
15	39.61	<	41.84	44.15	40.25	<	41.78	41.79
16	49.09	<	50.38	51.27	42.44		42.95	42.38
17	54.17	>	52.25	52.02	44.84	>	42.36	43.40
18	35.82	<	40.16	43.24	40.68		41.48	41.50
19	55.80	>	54.13	53.54	51.69	>>	42.82	45.67
20	55.43		54.91	50.22	40.34	<	42.63	42.01
21	39.73	<	41.10	42.10	40.50	<	42.02	42.35
22	62.69	>>	44.60	47.07	51.67	>>	39.98	42.75
23	37.80	<	41.46	42.86	41.66		41.61	41.83
24	44.67	<	46.98	43.88	44.17	>	42.67	41.65
25	42.51		41.51	42.40	42.77	>	41.47	42.11
26	38.24	<	39.99	42.86	43.40	>	41.28	42.41

A.2 Air Quality and Traffic

A.3 Noise and Traffic

Figure 4: The average of air pollution, for two pollutants, between 2014 and 2019 in Paris against the average of traffic (number of vehicles) around ten monitoring stations. Traffic is assigned to a monitoring station as a weighted average using inverse distance weighting of road sensors within a 50m radius of each station. The black line maps the number of vehicles, across the second x-axis, with the daily average pollution measurements, across the second y-axis. Pearson's correlation coefficient between traffic and daily pollution provided in the left bottom corner of each graph for each pollutant. Pollution data is provided by AirParif. Stars represent p-values: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.



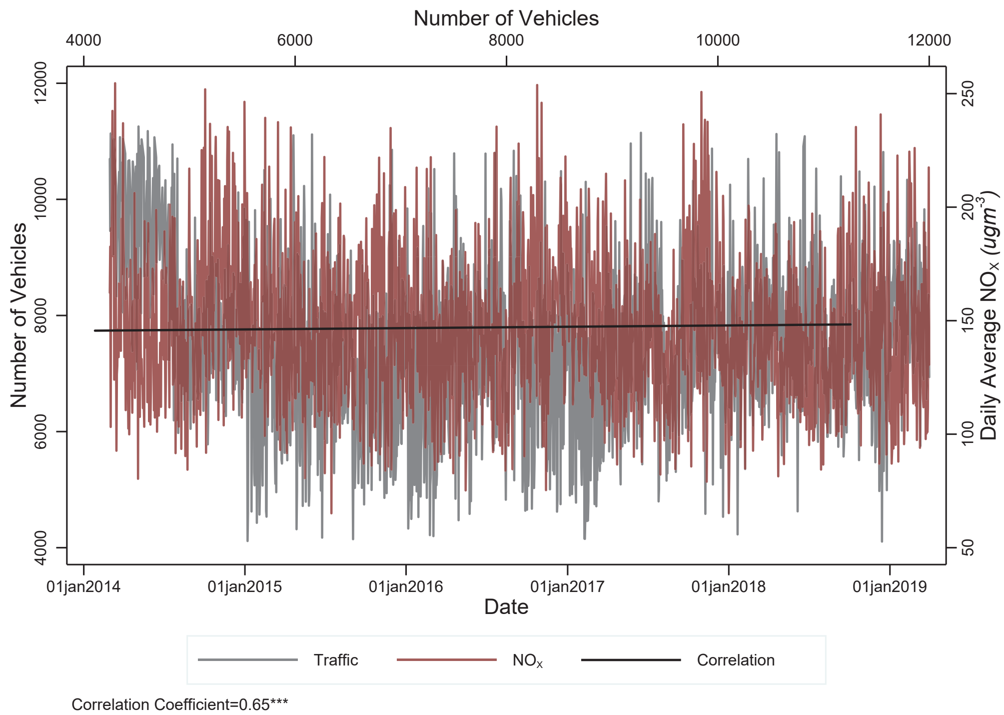


Table 8: Summary of all outcome variables considered

		Temporal Level	Spatial Level	Variable	Units	Description
Traffic		Hourly	Road Sensor	Traffic Count	Number of Vehicles	A count of the number of vehicles (i.e. a traffic count)
			Road Sensor	Congestion	Number of Vehicles	A fluidity-adjusted count of traffic calculated by multiplying the occupancy rate with the road count to obtain a weighted indicator of traffic.
		Daily	Road Sensor	Traffic Count	Number of Vehicles	A count of the number of vehicles (i.e. a traffic count)
			Road Sensor	Congestion	Number of Vehicles	A fluidity-adjusted count of traffic calculated by multiplying the occupancy rate with the road count to obtain a weighted indicator of traffic.
Sleep	Sleep Quantity	Daily (per night)	User	Duration in bed	Number of Minutes	The number of minutes a user spends in bed per night
			User	Total sleep time (TST)	Number of Minutes	The number of minutes a user spends in asleep overall per night, this involves time spent in all sleep phases
			User	Sleep onset latency	Number of Minutes	The number of minutes a user spends to fall asleep once in bed per night
			User	Sleep offset latency	Number of Minutes	The number of minutes a user spends to get up after waking up per night
	Sleep Quality		User	Duration in deep sleep	Number of Minutes	The number of minutes a user spends in deep sleep
			User	Duration in light sleep	Number of Minutes	The number of minutes a user spends in light sleep
			User	Duration in REM sleep	Number of Minutes	The number of minutes a user spends in REM sleep
			User	Sleep efficiency	Ratio	The ratio between the time one spends asleep to the time one spends in bed. A value of 1 relates to a night where an individual falls asleep as soon as they go to bed.
			User	Night efficiency	Ratio	The ratio between the time one spends awake at night to the time one spends asleep. A value of 0 relates to a night where an individual does not wake up at any point at night, suggesting low wakefulness.
	Sleep fragmentation \& Wakefulness		User	Total wake time	Number of Minutes	The number of minutes a user spends awake during the total recording per night
			User	Wake after sleep onset (WASO)	Number of Minutes	The number of minutes a user spends awake during the total recording after sleep onset per night

