Do teleworkers have lower transport carbon emissions? What are the most important factors?

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Highlight

- Workers who telework once or twice a week have around 40% higher overall transport carbon emissions than non-teleworkers
- One-way commute distance has the highest influence on transport carbon emissions
- Reducing carbon intensity of cars has low impact on teleworking's environmental effects

Abstract

With the increasing popularity of teleworking after the Covid 19 pandemic, and the urgent threat of climate change, there is growing interest in the potential of teleworking to reduce

carbon emissions from transport. However, despite three decades of research in this area, few studies have quantified the impact of teleworking on energy use and emissions. Instead, most studies estimate the impact of teleworking on distance travelled, and several find that the potential benefits of fewer commutes are offset by longer commutes and/or additional nonwork trips. Moreover, none of these studies have explored what factors matter the most in realizing the environmental benefits of teleworking, i.e., the sensitivity of travel and emission savings to relevant variables.

This study uses data from the English National Travel Survey (NTS) from year 2017 to 2019 to explore the difference in travel-related carbon emissions between teleworkers and non-teleworkers in England. Using the observed variance of relevant variables from NTS, we use Monte Carlo simulation to estimate the probability that teleworking results in lower travel-related carbon emissions. We then conduct a global sensitivity analysis to identify the relative influence of different variables on the variance of emission savings.

We find that workers who telework three or more days a week have lower carbon emissions for both commuting travel and total travel. In contrast, workers who telework once or twice a week have higher carbon emissions for total travel. The key variables influencing travel-related emissions are one-way commute distance, one-way non-commute distance and the number of non-commute trips. We also find that a given percentage reduction in the carbon intensity of cars has a much smaller impact on reducing travel emissions than the same percentage reduction in other variables. These results highlight the importance of preventing 'tele-sprawl' - where the increased adoption of teleworking encourages people to relocate to areas of low population density. The results also shows that good urban planning that allows residents to travel less for daily activities is important to maximize the environmental benefits of teleworking.

Keywords

Teleworking; carbon emissions; Monte Carlo simulation; global sensitivity analysis

1. INTRODUCTION

Researchers and policymakers have long recognized the potential of teleworking to reduce traffic congestion and local air pollution. Now there is growing interest in its potential to contribute to climate mitigation.

By avoiding commute trips, teleworking has the potential to significantly reduce the distance travelled by workers and the associated travel-related carbon emissions. However, several studies have found that teleworkers tend to live further from their place of work than non-teleworkers, with the result that the travel savings from fewer commuting trips are partly or wholly offset by longer commuting trips [1-9]. Similarly, several studies have found that teleworkers tend to take more non-work trips than non-teleworkers, consistent with the concept of stable travel time budgets [1, 6, 9-11]. If so, this will further offset the travel and emission savings from fewer commuting trips.

To date, the majority of studies have used distance travelled as the relevant metric. But the emissions associated with this travel will depend upon the relative use of different transport modes, together with the emission intensity of those modes. Different modes vary widely in emission intensity and these intensities will change over time as technologies improve. Hence, to fully explore the emission savings from teleworking, this study considers several variables, including the number of commute and non-commute trips, one-way commute distance, one-way non-commute distance, modal choice and the emission intensity of each mode. Using data on the historical variation in these variables for English commuters, we simulate the difference between a teleworker's travel-related carbon emissions and those of a non-teleworker. Our results suggest that people who telework three to five days a week have higher travel-related carbon emissions than non-teleworkers, while people who telework one to two days a week have lower emissions. We also find that one-way commute distance has the largest impact on travel carbon emissions.

The following section briefly reviews the literature on teleworking and emission savings. Section 3 describes our data sources and methodology, while Section 4 presents our results. Section 5 concludes.

2. LITERATURE REVIEW

Using Google Scholar, we searched for papers on teleworking and carbon emissions by combining the keywords "teleworking" or "work from home" with "energy" or "carbon emission". We identified around 50 studies in this area, but most of these did not estimate carbon emissions directly, but instead used proxies such as travel distance, travel time or energy use. The sample was dominated by studies from North America, and many of these were more than two decades old.

