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How can we maximize the environmental benefits of teleworking? — A simulation and global sensitivity analysis of English teleworkers

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ABSTRACT

With the increasing popularity of teleworking after the Covid-19 pandemic and the urgent threat of climate change, there is growing interest in its potential to reduce greenhouse gas (GHG) emissions from transport. While some studies have explored the environmental benefits of teleworking, most fail to address the significant uncertainty associated with it. Few of these studies have applied sophisticated mathematical methods to explore how we can maximize the environmental benefits of teleworking, and even fewer have considered the distributions of input variables. Our study aims to fill these gaps based on historical data observations.

This study employs simulation, global sensitivity analysis and scenario analysis methods to address the uncertainty and identify the most important variables affecting teleworkers' transport emissions. The study analyzes travel diaries from over 100,000 individuals in the English National Travel Survey (NTS) from 2002 to 2023. Our findings reveal that minimizing trip distance and reducing non-work trips, along with optimizing business travel, can lead to substantial emission reductions among teleworkers. Additionally, the decline in private car use contributes to emission reduction. Notably, the emission gap between teleworkers and non-teleworkers is larger for those living outside London.

1. Introduction

Teleworking is defined as working remotely from home and other locations with the assistance of information and communication technology (ICT) (Hook et al., 2020; Sullivan, 2003). It first emerged in the 1980s but gained popularity as developments in ICT and the Internet made remote work more feasible and attractive. Modern ICT enables timely and effective information exchange without face-to-face interactions; for instance, high-quality video calls allow people to attend meetings from home. Additionally, the digital economy has generated numerous remote jobs across all sectors, as the ICT sector and related businesses continue to expand. Nowadays, many jobs are based on ICT, some of which require little or no communication, allowing workers to work remotely. Approximately 37 % of employees across EU countries can technically carry out their work from home (Sostero et al., 2020).

Whilst interest in most topics related to teleworking has remained broadly stable over time, the focus on the impacts of teleworking on energy demand and carbon emissions has grown. This heightened interest is largely due to the climate crisis, which has prompted exploration of various mitigation opportunities, including teleworking. However, despite the increasing number of studies since the Covid-19 pandemic, there remains a significant gap in the teleworking literature. Most existing studies primarily examine *whether* teleworking is associated with less energy use, but they often overlook *how* it reduces energy use. There is also tremendous uncertainty involved in the topic of teleworking and sustainability, given that the impacts of teleworking can vary between different regions and households and may evolve over time. This significant uncertainty in teleworking requires not only more robust and sophisticated methods but also reflections on our research questions. With the unstoppable rise in the popularity of teleworking, it becomes more crucial to inform policymakers on *how* we can reduce its carbon footprint, rather than simply investigating *whether* teleworking is associated with sustainability.

This study aims to observe teleworkers' travel patterns, simulate their overall transport emissions, and identify the key factors influencing these emissions. Hence, we focus on the "how" question, providing practical suggestions on how to maximize the environmental benefits of teleworking. To fully explore the emission savings from

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teleworking, this study considers several variables, including trip purpose, trip distance, peak-time travel, modal choice, residential location, and carbon intensity. Using data on the historical variation in these variables for English commuters, we simulate the difference between a teleworker's transport greenhouse gas (GHG) emissions and those of a non-teleworker. We then test the global sensitivity of these variables to the transport emission difference. Global sensitivity analysis provides insights into the emission difference in total transport GHG emissions. Specifically, it highlights the factors that play a crucial role in explaining the disparities between high-frequency teleworkers and non-teleworkers, as well as between low-frequency teleworkers and non-teleworkers. These findings are essential for understanding the impact of teleworking on emissions and identifying strategies to maximize environmental benefits. Our results suggest that teleworkers have higher transport GHG emissions than non-teleworkers, but the emission gap is declining. Additionally, we find that business trip travel and private car use significantly impact on transport emissions. Interestingly, teleworkers do not exhibit obvious signs of off-peak travel. Furthermore, electric vehicle (EV) adoption could potentially increase the emission gap if all the other factors remain constant.

To this end, we fill in the literature gaps by addressing the large uncertainty in teleworking in a more systematic way using relatively advanced mathematical methods, such as simulation and global sensitivity analysis. By observing the full distributions of travel patterns, we identify population-wide features that represent a much wider variety of workers. With global sensitivity analysis, we identify the important factors in non-linear complex models while considering the impacts of correlations between variables on transport emissions.

Additionally, we have a few other contributions. First, we examine a list of variables that may explain the emission differences between teleworkers and non-teleworkers, including residential location, peak-time travel, travel mode, one-way distance, and trip purpose. Second, we consider teleworkers' transport emissions, instead of proxies of emissions such as distance traveled. Third, we estimate overall emissions, including all types of travel purposes, rather than only commute emissions. Fourth, we compare pre-pandemic data with post-pandemic data, offering policy implications for the recent developments in teleworking practices. Fifth, with a comparative static scenario analysis, we draw preliminary conclusions without needing extensive observations on EV adoption.

The following sections briefly review the literature on teleworking and emission savings. Section 3 describes our data sources and methodology, while Section 4 presents our results. Section 5 discusses and concludes our findings, and finally, Section 6 discusses the limitations.

2. Literature review

Using Google Scholar, we searched for papers on teleworking and GHG emissions by combining the keywords "teleworking" or "work from home" with "energy" or "emission". We identified around 70 studies in this area. However, most of these do not directly estimate GHG emissions; instead, they use proxies such as travel distance, travel time or energy use. Notably, the sample is dominated by studies from North America.

There have been three broad phases of research on teleworking and energy demand (Fig. 1). In the 1990s, as ICT gained popularity, most researchers focused on teleworking's potential to alleviate congestion and reduce air pollution by reducing travel distance (Kitamura et al., 1990a, 1990b; Koenig et al., 1996; Nilles, 1991; Olszewski and Mokhtarian, 1994; Sampath et al., 1991). As climate change became a concern, especially in the 21st century, researchers began to examine teleworking's influence on overall energy demand and carbon emissions, with a primary focus on transport energy use (Caldarola and Sorrell, 2022; Caldarola and Sorrell, 2024; Cerqueira et al., 2020; Chakrabarti, 2018, e Silva and Melo, 2018; Fu et al., 2012). Finally, the Covid-19 pandemic significantly increased teleworking's popularity and sparked new interest in its energy impacts, providing valuable data through a natural experiment (Anik and Habib, 2023; Bieser et al., 2022; Ceccato et al., 2022; Kiko et al., 2024; Li et al., 2023; López Soler et al., 2021; Motte-Baumvol et al., 2024; Stefaniec et al., 2024; Wöhner, 2022). Studies from each of these phases have explored whether teleworking is associated with lower energy demand. However, due to the complexity of teleworking's impacts, variations in data, methodology, and scope, results have been mixed, leading to continued uncertainty. Few studies have systematically assessed the relative importance of different variables in determining energy savings from teleworking, including factors such as peak-time travel, travel distance, and the mode share. This paper aims to partially address this gap in the literature by investigating the factors influencing the impact of teleworking on transport energy use, considering both work-related and non-work-related travel.

Two review papers (Hook et al., 2020; O'Brien and Aliabadi, 2020) have demonstrated that whether teleworking is associated with energy or emission savings remains an uncertain, ambiguous and complex issue. Travel behaviors vary across demographics, built environments and geographical regions, resulting in varying impacts of teleworking across different countries, times and populations. For instance, studies in Sweden, California, and Ireland indicate that teleworkers travel less than non-teleworkers (Elldér, 2020; Henderson et al., 1996; Koenig et al., 1996; O'keefe et al., 2016), while Van Lier et al. (2014) found that teleworkers in Belgium have shorter one-way commute distances. Additionally, whether teleworkers emit lower GHG emissions depends on whether the savings from reduced commuting trips and less time spent in the office outweigh the additional emissions from more non-work trips and increased time spent at home (Phoung et al., 2024; Sepanta and O'Brien, 2023; Sepanta et al., 2024; Shi et al., 2023; Wu et al., 2024). Given the complexities of modelling energy use and emissions in both offices and homes, most studies focus solely on transport emissions. We acknowledge that this approach provides only a partial picture. The following section highlights some of the uncertainties associated with transport emissions and discusses the results and methodologies of key studies in this field.

One reason for these more ambiguous results may be the rebound effects associated with teleworking (Cerqueira et al., 2020; Rietveld, 2011). Rebound effects in this context refer to unanticipated consequences of teleworking that erode the travel and energy savings achieved through fewer commuting trips. These rebound effects can take various forms. Here are three examples.

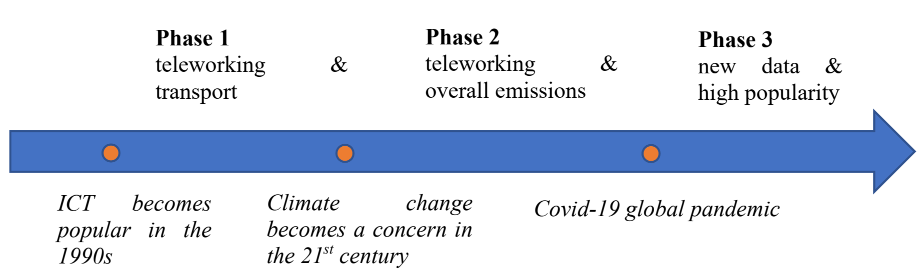

Fig. 1. Three phases of teleworking and energy demand research.

- Induced non-work travel: Teleworkers may actually travel more for non-work purposes than non-teleworkers. For instance, they might make additional shopping and leisure trips on the days when they work from home (Caldarola and Sorrell, 2022; Cerqueira et al., 2020; Henderson et al., 1996; Kim et al., 2015; Koenig et al., 1996; Zhu, 2013; Zhu and Mason, 2014).
- Induced relocation: Teleworkers' commuting trips may be longer than those of non-teleworkers. This could happen if they move to a residence farther from their workplace or take up a job that requires a longer commute (Caldarola and Sorrell, 2022; Cerqueira et al., 2020; e Silva and Melo, 2018; Helminen and Ristimäki, 2007; Henderson et al., 1996; Mokhtarian et al., 2004; Ravalet and Rérat, 2019; Zhu, 2013; Zhu and Mason, 2014).
- Induced car use: Teleworkers may make more trips by car. This could occur if they relocate to an area with low population density and/or poor public transport facilities. However, there is also evidence suggesting the opposite – that teleworkers are less likely to use cars (Chakrabarti, 2018; Lachapelle et al., 2018; Van Lier et al., 2014; Wang and Ozbilen, 2020).

The uncertainty surrounding whether ICT applications are environmentally friendly creates ambiguity about whether policies should encourage or discourage their widespread adoption. However, a more practical approach is to consider *how* we can enhance the sustainability of individual applications, such as teleworking and online shopping. To address this, we require a deeper understanding of the factors influencing energy use and emissions related to teleworking. Hence, this paper employs a global sensitivity analysis tool called Sobol indices to explore which factors have the greatest impact on teleworkers' transport emissions and domestic emissions.

Only a few studies have employed simulation methods to consider how variations in key variables impact energy and emission savings (Kitou and Horvath, 2003; Li et al., 2023; Motte-Baumvol et al., 2024). Simulation allows variables to vary based on statistical features derived from historical data, providing an effective way to handle uncertainty while remaining grounded in empirical observations.

Kitou and Horvath (2003) simulate the difference in energy use and emissions between teleworkers and non-teleworkers, considering transport, heating and cooling in homes and offices, lighting, and electronic equipment. They map statistical features of key variables (such as one-way commute distance, non-commute travel distance, number of commute trips, and number of non-commute trips) and draw random samples from the distributions of these variables to generate corresponding distributions of emission savings. Specifically, they find that one-day teleworking reduces transport carbon emissions by 17 % and overall carbon emissions by 2 % on heating days, while five-day teleworking reduces transport carbon emissions by 89 % and overall carbon emissions by 17 % on heating days.

Motte-Baumvol et al. (2024) use Bayesian analysis of Markov Chain Monte Carlo simulation to explore variation in trip frequency, distance, time, and carbon emissions across different days of the week, with and without commuting. They identify Friday as a distinct day for teleworkers, marked by a 20 % reduction in commuting and increased non-work trips. Additionally, they compare the conditional effects of five variables (including transport modes, workplace location, gender, occupation type, and employment status) and find that commuting mode and rural residency are key variables explaining the carbon emission difference between teleworkers and non-teleworkers.

Li et al. (2023) apply Monte Carlo simulation to assess carbon emissions among teleworkers in different industries in Beijing, China. Drawing distribution patterns from travel mode, travel purpose, and travel time based on a large-scale travel survey, they estimate the reduced commuting distance due to teleworking. Their results indicate that teleworking can lead to an average 7.05 % reduction in carbon emissions from road transport in Beijing, with information and communication, as well as professional, scientific, and technical service industries showing higher carbon reduction potential.

Given the uncertainty in emission savings from teleworking, it is essential to assess the drivers of these savings and how they can be maximized. Sensitivity analysis provides a valuable approach to identify key variables influencing these outcomes. However, only a few studies have systematically explored uncertainty using sensitivity analysis (Guerin, 2021; Marz and Şen, 2022; Tao et al., 2023).

Guerin (2021) conducts local sensitivity analysis on energy savings from teleworking in Australia, considering both commute-related and building-related energy use. Specifically, Guerin examines two transport-related variables: the percentage of employees commuting by car and the average distance for a return commute trip. His findings indicate that energy savings through teleworking are achievable if an employee commutes more than 30 km each workday.

Marz and Şen (2022) establish a monocentric urban model to investigate how household-level vehicle choice and residential location jointly influence teleworkers' GHG emissions. Through simulation analysis, they test the sensitivity of telecommuting frequency, transport technology cost, the amount of non-work driving, and commute travel time. Notably, they find that the value of commute travel time has a slightly larger, albeit still limited, influence on teleworkers' GHG emissions.

Tao et al. (2023) conduct local sensitivity analysis to assess the impact of EV adoption, office energy use, and residential energy use on teleworkers' GHG emissions. However, they have not specifically explored the influence of transport factors on teleworkers' emissions. Their results highlight that reducing building attendance from 50 % to 10 % can double the carbon footprint of an onsite worker, while seat sharing among workers under full building attendance can reduce GHG emissions by 28 %.