B Descriptive Statistics

Table 9: The frequency of observations across treatment distance groups for sleep and traffic

	Frequency	Percent
Sleep Users		
No Policy	429,175	83.94
During Policy, 0m	4,333	0.85
During Policy, 0-1km	62,512	12.23
During Policy, >1km	15,289	2.99
Road Sensors, Daily		
No Policy	1,064,375	82.96
During Policy, 0m	1,953	0.15
During Policy, 0-1km	92,673	7.22
During Policy, >1km	123,965	9.66
Road Sensors, Hourly		
No Policy	131,389,124	91.51
During Policy, 0m	83,317	0.06
During Policy, 0-1km	4,341,676	3.02
During Policy, >1km	7,758,172	5.40

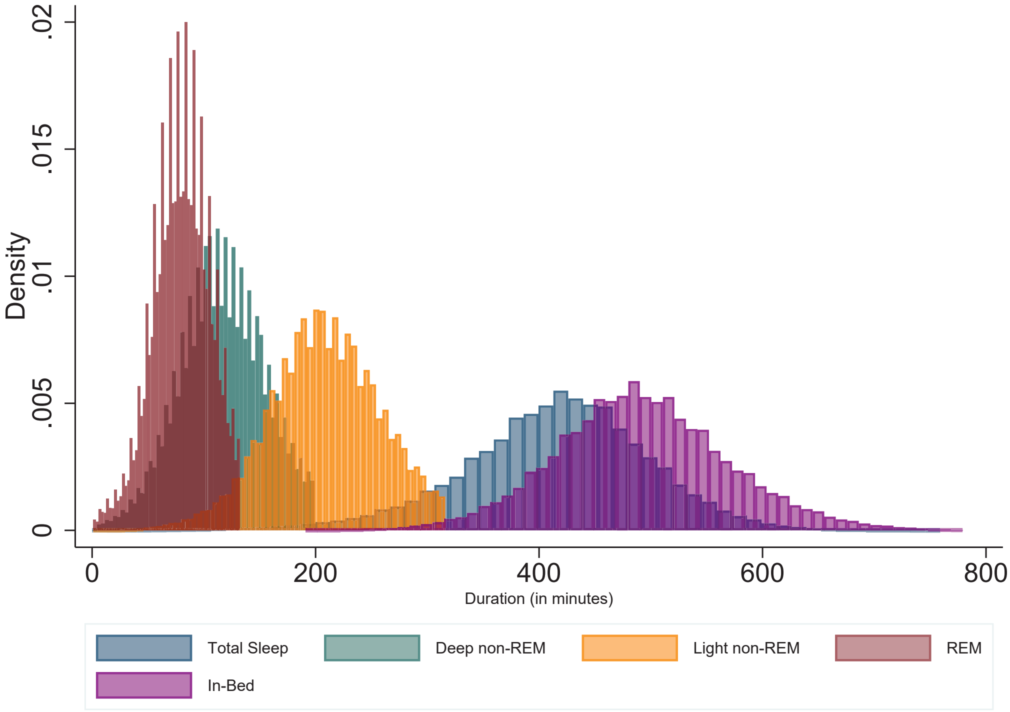
Table 10: Descriptive statistics: Traffic characteristics across all users in sample across Paris, France (2014-2019)

	Mean	SD	Min	Max	N
A. Treatment, No Policy					
Hourly Vehicles	558.80	565.30	0.00	33272.00	69,169,245
Hourly Congestion	53.03	114.55	0.00	33272.00	58,320,845
Daily Mean Vehicles	483.82	359.31	1.00	1588.00	530,070
Daily Mean Congestion	34.99	45.28	0.00	219.99	445,691
B. Treatment, During Policy 0km					
Hourly Vehicles	240.49	558.42	0.00	7212.00	83,317
Hourly Congestion	19.43	98.60	0.00	2255.98	83,317
Daily Mean Vehicles	512.57	372.65	4.00	1579.00	801
Daily Mean Congestion	30.40	38.48	0.00	216.24	691
C. Treatment, During Policy 0-1km					
Hourly Vehicles	590.20	459.71	0.00	8418.00	2,808,002
Hourly Congestion	49.41	85.81	0.00	2220.90	2,382,327
Daily Mean Vehicles	441.29	319.96	1.00	1588.00	57,917
Daily Mean Congestion	27.49	37.85	0.00	219.98	49,421
D. Treatment, During Policy >1km					
Hourly Vehicles	553.08	574.98	0.00	10850.00	3,592,956
Hourly Congestion	40.83	99.11	0.00	3216.99	3,006,407
Daily Mean Vehicles	390.67	325.03	0.50	1588.00	53,404
Daily Mean Congestion	20.31	33.59	0.00	219.95	45,097

Table 11: Descriptive statistics: Sleep episode characteristics across all users in sample across Paris, France (2014-2019)