Two review papers [12, 13] have demonstrated that whether teleworking is associated with energy or emission savings is an uncertain, ambiguous and complex issue. Whether teleworkers have less carbon emissions depends upon whether the savings from fewer commuting trips and less time spent in the office outweigh the additional emissions from more non-work trips and more time spent at home. However, few studies have quantified all these effects, and the research methods, geographical regions and assumptions vary widely, leading to a lack of consensus on the environmental benefits of teleworking. Given the complexities of modelling energy use and emissions in offices and at home, most studies focus solely upon travel-related emissions. We do the same here, while acknowledging that this presents only a partial picture.

The following highlights some of the uncertainties associated with travel-related emissions, and the results and methodologies of key studies in this field.

While several studies find that teleworkers tend to live further away from their workplaces than non-teleworkers [1-9], the direction of causality is unclear. That is, does living further from a workplace encourage more teleworking, or does teleworking encourage living further from a workplace? Whatever the reason, if teleworkers live further from their workplace the benefits of *fewer* commutes can be offset by *longer* commutes on the days people travel to the office. Studies also find that teleworkers travel further for non-work purposes such as shopping and visiting friends [1, 3, 4, 6, 9, 10, 14]. This is largely because they make more non-work trips than non-teleworkers, but in some cases the average distance of those trips is greater [1, 9].

Many studies focus upon the number of commute and non-commute trips, and the average distance of those trips. But travel-related carbon emissions also depend upon the choice of travel mode and the carbon intensity of those modes. Some studies find that teleworkers drive less than non-teleworkers, and also that they walk, cycle and use public transport more [15-18]. As a result, they may have lower emissions for the same distance travelled. However, travel behaviors vary across demographics, built environment and geographical regions; so the impact of teleworking varies between different countries, times and populations. Studies in Sweden, California and Ireland find that teleworkers travel *less* than non-teleworkers [6, 10, 19, 20], while Van Lier, de Witte [18] find that teleworkers in Belgium have *shorter* one-way commute distances.

Only one study [21] has employed a systematic approach to address the sensitivity of energy and emission savings to changes in key variables. Kitou and Horvath use Monte Carlo techniques to simulate the difference in energy use and emissions between a teleworker and a non-teleworker considering transport, heating and cooling in home and office, lighting and electronic equipment. They map the statistical features of key variables - such as one-way commute distance, non-commute travel distance, the number of commute trips, the number of non-commute trips, the hours of personal office occupancy and the power of home appliances – and draw random samples from the distributions of these variables to generate a corresponding distribution of emission savings. Kitou and Horvath find that one-day teleworking reduces transport carbon emissions by 17% and overall carbon emissions by 2% in heating days, while five-day teleworking reduces transport carbon emissions by 89% and overall carbon emissions by 17% in heating days.

Monte Carlo simulation allows variables to vary according to the statistical features of those variables, as derived from historical data. It therefore provides an effective way to handle uncertainty while at the same time being grounded in empirical observations. Monte Carlo simulation is widely used in modelling future uncertainties in environmental studies. For example, Craglia and Cullen [22] use Monte Carlo simulation to model UK passenger vehicle emissions and find that the main determinants of future emissions are the rate of uptake of electric vehicles (EVs) and the average size and power of those vehicles. Similarly, Smith, Forster [23] use Monte Carlo Simulation to model future global warming under 38 scenarios and find that a global average temperature increase below 1.5 C^{o} is only "attainable with ambitious and immediate emission reduction across all sectors".

Given the uncertainty in the emission savings from teleworking, it is important to assess the drivers of these savings and how they can be maximized. This can be achieved through the use of sensitivity analysis to identify the key variables influencing these savings. However, only one study [24] has systematically explored the causes of uncertainty with sensitivity analysis. Guerin conducts sensitivity tests on the energy savings from teleworking in Australia, including both commute-related and building-related energy use. He finds that energy savings can be achieved with teleworking if an employee commutes more than 30 km each workday. However, Guerin only considers two transport -related variables - the percentage of employees commuting by car and the average distance for a return commute trip - and ignores the correlation between these variables. For example, an employee may be more likely to choose to travel by car if s/he has a long commute distance. This omission could lead to an underestimation of the impact of commute distance on carbon emissions. In other words, Guerin conducts a local sensitivity analysis which does not capture the impact of correlations between the different variables.

