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The Carbon Footprint of Remote Workers' Travel Behavior: Evidence from Digital Phenotyping Data

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Abstract

Evidence on the travel-related environmental impact of remote work is mixed and inconclusive, partly due to limitations in measuring workers' mobility. Existing studies rely heavily on self-reported data, which increases exposure to measurement errors and response bias and risks overlooking relevant trips taken on homeworking days. This study leverages a digital phenotyping approach, estimating remote workers' average carbon footprint based on their observed travel behavior. Using smartphone GPS data, we track movement trajectories and estimate CO2 emissions for a sample of Italian workers. We find that working from home is associated with shorter distances traveled and reduces daily CO2 emissions by two-thirds. Carbon savings during typical commuting hours are not offset during non-commuting windows, when additional reductions are observed. Conversely, working from alternative remote locations provides no benefit. Emission savings are achieved especially by long-distance travelers on homeworking days, suggesting heterogeneity across workers in the outcomes observed. From a policy perspective, the proposed methodology has strong potential to support companies in calculating Scope 3 emissions (Category 7), thereby better assessing (and, if necessary, correcting) employees' carbon footprints. The method also supports an objective assessment of remote workers' actual mobility demand in a context where smart working is identified as a possible solution to shield workers from price shocks in fossil fuel markets. We find that homeworkers travel shorter distances using non-emissive modes, suggesting more sedentary behavior and highlighting the need for flexible work arrangements to be accompanied by initiatives that promote an active lifestyle, such as active-mobility incentive programs.

Keywords Digital phenotyping, CO2 emissions, Transport mode detection, Rebound effect, Mobility demand

1 Introduction

A growing stream of literature studies the environmental implications of remote work, particularly changes in air pollutant emissions (O'Brien & Aliabadi, 2020; Sepanta & O'Brien, 2023). As commuting is deemed a major contributor to urban carbon emissions (Noussan & Jarre, 2021), adjustments in travel behaviors associated with flexible arrangements are identified as a possible channel of impact (Halefom, Moglia, Nygaard, & Pojani, 2025). Understanding how remote work influences daily mobility has become increasingly relevant (Rietveld, 2011). The rising environmental awareness of consumers and producers has ignited the debate on workers' carbon footprints beyond core business tasks, bringing commuting-related emissions into focus. Besides, geopolitical tensions and fuel price shocks have strengthened the need to assess and measure how flexible arrangements affect workers' mobility demand.

Empirical studies have documented that teleworking reduces traffic congestion and air pollution by lowering commuting (e.g., Giovanis, 2018; Li, Liu, & Long, 2023; Shabanpour, Golshani, Tayarani, Auld, & Mohammadian, 2018). However, this is only one possible effect of remote work. Remote workers may increase the frequency and distance of non-work trips (Asgari, Jin, & Du, 2016; Obeid, Anderson, Bouzaghrane, & Walker, 2024; Zhu, 2012), and may change transport modes on telecommuting days Van Lier, De Witte, and Macharis (2014), generating rebound effects (Hook, Sovacool, Sorrell, et al., 2020; O'Brien & Aliabadi, 2020) that may offset environmental gains. Neglecting potential rebound effects could lead to an overestimation of the environmental benefits of remote working (Obeid et al., 2024).

A key methodological challenge is measuring workers' travel behaviors. Most studies rely on self-reported metrics from surveys, diaries, or existing regional statistics (e.g., Caldarola & Sorrell, 2024; Halefom et al., 2025; Henderson & Mokhtarian, 1996; Zhu & Mason, 2014), which are prone to measurement errors and response bias. The cross-sectional nature of many survey-based datasets also limits the possibility of controlling for unobservable workers' characteristics.

We measure travel behaviors for a sample of Italian residents to estimate changes in CO2 emissions associated with remote work practices. We do so by exploiting longitudinal GPS data collected from participants' smartphones with an average sampling rate of one point per minute using a digital phenotyping approach. This method enables a more precise characterization of workers' movements by tracking both location and travel speed.

Our results show that working from home is associated with shorter travel distances and lower CO2 emissions. On average, a day of home working reduces daily emissions by two-thirds and lowers traveled distance by 43.1%. Conversely, remote work from alternative locations offsets the expected benefits and increases daily emissions on Fridays. As the weekend approaches, remote workers running tasks from alternative workstations may travel additional kilometers during their daily trips. On homeworking days, emissions are lower both in typical commuting and non-commuting hours. The expected environmental benefits from lower commuting are not counteracted by increased emissions in midday time windows. Further disaggregations reveal that declines in distance traveled are observed during the 6 to 10 a.m. and 6 to 8 p.m. windows, especially, namely in typical commuting hours. Conversely, associated emission savings are not confined solely to the early morning and late evening but also occur during typical non-commuting hours. Homeworkers who take longer trips on office-work days are those achieving statistically significant reductions in emissions, especially during commuting hours, while short commuters don't exhibit statistically significant savings, suggesting residual mobility. Our analysis doesn't reveal any statistically significant mode rebound effect or change in workers' emission intensity profile on homeworking days.

Although we do not find any significant shift toward emissive modes on remote-working days, we still observe shorter distances traveled using non-emissive modes when working from home. This socially undesirable outcome may indicate a more sedentary lifestyle, raising concerns about remote workers' health and well-being.

This work makes several contributions. First, the digital phenotyping approach enables an improved measurement of travel behaviors compared with survey-based data for a more reliable quantification of fuel demand and transport-related air-pollutant emissions. Few studies to date exploit mobile-phone location data to track telecommuters' distance traveled or remote-work adoption (Dai et al., 2025; Melek & Kim, 2021; Obeid et al., 2024). To the best of our knowledge, none of them uses a digital phenotyping approach to quantify workers' travel-related emissions. Second, GPS-based mobility tracking allows us to capture both commuting and non-commuting trips throughout the day, providing data documenting actual daily mobility patterns to test rebound effects.

Our contribution has significant policy relevance. First, our approach has strong potential to guide the monitoring and reporting of commuting-related emissions classified as Scope 3 Category 7 in the GHG Protocol framework[1]. Although mandates to report employee commuting for sustainability purposes are still limited to a few countries[2], companies are increasingly being held accountable for emissions generated beyond their core business operations. Quantification approaches based on the direct observation of people's travel behaviors could play an important role in supporting voluntary reporting of employees' travel-related carbon footprints. Second, beyond meeting reporting needs, the digital phenotyping approach can inform the design of interventions to curb firms' commuting-related carbon footprint and maximize the expected gains. Given the heterogeneous environmental outcomes of homeworking across workers, firms (or policymakers) can promote its adoption based on objective evidence on employees' observed travel behaviors, targeting specific worker profiles and geographical areas. Third, made urgent by increasing geopolitical instability, a digital phenotyping-based method can inform on the actual contribution of homeworking to reducing workers' fuel demand for travel purposes, thereby guiding policymakers' recommendations aimed at relieving consumers from price pressures triggered by shocks in fossil-fuel markets. Fourth, by highlighting a decline in distance traveled by non-emissive means on homeworking days, we bridge the environmental and well-being perspectives and underscore that the adoption of remote working should be accompanied by initiatives aimed at incentivizing an active lifestyle on both office-work and homeworking days.