	Mean	SD	Min	Max	N
A. Treatment, No Policy					
Duration in bed (in mins)	488.41	78.61	196.00	779.00	429,175
Total sleep time (in mins)	411.89	84.59	0.00	757.00	429,175
Duration in deep sleep (in mins)	120.45	43.28	1.00	557.00	427,914
Duration in light sleep (in mins)	211.47	55.48	1.00	597.00	429,148
Duration in REM sleep (in mins)	81.94	27.86	1.00	346.00	420,653
Total wake time (in mins)	61.85	50.76	0.00	599.00	428,937
Sleep onset latency (in mins)	20.37	24.17	0.00	398.00	429,175
Sleep offset latency (in mins)	15.66	18.94	0.00	420.00	424,329
Duration spent awake at night (in mins)	26.79	37.17	0.00	598.00	415,795
Sleep efficiency	0.85	0.12	0.00	1.00	429,175
Night efficiency	0.08	0.34	0.00	118.00	415,785
B. Treatment, Policy 0km					
Duration in bed (in mins)	517.20	74.80	220.00	772.00	4,333
Total sleep time (in mins)	433.90	87.76	39.00	690.00	4,333
Duration in deep sleep (in mins)	124.26	43.18	4.00	360.00	4,326
Duration in light sleep (in mins)	224.03	54.70	27.00	590.00	4,333
Duration in REM sleep (in mins)	87.38	28.50	1.00	220.00	4,255
Total wake time (in mins)	63.48	49.80	1.00	448.00	4,332
Sleep onset latency (in mins)	18.71	22.89	0.00	192.00	4,333
Sleep offset latency (in mins)	16.04	18.57	0.00	200.00	4,282
Duration spent awake at night (in mins)	30.43	39.83	0.00	377.00	4,153
Sleep efficiency	0.84	0.13	0.08	1.00	4,333
Night efficiency	0.09	0.23	0.00	7.49	4,153
C. Treatment, Policy 0-1km					
Duration in bed (in mins)	516.32	73.26	196.00	779.00	62,512
Total sleep time (in mins)	434.53	84.93	0.00	759.00	62,512
Duration in deep sleep (in mins)	126.90	44.96	2.00	437.02	62,309
Duration in light sleep (in mins)	223.21	56.74	1.00	594.00	62,508
Duration in REM sleep (in mins)	86.66	28.46	1.00	300.00	61,195
Total wake time (in mins)	66.48	53.93	0.00	600.00	62,483
Sleep onset latency (in mins)	21.78	26.43	0.00	403.00	62,512
Sleep offset latency (in mins)	16.02	19.58	0.00	523.00	61,917
Duration spent awake at night (in mins)	29.70	39.51	0.00	578.00	60,678
Sleep efficiency	0.84	0.12	0.00	1.00	62,512
Night efficiency	0.09	0.58	0.00	133.00	60,676
D. Treatment, Policy >1km					
Duration in bed (in mins)	516.51	74.57	193.00	772.00	15,289
Total sleep time (in mins)	435.14	86.59	0.00	749.00	15,289
Duration in deep sleep (in mins)	124.82	43.78	1.00	376.00	15,235
Duration in light sleep (in mins)	225.85	56.79	5.00	594.00	15,288
Duration in REM sleep (in mins)	86.81	28.43	1.00	252.00	14,956
Total wake time (in mins)	64.38	54.75	0.00	556.00	15,286
Sleep onset latency (in mins)	20.01	25.18	0.00	284.00	15,289
Sleep offset latency (in mins)	15.98	20.13	0.00	368.00	15,066
Duration spent awake at night (in mins)	29.85	40.36	0.00	432.00	14,653
Sleep efficiency	0.84	0.13	0.00	1.00	15,289
Night efficiency	0.09	0.64	0.00	60.80	14,652

Figure 5: Histogram showing the distributions for various elements of sleep durations (in minutes)