Although the studies mentioned above all conduct local sensitivity analyses, they do not fully capture the impact of correlations between different variables. For instance, an employee may be more likely to choose to travel by car if they have a long commute distance. This omission could lead to an underestimation of the impact of commute distance on GHG emissions. To address this gap, our study proposes a global sensitivity analysis that considers the influence of correlations between variables on teleworkers' transport emissions. Notably, the application of global sensitivity analysis in the context of teleworking is novel within the transport field.

Additionally, there are several other literature gaps we have addressed in this paper.

- Neglect of non-work travel emissions: many studies focus solely on emissions from commuting but overlook emissions related to non-work travel.
- Poor proxies for transport emissions: Some studies rely on inadequate proxies for transport emissions, such as trip distance, while neglecting other critical factors like travel modes and the carbon intensity associated with those modes, as well as off-peak travel.
- Electric vehicle (EV) consideration: Very few studies have explored the impact of EVs on teleworkers' transport emissions. Tao et al. (2023) conduct a scenario analysis and find that replacing conventional cars with electric ones could reduce workers' carbon footprint by 13 %–19 % in the US. Furthermore, progressively decarbonized US power grids could enable an additional 38 % reduction by 2050.

This study addresses the above literature gaps in the following ways. First, we employ a simulation method to understand how key variables influence teleworkers' transport emissions. Second, we explore the question of *how* teleworking's environmental benefits can be maximized through a global sensitivity analysis. Specifically, we utilize the 'Sobol indices' technique, a type of global sensitivity analysis, to assess the overall impact of each variable on transport emissions, considering its correlations with other variables. Third, we examine overall transport GHG emissions, considering not only distance traveled for commuting but also emissions from all types of trip purposes. To simulate overall transport emissions, we consider travel mode, carbon intensity, off-peak travel, and residential location. Finally, we investigate how the ongoing shift from conventional to EVs may impact future emission savings from teleworking. Our focus is on the EV shift for private vehicles, as most trips in our sample are by car, while rail and bus trips constitute only a small proportion.

Our research questions are.

(1) Under what conditions do teleworkers have lower transport greenhouse gas (GHG) emissions than non-teleworkers?
(2) What factors influence these emission savings, and what is their relative importance?

3. Data and methodology

3.1. Data

Our primary data sources include the English National Travel Survey (NTS) for the years 2002–2023 (Department for Transport, 2024) and the 2023 UK Government Greenhouse Gas Conversion Factors for Company Reporting (CF) (Department for Energy Security and Net Zero, 2023). We utilize the NTS data to compare the weekly travel distance of teleworkers and non-teleworkers, while the CF data helps us estimate the GHG emissions associated with travel.

The NTS is an annual survey that captures the travel patterns of a stratified, two-stage, random probability sample of approximately 13,000 English households. Participants complete detailed travel diaries over a seven-day period, recording information such as the purpose of each trip, the mode of transport used, self-assessed trip distance and duration, and other relevant details. Our analysis focuses on NTS data from 2002 to 2023, excluding the major shifts in travel patterns caused by the Covid-19 pandemic. To create our sample, we consider only full-time employed or self-employed workers. We categorize workers based on their responses to the question “how often do you work from home?” (Table 1). High-frequency teleworkers work from home 3–5 days a week, low-frequency teleworkers work from home 1–2 days a week, and the remaining individuals are non-teleworkers. Additionally, we exclude home workers who do not use ICT devices (e.g., farmers) based on their answer to the question “is it possible to work from home without telephone or Internet?“. After data cleaning, our sample comprises approximately 109,000 individuals, with around 3 % working from home 3–5 days a week and approximately 6 % working from home 1–2 days a week.

To understand the demographics of teleworkers, we summarize information related to gender, residential area, age, income and marital status by teleworking type (Table 2).

Table 1
Classification of sample by teleworking frequency.

Teleworker type	Teleworking frequency	Number of observations	Percentage
High-frequency teleworker	3 or more times a week	3307	3.0 %
Low-frequency teleworker	Once or twice a week	6248	5.7 %
Non-teleworker	Less than once a week more than twice a month	1876	1.7 %
	Once or twice a month	4294	3.9 %
	Less than one a month more than twice a year	2929	2.7 %
	Once or twice a year	2431	2.2 %
	Less than once a year or never	50,920	46.6 %
	Does not apply	37,233	34.1 %
	No answer	54	0.05 %
Total		109,292	100.0 %

Table 2
Demographics of teleworkers and non-teleworkers.

	Non-teleworkers (less than 1 day/ week or never)	Low-frequency teleworkers (1–2 days/week)	High-frequency teleworkers (3–5 days/week)
Gender			
Male (%)	61.7 %	65.7 %	64.5 %
Area			
Urban conurbation	37.8 %	37.0 %	36.6 %
Urban city and town	44.1 %	38.2 %	42.7 %
Rural town and fringe	9.4 %	9.9 %	9.9 %
Rural village, hamlet and isolated dwelling	8.7 %	14.8 %	10.8 %
Age (years old)			
16–20	3.2 %	0.3 %	0.3 %
21–29	17.4 %	9.4 %	8.9 %
30–39	24.2 %	28.1 %	24.5 %
40–49	25.7 %	31.8 %	28.3 %
50–59	22.2 %	23.3 %	26.0 %
60+	7.3 %	7.0 %	11.9 %
Income (£/year)			
<25,000	54.1 %	22.4 %	31.4 %
25,000–50,000	34.7 %	43.7 %	38.7 %
>50,000	11.2 %	33.9 %	30.0 %
Marital status			
Married and living with spouse	53.9 %	62.9 %	61.8 %
Separated	2.2 %	2.1 %	2.0 %
Single	35.4 %	26.6 %	27.4 %
Divorced	7.6 %	7.6 %	7.6 %
Widowed	1.0 %	0.8 %	1.2 %
Total	**99,852**	**6196**	**3244**

Table 2 reveals that, compared to non-teleworkers, teleworkers are more likely to be male, older, wealthier, married and living with a spouse in rural areas. For instance, teleworkers have a 3–4 % higher chance of being male than non-teleworkers. Teleworkers are 7–11 % more likely to be over 40 years old, and have a 19–23 % higher chance of earning over £ 50,000 annually. However, these differences could vary over time, and we will examine the demographic change by year in Section 4.1.

Following the work of Caldarola and Sorrell (2022) and Crawford (2020), trip purposes are classified as commuting, business, and non-work trips based on trip origination and destination (see Fig. 2). Specifically, commuting refers to trips between an individual’s usual place of residence and usual place of work.[1] Business trips encompass any travel involving a “course of work” location, such as a client’s workplace. All other trips fall into the non-work category.

We utilize CF data to estimate GHG emissions from trips. CF provides information on the well-to-wheel emission intensity of various transport modes, encompassing emissions from fuel production, processing, distribution, and use, while excluding those associated with vehicle manufacture. Specifically, CF disaggregates private cars by fuel type (diesel, petrol, hybrid, plug-in hybrid, and electric vehicles) and size category (small, medium, large), as shown in Table 3. GHG emissions are quantified as the equivalent of carbon emissions that contribute to climate change effects. These emissions include the seven main GHGs defined by the Kyoto Protocol (1997). Additionally, CF offers emission intensity details for other travel modes, as presented in Table 4.

[1] The NTS may underestimate commute trips from chained trips, because the NTS includes direct trips to work and excludes chained trips from commute trips. For example, the NTS classifies dropping a child at school as ‘escort education’ and the subsequent journey to work as ‘personal business’.

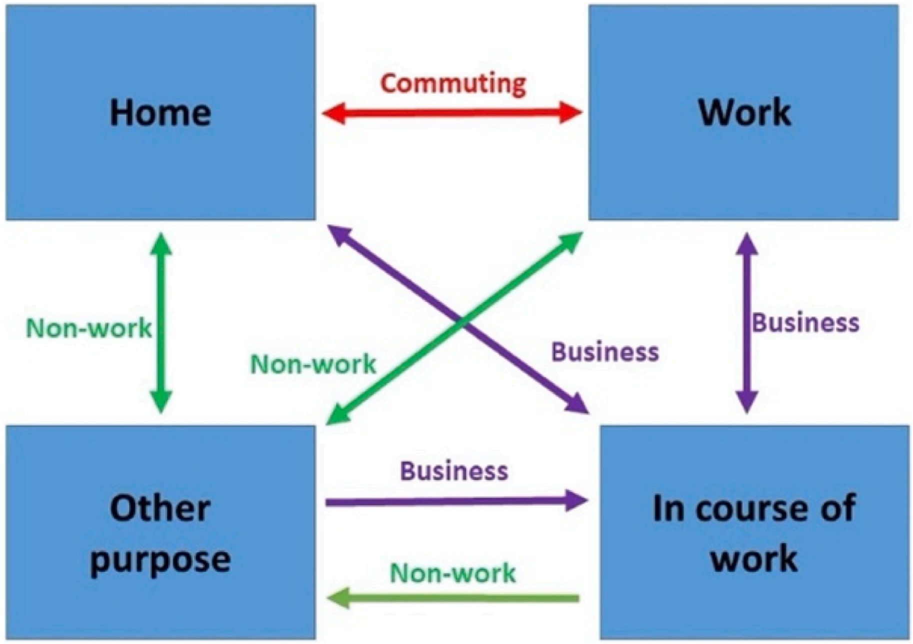

Fig. 2. Classification of trip purpose
Source: Caldarola and Sorrell (2022), Crawford (2020).

Table 3
Emission intensity of private vehicle transport by size and fuel type.

	Emission intensity (kg CO_2e/vehicle km)				
	diesel	petrol	hybrid	plug-in hybrid EV	battery EV
Small car	0.034	0.039	0.027	0.013	0.011
Medium car	0.041	0.049	0.028	0.022	0.012
Large car	0.051	0.076	0.039	0.026	0.013
Light van	0.035	0.051	–	–	0.009

Table 4
Emission intensity of other transport modes.

	Emission intensity (kg CO_2e/passenger km)
Walk/cycle	0.000
Motorcycle	0.030
Rail	0.009
Underground	0.007
London bus	0.019
Other local bus	0.029
Coach	0.007

The unit “kg CO_2/*vehicle* kilometer” is converted to “kg CO_2/*passenger* kilometer” by occupancy rate which is provided in the dataset.

$$CO_2 \Big/ passenger\ km = \frac{CO_2\ /\ vehicle\ km}{occupancy\ rate} \tag{1}$$

3.2. Methodology

To investigate whether teleworking is associated with GHG emission savings and to understand the relative importance of different factors in determining those savings, we utilize historical simulation and global sensitivity analysis (as shown in Fig. 3). Furthermore, we conduct a scenario analysis to assess the effects of EV adoption on teleworkers’ emissions. The following section will first explain why we chose this method and then delve into each step.

There are several methods to analyze teleworking and transport energy demand, including agent-based modelling (ABM) (Wang et al., 2022), machine learning (ML) (López Soler et al., 2021), regression (Giovanis, 2018; Zhu and Mason, 2014), structural equation modelling (SEM) (Caldarola and Sorrell, 2022). However, none of these methods are suitable for addressing uncertainty or identifying the relative importance of variables beyond assessing statistical significance. In contrast, a simulation method observes variable distributions and generates results in the form of distributions, providing more comprehensive information beyond averages. Sensitivity analysis explicitly ranks importance and is better suited for handling non-linear models. A scenario analysis method predicts future circumstances without relying on observations. Additionally, our dataset is not well-suited for ABM or ML.

ABM and ML typically require abundant variables to distinguish teleworkers from non-teleworkers, such as individual vehicle ownership, family structure, socioeconomic status, and preferences related to teleworking. These algorithms implicitly assume that the features of teleworkers have a causal effect on their emissions. Although a few variables might causally determine teleworkers’ energy use differences (e.g., car ownership can lead to higher emissions), linking most of the features of teleworkers directly to transport energy use remains challenging. What is more, the substantial amount of missing data in the NTS on vehicle type complicates our ability to analyze and provide meaningful insights (see Appendix 1).

SEM and regression methods are commonly used to identify features of teleworkers or characteristics associated with high transport energy use (Caldarola and Sorrell, 2022; Cerqueira et al., 2020; Giovanis, 2018; Zhu and Mason, 2014). While SEM and regression methods can reveal characteristics of teleworkers (such as income, age, and gender) and identify statistically significant factors influencing transport energy use, they do not account for input variable uncertainty—such as commute distance. In the following sections, we will explain our methodology step by step.

For the historical simulation, we first construct a deterministic model that calculates the weekly transport GHG emissions for teleworkers and non-teleworkers. Using data from the NTS, we observe the distribution patterns of each variable in this model. Subsequently, we randomly draw values from these distributions to use as iterations in a simulation of the difference in transport emissions between teleworkers and non-teleworkers. The output takes the form of a probability distribution

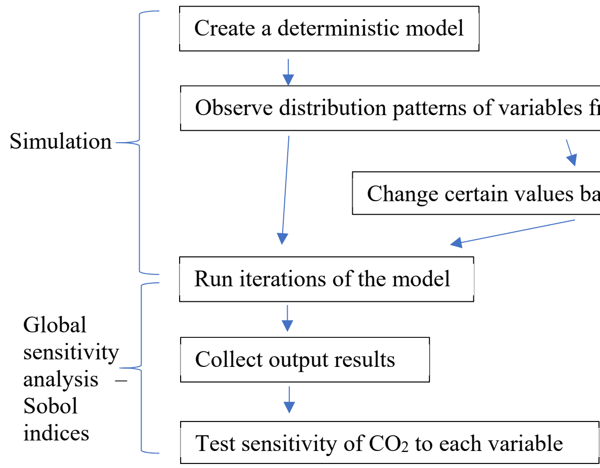

Fig. 3. Simulation and global sensitivity analysis.

representing the difference in emissions between the two groups.