2 Literature review

The investigation of the socio-environmental implications of remote work has generated parallel streams of research. Some studies focus on directly quan-

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[1] GHG (greenhouse gas) Protocol.

[2] See Section 5 for further details.

tifying travel-related air pollutant emissions associated with remote work practices (e.g., Cerqueira, Motte-Baumvol, Chevallier, & Bonin, 2020; Shi, Sorrell, & J Foxon, 2022), while others examine the changes remote work induces in travel behaviors (e.g., He & Hu, 2015; Kim, Choo, & Mokhtarian, 2015) implicitly assuming potential environmental implications. Travel, indeed, is one of the major contributors to individuals' carbon footprints. Employee commuting is classified by the GHG Protocol framework as one of the critical sources of pollutants from companies' value chain activities.

Flexible work arrangements are typically associated with environmental benefits as they reduce commuting and generate transport savings (Hamer, Kroes, & Van Ooststroom, 1991; Nilles, 1988; Van Lier et al., 2014). Empirical studies have documented a positive effect of teleworking on traffic congestion measures, like vehicle miles traveled (e.g., Helminen & Ristimäki, 2007; Shabanpour et al., 2018; Wang & Mokhtarian, 2024), on pollution-related metrics (e.g., Giovanis, 2018; Li et al., 2023) or on both (e.g., Henderson & Mokhtarian, 1996; Koenig, Henderson, & Mokhtarian, 1996; Mokhtarian & Varma, 1998), with possible heterogeneity. According to Lachapelle, Tanguay, and Neumark-Gaudet (2018), working full-day from home reduces overall travel time and peak hour travel. Giovanis (2018) claims that teleworkers contribute to reducing both traffic volume and air pollutant emissions. Evidence from Italy quantifies daily emission savings of 4.1 kgCO2e from avoiding home-work trips (de Pinto et al., 2026), while another study estimates reduced emissions by 6 kgCO2e if part of the trip is by car (Roberto, Zini, Felici, Rao, & Noussan, 2023).

While there is consensus that remote working solutions can, in principle, reduce travel and related emissions, evidence is mixed. Remote work can, indeed, cause unintended behaviors that might offset the expected benefits. Potential rebound effects of working outside the office premises have been discussed in the literature (Hook et al., 2020; O'Brien & Aliabadi, 2020). Travel-related rebound effects have a multifaceted nature. They may arise for additional non-work travel (Cerqueira et al., 2020; Zhu, 2012), shifts in transport modes on remote work days (Van Lier et al., 2014), or induced travel by other household members (de Abreu e Silva & Melo, 2017; Kim et al., 2015; Zhu, 2013). Zhu (2012) finds that U.S. teleworkers make 10.8% more non-work trips per day than non-teleworkers, and that these trips are on average 15.7% longer. Similarly, Zhu and Mason (2014) observe that telecommuters in the U.S. accumulate more vehicle miles traveled for both work and non-work trips than non-telecommuters, while telecommuting has no effect on the daily non-work trips of other (non-working) household members, leading overall to an increase in household vehicle miles traveled. Consistently, Obeid et al. (2024) shows that telecommuting in the U.S. results in the generation of additional non-commute trips that offset a significant portion of the gains from reduced commuting. However, the authors find these trips to be shorter on average than the commute trips they replace, with a positive net effect in terms of lower daily travel distance on telecommuting days than on commuting days. The implications in terms of generated emissions are not straightforward, as a net reduction in air pollution is not guaranteed.

The frequency of teleworking may play a role in eliciting rebounds. By studying the English context, Shi et al. (2022) show that lower frequencies (one or two days per week) are often associated with greater overall travel and related carbon emissions, whereas higher frequencies are associated with lower emissions.

Rebound effects could also emerge conditional on distance traveled. Evidence from Australia suggests that environmental benefits are achieved when employees travel at least 30 kilometers (or above), whereas for shorter trips the environmental impact of teleworkers overcomes the one of non-teleworkers (Guerin, 2021).

Concerning modal changes, evidence from Van Lier et al. (2014) in the Brussels region suggests that remote work may encourage a shift from public transportation to private cars. Public transportation modes can be perceived as less efficient or less flexible for non-work trips, prompting workers to opt for private vehicles, thus resulting in additional car kilometers driven and higher per-capita emissions.

Overall, existing evidence remains mixed and at times contradictory. Contrasting results may stem from substantial methodological differences or from measurement limitations (O'Brien & Aliabadi, 2020; Zhu, 2012). First, most studies do not directly measure individuals' travel behaviors but rely on self-reported data drawn from national travel surveys (e.g., de Abreu e Silva & Melo, 2017; Elldér, 2020; Lachapelle et al., 2018), which are prone to measurement errors and response bias. Survey-based studies also face difficulties in precisely characterizing and measuring actual fuel consumption, as they can't always infer the mode used for every single trip taken throughout the day. This can hinder the assessment of whether declines in distance traveled translate into actual emission savings. Furthermore, regional and national travel surveys are seldom longitudinal, limiting the possibility of controlling for time-invariant confounders (e.g., Caldarola & Sorrell, 2022; Cerqueira et al., 2020; Kim et al., 2015; Melo & e Silva, 2017). Another limitation lies in the extensive reliance on general indicators of teleworking practices that cannot properly capture how much respondents have actually worked from remote in the period covered by travel data (e.g., Melo & e Silva, 2017; Noussan & Jarre, 2021; Zhu & Mason, 2014). In addition, some studies quantify the environmental savings of working from remote, focusing on avoided one-way or round-trip commutes (de Pinto et al., 2026; Roberto et al., 2023) based on self-reported average commuting distance, thereby missing potential rebound effects from additional trips taken throughout a homeworking day.

Few recent contributions have exploited passively collected commuter location data from smartphones to characterize travel and work behaviors. Obeid et al. (2024) used individual-level point of interest (POI) visit information to quantify the effects of changes in the frequency of telecommuting on the number of trips and distance traveled by a panel of workers. Dai et al. (2025) collected locations and timestamps associated with mobile phone usage for a sample of individuals based in Chicago to infer their work-related mobility patterns and correlate them with socio-demographic attributes. Similarly, Melek and Kim (2021) exploited high-frequency cell phone geolocation data to characterize workers' profiles and study the evolution of homeworking since the COVID-19 pandemic.