C Maps

Figure 6: Noise Monitoring stations identified in black

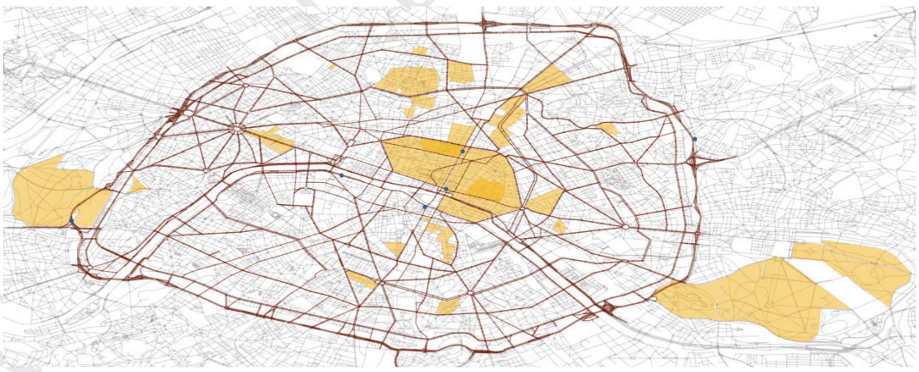


Figure 7: Air Pollution Monitoring stations identified in black

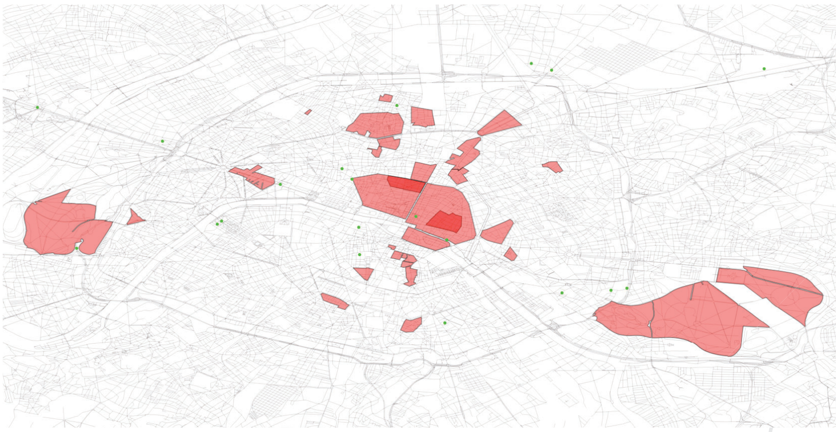
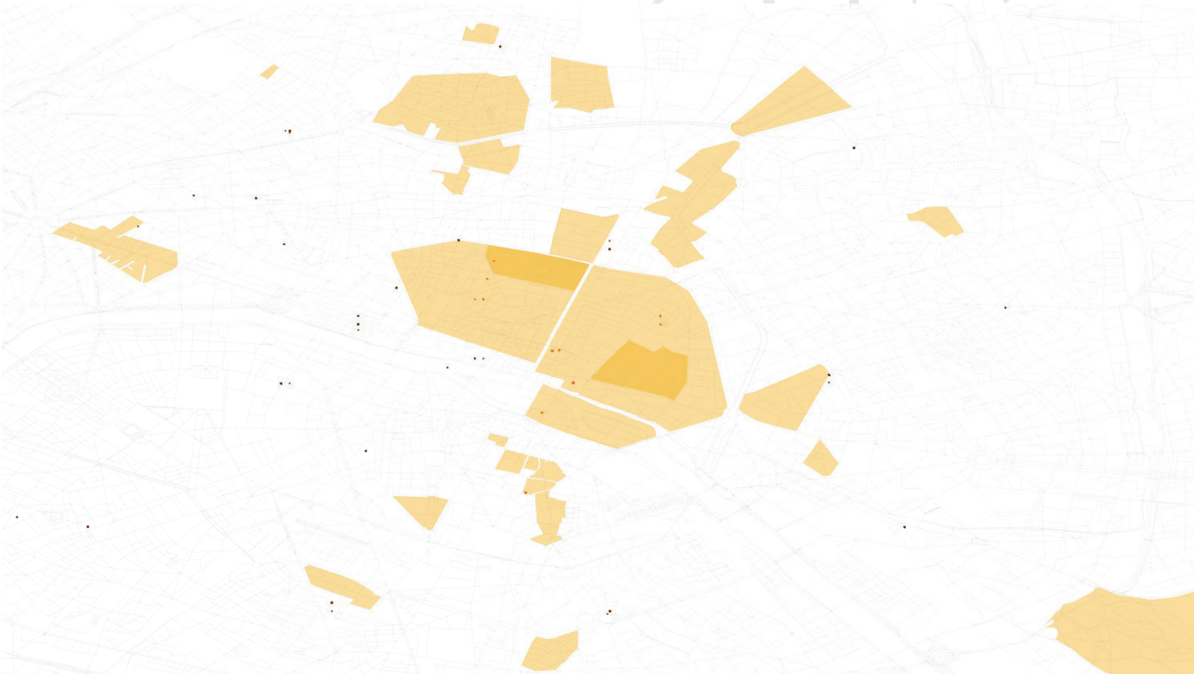


Figure 8: A map of Paris, France. Dots represent roads which traffic is monitored. Yellow polygons represent target zones. Orange dots represents users in the target zones as part of the *Paris Respire* pedestrianisation campaign. Brown dots represent users that are not targeted by the policy



D Specification for linear regressions using non-count measures of sleep

$$
\begin{aligned}
Y_{it} = \alpha + \beta_t PolicyDay_{it} + \sum_{d=2}^{3} \beta_{dt}(MinDistanceBin_{idt} \times PolicyDay_t) + \\
+ \tau MeanTemperature_t + \rho MeanPrecipitation_t \\
+ \zeta AnnualCarFreeDay + \eta MeanHumidity_t + S_t + \theta_{User} + \epsilon_{it} \quad (4)
\end{aligned}
$$

where Y_{it} represents a sleep outcome for user, u, on day t. Sleep quality outcomes considered here include: the ratio between the time a user spends asleep against the time spent in bed (*sleep efficiency*), the ratio between the time spent awake at night against the total time spent asleep (*night efficiency*), and the number times a user wakes up during a single sleep episode.

$PolicyDay_{it}$, $PolicyDay_t$, $MinDistanceBin_{idt}$, $MeanTemperature_t$, $MeanPrecipitation_t$, $MeanHumidity_t$, $AnnualCarFreeDay$, and ϵ_{it} are defined as before.

Similar to the other models, we use distance bins of 1km increments as our preferred specification. Sensitivity tests are also conducted using different distance increments.

E Sensitivity Analyses: Distance Indicator Bins

E.1 Impact on Sleep

Table 12: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes.

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.982	0.966	1.003	1.048
	(0.029)	(0.029)	(0.019)	(0.035)
PolicyDay x Distance 0-1km	0.994	1.013	1.020	1.039
	(0.024)	(0.025)	(0.016)	(0.029)
PolicyDay x Distance >1km	0.989	1.015	1.019	1.045
	(0.027)	(0.027)	(0.018)	(0.032)
Annual Car Free Day	0.948	0.933*	0.985	1.045
	(0.036)	(0.032)	(0.022)	(0.042)
Mean Temperature	0.998***	1.000	1.002***	1.006***
	(0.00046)	(0.00045)	(0.00029)	(0.00053)
Mean Humidity	1.000	1.000	0.999***	0.998***
	(0.00017)	(0.00017)	(0.00011)	(0.00020)
Mean Precipitation	1.010	1.005	1.024***	1.027**
	(0.0090)	(0.0085)	(0.0055)	(0.0100)
Day of Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes
pseudo R^2	0.239	0.230	0.331	0.268
N	504,886	510,884	510,630	494,894

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes.