The deterministic model involves two equations and thus two basic steps. In Step 1 (Equation (2)), we calculate the baseline scenario of one non-teleworker's weekly travel GHG emissions (GHG_{NTW}). This sum includes emissions from business trip ($GHG_{NTW-busi}$), commuting trips ($E_{NTW-com}$) and non-commute trips ($GHG_{NTW-non}$). In Step 2 (Equation (3)), we calculate the corresponding emissions for teleworkers (GHG_{TW}). Finally, we compare teleworker's emissions with non-teleworker's emissions.

$$GHG_{NTW} = GHG_{NTW-busi} + GHG_{NTW-com} + GHG_{NTW-nw} \tag{2}$$

$$GHG_{TW} = GHG_{TW-busi} + GHG_{TW-com} + GHG_{TW-nw} \tag{3}$$

For each type of trip, we estimate weekly emissions by multiplying the weekly commute distance (L) with the sum of the product of the share of each mode i by distance ($\varnothing_I$) and the emission intensity of mode i (CF_i). For example:

Non-teleworker's commute CO_2 in a week:

$$GHG_{NTW-com} = L_{NTW-com} \times \sum_i (\varnothing_I \times CF_i) \tag{4}$$

For the sensitivity analysis, we estimate the contribution of each variable to the total variance of the output, allowing us to rank the relative importance of each variable in the uncertainty of emission savings. To conduct global sensitivity analysis, we input all the simulation's inputs and output results into a function called "SobolEff" within an R package named "sensitivity" (Iooss et al., 2021). The R programming environment automatically calculates Sobol indices, a type of global sensitivity analysis. Let us first explain the distinction between local and global sensitivity analysis, followed by a mathematical explanation of Sobol indices.

Local sensitivity analysis disregards correlations between variables, whereas *global* sensitivity analysis accounts for these correlations. We choose global sensitivity analysis because we anticipate that these correlations are significant. For instance, if the proportion of distance traveled by private vehicles positively correlates with one-way commute distance, the overall influence of one-way commute distance should consider its association with private vehicle use. In the following sections, we will delve into the mathematical differences between local and global sensitivity and then explore Sobol indices as a form of global sensitivity analysis.

Mathematically, local sensitivity analysis involves changing one variable at a time from the base-case scenario (Razavi and Gupta, 2015). Suppose the output value is denoted as y, and we have n input variables $x_1, x_2, \ldots, x_n$. The local sensitivity of x_i is given by:

$$s_i = \frac{\partial y}{\partial x_i}, \textit{given base case}\left(x_1^*, x_2^*, \ldots, x_n^*\right) \tag{5}$$

Equation (1) measures the relative change of y with respect to x_i, allowing x_i to vary within its domain while keeping other variables fixed at the base case values $\left(x_1^*, x_2^*, \ldots, x_n^*\right)$. However, Equation (1) accurately measures the sensitivity of y to x only if there is no correlation between x_i and other variables. When x_i is correlated with other variables, the base case $\left(x_1^*, x_2^*, \ldots, x_n^*\right)$ may no longer be valid, resulting in a different value of y. Consequently, $\frac{\partial y}{\partial x_i}$ becomes less accurate. Local sensitivity analysis does not account for correlations between input variables and other factors (Tian, 2013; Xu et al., 2004).

Another way to interpret local sensitivity analysis is by decomposing the total variance. Each input variable $x_1, x_2, \ldots, x_i, \ldots, x_n$ contributes to some of the variance and uncertainty in the final output y. The importance of a variable is determined by how much it explains the total variance. Local sensitivity analysis involves changing one variable x_i at a time, observing its impact on the variance of the output, denoted as $V(y)$. Equation (1) can be rewritten as Equation (6) (Saltelli et al., 2010).

$$S_i = \frac{V(E(y|x_i = \widetilde{x}_i))}{V(y)} \tag{6}$$

where $\widetilde{x}_i$ is a generic value of x_i, which can take any specific value within its domain. $V(E(y|x_i = \widetilde{x}_i))$ measures the variance of the expected value of y given a specific x_i. The entire index S_i quantifies the share of variance in y that depends on the input variable x_i, ignoring the correlations between x_i and other input variables.

In contrast, the global sensitivity of x_i captures the change in y not only due to the change in x_i itself, but also due to changes in other variables resulting from their correlation with x_i. Let us denote the global sensitivity of x_i as s_{Ti}.

$$s_{Ti} = \frac{\partial y}{\partial x_i}, \textit{where values of } (x_1, x_2, \ldots, x_n) \textit{ are not fixed} \tag{7}$$

Specifically, this study employs a 'the total effect Sobol index' which accounts for this global sensitivity (Craglia and Cullen, 2020; Saltelli et al., 2010; Sobol, 2001). This index measures the contribution to the variance of y from x_i, considering x_i's correlation with other input variables. Denoting variables other than x_i as $x_{\sim i}$, Sobol indices can be estimated in three steps, see Appendix 1.

Finally, we also compare the above simulation with a comparative static scenario in which all fossil fuel cars and vans are replaced with battery EVs. This scenario aligns with the UK government policy that mandates all new cars and vans to be fully zero-emission at the tailpipe by 2030 (Department for Transport & Office for Zero Emission Vehicles, 2020). However, in our scenario, battery EVs are not entirely emission-free, as we assume the electricity generation mix remains unchanged from 2019.

4. Results

The results are divided into three parts: a) simulation results (presented in Section 4.1); b) sensitivity analysis results (presented in Section 4.2); c) scenario analysis results (presented in Section 4.3). The simulation results highlight the main differences in transport emissions between teleworkers and non-teleworkers. The sensitivity analysis identifies the most critical factors explaining such differences. Additionally, the scenario analysis predicts emission changes with EVs in a static comparative scenario.

4.1. Simulation results

We conduct a historical simulation to estimate overall transport GHG emissions by analyzing distribution patterns from weekly travel diaries of over 100,000 individuals in the UK. We calculate the average emissions per week by three teleworking types: a) high-frequency teleworkers (teleworking 3–5 days per week); b) low-frequency teleworkers (teleworking 1–2 days per week); c) non-teleworking individuals. We first summarize the main differences in transport emissions between teleworkers and non-teleworkers (Figs. 4 and 5). Then, we delve into the reasons behind these emission differences by comparing their demographics (Figs. 6 and 7), travel modes (Figs. 8 and 9), peak day trips (Fig. 10), peak hour trips (Fig. 11), travel purposes (Fig. 12), dwelling environments (Fig. 13). These analyses compare between pre- and post-pandemic periods. With data availability, some analyses only include pre-pandemic data, which are shown in Appendix 2, including vehicle type (Fig.2a), fuel type (Fig. 2b), and occupation (Fig. 2c).

Fig. 4 illustrates the trend of weekly transport emissions by teleworking type from 2002 to 2023.

As illustrated in Fig. 4, low-frequency teleworkers have the highest transport emissions, followed by high-frequency teleworkers and non-teleworkers. All three types of workers have experienced a decline in transport emissions and gradually converge to a similar level of emissions. Low-frequency teleworkers' transport emissions exhibit the sharpest decline, with an 85 % reduction from 2002 to 2019, followed by high frequency teleworkers. Non-teleworkers have the lowest rate of decline, with only a 22 % reduction from 2002 to 2019. In terms of variance over time, high-frequency teleworkers' transport emissions exhibit the highest fluctuations over the last two decades. The Covid-19 pandemic led to a significant reduction of transport emissions for all worker types, causing high-frequency teleworkers' emissions to drop below those of non-teleworkers in 2020 and 2021. Transport emissions began to rise again from 2022 and remained stable in 2023. This suggests that we should analyze travel patterns separately for the periods before and after the pandemic. In the subsequent paragraphs, we will compare the differences between these two periods.

Fig. 5 displays the probability distribution patterns of weekly transport emissions by teleworking type. The horizonal axis represents the weekly emissions values, while the vertical axis indicates the probability associated with specific emission values.

Fig. 5 shows that the emission gap between teleworkers and non-teleworkers has narrowed after the pandemic. All three worker types exhibit a similar distribution pattern centered around a low value but with a long tail. Most people have low transport emissions (around 4 kg CO_2e per week), but a small proportion experience extremely high emissions (possibly exceeding 40 kg CO_2e per week). The flatter the distribution curve, the higher the chance of extremely high emissions. We can see that the difference between the curves is much larger before the pandemic than after. Before the pandemic, non-teleworkers have the highest likelihood of relying solely on sustainable travel modes, followed by high-frequency teleworkers (3–5 days/week), while low-frequency teleworkers (1–2 days/week) have the lowest probability of doing so. After the pandemic, the three types of workers exhibit very similar distribution patterns in overall transport emissions, with non-teleworkers slightly less likely to emit high emissions. It is possible, albeit unlikely (2–4 % probability), for any type of worker to have no emissions for a week. This phenomenon may be attributed to sustainable travel modes such as walking and cycling.

We explore the factors that may drive the emission change over time. First, we investigate the demographic changes of high-frequency teleworkers from 2002 to 2023 in Fig. 6 and those of low-frequency teleworkers in Fig. 7. On the left x-axis of each figure, we present the shifts in the proportions of teleworkers who are female, high-income individuals (with an income of over £50,000 a year), single,[2] and residing in urban conurbations. On the right x-axis, we illustrate the changes in the number of teleworkers among the entire population of workers.

In Figs. 6 and 7, there is a gradual rise in the proportion of teleworkers among the working population before the pandemic, followed by a sharp increase after the pandemic. Regarding demographics, we observe an increasing trend in the proportions of teleworkers who are single females, earning high incomes, and living in urban conurbations. This indicates an increase in the demographic diversity of teleworkers, as they previously tended to be male, married, and living with a spouse. Between 2002 and 2023, female teleworkers increased by 15–20 %, and single teleworkers increased by 13–18 %. However, there is no strong evidence to suggest whether teleworkers are moving to more urban or rural areas. Additionally, since the income data cannot be adjusted for inflation due to data limitations, we cannot robustly conclude whether teleworkers are earning higher incomes. There are more fluctuations in the demographic features of high-frequency teleworkers in Fig. 6, which can be attributed to either a relatively smaller sample size or intrinsic periodic instability. Nevertheless, the demographic shifts are only part of the reasons for the narrowing emission gap. We will analyze the differences in travel patterns next.

We explore the differences in travel modes between teleworkers and non-teleworkers from 2002 to 2023 in Figs. 8 and 9. Fig. 8 compares the average weekly travel distance of high-frequency teleworkers with that of non-teleworkers, while Fig. 9 focuses on low-frequency teleworkers. In both figures, dotted lines represent teleworkers, and solid lines represent non-teleworkers. The analysis considers the three primary travel modes, which account 90 % of the total travel distance: "driving a car or a van", "being a passenger in a car or van", and "by rail". All other modes fall under the category of "others", except for air travel due to data availability.

As shown in Figs. 8 and 9, driving a car or a van (car/van) is the dominant travel mode for all three types of teleworkers across all the years. The average distance traveled by driving a car/van is approximately 1–3 times the distance traveled by all other modes combined. However, there is a trend of declining distance traveled by car/van. This is particularly evident among teleworkers, as the average distance traveled by car/van for both high-frequency and low-frequency teleworkers has decreased by around 50 %. The pandemic had a negative impact on travel distances in 2020 and 2021, but they returned to normal in 2022 and 2023. Distance traveled by other modes remains consistently low, averaging under 50 km/week. Notably, low-frequency teleworkers' railway travel increased from an average of 55 km/week in 2002 to 100 km/week in 2019 but dropped sharply after the pandemic. This may be explained by the sharp increase in train fares after the pandemic (BBC News, 2022), but further analysis is needed.

Fig. 10 illustrates and compares the average daily travel distance for three types of workers by day of the week, between pre- and post-pandemic periods. The figure categorizes trips into three types: business trips, commute trips, and non-work trips. As explained in Fig. 2, a

[2] "Single" refers to marital status being single, which means that the individual could have an unmarried partner.

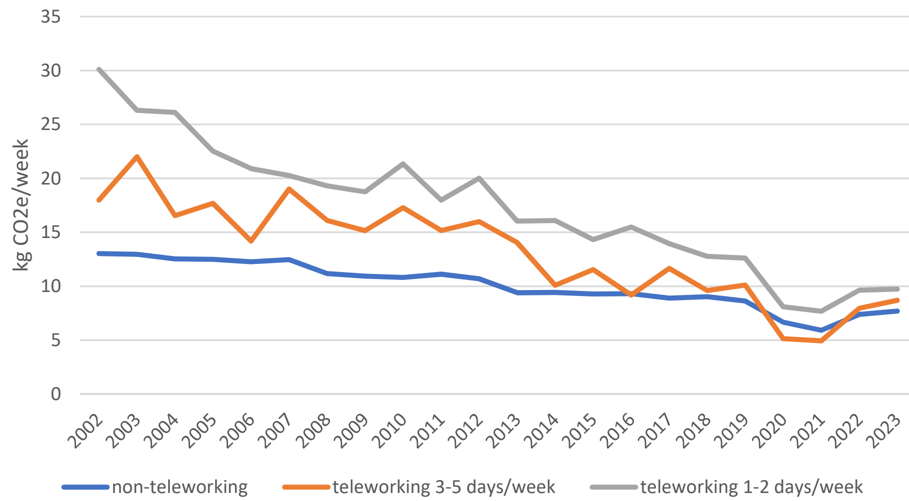

Fig. 4. Transport greenhouse gas emissions by year and teleworking type.

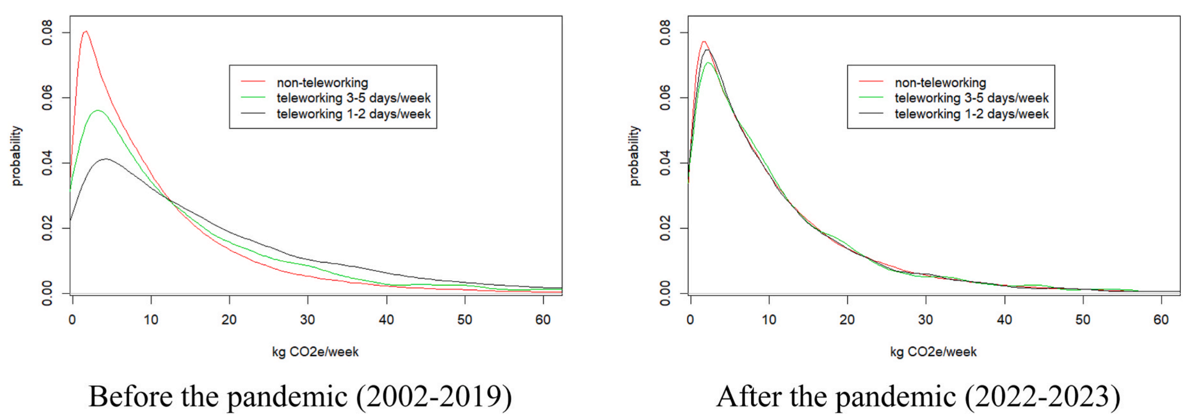

Fig. 5. Distribution patterns of transport emissions by teleworking types.