To the best of our knowledge, the digital phenotyping approach remains largely underexplored in this field, yet the potential contribution is substantial. Recent studies show how high-resolution bottom-up accounting methods based on GPS data are promising in reflecting the complexity and heterogeneity of urban mobility to construct more accurate GHG inventories and guide targeted interventions (Tian et al., 2024; Zhang, Cheng, & Yang, 2026). Yet, the quantification of remote work's carbon footprint is still new to this approach, as existing studies have limited the use of smartphone location data to exploring workers' mobility patterns without providing an explicit emission calculation. We tackled this gap by leveraging high resolution digital phenotyping data to estimate the change in CO2 emissions associated with remote work practices. This allowed us to directly observe workers' travel behaviors over time and match the observed trajectories with actual remote work days, thereby overcoming part of the methodological limitations that have affected past research in this field.

3 Empirical approach

3.1 Data collection and the digital phenotyping approach

We conducted our study on a sample of Italian residents of working age recruited at different points in time between April and July 2025. Individuals were eligible if employed, living alone, and without children at the time of recruitment. While the employment criterion ensured the inclusion of individuals engaged in forms of remote work relevant to this study, the other two criteria allowed us to rule out potential intra-household compensatory mobility patterns that might counterbalance the observed effects (de Abreu e Silva & Melo, 2018).

Our approach leverages passive smartphone sensor data gathered using a digital phenotyping smartphone application. Digital phenotyping allows for collecting behavioral data, including spatial trajectories, from personal digital devices (Onnela & Rauch, 2016; Torous, Kiang, Lorme, Onnela, et al., 2016).

We gathered data from smartphones' GPS[3] sensors. These data allow us to characterize people's movements and track their travel behaviors, including distance traveled and movement speed. Participants installed the Beiwe smartphone application, developed by Onnela Lab (Onnela et al., 2021), and were monitored for 30 working days. The sampling rate of GPS data was 1 point per minute on average.

The digital phenotyping approach offers significant methodological improvements as it tracks individuals' location and speed, minimizing the risk of measurement errors and response bias.

Smartphone sensor data were combined with survey data on participants' demographics, occupation type, and remote work habits[4]. The survey was administered at the beginning of the monitoring period. At the end of the period, participants completed a brief follow-up questionnaire to report any changes in employment status or household composition, and provide complementary information on travel behaviors (usual transportation mode for commuting). During the monitoring period, respondents had to report remote-working days and indicate any sick-leave or business-travel days. So,

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[3] Global Positioning System.

[4] Further information on the data collection procedure and survey content is provided in the Supplementary Material.

we were able to precisely identify the days on which participants actually worked outside the office, and build a daily binary variable to associate with distance and emission metrics.

3.2 Computation of distance traveled

We computed the distance traveled by participants using raw GPS trajectory data.

First, trajectories have been segmented into stop (stationary) and move (traveling) periods. A GPS point was assigned to a stop segment if its speed is at most 5 km/h (or it is the first point in the stream), all points in the candidate segment lie within a 100 m radius of their spatial centroid, and the stop lasts at least five minutes (Zheng, 2015). After the initial labelling, consecutive segments of the same type were merged when separated by at most five minutes, and segments with fewer than three points were merged into neighbours to avoid spurious fragmentation. This reduced fragmentation caused by brief GPS signal interruptions. Notice that the initial three conditions (i.e., speed limit, spatial radius, and temporal duration) constitute the standard for extracting stop/move segments in trajectory mining (Alvares et al., 2007; Zheng, 2015). The work in Cich, Knapen, Bellemans, Janssens, and Wets (2016) is an empirical study on trip/stop detection from GPS that explicitly shows that results are sensitive to these thresholds and discusses how to set them in practice. Our values sit within the ranges commonly adopted in the literature. In particular, with the speed limits of a few km/h used to separate drift from movement, the spatial radius on the order of tens to a few hundred meters to absorb positioning error, and minimum durations of several minutes to distinguish activities from short halts.

We computed total distance traveled and emissions generated over the day (6 a.m. to 8 p.m.), and then we obtained travel distances for time windows (commuting vs non-commuting windows and 2-hour time windows) to study whether (and to what extent) working from remote affects distance traveled at specific times of the day. For each time window, we included in the computation the distance from the last point before the window starts to the first point falling within the window.

The great-circle distance between two GPS points has been calculated using the Haversine formula as:

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \quad (1)$$

where r is the Earth's radius (6,371 km), ϕ_1, ϕ_2 represent the latitudes of points 1 and 2 (in radians), $\Delta\phi$ is the difference in latitudes, and $\Delta\lambda$ stands for the difference in longitudes. Distances are counted only when the time gap between consecutive points is 30 minutes or less. This prevents including unrealistic distances when the device was off or counting "teleportation" artifacts from GPS signal loss.

Outliers in GPS points were removed[5].

3.3 Transport mode detection

We classified GPS trajectory segments into five transport modes to study differences in the use of emissive and non-emissive modes on remote work days and for a more reliable quantification of transport-related emissions. The classification method leverages per-user travel survey declarations as hard constraints for segment labeling, combined with a Random Forest classifier trained on kinematic features for ambiguous cases. We started from an initial sample of 37,007 GPS segments.

First, data were cleaned, removing segments with insufficient GPS data or implausible values according to a set of criteria based on features like speed and distance[6]. After the filtering stages, 16,009 segments remained.

Then, for each user, we extracted declared transport modes from survey items to build user-specific "constraints". The survey includes two multiple-choice questions about transport mode usage, one asking which modes of transport are habitually used for the home-work commute ("During the monitoring period, which mode(s) of transportation did you typically use for commuting from your private residence to your workplace?"), the other asking which modes are habitually used for non-work-related trips ("During the monitoring period, which mode(s) of transportation did you typically use for non-work trips?"). Each question offered 11 response options, which were collapsed into five transport modes: walking, bicycle, public transit, train, and

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[5] For further details see the Supplementary Material, Section 3.1.

[6] Details on the data cleaning steps are reported in the Supplementary Material, Section 3.1.

car. Participants could select one or more modes. Based on their answers on transport modes, participants were classified into four *constraint categories*: single-motor (who declared to use one motorized mode), multi-motor (who declared to use two or more motorized modes), active-only (who declared to use transport modes none of which is motorized), and no-declaration (people who did not provide an answer).