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.000665	0.00566
	(0.0029)	(0.0061)
PolicyDay x Distance 0-1km	0.000555	0.00329
	(0.0023)	(0.0051)
PolicyDay x Distance >1km	0.000731	0.00841
	(0.0026)	(0.0065)
Annual Car Free Day	-0.00120	0.00365
	(0.0039)	(0.0057)
Mean Temperature	-0.000615***	0.000855***
	(0.000046)	(0.00015)
Mean Humidity	0.0000153	-0.000141**
	(0.000017)	(0.000054)
Mean Precipitation	-0.00183*	0.00422*
	(0.00088)	(0.0021)
Constant	0.851***	0.0796***
	(0.0014)	(0.0040)
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.337	0.052
N	510,901	494,887

Robust S.E. clustered by User x Day of Week in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes.

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.982	0.966	1.003	1.048
	(0.029)	(0.029)	(0.019)	(0.035)
PolicyDay x Distance 0-2km	0.992	1.014	1.019	1.038
	(0.024)	(0.025)	(0.016)	(0.029)
PolicyDay x Distance >2km	1.007	1.010	1.028	1.066
	(0.033)	(0.033)	(0.021)	(0.037)
Annual Car Free Day	0.948	0.933^{*}	0.985	1.045
	(0.036)	(0.032)	(0.022)	(0.042)
Mean Temperature	0.998^{***}	1.000	1.002^{***}	1.006^{***}
	(0.00046)	(0.00045)	(0.00029)	(0.00053)
Mean Humidity	1.000	1.000	0.999^{***}	0.998^{***}
	(0.00017)	(0.00017)	(0.00011)	(0.00020)
Mean Precipitation	1.010	1.005	1.024^{***}	1.027^{**}
	(0.0090)	(0.0085)	(0.0055)	(0.0100)
Day of Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes
pseudo R^2	0.239	0.230	0.331	0.268
N	504,886	510,884	510,630	494,894

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes.

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.000665	0.00565
	(0.0029)	(0.0061)
PolicyDay x Distance 0-2km	0.000601	0.00439
	(0.0023)	(0.0051)
PolicyDay x Distance >2km	0.000459	0.00314
	(0.0031)	(0.0056)
Annual Car Free Day	-0.00120	0.00366
	(0.0039)	(0.0057)
Mean Temperature	-0.000615***	0.000855***
	(0.000046)	(0.00015)
Mean Humidity	0.0000153	-0.000141**
	(0.000017)	(0.000054)
Mean Precipitation	-0.00183*	0.00421*
	(0.00088)	(0.0020)
Constant	0.851***	0.0796***
	(0.0014)	(0.0040)
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.337	0.052
N	510,901	494,887

Standard errors in parentheses
Robust S.E. clustered by UserID x Day of Week
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F Sensitivity Analyses: Alternative Sleep Filters

F.1 Using Roenneberg et al. (2012)

Table 16: Incidence Rate Ratios (IRR) of the effect of *Paris Respire*-induced changes in air quality on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with duration in bed, total sleep, deep sleep, REM sleep, and light sleep as sleep outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	In Bed	Total Sleep Time	Deep Sleep	REM Sleep	Light Sleep
PolicyDay, β (in target zone)	1.061	1.063	1.041	0.845**	1.197***
	(0.037)	(0.041)	(0.081)	(0.051)	(0.061)
PolicyDay x Distance 0-1km	1.075*	1.080*	1.047	0.844**	1.237***
	(0.032)	(0.037)	(0.075)	(0.048)	(0.059)
PolicyDay x Distance >1km	1.075*	1.075*	1.059	0.830***	1.226***
	(0.032)	(0.037)	(0.076)	(0.047)	(0.059)
Mean Temperature	0.999***	0.998***	0.997***	0.998***	0.999***
	(0.000075)	(0.000082)	(0.00012)	(0.00014)	(0.000097)
Mean Humidity	1.000	1.000	1.001***	1.000*	1.000***
	(0.000030)	(0.000032)	(0.000050)	(0.000054)	(0.000039)
Mean Precipitation	1.003*	0.999	0.998	1.002	1.000
	(0.0015)	(0.0016)	(0.0024)	(0.0028)	(0.0019)
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
pseudo R^2	0.177	0.203	0.290	0.147	0.253
N	435,229	435,229	434,096	426,588	435,203

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	1.020	1.150	0.931	0.959
	(0.069)	(0.25)	(0.100)	(0.076)
PolicyDay x Distance 0-1km	1.013	1.244	0.944	0.976
	(0.026)	(0.25)	(0.091)	(0.029)
PolicyDay x Distance >1km		1.211	0.937	
		(0.24)	(0.091)	
Mean Temperature	0.997***	1.001	1.001***	1.006***
	(0.00049)	(0.00050)	(0.00032)	(0.00058)
Mean Humidity	1.000	1.000	0.998***	0.998***
	(0.00019)	(0.00019)	(0.00013)	(0.00022)
Mean Precipitation	1.006	1.008	1.037***	1.056***
	(0.0096)	(0.0097)	(0.0063)	(0.012)
Day of Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes
pseudo R^2	0.235	0.229	0.332	0.272
N	429,565	435,206	434,961	420,706

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.0103	-0.00365
	(0.017)	(0.0067)
PolicyDay x Distance 0-1km	0.0116	-0.00336
	(0.016)	(0.0032)
PolicyDay x Distance >1km	0.00852	
	(0.016)	
Mean Temperature	-0.000612***	0.000628***
	(0.000047)	(0.000053)
Mean Humidity	0.0000358*	-0.000175***
	(0.000018)	(0.000020)
Mean Precipitation	-0.00358***	0.00475***
	(0.00093)	(0.0010)
Constant	0.848***	0.0838***
	(0.0015)	(0.0017)
Annual Car Free Day	Yes	Yes
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.327	0.271
N	435,229	420,714