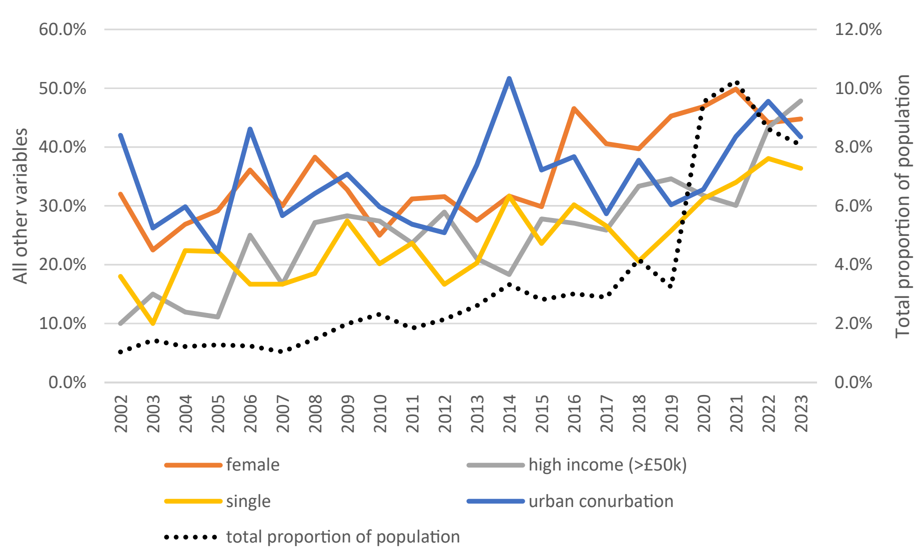

Fig. 6. Demographic change of high-frequency teleworkers.

business trip includes a location related to work, a commute trip occurs between an individual's usual workplace and usual accommodation, and all other trips are considered non-work trips.

Fig. 10 shows no evidence that teleworkers travel less on peak days; in fact, there may be an opposite tendency, i.e., teleworking increases peak-day travel. Teleworkers have more obvious peak-day travel patterns compared to non-teleworkers, especially after the pandemic. After the pandemic, high-frequency teleworkers travel extensively on Sunday

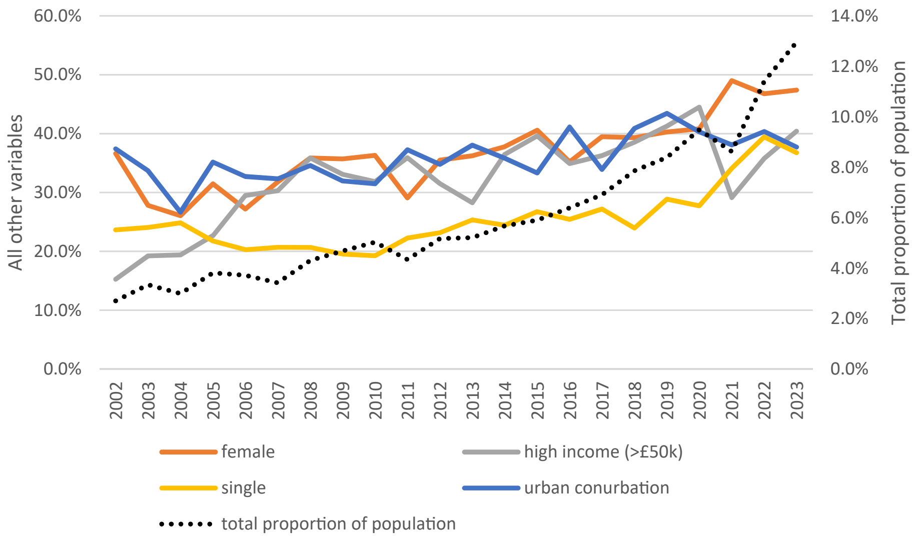

Fig. 7. Demographic change of low-frequency teleworkers.

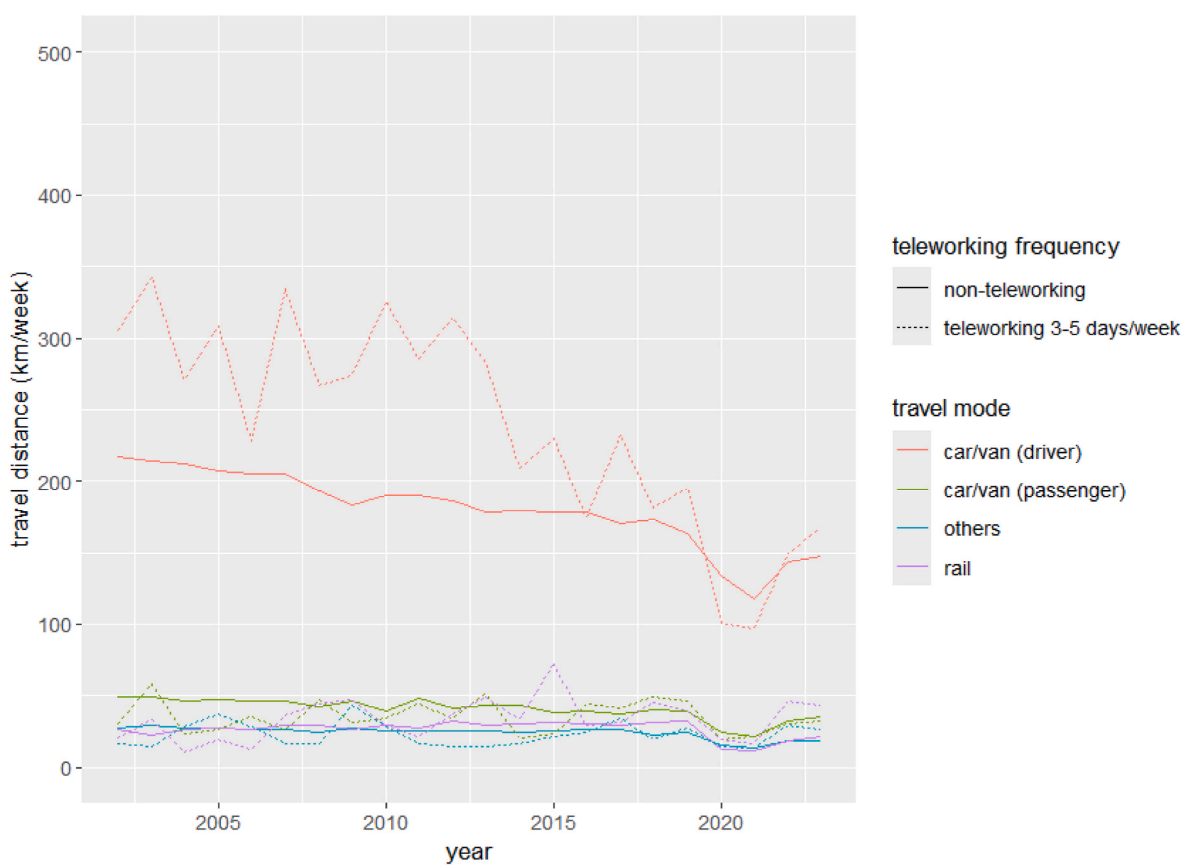

Fig. 8. High-frequency teleworkers' travel mode shift by year
Note: Due to data availability, air travel is not analyzed.

for business purposes, while non-teleworkers do not travel much for business purposes on any day of the week. This may be attributed to the rising popularity of long-distance business trips among high-frequency teleworkers who might work across various places. Peak-day travel has significantly contributed to the emission gap between teleworkers and non-teleworkers. On Wednesday and Thursday, teleworkers have 75–100 % higher emissions from business trips than non-teleworkers. On Saturday, teleworkers more than double the commute-trip emissions of non-teleworkers.

The peak days for commuting have shifted after the pandemic. Before the pandemic, non-teleworkers commuted mostly from Monday to Friday; teleworkers, in comparison, commuted from Monday to Thursday, which aligns with the findings from (Motte-Baumvol et al., 2024). After the pandemic, teleworkers commute more on Saturday. This may be explained by either the measurement error of commute trips, or the increased flexibility in working days for teleworkers

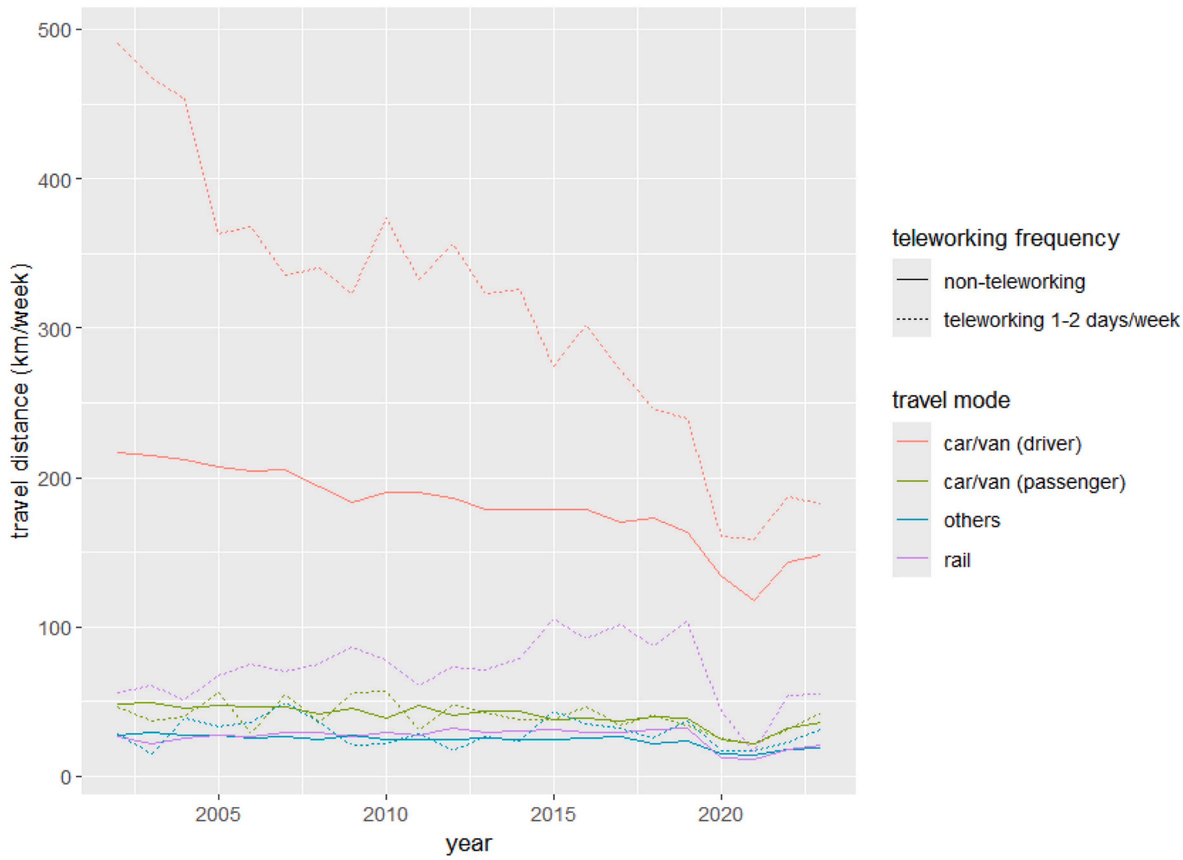

Fig. 9. Low-frequency teleworkers' travel mode shift by year
Note: Due to data availability, air travel is not analyzed.

post-pandemic.

Fig. 10 demonstrates that business trips and commute trips explain most of the emission gap between non-teleworkers and teleworkers. Teleworkers have much longer one-way business trips and one-way commute trips, even though both are declining after the pandemic. Post-pandemic teleworkers still have 75–140 % longer commute trips than non-teleworkers. There could be an underestimation of commute trips due to trip chaining in the NTS. However, since this error occurs across all types of workers, we can still extract useful information. Fig. 12 will further investigate emissions by examining more detailed trip purposes.

Fig. 11 compares the probability of a trip occurring at any hour of the day for three types of workers, by three trips purposes, before and after the pandemic. For example, a value of 0.22 indicates that a worker has a 22 % chance of taking a trip at that specific hour of the day.

In Fig. 11, we can identify three main peak hours, which are consistent pre- and post-pandemic. The morning peak for commute trips is around 9 a.m., which has the highest probability of travel (20–32 %). This is followed by the morning peak for business trips, also around 9 a.m., and the evening peak for commute trips around 6 p.m., both with probabilities of 15–26 %. Throughout the rest of the day, business trips and non-work trips have very similar probabilities (8–15 %), while commute trips have a much lower probability (2–5 %). As both business trips and commute trips peak around 9 a.m., they result in a combined probability of 40–50 %. Additionally, non-work trips lack a specific peak time but slightly increases from 9 a.m. to 8 p.m. After 8 p.m., the overall probability of any trips (business, commute, and non-work) decreases gradually, reaching almost 0 % between midnight and 5 a.m.

Although teleworkers are slightly more likely to travel off-peak for business trips (0–3 %), this does not reduce their chances of traveling at peak times. In fact, Fig. 11 suggests quite the opposite: teleworkers have a higher likelihood of commuting during peak hours, especially after the pandemic. Post-pandemic teleworkers are approximately 11 % more likely to commute at peak hours than non-teleworkers.

Fig. 12 compares the average weekly transport emissions by trip purpose for three types of workers. There are 12 types of trip purposes: one type of escort trip and 11 types of non-escort trips. Escort trips involve accompanying someone else (e.g., taking someone to school, work, or shopping). Non-escort trips are made by individuals for various purposes, including work (business and commute), essentials (education, medical, food shopping, other personal business), exercise (sports and walking), entertainment (excursions, non-food shopping), and other non-escort activities. Specifically, business trips include a "course of work" location, while commute trips occur between an individual's usual workplace and home (Fig. 2). To test whether the emission differences are statistically significant, we use a Welch two sample *t*-test, assuming zero-inflated log-normal distribution as indicated by Fig. 5. A "+" sign following a trip purpose label indicates that the emissions differences are statistically significant between *very frequent teleworkers* and non-teleworkers. A "*" sign indicates *frequent teleworkers* are significantly different from non-teleworkers. The error bars are the median, 20th percentile and 80th percentile values.[3]

In Fig. 12, we can see that there is a general decline in emissions post-pandemic, as well as obvious emission changes in certain trip purposes among teleworkers. After the pandemic, teleworkers travel much less for business purposes. Pre-pandemic teleworkers had around 66–87 %

[3] Since our data includes extremely low and high values, and does not follow a normal distribution, this type of error bar provides more information than the traditional one, such as the 10 % and 90 % confidence intervals assuming normality.