As the third step of the classification pipeline, we assigned labels based on kinematic rules and/or survey answers. We identified "Walking" segments through some kinematic rules, regardless of survey data. Walking, indeed, is deemed to be characterized by a set of universal kinematic characteristics. Micro-movements with a distance of less than 30 meters, or less than 80 meters with a mean speed below 8 km/h, as well as broader segments characterized by a mean speed below 7 km/h, a distance under 2 km, and a median speed below 6 km/h were included in this category. This pre-classification identifies 5,461 segments (34.1%). Then, labels were assigned driven by survey answers. "Bicycle" labels were assigned only to active-only users (those who declare "Walking and/or Bicycle", but no motorized modes). For these users, all non-walking segments were labeled as "Bicycle" by exclusion. "Bicycle" was not predicted by the supervised classifier due to insufficient training data and kinematic overlap with slow motorized modes. For single-motor users, all non-walking, non-bicycle segments with a distance greater than 0.5 km are assigned the declared mode. The 500 m threshold ensures that only segments with clear motorized kinematic signatures enter the training set. For multi-motor users declaring "Train", a distance-based rule identified likely "Train" segments. Three conditions were set, namely $d > 10$ km, SI > 0.4, and $\bar{v} > 15$ km/h, where d denotes distance, SI is the straightness index (ratio of displacement to total distance), and $\bar{v}$ is the mean speed.

Segments that were still unlabeled after the kinematic rules and the survey-based labeling step for single-motor users reached the supervised classification step. We extracted 20 features for the supervised classification task[7]. All features were standardized using z-score normalization before model training. Two classifiers, Random Forest (RF) and XGBoost, were evaluated via 5-fold stratified cross-validation with grid search[8]. The model with the higher weighted F1 score, the Random Forest, was selected. The

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[7] See Table 1 in the Supplementary Material.

[8] See the Supplementary Material for information on the set of hyperparameters.

winning model's probabilities were calibrated using isotonic regression (5-fold). The classifier was trained on three classes, namely "Walking", "Car", and "Public Transit", using 9,583 labeled segments. "Bicycle" and "Train" were excluded from training due to insufficient sample sizes and poor kinematic separability from other modes. The classifier also predicted "Walking" for segments that did not trigger the kinematic rules[9].

Prediction from the model was constrained and unconstrained, depending on the specific case. Prediction was constrained for users with declared modes (multiple modes): Random Forest probabilities were masked to the declared motorized set plus "Walking" and the mode with the highest constrained probability was assigned. Conversely, for users with no declaration, namely those that did not answer the survey question on habitual transport modes, the Random Forest predicted freely among "Walking", "Car", and "Public Transit", yielding an unconstrained classification.

A set of plausibility checks was performed to verify the physical coherence of each classification[10]. Plausibility failures triggered reassignment to the most probable plausible alternative for model-predicted segments. For survey-labeled segments, failures were flagged but labels were preserved, as the survey provides ground-truth constraints. Car segments have been post-hoc sub-typed into *urban* and *extra-urban* based on the fraction of moving time above 20 km/h. If the fraction is above 0.3, then the car movement is identified as extra-urban (urban if below the threshold)[11].

3.4 Emission metrics computation

We leveraged the classification of move segments based on the detected transport modes to better quantify travel-related emissions. Specifically, we computed per-segment CO2 emissions using Italian-specific emission factors expressed in grams of CO2 per passenger-kilometer (gCO2/p-km). We adopted factors representative of the Italian context, informed by data from ISPRA[12] (The Italian Institute for Environmental Protection and Research) and IS-

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[9] For instance, a segment with a mean speed of 7.5 km/h and a distance equal to 2.5 km would pass the kinematic filters, but the classifier might still assign the "Walking" label based on the full feature vector.

[10] Plausibility rules are displayed in Table 2, in the Supplementary Material.

[11] Table 4 in the Supplementary Material reports the major characteristics of urban and extra-urban car segments

[12] For further information, see the ISPRA database.

FORT (High Institute for Transport Education and Research) national mobility reports. ISPRA data on emission factors are the typical reference for the computation of travel-related air pollutant emissions in the Italian context (de Pinto et al., 2026; Roberto et al., 2023).

The emission factors applied to each transport mode are presented in Table 1. The car sub-typing is directly leveraged here: urban car travel is assigned a higher emission factor (200 gCO2/p-km) than extra-urban travel (130 gCO2/p-km), reflecting the well-established difference in fuel efficiency between stop-and-go urban driving and steady-speed highway driving.

For each classified GPS segment i with transport mode m_i and travel distance d_i (km), the CO2 emissions were computed as:

$$E_i = d_i \times f_{m_i} \tag{2}$$

where f_{m_i} is the emission factor (gCO2/p-km) for mode m_i.

Emissions were then aggregated across all transport modes by computing a weighted sum where the distance traveled by each mode acts as the weight. In this way, we got a daily measure per user (from 6 a.m. to 8 p.m.). We also computed disaggregated emission metrics by commuting and non-commuting periods and by 2-hour time windows to examine the heterogeneity of the effect throughout the day. The final metrics are provided in grams of CO2.

3.5 The econometric model

The longitudinal design of the study enabled the observation of a pool of participants repeatedly over time. This allowed for estimating a longitudinal linear model controlling for individual-specific time-invariant unobservable confounders and time trends. Combinations of participants (i) and calendar weeks (c) are the observational units, while the time dimension is given by weekdays (Monday to Friday). Participants were recruited at different points in time, which prevented us from using calendar days as the time unit because of the small number of observations per calendar day. Calendar days in the estimation sample span from April 10 to July 17.

The model is specified as follows:

$$\ln(\mathrm{Y}+1)_{ict} = \beta_0+\beta_1\mathrm{WfH}_{ict}+\beta_2\mathrm{WfR}_{ict}+\beta_3\mathrm{L}_{ict}+\beta_4\mathrm{BT}_{ict}+\gamma'\mathbf{w}_{ict}+\eta_c+\mu_t+\alpha_i+\epsilon_{ict} \tag{3}$$

where Y is the dependent variable. We used the metrics capturing kilometers traveled and travel-related emissions at different levels of temporal aggregation as dependent variables[13]. The binary regressor WfH (*Working from Home*) equals 1 on remote-work days for participants who declared that they worked remotely exclusively from home, while the binary variable WfR (*Working from Remote*) equals 1 on remote-work days for participants who declared that they worked remotely from any non-office location, such as a private residence or a co-working space. Binary variables L and BT identify days of leave or business trips. Vector **w** denotes the weather conditions, namely total precipitation and wind speed at the participant's home location. Sets η_c, and μ_t control for time trends at the calendar week and weekday levels, while α_i denotes individual fixed effects. Finally, ϵ_{ict} is the error term.