Robust S.E. clustered by User x Day of Week in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.966	1.150	0.931	0.937
	(0.072)	(0.25)	(0.100)	(0.081)
PolicyDay x Distance 0-1km	0.959	1.244	0.944	0.953
	(0.040)	(0.25)	(0.091)	(0.044)
PolicyDay x Distance 1-2km	0.917	1.219	0.921	0.964
	(0.044)	(0.25)	(0.091)	(0.053)
PolicyDay x Distance >2km		1.199	0.967	
		(0.24)	(0.095)	
Mean Temperature	0.997***	1.001	1.001***	1.006***
	(0.00049)	(0.00050)	(0.00032)	(0.00058)
Mean Humidity	1.000	1.000	0.998***	0.998***
	(0.00019)	(0.00019)	(0.00013)	(0.00022)
Mean Precipitation	1.006	1.008	1.037***	1.056***
	(0.0096)	(0.0097)	(0.0063)	(0.012)
Day of Week FE	Yes	Yes	Yes	Yes
Yes				
Month FE	Yes	Yes	Yes	Yes
Yes				
Year FE	Yes	Yes	Yes	Yes
Yes				
Holidays FE	Yes	Yes	Yes	Yes
Yes				
User FE	Yes	Yes	Yes	Yes
Yes				
pseudo R^2	0.235	0.229	0.332	0.272
N	429,565	435,206	434,961	420,706

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.0103	-0.00564
	(0.017)	(0.0076)
PolicyDay x Distance 0-1km	0.0116	-0.00534
	(0.016)	(0.0049)
PolicyDay x Distance 1-2km	0.00881	-0.00318
	(0.016)	(0.0060)
PolicyDay x Distance >2km	0.00803	
	(0.016)	
Mean Temperature	-0.000612***	0.000628***
	(0.000047)	(0.000053)
Mean Humidity	0.0000358*	-0.000175***
	(0.000018)	(0.000020)
Mean Precipitation	-0.00358***	0.00475***
	(0.00093)	(0.0010)
Constant	0.848***	0.0838***
	(0.0015)	(0.0017)
Annual Car Free Day	Yes	Yes
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.327	0.271
N	435,229	420,714

Robust S.E. clustered by User x Day of Week in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Incidence Rate Ratios (IRR) of the effect of *Paris Respire*-induced changes in air quality on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with duration in bed, total sleep, deep sleep, REM sleep, and light sleep as sleep outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	In Bed	Total Sleep Time	Deep Sleep	REM Sleep	Light Sleep
PolicyDay, β (in target zone)	1.061	1.063	1.041	0.845**	1.197***
	(0.037)	(0.041)	(0.081)	(0.051)	(0.061)
PolicyDay x Distance 0-2km	1.076*	1.079*	1.049	0.842**	1.235***
	(0.032)	(0.037)	(0.075)	(0.047)	(0.059)
PolicyDay x Distance >2km	1.073*	1.072*	1.048	0.826***	1.235***
	(0.032)	(0.038)	(0.076)	(0.047)	(0.060)
Mean Temperature	0.999***	0.998***	0.997***	0.998***	0.999***
	(0.000075)	(0.000082)	(0.00012)	(0.00014)	(0.000097)
Mean Humidity	1.000	1.000	1.001***	1.000*	1.000***
	(0.000030)	(0.000032)	(0.000050)	(0.000054)	(0.000039)
Mean Precipitation	1.003*	0.999	0.998	1.002	1.000
	(0.0015)	(0.0016)	(0.0024)	(0.0028)	(0.0019)
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
pseudo R^2	0.177	0.203	0.290	0.147	0.253
N	435,229	435,229	434,096	426,588	435,203

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.966 (0.072)	1.150 (0.25)	0.931 (0.100)	0.937 (0.081)
PolicyDay x Distance 0-2km	0.954 (0.040)	1.240 (0.25)	0.941 (0.090)	0.955 (0.044)
PolicyDay x Distance >2km		1.198 (0.24)	0.966 (0.095)	
Mean Temperature	0.997*** (0.00049)	1.001 (0.00050)	1.001*** (0.00032)	1.006*** (0.00058)
Mean Humidity	1.000 (0.00019)	1.000 (0.00019)	0.998*** (0.00013)	0.998*** (0.00022)
Mean Precipitation	1.006 (0.0096)	1.008 (0.0097)	1.037*** (0.0063)	1.056*** (0.012)
Day of Week FE Yes	Yes	Yes	Yes	Yes
Month FE Yes	Yes	Yes	Yes	Yes
Year FE Yes	Yes	Yes	Yes	Yes
Holidays FE Yes	Yes	Yes	Yes	Yes
User FE Yes	Yes	Yes	Yes	Yes
pseudo R^2	0.235	0.229	0.332	0.272
N	429,565	435,206	434,961	420,706

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes. Analysis uses time filter as per Roenneberg et al. (2012).

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.0103	-0.00564
	(0.017)	(0.0076)
PolicyDay x Distance 0-2km	0.0112	-0.00505
	(0.016)	(0.0049)
PolicyDay x Distance >2km	0.00802	
	(0.016)	
Mean Temperature	-0.000612***	0.000628***
	(0.000047)	(0.000053)
Mean Humidity	0.0000358*	-0.000175***
	(0.000018)	(0.000020)
Mean Precipitation	-0.00359***	0.00475***
	(0.00093)	(0.0010)
Constant	0.848***	0.0838***
	(0.0015)	(0.0017)
Annual Car Free Day	Yes	Yes
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.327	0.271
N	435,229	420,714

Robust S.E. clustered by User x Day of Week in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F.2 Using Walch et al. (2016)

Table 24: Incidence Rate Ratios (IRR) of the effect of *Paris Respire*-induced changes in air quality on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with duration in bed, total sleep, deep sleep, REM sleep, and light sleep as sleep outcomes. Analysis uses time filter as per Walch et al. (2016).