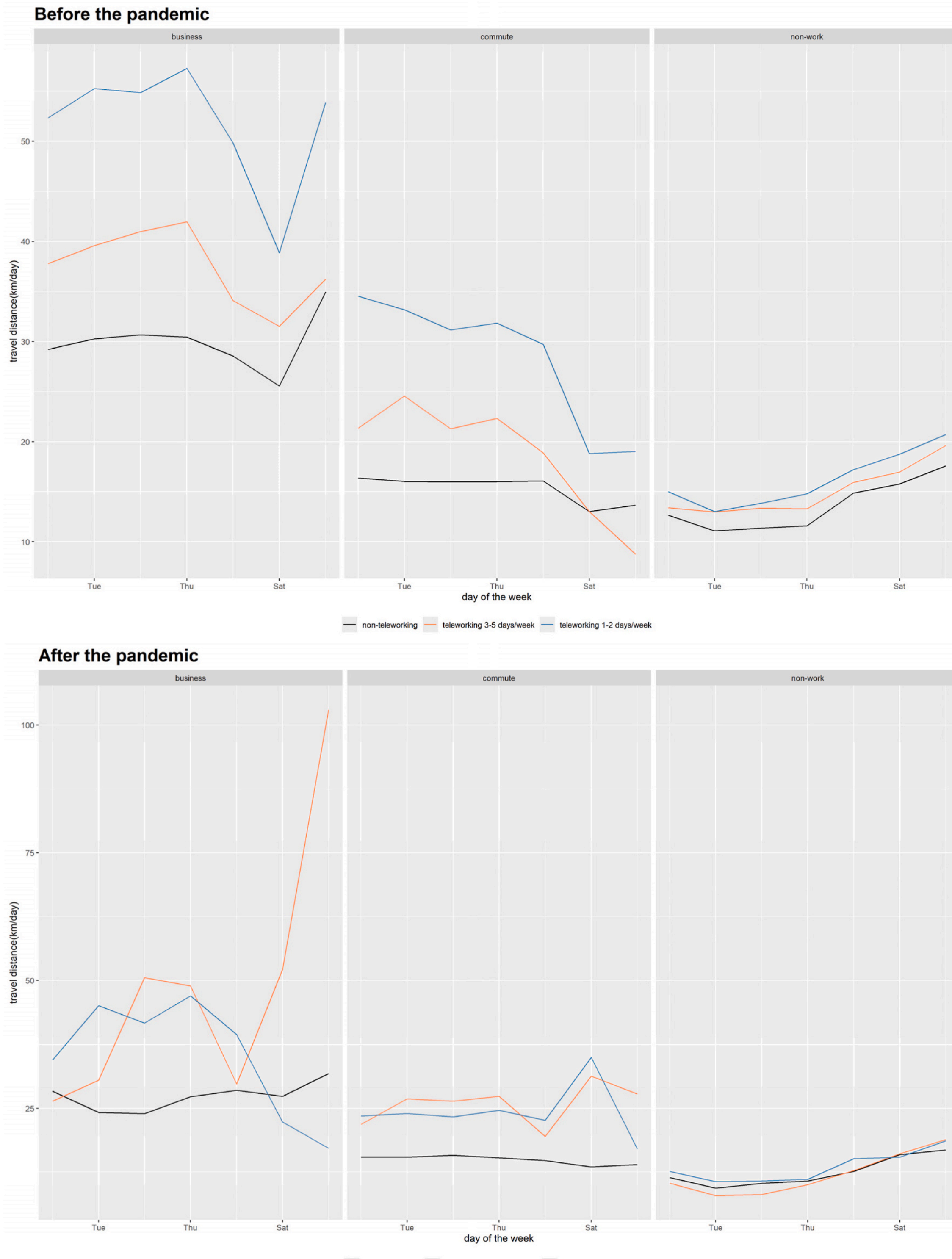

Fig. 10. Travel distance by day of the week and trip purpose.

higher emissions than non-teleworkers, while post-pandemic teleworkers only have approximately 22 % higher emissions. This is probably explained by the fact that post-pandemic teleworkers are less likely to drive a car or van (as shown in Figs. 8 and 9).

In terms of commute trips, pre-pandemic low-frequency teleworkers had approximately 36 % higher GHG emissions from commute trips compared to non-teleworkers, but post-pandemic teleworkers have less emissions than non-teleworkers. This shows that after the pandemic, the benefits of fewer commuting trips among teleworkers are higher than the drawbacks of their higher likelihood of driving and longer one-way commute distances (as depicted in Fig. 10). However, high-frequency teleworkers travel extremely often for education purposes after the pandemic. This could probably be a measurement error from the NTS, such as trip chaining, or a misclassification of “education” trips. The “education” trips may include work events with educational features such as conferences and workshops.

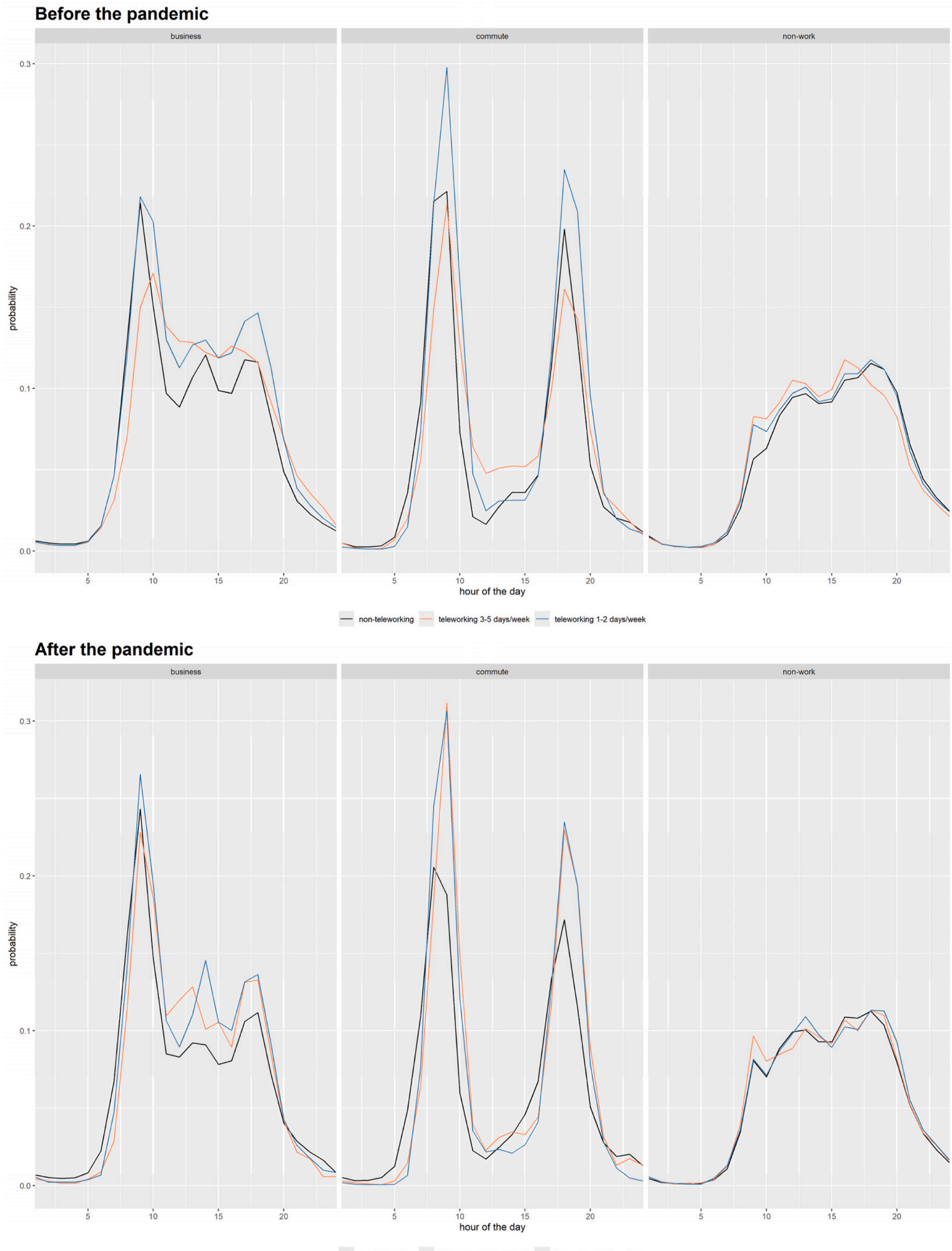

Fig. 11. Probability of trips by hour of the day and trip purpose.

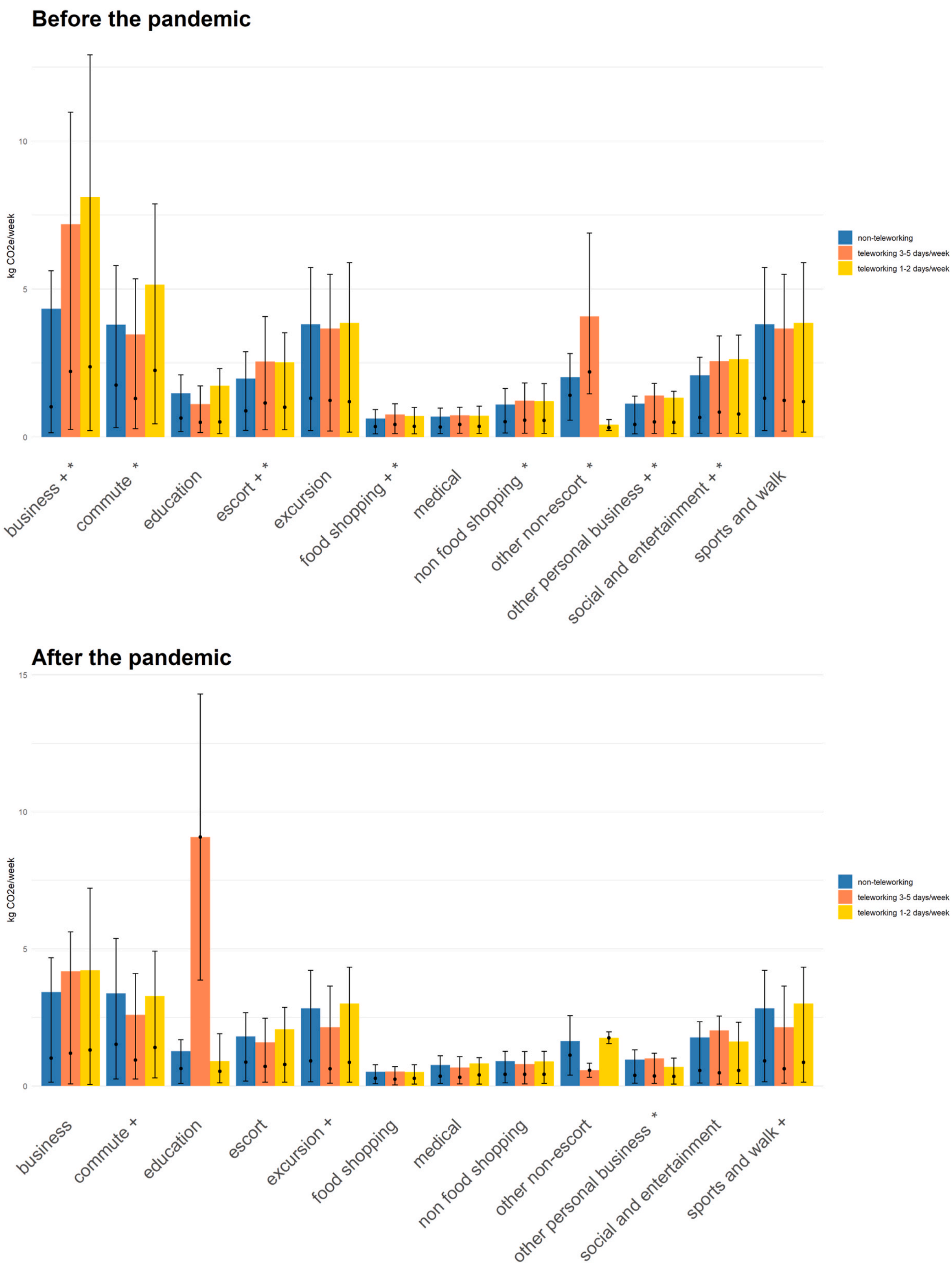

Fig. 12. Transport emissions by trip purpose and teleworking type

Note: the error bars show the median, the 20th percentile and 80 % percentile observations. A "+" sign besides label denotes that very frequent teleworkers' emissions are significantly different from those of non-teleworker with 99 % confidence, while a "*" sign denotes that frequent teleworkers' emissions are significantly different from non-teleworkers'. "escort" means trips people make to accompany someone else. "non-escort" means trips made by someone on their own behalf. "other non-escort" means non-escort reasons other than the ones listed here, e.g., business, excursion, sports and walk, etc. "other personal business" means other non-medical personal business.