Individual fixed effects allow for capturing individual-specific time-invariant confounders such as basic demographics or stable behaviors shaped by lifestyle, personal preferences, or the characteristics of their place of residence. Time-specific indicators capture calendar trends related to the time of year when the individual is observed, as well as weekday trends shaped by weekly routines. To rule out potential interference with typical daily routines, we excluded festivities and weekends from the estimation sample.

4 Results

4.1 Transport mode detection results

The Random Forest classifier achieved a cross-validated weighted F1 score of 0.946 (vs. XGBoost at 0.848) and was selected as the final model. The out-of-bag (OOB) accuracy was 0.949. Weighted F1 and OOB accuracy are high in part because "Walking" and "Car" dominate the training set, while "Public Transit" is rare. Per-class metrics reveal that Public Transit remains the weakest class[14]. The best hyperparameters were: no maximum depth constraint, 50% of features per split, minimum 3 samples per leaf, and 300 estimators. The transport mode detection task yielded 6,144 model-predicted

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[13] We took the logarithm as the variables in original units are right-skewed. See the Supplementary Material, Fig. 5.

[14] Per-class performance, the cross-validated confusion matrix and feature importance from the final Random Forest model are displayed in the Supplementary Material.

segments, of which 3,900 constrained and 2,244 unconstrained.

The final mode distribution across 16,009 segments is presented in Table 2. "Car" movements are the most prevalent, with approximately 51% of segments assigned to this class, followed by "Walking" and "Public Transport". This pattern is plausible and consistent with national statistics on Italian mobility. Figures from ISFORT (High Institute for Transport Education and Research) indicate that workers chose the private car for most of their trips, with walking as the second most common mode, followed by public transport, while bicycles remain the least represented[15]. This is confirmed by data from ISTAT (Italian National Institute of Statistics)[16].

Overall, 60.1% of segments are classified without the Random Forest model (using kinematic rules or survey labels), while 38.4% rely on model prediction[17]. The extent to which rules or classifiers are used to assign the label varies across transport modes. Indeed, some modes were easier to identify based on kinematic rules (e.g., walking) or using survey information by exclusion (e.g., bicycle). In other cases, the declared use of multiple motorized modes with poor kinematic separability or the absence of survey answers required a data-driven approach (classification algorithms). This led to a different composition of label sources by transport mode (see Fig. 1).

4.2 Econometric estimates

After cleaning the data, the estimation sample includes daily observations for 103 participants, for a total of 1,354 observations, net of missing values. The sample is distributed across 82 Italian municipalities, having a mean (median) size of 137,995 (29,073) inhabitants and a mean (median) density of 1,096 (643) inhabitants per km2[18]. Fig. 2 displays the geographical distribution of the sample across the Italian territory.

43 individuals (41.7%) worked remotely for at least one day during the observed period. Of these, 23 declared to work exclusively from home, while 20 reported performing remote work from alternative locations as well (e.g.,

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[15] Statistics from the Audimob observatory. For further information, see the ISFORT report

[16] 2024 figures from the ISTAT report

[17] Segment counts by label sources as shown in Table 5 in the Supplementary Material.

[18] The statistics have been computed across 82 municipalities. The average population size, weighted by the number of participants per municipality, is 315,989 inhabitants, with a standard deviation of 644,265.

co-working spaces).

The average daily per capita traveled distance on a day of work from the office is 18.08 km, consistent with ISFORT 2025 national statistics.[19]. The average distance traveled on a day of homeworking is 8.77 km, whereas working from other locations is associated with an average of 11.49 km traveled. Simple univariate statistics thus suggest an average of 9.3 km saved when working from home (almost 50% reduction) and 1 kg of CO2 avoided (47% less than on office days)[20]. Not accounting for potential confounders could, however, be misleading.

Econometric estimates in Table 4 show that, on average, working from home reduces daily distance traveled by 43.1% (column 1). This is related to an average decline in CO2 emissions of 66.05% per day (column 4). The effect is concentrated among individuals working from home, as remote work from alternative locations does not significantly reduce travel or emissions. Plausibly, these workers still need to travel to reach an alternative workstation.

By interacting remote-work dummies with weekday controls (see Table 7 in the Supplementary Material and Fig. 3), we see that working from home generally lowers distance traveled with stronger effects early in the week. Working from home consistently reduces CO2 emissions throughout the week, though differences across days are not statistically significant, while remote work from alternative locations is associated with higher emissions on Fridays.

When disentangling between emissive (e.g., car, bus) and non-emissive (e.g., walking, cycling) transport modes (see Table 4, columns 2 and 3), we found a decrease in total distance traveled using both emissive and non-emissive modes. The latter result suggests increased sedentary behavior among employees working from home, raising concerns about their well-being.

We also estimated potential rebound effects stemming from increased emissions in non-commuting hours, which may counterbalance potential savings during commuting hours (Hook et al., 2020). We examined the heterogeneity of such effects (Elldér, 2020), and assessed rebounds arising from potential increased emission intensity or shifts toward emissive modes on

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[19] Statistics from the Audimob observatory. For further information, see the ISFORT report.

[20] See Table 6, Supplementary Material. Statistics computed before the log transformation of the distance and emission metrics.

homeworking days (Van Lier et al., 2014)[21]. Trips (and associated emissions) between 6 and 10 a.m. and 6 and 8 p.m. are regarded as commuting, while trips between 10 a.m. and 6 p.m. are defined as non-commuting. Non-commuting rebound is defined as the share of commuting savings that are offset by a potential increase in distance traveled and/or emissions during midday hours, and was measured as:

$$R = \begin{cases} \dfrac{|\beta_1^{nc}|}{|\beta_1^{c}|} \times 100 & \text{if } \beta_1^c < 0 \text{ and } \beta_1^{nc} > 0 \\ 0 & \text{if } \beta_1^c < 0 \text{ and } \beta_1^{nc} \leq 0 \end{cases} \tag{4}$$

where β_1^{nc} and β_1^c estimate the effect of homeworking in non-commuting and commuting hours, respectively. The same is done for β_2, associated with remote work from alternative locations.

We observed that homeworking is associated with lower emissions during both commuting and non-commuting hours (Table 5). Thus, homeworkers' behaviors in non-commuting hours do not offset the commuting-related benefits. Further disaggregation in 2-hour time intervals reveals that reductions in travel distance occur mainly in the early morning and late evening (6–10 a.m. and 6–8 p.m.), that is, during typical commuting hours (Table 8, Supplementary Material). Associated emission declines, instead, occur across typical commuting and non-commuting windows, especially in the afternoon, when statistically significant savings are observed between 4 and 8 p.m. (Table 9, Supplementary Material).