Based on the above review, this study seeks to fill three gaps in the literature. First, we study travel-related carbon emissions instead of distance travelled, since the latter is a poor proxy for the climate impacts of teleworking. Second, we use Monte Carlo simulation to explore the sensitivity of emission savings to changes in key variables. Third, we employ a global sensitivity analysis to explore the overall impact of each variable on transport carbon emissions taking into account its correlations with other variables. Specifically, we use the 'Sobol indices' technique, a type of global sensitivity analyses. Our key variables are the number of commute trips, the number of non-commute trips, one-way commute distance, one-way non-commute distance, modal choice and the carbon intensity of each mode. Finally, we examine how the ongoing shift from conventional to electric vehicles (EVs) may impact the future emission savings from teleworking. We only consider the EV shift of private vehicles because most trips in our sample are by car, and rail and bus trips are only a small proportion.

Our research questions are:

1. Under what conditions do teleworkers have lower transport-related carbon 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 are the English National Travel Survey (NTS) for 2017 to 2019 [25], the 2020 UK Government Greenhouse Gas Conversion Factors for Company Reporting (CF) [26], and the 2019 Vehicle Licensing Statistics (VLS) [27]. We use NTS data to compare the weekly travel distance of teleworkers and non-teleworkers, CF to estimate the carbon emissions associated with this travel, and VLS to estimate the carbon intensity of private cars.

The NTS is an annual survey of the travel patterns of a stratified, two-stage, random probability sample of ~13k English households. Participants fill out detailed travel diaries over a seven-day period, recording the purpose of each trip, the mode of transport used, the (self-assessed) trip distance and duration, and other relevant information. We use NTS data for the period 2017 to 2019 and hence exclude the major shifts in travel patterns triggered by the Covid-19 pandemic. To create our sample, we only consider workers who are employed or self-employed full-time and we exclude holiday trips, business trips and trips where the mode of transport was not recorded. We separate workers into three categories according to their answers to the question "how often do you work from home?" (Table 1). We then compare the travel patterns of workers in each category, including trip distance, trip purpose and modal choice. We classify trips into commute and non-commute trips, then calculate one-way commute and one-way non-commute distance as well as the number of commute and non-commute trips in a week. See Table 2 for summary statistics. Table 2 shows over a quarter of the workers in our sample have

Table 1 Classification of sample by teleworking frequency

Teleworker type	Teleworking frequency	Number of observations	Percentage
Very frequent teleworker	3 or more times a week	405	3.7%
Frequent teleworker	Once or twice a week	908	8.4%
Non-teleworker	Less than once a week more than twice a month	269	2.5%
	Once or twice a month	563	5.2%
	Less than one a month more than twice a year	387	3.6%
	Once or twice a year	288	2.7%
	Less than once a year or never	7527	69.2%
	Does not apply	526	4.8%
	No answer	7	0.06%
Total		10880	100.0%

zero commute trips. However, we have not deleted any zero commute trips, because a measurement error[1] occurs for both teleworkers and non-teleworkers, and our purpose is only to estimate the difference of zero commute trips between the two types of workers.

CF provides data on the well-to-wheel emission intensity of transport modes, which includes the emissions from fuel production, processing, distribution and use, but excludes those associated with vehicle manufacture. CF disaggregates private cars by fuel type (diesel, petrol, hybrid, plug-in hybrid and EV) and size category (small, medium, large). VLS provides data

Table 2 Summary Statistics of Distance and Trips

Variables	min.	1st Quartile	median	mean	3rd Quartile	max.
Average one-way commute distance (miles)	0.0	0.0	5.0	9.6	12.0	364.0
Average number of commute trips per week	0.0	0.0	6.0	6.0	10.0	64.0
Average one-way non-commute distance (miles)	0.0	3.0	5.3	8.6	9.7	222.3
Average number of non-commute trips per week	0.0	6.0	12.0	14.2	20.0	120.0

Note: A return journey to work is counted as two trips. The values of distance and trips are lower than expected, probably because some workers reported no commute trips or no non-commute trips.