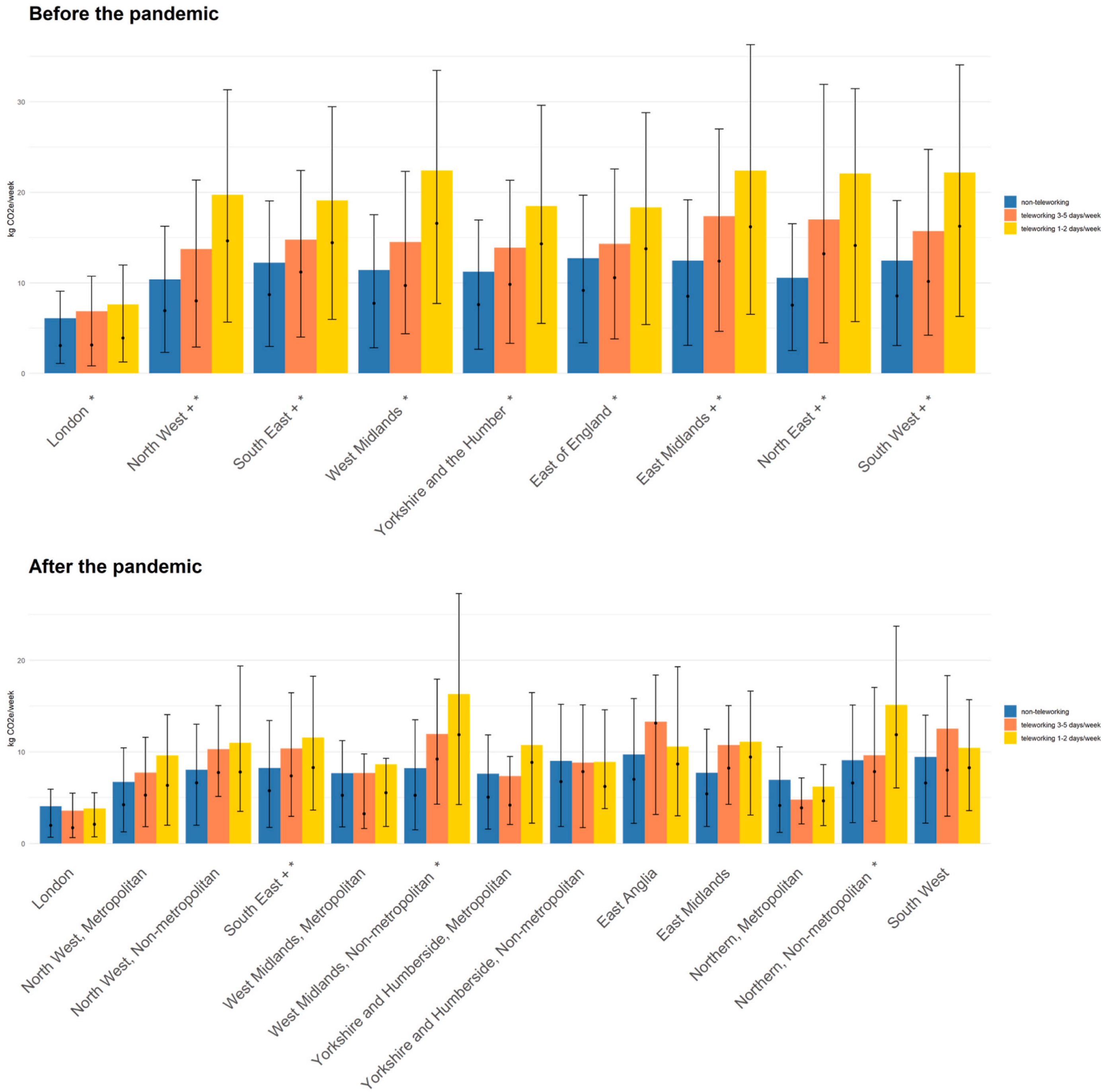

Fig. 13. Transport emissions by area and teleworking type
Note: the error bars show the median, the 20th percentile and 80 % percentile observations. A "+" sign besides label denotes that very frequent teleworkers' emissions are significantly different from those of non-teleworker with 99 % confidence, while a "*" sign denotes that frequent teleworkers' emissions are significantly different from non-teleworkers'. The geographical categorization differs before and after the pandemic due to data availability.

Almost all error bars show that the median value is lower than half of the mean value, which again confirms that a small number of high emitters increase the average value (as seen in Fig. 5). Nevertheless, the error bars are shorter after the pandemic, which suggests that there are fewer high emitters post-pandemic, especially among teleworkers. Considering statistical significance, most pre-pandemic trip purposes exhibit statistical significance, while post-pandemic data shows less statistical significance. This confirms that the emission gap between teleworkers and non-teleworkers is narrowing. Nonetheless, we expect biases with these significance tests, given that the pre-pandemic sample comprises around 90,000 individuals, while the post-pandemic one only has around 10,000 individuals.

Fig. 13 compares the average weekly transport emissions by dwelling area for the three types of workers. The nine areas in the pre-pandemic figure are sorted by population density from large to small. For instance, London represents the most densely populated area, while the South-west of England corresponds to the least populated area. However, with data availability, there is a slight adjustment in the classification of areas post-pandemic.

In Fig. 13, the emission gap between teleworkers and non-teleworkers is particularly pronounced outside London, which may be explained by poorer public transport facilities that trigger emissions from driving. This geographical feature remains the same post-pandemic, except the Northen Metropolitan area, which has better public transport facilities. Outside London, low-frequency teleworkers have up to 95 % higher transport emissions than non-teleworkers, while high-frequency teleworkers have up to 40 % higher transport emissions. This difference between high- and low-frequency teleworkers may be due to the fact that low-frequency teleworkers still commute to work 3–4 days a week.

4.2. Global sensitivity analysis

This section analyzes how we can maximize the environmental benefits of post-pandemic teleworking through global sensitivity analysis comparing pre- and post-pandemic results. In this analysis, we model the variation of overall transport emissions with respect to each input variable. Essentially, it reveals the relative contribution of different variables to the variance in total emissions. We measure global sensitivity using Sobol indices (as discussed in Section 3.2), where a

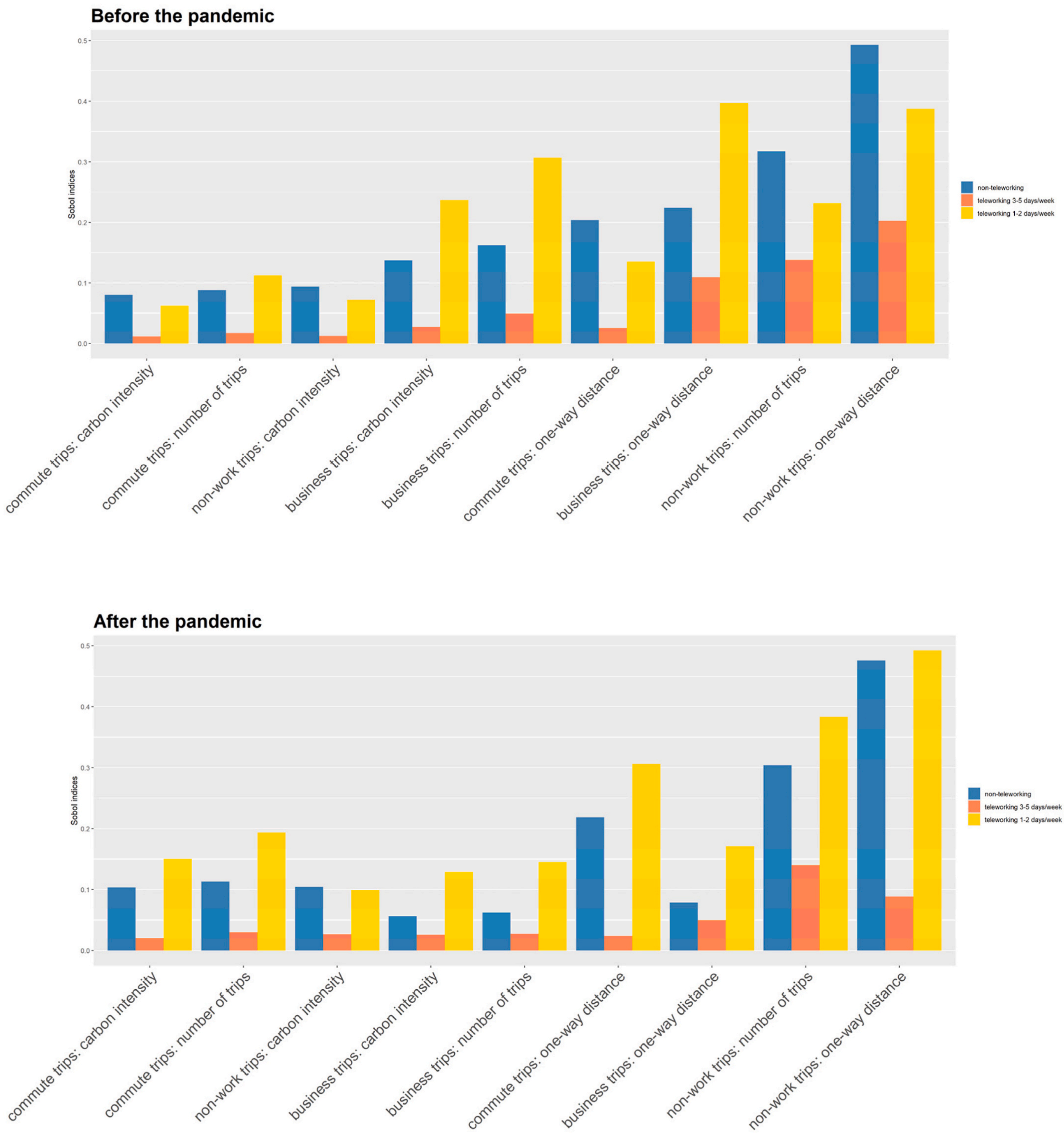

Fig. 14. Global sensitivity of total transport emissions by teleworking type
Note: the higher the Sobol indices, the more important a variable is.

higher index indicates a larger impact on total GHG emissions. As we are analyzing global sensitivity which considers correlations between variables, these three variables are important factors not only because of themselves, but also their correlations with other variables.

Fig. 14 investigates the contributions to total emissions from the carbon intensity, the number of trips and the one-way distance of three trip purposes for three types of workers, comparing the results before and after the pandemic.

Fig. 14 reveals that the most critical variable determining transport emissions is the one-way distance of non-work trips, followed by the number of non-work trips. In other words, reducing the total distance of non-work trips is crucial for reducing transport emissions. This not only directly affects emissions but also influences other variables. For example, individuals who travel longer distances for non-work purposes often reside in rural areas, further from business locations. Consequently, they tend to cover greater distances for work purposes and rely more on private vehicles, resulting in higher emissions due to these correlated effects.

Fig. 14 shows that after the pandemic, the importance of business trips has decreased, while the importance of commute trips has increased. Instead of one-way distance in business trips, one-way commute distance has become the third most important variable for low-frequency teleworkers and non-teleworkers. This can be explained by the decline in emissions from business trips (as shown in Fig. 12). However, for high-frequency teleworkers, one-way business trip distance remains the third most important variable in determining their

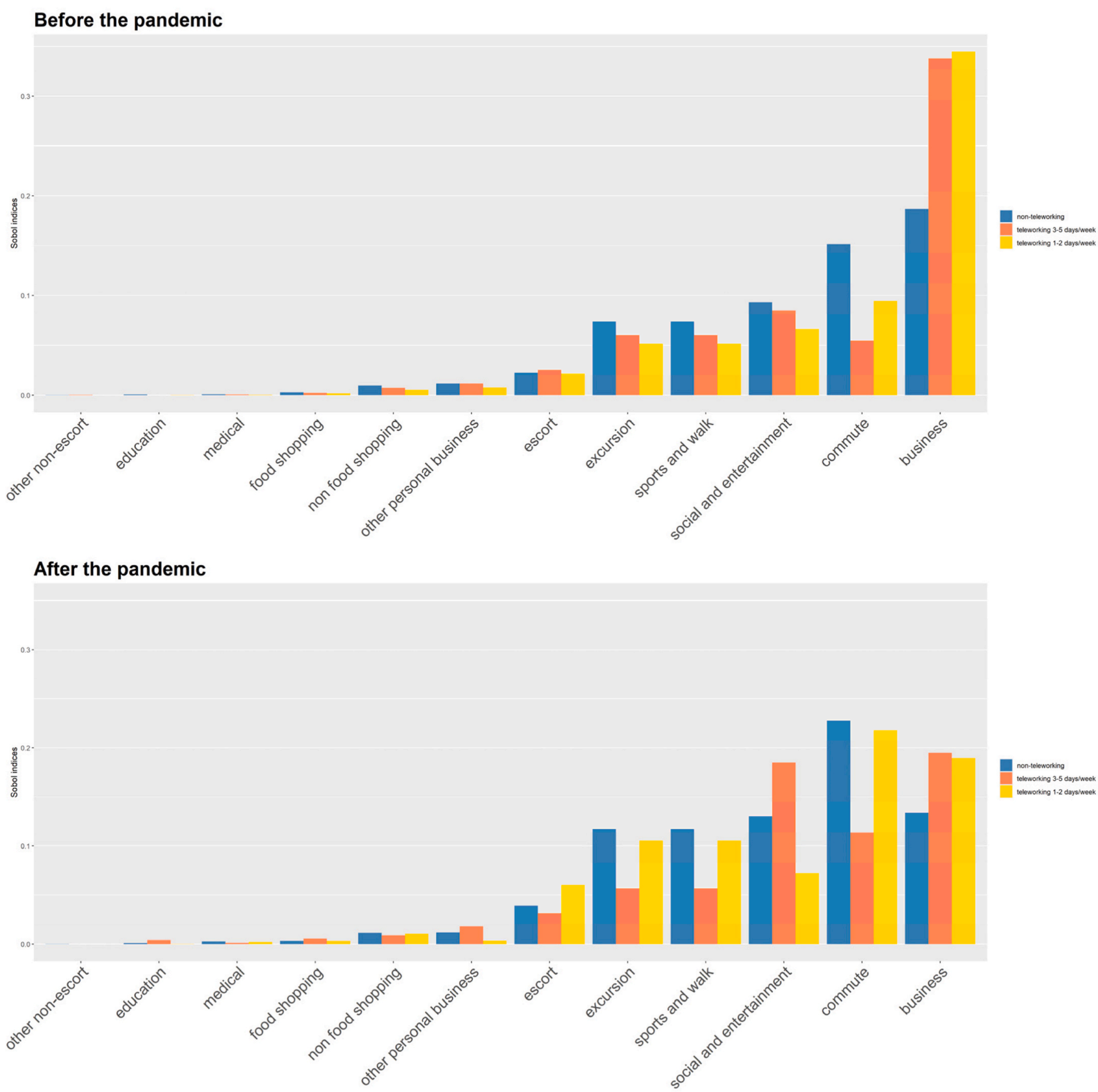

Fig. 15. The importance of emissions by trip purpose and teleworking type
Note: the higher the Sobol indices, the more important a variable is.

overall transport emissions, probably due to their long-distance business travel (as indicated by Fig. 10).

To further investigate how emissions from various trip purposes influence the variation in total transport emissions, Fig. 15 provides the global sensitivity results by more detailed trip purposes for the three types of workers pre- and post-pandemic.