The examination of heterogeneous effects reveals that a statistically significant decline in emissions is achieved by long commuting homeworkers (those traveling an average distance above the median of 13.4 km on office days) in both commuting and non-commuting hours (thus ruling out a non-commuting rebound effect for them). The decline for long commuters is larger during commuting hours than during non-commuting hours. Avoiding commuting over long distances seems to drive much of the effect for these worker profiles. On homeworking days, workers may still undertake personal trips during midday hours, while they typically tend to travel less in this time window on office-work days, thereby mitigating the carbon savings achieved during this period. Savings for short commuters are not significantly different than zero, suggesting residual mobility also during commuting hours on

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[21] Further details are provided in the Supplementary Material.

homeworking days. In addition, statistically significant savings are observed in municipalities with higher population density (Table 11, Supplementary Material).

Finally, the intensity of CO2 emissions per km traveled and the share of km traveled by emissive modes do not significantly differ between office days and homeworking days, revealing a non-statistically significant shift in transport modes or change in emissions intensity profile (Table 10, Supplementary Material).

5 Conclusions and policy implications

This paper proposes a digital phenotyping-based approach by leveraging GPS data to estimate the average change in CO2 emissions on a remote work day. We provide evidence on a sample of workers based in Italy, a country that experienced a widespread diffusion of smart working practices, with 95% of large enterprises and 45% of small and medium-sized enterprises adopting remote work solutions in 2025[22]. Existing studies based in Italy (e.g., de Pinto et al., 2026; Roberto et al., 2023) generally adopt a direct, unconditional accounting approach, estimating emissions savings from avoided home–work travel based on self-reported average commuting distance. Our approach enables a conditional assessment by tracking movements throughout the day, thus measuring savings in total daily trips, rather than only avoided round-trip commutes. This allows testing for rebound effects and better estimating net emission savings while controlling for individuals' time-invariant characteristics (including stable behaviors) and time trends. It also supports a survey-constrained data-driven detection of transport modes based on actual movement traces.

We observe that working from home is associated with a 43% reduction in daily travel distance and a two-thirds reduction in CO2 emissions, with long commuters driving the effect. When considering workers travelling short commuting distances, savings are not significantly different from zero. Evidence-based data reveal no rebound from travel in non-commuting hours (Hook et al., 2020). Remote work carried out from alternative workstations not necessarily located at home still requires daily travel, offsetting the expected savings and increasing daily emissions on Fridays.

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[22] These figures are provided by the Smart Working Observatory of the Politecnico di Milano. For further information, please see the website.

The proposed digital phenotyping-based methodology has significant policy relevance, both for supporting compliance and for informing policy design. On the one hand, the GPS-based quantification of commuting emissions can help companies to report on their carbon footprint and disclose environmentally sustainable initiatives. Employee commuting emissions fall under Scope 3, Category 7 of the GHG Protocol, and their examination is recommended for a comprehensive assessment of generated emissions beyond a company's core business operations. The GHG Protocol framework also provides guidance for calculating distance traveled and obtaining related emissions by applying distance-based methods. Suggested data collection approaches are mostly survey-based and invite asking information on daily distance traveled or residence-office distance to estimate one-way commuting length[23]. This approach remains subject to the limitations discussed above and requires information on transport modes used for commuting, which are typically difficult to get for every single movement made throughout the day. Alternative methodologies based on direct tracking of employee commuting trajectories are particularly valuable for companies in this regard. The digital phenotyping-based approach replaces subjective reporting with direct observation of trajectories, enables algorithmic classification of actual transportation modes, and, by tracking mobility across the day, provides net estimates of environmental benefits, including substituted mobility during commuting and non-commuting hours. This is especially relevant for firms subject to disclosure mandates such as the EU's CSRD (Corporate Sustainability Reporting Directive)[24], for which Scope 3 emissions are material (e.g., in the tertiary sector), or for firms reporting voluntarily Scope 3 emissions mitigation actions under frameworks such as the SBTi[25] or the GRI[26]. The measurement issue is timely, as countries have begun mandating reporting on employee commuting to promote sustainable practices. With the Dutch WPM Reporting Duty, the Netherlands requires companies with 100 or more employees to report on the business traffic and commuting of their workers[27]. Companies below such a dimensional threshold are invited to submit data on a voluntary basis. The legislation has the declared pur-

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[23] For further information on Category 7 (Scope 3) and the GHG Protocol related guidance, see this documentation

[24] Corporate Sustainability reporting.

[25] Science Based Targets initiative.

[26] Global Reporting Initiative.

[27] For further information on the Dutch WPM Reporting Duty, see here.

pose of monitoring and improving the sustainability of work-related mobility. France provides a second example: the French Plan de Mobilité mandates companies with 50 or more employees located in an agglomeration of more than 100,000 inhabitants to develop an employer mobility plan. The intervention was implemented to increase work-related travel efficiency and curb air pollutant emissions generated by employee commuting in large urban agglomerations[28]. These initiatives remain limited in scope and adopted by few countries, yet further adoptions are expected, underscoring the need for evidence-based methodologies to quantify employee environmental impact.

Then, beyond reporting duties, firms can implement corrective actions to narrow their carbon footprint based on a data-driven quantification of their commuting-related impact on office and remote work days. If private initiatives fall short, policymakers can incentivize the adoption of flexible work solutions to curb emissions. However, generalized adoptions of remote work arrangements could not be as effective as anticipated. A digital phenotyping-based analysis can guide targeted interventions. Our findings, indeed, highlight that the mobility and environmental outcomes of working from home are uneven, suggesting that designing policies that incentivize remote work based on actual evidence on workers' heterogeneous behaviors could produce more aggregate benefits. When designing effective incentives, an important requirement is that decision makers have reliable information on the behavior of the intervention recipients. The digital phenotyping approach can substitute traditional tools like self-reported surveys, which are not able to fully capture the actual behavior of travelers. This enables a shift from undifferentiated interventions based on uniform assumptions to specific data-driven policies calibrated according to specific observed mobility profiles. Homeworking can be incentivized in cases where greater benefits are expected, such as for long-distance commuters or during early- to mid-week days, and can also be targeted toward specific areas like higher-density ones. Nudging strategies can also be considered to stimulate environmentally conscious behaviors in cases where no benefit is observed.

The presented approach can also support an objective assessment of fuel consumption from employee commuting in a scenario where geopolitical tensions, coupled with energy price shocks, invite consideration of the reactivation of remote work protocols to reduce fossil-fuel demand, issuing adhoc policies. Upon the outbreak of the recent Iranian conflict, the Interna-

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[28] For further information on the Plan de mobilité employeur, see here.

tional Energy Agency (IEA) included working from home among the possible demand-side solutions to ease oil price pressure on consumers[29].