	In Bed	Total Sleep Time	Deep Sleep	REM Sleep	Light Sleep
PolicyDay, β (in target zone)	1.017***	1.021***	1.020*	1.033***	1.022***
	(0.0046)	(0.0050)	(0.0078)	(0.0087)	(0.0059)
PolicyDay x Distance 0-1km	1.023***	1.024***	1.024***	1.032***	1.028***
	(0.0033)	(0.0038)	(0.0062)	(0.0070)	(0.0047)
PolicyDay x Distance >1km	1.024***	1.025***	1.026***	1.033***	1.026***
	(0.0039)	(0.0044)	(0.0067)	(0.0076)	(0.0053)
Annual Car Free Day	0.994	0.994	0.983	0.999	0.999
	(0.0048)	(0.0054)	(0.0089)	(0.0094)	(0.0073)
Mean Temperature	0.999***	0.998***	0.997***	0.998***	0.999***
	(0.000057)	(0.000064)	(0.00011)	(0.00012)	(0.000079)
Mean Humidity	1.000*	1.000*	1.001***	1.000*	1.000***
	(0.000022)	(0.000024)	(0.000042)	(0.000045)	(0.000031)
Mean Precipitation	1.000	0.999	1.000	1.002	0.999
	(0.0011)	(0.0012)	(0.0021)	(0.0022)	(0.0015)
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
pseudo R^2	0.156	0.187	0.297	0.137	0.253
N	548,011	548,011	546,583	537,118	547,997

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 25: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes. Analysis uses time filter as per Walch et al. (2016).

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.971	0.973	1.010	1.056
	(0.028)	(0.028)	(0.019)	(0.035)
PolicyDay x Distance 0-1km	0.982	1.007	1.038*	1.073*
	(0.023)	(0.025)	(0.016)	(0.030)
PolicyDay x Distance >1km	0.972	1.005	1.034	1.078*
	(0.025)	(0.027)	(0.018)	(0.034)
Annual Car Free Day	0.980	0.958	0.996	1.036
	(0.035)	(0.030)	(0.022)	(0.042)
Mean Temperature	0.998***	1.001	1.001***	1.006***
	(0.00044)	(0.00044)	(0.00028)	(0.00052)
Mean Humidity	1.000	1.000	0.999***	0.998***
	(0.00017)	(0.00016)	(0.00011)	(0.00019)
Mean Precipitation	1.010	1.008	1.024***	1.027**
	(0.0084)	(0.0081)	(0.0052)	(0.0095)
Day of Week FE	Yes	Yes	Yes	Yes
Yes				
Month FE	Yes	Yes	Yes	Yes
Yes				
Year FE	Yes	Yes	Yes	Yes
Yes				
Holidays FE	Yes	Yes	Yes	Yes
Yes				
User FE	Yes	Yes	Yes	Yes
Yes				
pseudo R^2	0.238	0.229	0.315	0.249
N	541,415	547,990	547,728	531,025

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes. Analysis uses time filter as per Walch et al. (2016).

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.00224	0.00202
	(0.0026)	(0.0027)
PolicyDay x Distance 0-1km	0.000263	0.00339
	(0.0021)	(0.0024)
PolicyDay x Distance >1km	0.000798	0.00348
	(0.0023)	(0.0026)
Annual Car Free Day	-0.000673	0.00345
	(0.0032)	(0.0032)
Mean Temperature	-0.000501***	0.000519***
	(0.000038)	(0.000040)
Mean Humidity	0.00000844	-0.000117***
	(0.000014)	(0.000015)
Mean Precipitation	-0.00126	0.00192**
	(0.00072)	(0.00073)
Constant	0.861***	0.0700***
	(0.0012)	(0.0013)
Annual Car Free Day	Yes	Yes
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.315	0.256
N	548,011	531,038

Robust S.E. clustered by User x Day of Week in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 27: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes. Analysis uses time filter as per Walch et al. (2016).

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.971	0.973	1.010	1.056
	(0.028)	(0.028)	(0.019)	(0.035)
PolicyDay x Distance 0-1km	0.982	1.007	1.038*	1.073*
	(0.023)	(0.025)	(0.016)	(0.030)
PolicyDay x Distance 1-2km	0.962	1.007	1.030	1.073*
	(0.026)	(0.028)	(0.019)	(0.036)
PolicyDay x Distance >2km	0.990	1.001	1.041	1.087*
	(0.030)	(0.033)	(0.022)	(0.038)
Annual Car Free Day	0.979	0.958	0.996	1.036
	(0.035)	(0.030)	(0.022)	(0.042)
Mean Temperature	0.998***	1.001	1.001***	1.006***
	(0.00044)	(0.00044)	(0.00028)	(0.00052)
Mean Humidity	1.000	1.000	0.999***	0.998***
	(0.00017)	(0.00016)	(0.00011)	(0.00019)
Mean Precipitation	1.010	1.008	1.024***	1.027**
	(0.0084)	(0.0081)	(0.0052)	(0.0095)
Day of Week FE Yes	Yes	Yes	Yes	Yes
Month FE Yes	Yes	Yes	Yes	Yes
Year FE Yes	Yes	Yes	Yes	Yes
Holidays FE Yes	Yes	Yes	Yes	Yes
User FE Yes	Yes	Yes	Yes	Yes
pseudo R^2	0.238	0.229	0.315	0.249
N	541,415	547,990	547,728	531,025

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 28: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes. Analysis uses time filter as per Walch et al. (2016).