Fig. 15 confirms that after the pandemic, the dominating importance of business trips is overtaken by that of commute trips. Before the pandemic, teleworkers' business trips were 3–6 times as important as their commute trips. After the pandemic, commute trips have a higher influence than commute trips for low-frequency teleworkers and non-teleworkers. Other trip purposes that also contribute significantly to workers' emissions are leisure- and exercise-related, including social, entertainment, sports, walking, and excursions. Trip purposes of low importance include essential trips such as personal business, shopping, medical, and education. This suggests that both teleworkers and non-teleworkers may not be taking family responsibilities for essential travel but are traveling more for their own leisure or exercise purposes.

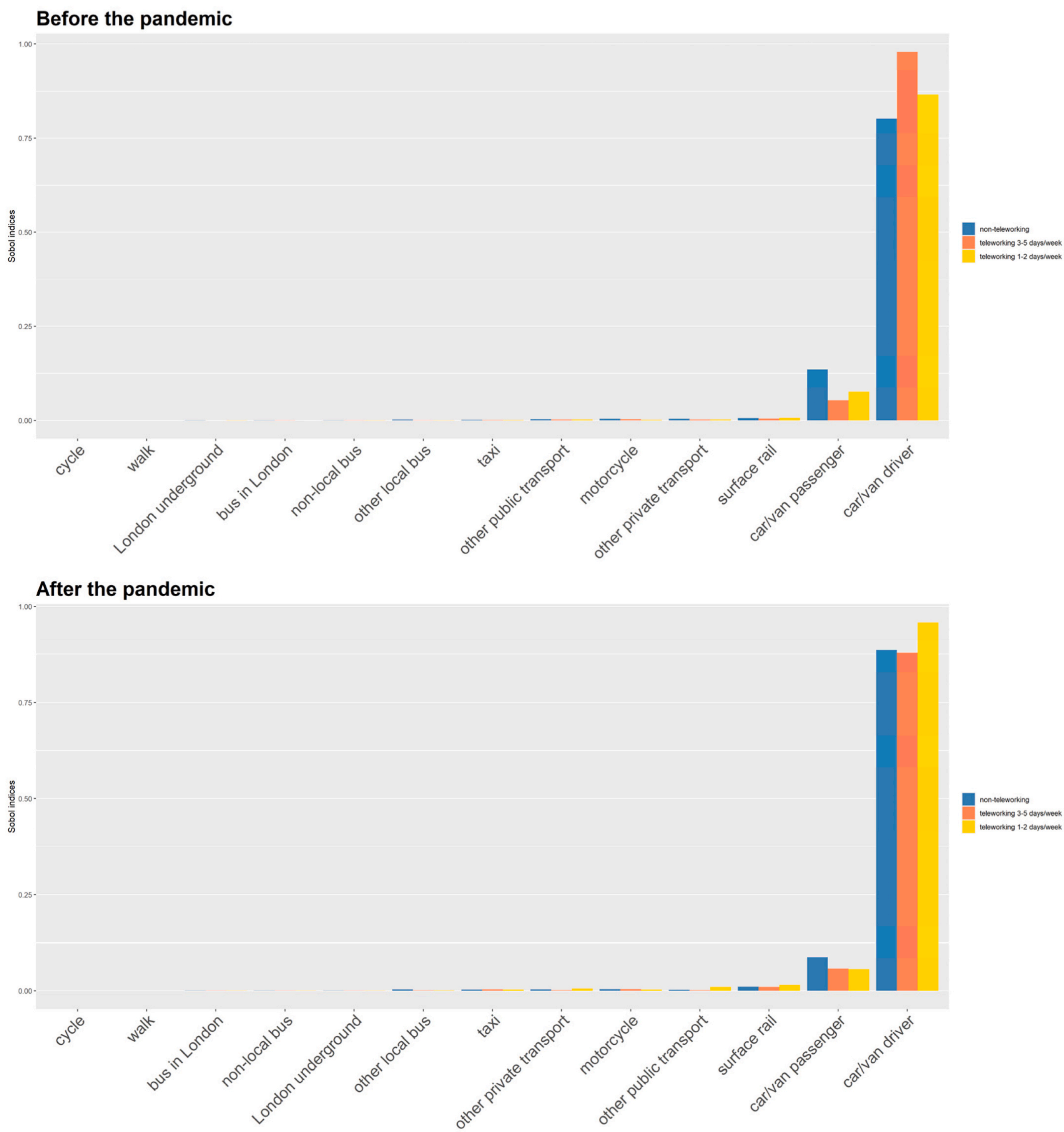

Fig. 16. The importance of emissions by travel mode and teleworking type
Note: the higher the Sobol indices, the more important a variable is.

To analyze the impact of various travel modes on the transport emissions, Fig. 16 illustrates the global sensitivity of weekly total transport emissions by travel mode for the three types of workers pre- and post-pandemic.

Fig. 16 indicates that the importance rankings of trip purposes remain very similar after the pandemic. Driving a car or van is the predominant travel mode influencing teleworkers' high transport emissions, being 30 times more significant than any other travel mode. The second most impactful is traveling as a passenger in a car or van, followed by motorcycle use. Emissions from private vehicle transport are more critical than those from public transport in determining teleworkers' total transport emissions. Conversely, emissions from cycling and walking are the least significant. This is logical, as private vehicle transport, particularly driving, not only possesses a high emission intensity but also accounts for the majority of the travel distance (as shown in Figs. 8 and 9).

4.3. Scenario analysis

Fig. 17 presents a comparative static scenario analysis of workers' total transport emissions when all cars and vans are EVs, compared to the pre-pandemic proportion of EVs among cars and vans. The figure compares their emissions under the EV scenario with those under the pre-pandemic scenario for non-teleworkers, high-frequency teleworkers, and low-frequency teleworkers. Due to data limitations, only pre-pandemic data is used for analysis.

Fig. 17 demonstrates that when replacing conventional cars and vans with EVs, the emission difference by percentage becomes larger between teleworkers and non-teleworkers than that in the current scenario. The emission gap increases to 38–80 % in the EV scenario, compared to 24–65 % in the pre-pandemic scenario. The expanding emission gap may be attributed to the fact that teleworkers travel further for business and non-work purposes compared to non-teleworkers. Although the post-pandemic data could include different travel patterns with an uptake of EVs, the pre-pandemic conclusion still remains informative as post-pandemic teleworkers have most of the travel patterns as their pre-pandemic counterparts, including more non-work travel, longer one-way commute distance, etc. However, further research is necessary to evaluate the comprehensive impact of EV adoption on teleworking patterns. This result is derived from a simple comparative static scenario analysis that does not account for any interactive effects between EV adoption and other travel behaviors. It is limited to cars and vans, excluding other vehicles such as buses and trains.

5. Discussion and conclusion

Literature on the environmental benefits of teleworking often neglects its significant uncertainty and attempts to provide an arbitrary conclusion that teleworking does or does not reduce emissions. This paper bridges this major literature gap by employing more advanced statistical methods to observe the full travel patterns of teleworkers across a large sample of the population. This sheds light on the main contributors to emission savings. Our main research question differs from many previous studies. We aim to answer *how* we can maximize the environmental benefits of teleworking, rather than simply determining *whether* teleworking is environmentally friendly. Focusing on English teleworkers, this paper has addressed these limitations with simulation and global sensitivity analysis. The distribution of each variable was based on the observed distribution of over 100,000 English workers during the period from 2002 to 2023. Additionally, we compared the travel emissions between teleworkers and non-teleworkers pre- and post-pandemic. We also explored a comparative static scenario where conventional vehicles were replaced by EVs.

Most studies have paid insufficient attention to the variations in key variables by estimating an average value of emissions. They have also employed proxies for environmental impact, such as distance traveled, rather than more direct measures like GHG emissions. Our simulation method addresses these problems by observing the full statistical travel

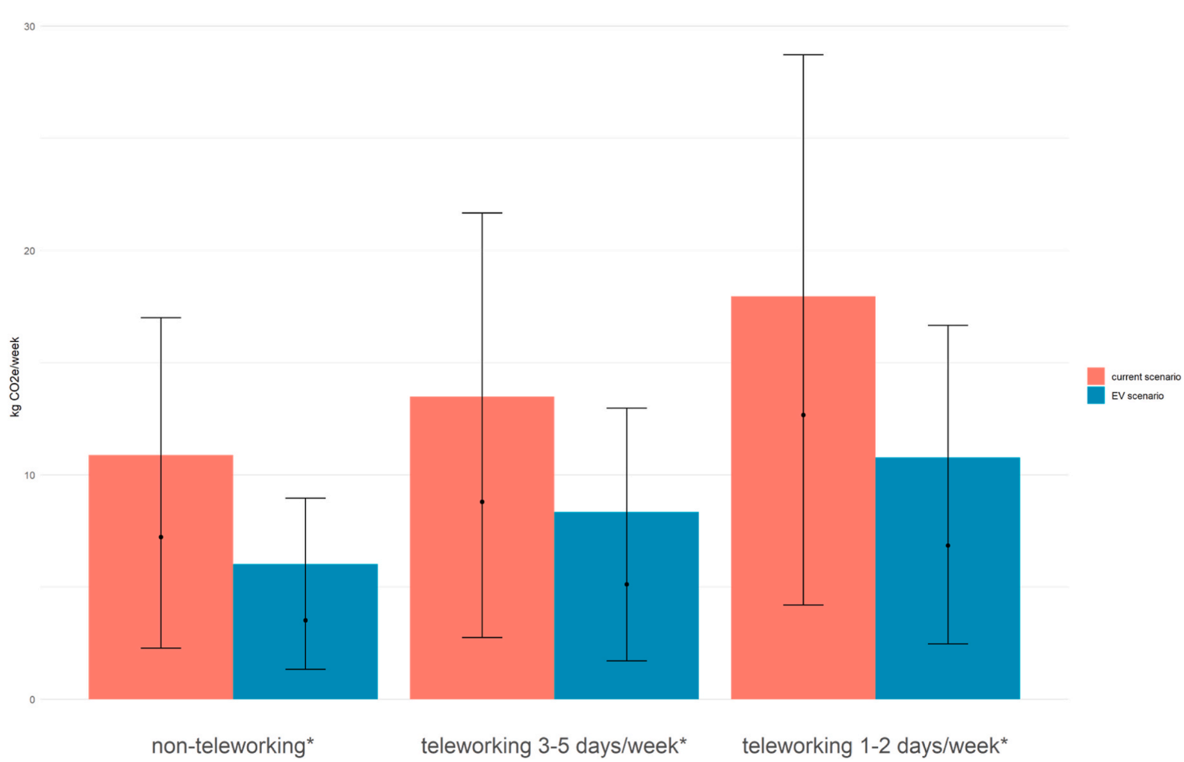

Fig. 17. Scenario analysis of teleworkers' emissions with electric vehicles
Note: "*" denotes that the difference between current scenario and EV scenario is significant at 99 % confidence level; no post-pandemic analysis is shown due to data availability on vehicle type.

patterns of teleworkers and providing GHG emission estimations in a distribution form. The simulation results reveal that individuals who telework 1–2 days a week generate the highest overall transport emissions, followed by those who telework 3–5 days a week. Non-teleworkers have the lowest overall transport emissions. Several factors can explain this pattern. Firstly, teleworkers are less inclined to adopt sustainable travel modes, such as walking and cycling. Secondly, a small subset of teleworkers produce exceptionally high transport emissions—exceeding 50 kg CO2e per week. Thirdly, teleworkers generally reside farther from their workplaces than non-teleworkers, resulting in longer business and commute distances, and they also live further from amenities, leading to longer non-work travel distances. However, the emission disparity between teleworkers and non-teleworkers has been decreasing rapidly from 2002 to 2023. This trend may be attributed to workers being less likely to drive cars or vans.

Regarding peak-time travel and geographical areas, the simulation analysis suggests little evidence that teleworkers travel on off-peak days or at off-peak time. This contradicts the belief that teleworking may reduce congestion but is not entirely surprising considering that teleworkers travel more for business purposes. Geographical areas do not make a huge difference to workers' transport emissions, except that those living in London have substantially lower emissions. London is known for its high-density of living and good public transport facilities, which indicates that convenient public transport helps maximize the environmental benefits of teleworking.

Global sensitivity analysis is a useful tool to identify the sources of uncertainty by ranking the importance of variables. In this paper, it measures the contribution of travel-related variables to the variance in transport emissions, considering their correlation with other variables. The global sensitivity analysis results indicate that the disparity in one-way distance for non-work trips between teleworkers and non-teleworkers is the most significant factor in explaining the difference in their transport emissions. This significance stems not only from the direct impact of one-way non-work distance on emissions but also from its correlation with other variables that substantially affect emissions. For example, individuals residing in more rural areas, away from local amenities, are likely to live farther from their workplaces and to rely more heavily on private vehicles. These findings underscore the importance of a well-designed built environment in realizing the environmental benefits of teleworking. An optimal built environment enables people to live closer to their workplaces and amenities, reducing the need for frequent travel to access their daily needs in business and social activities.

In terms of trip purposes and travel modes, our global sensitivity analysis results indicate that business trips are the most significant trip purpose in explaining the emission differences between teleworkers and non-teleworkers. The use of private cars and vans is the most influential travel mode in terms of emissions. Additionally, our comparative static scenario analysis suggests that the adoption of EVs will substantially reduce transport emissions, yet it may increase the emission disparity between teleworkers and non-teleworkers. This is likely because EV adoption does not reduce teleworkers' transport emissions to the same extent as it does for non-teleworkers, given that teleworkers generally have longer distances for business and non-work travel.

A key implication of our study is the necessity to ensure that the growing popularity of teleworking does not prompt individuals to move to low-density areas where public transport is inadequate or sustainable travel options are impractical, a phenomenon known as 'telesprawl.' This paper has not found any growing 'telesprawl' trend. However, after the pandemic teleworkers still have longer one-way distance in business and commute trips than non-teleworkers. The environmental advantages of teleworking could be fully maximized if a greater number of teleworkers transition to full-time remote work and conduct business meetings exclusively via video calls.

A second implication concerns the impact of urban planning on the environmental effects of teleworking. Effective urban planning allows teleworkers to travel shorter distances to access essential facilities, such as schools and shops. In the UK, home builders are mandated to allocate funds for local infrastructure development; however, there have been debates and issues regarding the efficacy of this regulation (Grimwood, 2019). To foster a clean and green environment, it is crucial to ensure the implementation of such regulations, enabling teleworkers to reside in well-planned neighborhoods that negate the need for extensive travel for daily activities.