As an additional policy-relevant finding, our results document a reduction in distance traveled by foot or using non-emissive modes (such as bikes) on work-from-home days. Although past studies have pointed to greater odds of non-motorized travel on remote work days (Elldér, 2020; Lachapelle et al., 2018), our results warrant further consideration, as lower distance traveled on average by non-motorized modes may actually indicate more sedentary behavior among home workers. This warns against possible undesirable consequences on remote workers' well-being and health and poses a coherence problem for remote-work-based environmental policies. Active mobility incentive programs for home-work travel, such as the Bike to Work program promoted by the Emilia Romagna Region[30] (providing employees of participating companies with an incentive of 0.20 euros per kilometer traveled by bicycle), offer a model for integrating remote work policies with measures that prevent this side effect. The Emilia Romagna program has already incorporated a methodological principle similar to digital phenotyping: verifying actual behavior as a condition for the incentive payment. This could result in an integrated policy able to incentivize work-from-home for the workers' profiles with the greatest expected environmental benefit while promoting active mobility during the remaining days of office presence, avoiding solving one problem (i.e., transport emissions) by transferring its cost to another dimension of collective well-being.

This work has limitations that pave the way for future developments. Evidence is provided for a limited sample of workers selected from the population of employed people with no children and living alone. Future research should increase participation to expand the sample size. Future studies, supported by additional observations, could focus on a deep examination of rebound effects generated by a shift towards more (or less) emissive modes or by changes in the emission intensity profile of individuals on homeworking days, especially during non-commuting windows. Our findings show that distance traveled declines to a greater extent during typical commuting windows than during non-commuting ones. Conversely, the estimated decrease in emissions is greater during non-commuting hours, even though the magnitude of the decline is just slightly different. However, we do not observe

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[29] For further information, see here.

[30] For further information, see the website.

any statistically significant variation in emissions per kilometer traveled or in the share of distance covered by emissive modes on homeworking days, so we cannot hypothesize the asymmetric decline between commuting and non-commuting hours to be linked to shifts in transport modes or changes in emissive travel behaviors. Developments of this research line could shed more light on these dynamics. Finally, future studies should also integrate the implications of homeworking for residential energy consumption to enable a broader assessment of the phenomenon. Since previous contributions suggest that homeworking can lead to additional domestic energy consumption (e.g., Shi, Sorrell, & Foxon, 2023), a holistic approach can help capture potential counterbalancing effects and assess the overall environmental impact of remote work arrangements.

6 Tables and plots

Table 1: Italian-specific CO2 emission factors by transport mode.

Mode	**Factor (gCO2/p-km)**	**Rationale**
Walking	0	Zero direct emissions
Bicycle	0	Zero direct emissions
Car (urban)	200	Italian fleet mix, stop-and-go driving, cold starts
Car (extra-urban)	130	Italian fleet mix, higher efficiency at steady speeds
Public Transit	80	National avg. across electric metro and diesel bus
Train	40	Mostly electrified network, moderate grid intensity

Table 2: Final classification results: mode distribution and kinematic profiles.

Mode	**Seg.**	**%**	**Dist. (km)**	**% Dist.**	**$\bar{v}$ (km/h)**	**$\bar{d}$ (km)**	**Plaus.**
Walking	6,429	40.2	3,168	4.1	5.9	0.49	87.8%
Bicycle	106	0.7	1,046	1.4	7.5	9.86	89.6%
Public Transit	1,189	7.4	5,947	7.7	13.5	5.00	98.2%
Train	176	1.1	3,963	5.1	19.9	22.51	65.3%
Car	8,109	50.7	62,903	81.7	14.0	7.76	97.2%
Total	**16,009**		**77,027**				**93.1%**

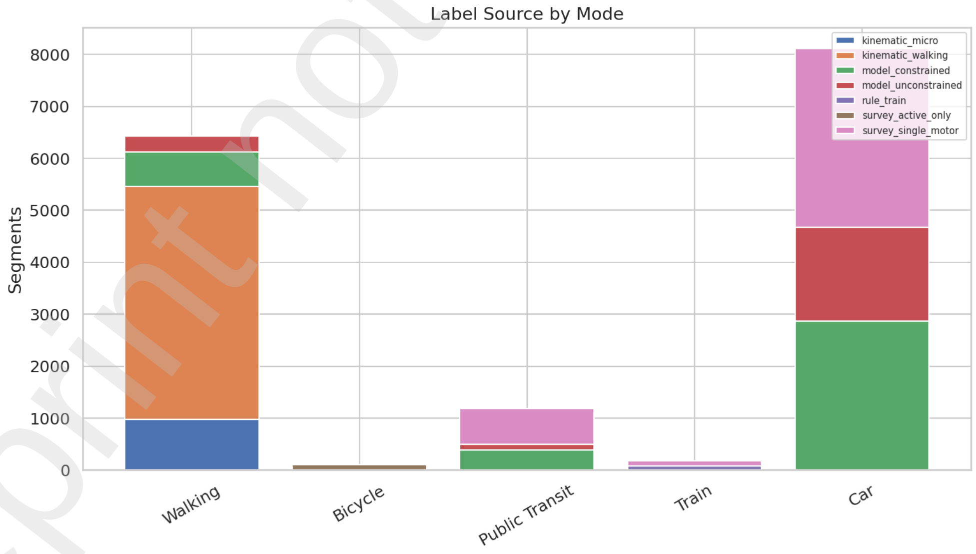


Figure 1: Composition of label sources for each transport mode.

Table 3: Variable descriptives

Variable	Obs.	Mean	St.Dev.	Min	p25	p50	p75	Max
Distance (6am - 8 pm)[1]	1354	1.920	1.484	0	0	2.109	3.084	5.886
Emissions (6am - 8pm)[1]	1354	4.920	3.672	0	0	6.675	7.940	10.700
Distance (emissive modes)[1]	1354	1.774	1.554	0	0	1.946	3.062	5.882
Distance (non-emissive modes)[1]	1354	0.364	0.532	0	0	0	0.668	3.239
Working from Home[b]	1354	0.083	0.276	0	0	0	0	1
Working from Remote[b]	1354	0.069	0.254	0	0	0	0	1
Leaves[b]	1354	0.078	0.268	0	0	0	0	1
Business trips[b]	1354	0.023	0.150	0	0	0	0	1
Precipitations[2]	1354	2.879	5.412	0	0.020	0.510	3.160	32.500
Wind speed	1354	2.767	1.347	0.660	1.880	2.425	3.280	11.850

[1] Variables expressed in natural logarithm.

[2] Winsorized at the 1st and 99th percentiles.

[b] Binary variables.