on the proportions of car/van ownership by fuel type from all the vehicle licenses in the UK. We combine CF and VLS data with NTS data to calculate the weighted average values of carbon intensity (kgCO_2/passenger mile) of private vehicle transport and other transport (Table 3 and Table 4) over the three-year survey period - assuming the average carbon intensity of the sample is the same as that for the fleet. We calculate weighted average values by weighting the emission factors of each type of vehicle by the proportion of passenger miles accounted for that vehicle in our NTS sample. We do this separately for commute and non-commute travel,

[1] Because how the NTS treats trip chaining, it is likely to underestimate the total number of commute trips. For example, a trip to escort children to school before commuting to work is recognised as a non-commute trip (Caldarola and Sorrell, 2022).

and for both current travel and for a scenario in which petrol and diesel cars have been replaced by battery-electric cars. The following explains the calculations in detail.

First, the unit "kg CO_2/*vehicle* mile" is converted to "kg CO_2/*passenger* mile" by occupancy rates.

$$CO_2 \text{ / } passenger\ mile = \frac{CO_2 \text{ / } vehicle\ mile}{occupancy\ rate}$$

Then, the **weighted average carbon intensity of private vehicle transport for commuting** is estimated from:

Table 3 Carbon Intensity of Private Vehicle Transport

	Data from CF **Carbon intensity** (kg CO_2/vehicle mile)					***Data from NTS***	
	diesel	petrol	hybrid	plug-in hybrid EV	battery EV	***Proportion of commute trips***	***Proportion of non-commute trips***
Large car/taxi	0.33	0.45	0.23	0.17	0.11	*21.6%*	*21.9%*
Medium car/taxi	0.26	0.3	0.17	0.15	0.09	*27.5%*	*27.9%*
Small car/taxi	0.22	0.24	0.16	0.09	0.07	*30.3%*	*30.7%*
van	0.39	0.35	-	-	0.1	*3.3%*	*3.3%*
motorbike	0.18					*0.80%*	*0.32%*

	Data from VLS **Ownership by Fuel Type**					***Data from NTS*** ***Occupancy Rate*** *(persons/vehicle)*
	diesel	petrol	hybrid	plug-in hybrid EV	battery EV	
Car	*59.1%*	*38.6%*	*1.6%*	*0.5%*	*0.3%*	*Commute: 1.17* *Non-commute: 1.67*
Van	*3.2%*	*96.6%*	*-*	*-*	*0.2%*	
motorcycles	-					*Commute 1.0* *Non-commute: 1.1* *(assumed)*

CF_{com}^{pv}

$= (CF_d^{car} \times \emptyset_d^{car} + CF_p^{car} \times \emptyset_p^{car} + CF_{hb}^{car} \times \emptyset_{hb}^{car} + CF_{pg}^{car} \times \emptyset_{pg}^{car} + CF_{be}^{car} \times \emptyset_{be}^{car}) \times \emptyset_{com}^{car}$

$+ (CF_d^{van} \times \emptyset_d^{van} + CF_p^{van} \times \emptyset_p^{van} + CF_{be}^{van} \times \emptyset_{be}^{van}) \times \emptyset_{com}^{van}$

$+ CF_{com}^{mc} \times \emptyset_{com}^{mc}$

$= 0.246\ kg\ CO_2/passenger\ miles$

, where *CF* denotes carbon intensity, ∅ denotes proportion, *com* denotes commute trips, *d*, *p*, *hb*, *pg* and *be* denotes diesel, petrol, hybrid, plug-in hybrid EV and battery EV respectively, *mc* denotes motorcycles.

Similarly, **weighted average carbon intensity of private vehicle transport for non-commute trips** is calculated.

$$CF_{non}^{pv} = 0.170\ kg\ CO_2/passenger\ mile$$

, where *non* denotes non-commute trips.

The above relates to current travel patterns. Corresponding estimates are then derived from a scenario in which petrol and diesel vehicles are replaced with battery-electric cars and vans:

0.077 kg CO2/passenger mile in commute trips;

0.053 kg CO2/passenger mile in non-commute trips.