A third implication highlights the need to curtail private car usage. Among all travel modes, driving is the primary factor contributing to teleworkers' high transport emissions and the recent decline in these emissions. The availability of robust public transport facilities and sustainable travel options could significantly enhance the environmental benefits of teleworking. Should teleworkers opt for low-emission travel modes, their extended business travel distances or increased frequency of non-work trips would not compromise the potential emissions savings offered by teleworking.

A fourth implication suggests that teleworkers may travel more due to social isolation or physical inactivity. Teleworkers often travel for business, social, and sports-related purposes, which could be because the teleworking lifestyle necessitates traveling further to engage in social interactions and physical activities, essential for maintaining mental and physical well-being. This highlights the need to consider teleworkers' health in transport policy design. For example, providing more local co-working spaces could help teleworkers maintain social connections while reducing their transport emissions.

6. Limitations and avenues for future research

The primary limitation of this study is that it relies on a partial equilibrium model, which permits certain key variables to fluctuate while keeping all others constant. Due to data availability, we focus on the current observed changes in a few key determinants, such as travel mode, trip purpose, peak-time travel and population density. There is a possibility that numerous other variables may shift in the long term, potentially altering the outcomes. These include public transport availability, transport costs, and technologies beyond EVs. Further qualitative analysis may be necessary. For example, if public transport prices decrease significantly, encouraging teleworkers to use it more frequently, then teleworkers might have lower transport emissions than non-teleworkers. Furthermore, if drones begin to replace vehicles for delivering goods to remote locations (Koiwanit, 2018), 'telesprawl' might not lead to an increase in emissions from non-work trips for accessing essentials such as groceries.

The policy implications of this study are subject to feasibility. For example, the research identifies one-way non-work distance as the most significant factor affecting teleworkers' transport emissions. However, the feasibility of reducing the distance between home and local facilities depends on numerous factors, such as housing prices, personal preferences, household composition, and occupation. For instance, in a dual-occupancy household where one partner teleworks and the other commutes, relocating closer to the commuter's workplace to minimize energy consumption is a practical option. Other factors, including the cost of living and children's education, may pose challenges for teleworkers seeking proximity to their workplaces or urban centers.

The research has not considered selection bias. First, there is a possibility that people who live in remote areas are more likely to *choose* teleworking. If this is true, teleworking facilitates employment opportunities for individuals in their local area, offering job access to those with mobility issues or disabilities and enabling firms to hire individuals with in-demand skills or those who are well-suited for specific roles. These advantages could surpass the potential downside of teleworkers having higher transport energy consumption than non-teleworkers. Second, it is possible that after the pandemic, some of the pre-pandemic non-teleworkers—who may inherently have lower travel demand—started teleworking. This shift could lower the average emissions of the post-pandemic teleworker group and therefore narrow the emission gap between teleworkers and non-teleworkers. Future research could address the selection bias during the model development stage, for example, by using questionnaires to explore why individuals chose to become teleworkers after the pandemic.

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CRediT authorship contribution statement

Yao Shi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Steven Sorrell:** Supervision, Project administration, Funding acquisition. **Tim Foxon:** Supervision, Project administration, Funding acquisition.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT to proofread. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Appendix ASupplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2025.103865.

Appendix 1. Sobol indices estimation

Appendix 1 shows the three steps to estimate Sobol indices. First, allow all the other inputs $x_{\sim i}$ to vary for each possible value of x_i, and record the expected values of output y:

$$E_{x_{\sim i}}(y|x_i) \tag{1}$$

Equation (1) measures all the expected values of y given a possible value of x_i, when all the other non-x values vary in their own domains conditional on the value of x_i.

Second, measure the variance of these expected values for each possible value of x_i:

$$V_{x_i}\left(E_{x_{\sim i}}(y|x_i)\right) \tag{2}$$

Equation (2) measures the total variance of y by changing x_i and considering its correlations with other variables.

Finally, we compare the variance caused by x_i with the total variance of y, and obtain a global sensitivity score S_{Ti}, which is a percentage value measuring how much x_i contributes to the total variance of y:

$$S_{Ti} = \frac{V_{x_i}\left(E_{x_{\sim i}}(y|x_i)\right)}{V(y)} \tag{3}$$

Equation (3) indicates the contribution to the total variance of y by x_i considering its correlations with other variables. In Equation (3), the higher the sensitivity score S_i, the more important variable x_i is in explaining the total variance of output y considering its impact on other variables $x_{\sim i}$.

To further demonstrate how Sobol indices measure global sensitivity, let us have an example of a model with only three input variables x_1, x_2 and x_3. Then one will have the following decomposition of total variance S_T (Sobol, 2001). S_T is the sum of all sensitivity scores, which equals to one.

$$\mathrm{S_T} = \mathrm{S_1} + \mathrm{S_2} + \mathrm{S_3} + \mathrm{S_{12}} + \mathrm{S_{13}} + \mathrm{S_{23}} + \mathrm{S_{123}} = 1 \tag{4}$$

, where S_{12} is the share of variance caused by the correlation between variables x_1 and x_2, S_{123} is the share of variance caused by the correlation between all three variables x_1, x_2 and x_3. S_{12}, S_{23} and S_{13} are the so-called second-order sensitivity indices, and S_{123} is the so-called third-order sensitivity indices.

The local sensitivity for x_1 is $\mathrm{S_1}$.

The global sensitivity for x_1 is a sum of x_1's first-order, second-order and third-order sensitivity indices. Let the global sensitivity of x_1 be denoted as S_{T1}.

$$\mathrm{S_{T1}} = \mathrm{S_1} + \mathrm{S_{12}} + \mathrm{S_{13}} + \mathrm{S_{123}} \tag{5}$$

S_{T1} includes variances when x_1 correlates with x_2 and/or x_3, hence differs from local sensitivity.

Appendix 2. Additional tables and figures

Fig. 2a compares the vehicle sizes among non-teleworkers, high-frequency teleworkers, and low-frequency teleworkers. It reveals that teleworkers tend to prefer larger vehicles. However, the considerable proportion of missing data—at least 40 % for each category of teleworking—substantially undermines the reliability of this conclusion.

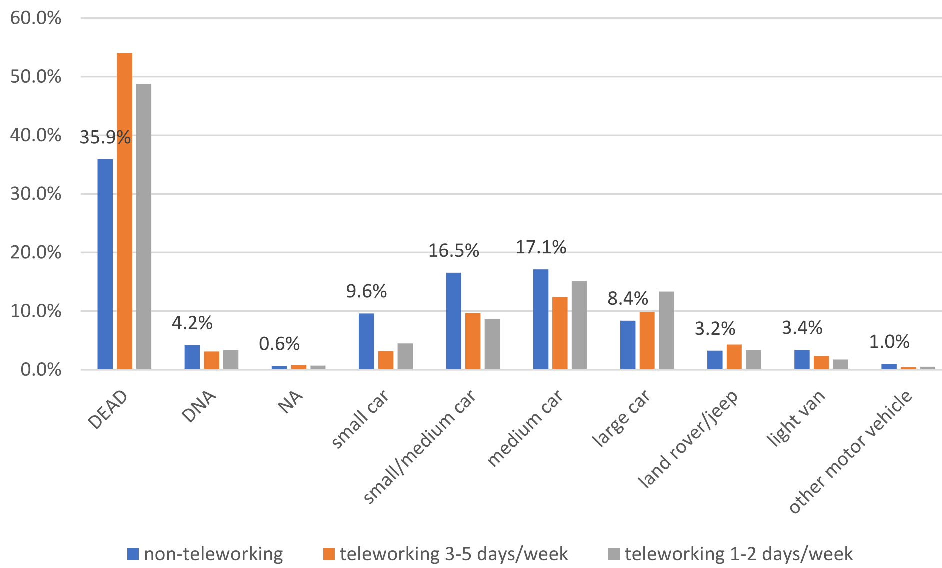

Fig. 2a. Comparison of vehicle sizes by teleworking type
Note: DEAD indicates that the question was not asked in this year of the survey; DNA indicates that the question was asked, but the respondent did not answer, or response could not be coded; NA indicates that the question was not asked, mostly due to question routing.

Fig. 2b examines the fuel types of vehicles owned by three distinct groups of workers: non-teleworkers, high-frequency teleworkers, and low-frequency teleworkers. It is evident that petrol and diesel vehicles are predominant in the vehicle stock across all worker categories, indicating that electric vehicles have not yet gained widespread popularity among England's workforces. Notably, teleworkers show a higher propensity for diesel vehicle ownership compared to non-teleworkers, with approximately 10 % more teleworkers possessing diesel vehicles. Conversely, non-teleworkers tend to favor petrol vehicles.

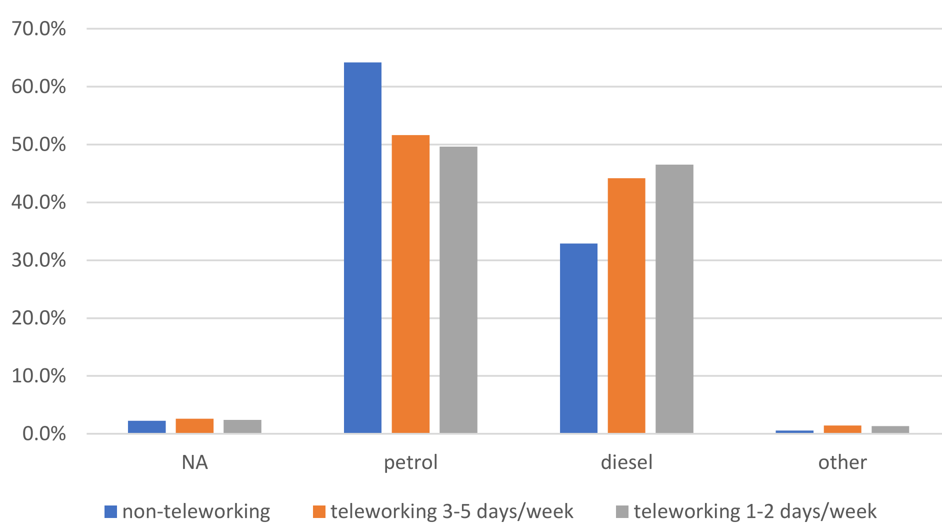

Fig. 2b. Comparison of vehicle fuel types by teleworking type
Note: NA indicates that the question was not asked, mostly due to question routing.

Fig. 2c illustrates the average weekly transport emissions by occupation type among the three types of workers before the pandemic. The six occupation types considered are managerial and technical occupations, professional occupations, skilled non-manual occupations, skilled manual occupations, partly skilled occupations and unskilled occupations.

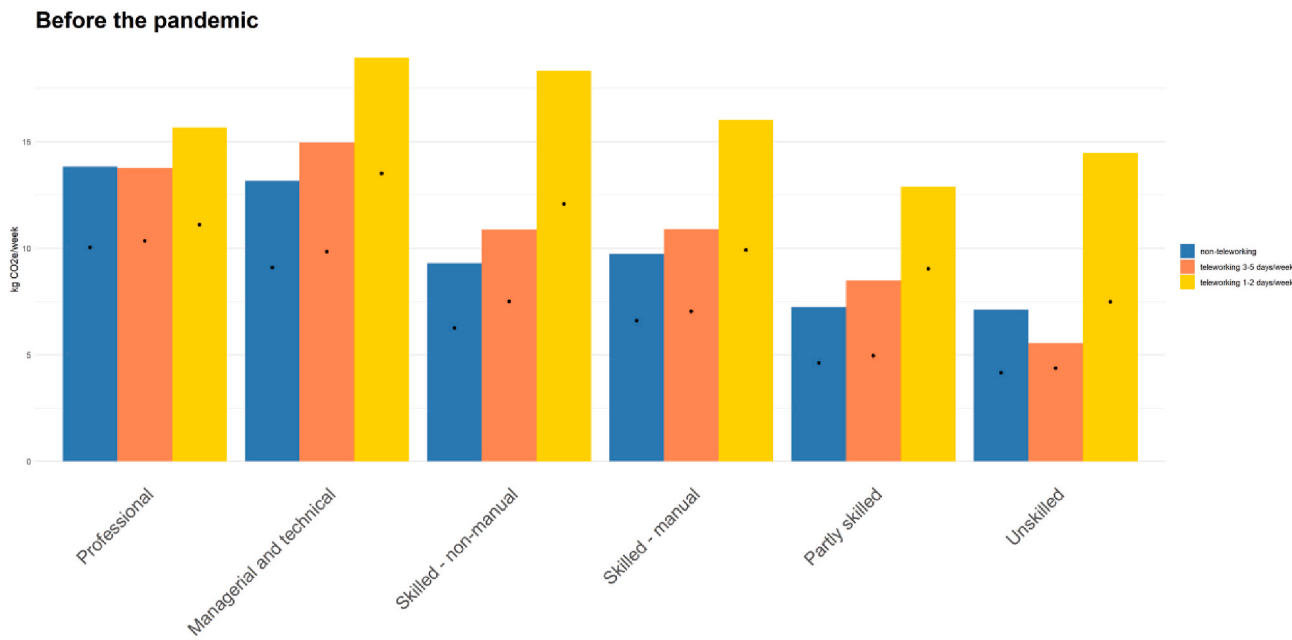

Fig. 2c. Transport emissions by occupation type and teleworking type
Note: the dot shows the median value. Due to data availability, other values, including post-pandemic data, are not shown.

Fig. 2c reveals that, in general, higher-skilled workers have greater transport emissions than low-skilled workers. This trend is particularly pronounced among non-teleworkers and high-frequency teleworkers. Specifically, high-skilled workers in these two categories exhibit emissions approximately two to three times higher than their low-skilled counterparts. Interestingly, even when low-skilled, low-frequency teleworkers' transport emissions remain significantly elevated. High-skilled low-frequency teleworkers have 50 % more emissions than their low-skilled counterparts.

Another noteworthy observation from Fig. 2c is that the emission gap between non-teleworkers and low-frequency workers widens as workers become less skilled. Specifically, all types of workers in professional occupations have very similar transport emissions. In contrast, among unskilled occupations, low-frequency teleworkers have twice the emissions of non-teleworkers. However, the emission gap does not differ significantly by occupation between non-teleworkers and high-frequency teleworkers.

Data availability

I have shared the link to the data at the Attach File step English_National_Travel_Survey_2002_2023 (Reference data) ()

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