The variable *Precipitations* is expressed in mm per day, while *Wind speed* measures wind speed at 10 meters and it is expressed in meters per second. Weather data are collected from NASA POWER (Prediction Of Worldwide Energy Resources).

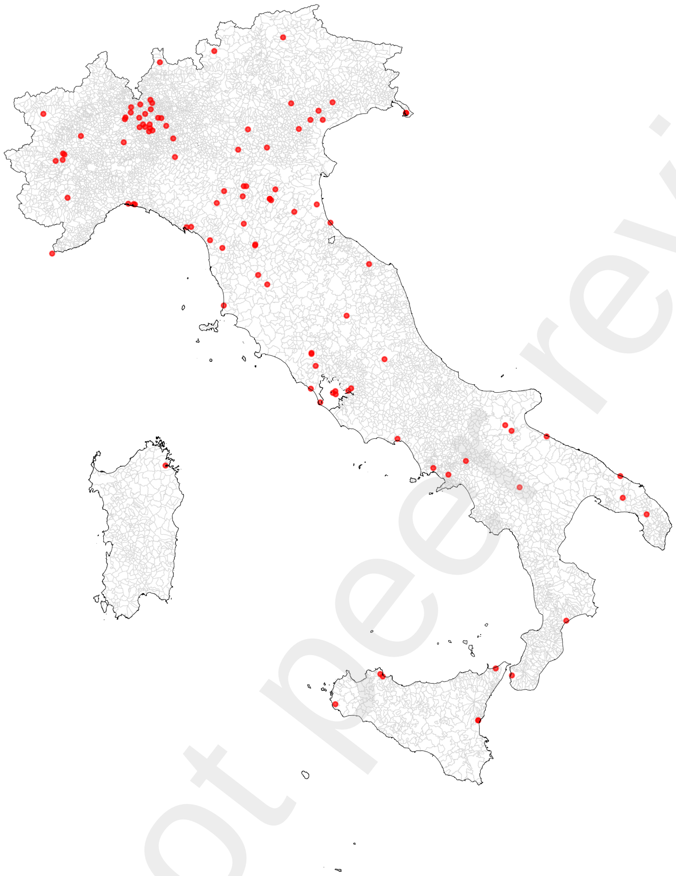


Figure 2: Geographical distribution of the estimation sample (103 individuals). Individuals have been geolocated using their home location. Home location has been detected by clustering stop locations using DBSCAN (within approximately 100 meters) and scoring clusters based on the number of distinct days present, late-night presence (11 p.m. to 6 a.m.), weekend presence, and total duration. The centroid of the highest-scoring cluster was selected as home.

Table 4: Daily distance and travel-related emissions (6 a.m. - 8 p.m.)

	(1) Distance	(2) Distance Non-emissive modes	(3) Distance Emissive modes	(4) Emissions
Working from Home	-0.563***	-0.182***	-0.480***	-1.080***
	(0.161)	(0.051)	(0.165)	(0.393)
Working from Remote	0.039	-0.014	0.092	0.506
	(0.215)	(0.101)	(0.216)	(0.538)
Leave	-0.020	-0.014	-0.004	-0.328
	(0.176)	(0.057)	(0.185)	(0.412)
Business Trips	0.214	-0.005	0.211	0.600
	(0.286)	(0.105)	(0.290)	(0.704)
Precipitations	-0.010	-0.000	-0.012	-0.041**
	(0.007)	(0.003)	(0.008)	(0.019)
Wind speed	-0.026	0.017	-0.035	-0.061
	(0.034)	(0.012)	(0.035)	(0.085)
Constant	2.061***	0.335***	1.934***	5.272***
	(0.100)	(0.035)	(0.102)	(0.250)
Observations	1354	1354	1354	1354
R2	0.407	0.381	0.437	0.434
Root MSE	1.200	0.439	1.224	2.900
Calendar week FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Individual-specific FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. To rule out potential interference with typical daily routines, we excluded festivities and weekends from the estimation sample.

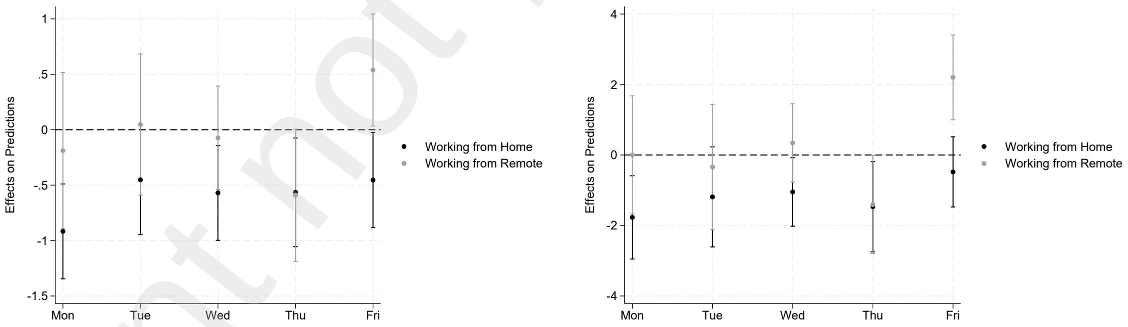
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Commuting vs. non-commuting decomposition

	WfH		WfR		
Outcome	β_1	(SE)	β_2	(SE)	R^2
Emissions, day (6 a.m. to 8 p.m.)	-1.083^{***}	(0.391)	+0.550	(0.542)	0.435
Commuting hours	-0.750^{**}	(0.363)	+0.803	(0.525)	0.411
Non-commuting hours	-0.851^{**}	(0.380)	+0.127	(0.517)	0.406
Distance, day (6 a.m. to 8 p.m.)	-0.563^{***}	(0.160)	+0.049	(0.216)	0.408
Commuting hours	-0.451^{***}	(0.127)	+0.134	(0.188)	0.403
Non-commuting hours	-0.295^{**}	(0.145)	−0.036	(0.193)	0.369
Calendar week FE		Yes			
Weekday FE		Yes			
Individual-specific FE		Yes			
Weather controls		Yes			
Leaves and business trips controls		Yes			
Observations		1,354			

Robust standard errors (HC1) in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Commuting hours: 6–10 a.m. and 6–8 p.m. Non-commuting hours: 10 a.m.–6 p.m.



(a)

(b)

Figure 3: Average marginal effect of a day of remote work from home and from alternative workstations on distance traveled (a) and emissions (b) by weekday. 90% confidence intervals.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

Parts of this work used an AI coding and writing assistant (Cursor, Claude-based) for exploratory coding, refactoring, documentation, and drafting explanatory text. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content (scientific claims, methods, results, and final wording) of the published article.

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