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.00224	0.00202
	(0.0026)	(0.0027)
PolicyDay x Distance 0-1km	0.000264	0.00339
	(0.0021)	(0.0024)
PolicyDay x Distance 1-2km	0.000749	0.00348
	(0.0024)	(0.0028)
PolicyDay x Distance >2km	0.000875	0.00347
	(0.0027)	(0.0028)
Annual Car Free Day	-0.000674	0.00345
	(0.0032)	(0.0032)
Mean Temperature	-0.000501***	0.000519***
	(0.000038)	(0.000040)
Mean Humidity	0.00000844	-0.000117***
	(0.000014)	(0.000015)
Mean Precipitation	-0.00126	0.00192**
	(0.00072)	(0.00073)
Constant	0.861***	0.0700***
	(0.0012)	(0.0013)
Annual Car Free Day	Yes	Yes
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.315	0.256
N	548,011	531,038

Robust S.E. clustered by User x Day of Week in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 29: Incidence Rate Ratios (IRR) of the effect of *Paris Respire*-induced changes in air quality on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with duration in bed, total sleep, deep sleep, REM sleep, and light sleep as sleep outcomes. Analysis uses time filter as per Walch et al. (2016).

	In Bed	Total Sleep Time	Deep Sleep	REM Sleep	Light Sleep
PolicyDay, β (in target zone)	1.017***	1.021***	1.020*	1.033***	1.022***
	(0.0046)	(0.0050)	(0.0078)	(0.0087)	(0.0059)
PolicyDay x Distance 0-2km	1.023***	1.025***	1.025***	1.032***	1.027***
	(0.0033)	(0.0038)	(0.0061)	(0.0069)	(0.0047)
PolicyDay x Distance >2km	1.022***	1.024***	1.022**	1.031***	1.028***
	(0.0050)	(0.0057)	(0.0083)	(0.0092)	(0.0071)
Annual Car Free Day	0.994	0.994	0.983	0.999	0.999
	(0.0048)	(0.0054)	(0.0089)	(0.0094)	(0.0073)
Mean Temperature	0.999***	0.998***	0.997***	0.998***	0.999***
	(0.000057)	(0.000064)	(0.00011)	(0.00012)	(0.000079)
Mean Humidity	1.000*	1.000*	1.001***	1.000*	1.000***
	(0.000022)	(0.000024)	(0.000042)	(0.000045)	(0.000031)
Mean Precipitation	1.000	0.999	1.000	1.002	0.999
	(0.0011)	(0.0012)	(0.0021)	(0.0022)	(0.0015)
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Holidays FE	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
pseudo R^2	0.156	0.187	0.297	0.137	0.253
N	548,011	548,011	546,583	537,118	547,997

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 30: Incidence Rate Ratios (IRR) of the effect of *Paris Respire* on the number of minutes, in a sleep phase, per user. Regression results correspond to Eq. 3 with durations of sleep onset latency, sleep offset latency, total wake time, and wake after sleep onset (WASO) as sleep outcomes. Analysis uses time filter as per Walch et al. (2016).

	Sleep Offset	Sleep Onset	Total Wake Time	WASO
PolicyDay, β (in target zone)	0.971	0.973	1.010	1.056
	(0.028)	(0.028)	(0.019)	(0.035)
PolicyDay x Distance 0-2km	0.980	1.007	1.037*	1.073*
	(0.023)	(0.025)	(0.016)	(0.030)
PolicyDay x Distance >2km	0.989	1.001	1.041	1.087*
	(0.030)	(0.033)	(0.022)	(0.038)
Annual Car Free Day	0.980	0.958	0.996	1.036
	(0.035)	(0.030)	(0.022)	(0.042)
Mean Temperature	0.998***	1.001	1.001***	1.006***
	(0.00044)	(0.00044)	(0.00028)	(0.00052)
Mean Humidity	1.000	1.000	0.999***	0.998***
	(0.00017)	(0.00016)	(0.00011)	(0.00019)
Mean Precipitation	1.010	1.008	1.024***	1.027**
	(0.0084)	(0.0081)	(0.0052)	(0.0095)
Day of Week FE	Yes	Yes	Yes	Yes
Yes				
Month FE	Yes	Yes	Yes	Yes
Yes				
Year FE	Yes	Yes	Yes	Yes
Yes				
Holidays FE	Yes	Yes	Yes	Yes
Yes				
User FE	Yes	Yes	Yes	Yes
Yes				
pseudo R^2	0.238	0.229	0.315	0.249
N	541,415	547,990	547,728	531,025

Robust S.E. clustered by User x Day of Week in parentheses

Exponentiated coefficients; A value of 1 represents no percentage change in vehicles.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 31: The effect of *Paris Respire* on sleep quality measurements per user. Regression results correspond to Eq. 4 with sleep efficiency and night efficiency as outcomes. Analysis uses time filter as per Walch et al. (2016).

	Sleep Efficiency	Night Efficiency
PolicyDay, β (in target zone)	0.00224	0.00202
	(0.0026)	(0.0027)
PolicyDay x Distance 0-2km	0.000330	0.00340
	(0.0021)	(0.0024)
PolicyDay x Distance >2km	0.000878	0.00347
	(0.0027)	(0.0028)
Annual Car Free Day	-0.000679	0.00345
	(0.0032)	(0.0032)
Mean Temperature	-0.000501***	0.000519***
	(0.000038)	(0.000040)
Mean Humidity	0.00000846	-0.000117***
	(0.000014)	(0.000015)
Mean Precipitation	-0.00126	0.00192**
	(0.00072)	(0.00073)
Constant	0.861***	0.0700***
	(0.0012)	(0.0013)
Annual Car Free Day	Yes	Yes
Day of Week FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Holidays FE	Yes	Yes
User FE	Yes	Yes
R^2	0.315	0.256
N	548,011	531,038

Robust S.E. clustered by User x Day of Week in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$