Table 4 Carbon Intensity of Other Transport

	Carbon intensity (kg CO_2 / psg mile)	*Proportions in commute trips*	*Proportions in non-commute trips*
Walk / cycle	0.00	*5.8%*	*10.7%*
rail	0.06	*7.2%*	*2.9%*
Underground	0.04	*1.9%*	*0.6%*
London bus	0.13	*0.6%*	*0.3%*
Other bus	0.19	*0.9%*	*0.5%*
coach	0.04	*0.01%*	*0.1%*

The **weighted average carbon intensity of other transport for commute trips** is calculated as follows:

$$CF_{com}^{other} = CF_{w/c} \times \emptyset_{w/c} + CF_{rail} \times \emptyset_{rail} + CF_{ug} \times \emptyset_{ug} + CF_{Lb} \times \emptyset_{Lb} + CF_{ob} \times \emptyset_{ob} + CF_{cc} \times \emptyset_{cc} = 0.041\ kg\ CO_2/passenger\ mile$$

, where *w/c* denotes walking or cycling, *ug* denotes underground, *Lb* denotes London bus, *ob* denotes other bus, *cc* denotes coach; every other symbol follows the definitions above.

Similarly, the **weighted average carbon intensity of other transport in non-commute trips** is calculated.

$$CF_{non}^{other} = 0.020\ kg\ CO_2/passenger\ mile$$

3.2 Methodology

To study whether teleworking is associated with carbon emission savings and the relative importance of different factors in determining those savings, we employ Monte Carlo simulation and global sensitivity analysis (Figure 1). The following expands upon each step.

For the Monte Carlo simulation, we first construct a deterministic model that calculates the weekly travel-related carbon emissions for teleworkers and non-teleworkers. Using data from the NTS, we fit probability distributions to each of the variables in this model and estimate the associated parameters (we test two or more distributions for each variable and choose between them on the basis of goodness of fit). We then randomly draw values from these distributions to use as inputs in a Monte Carlo simulation of the difference in travel-related emissions between teleworkers and non-teleworkers. The output takes the form of a probability distribution of the difference in carbon emissions between teleworkers and non-teleworkers.

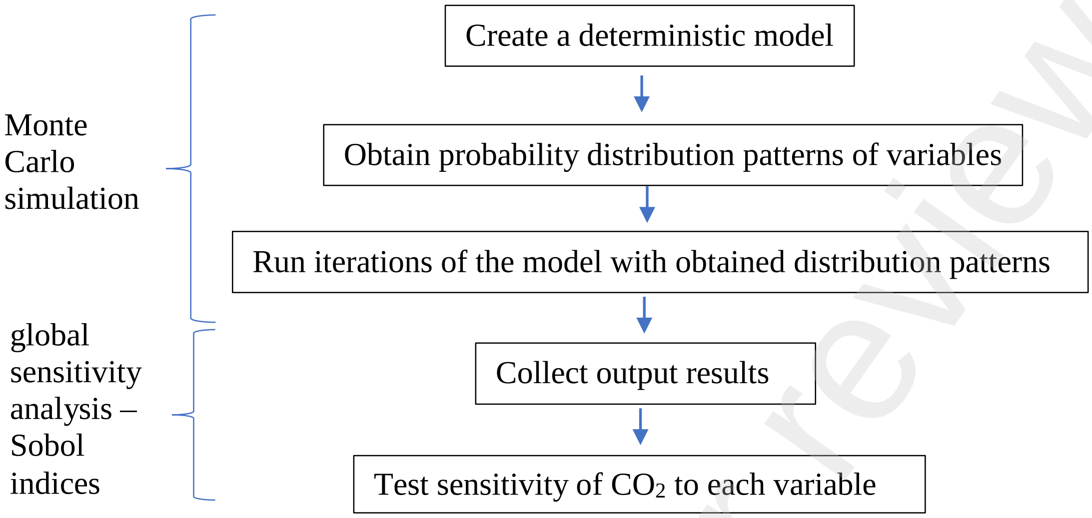


Figure 1

We also compare the above simulation with a second in which all fossil fuel cars and vans are replaced with battery EVs. This simulation is informed by the UK government policy that all new cars and vans must be fully zero emission at the tailpipe from 2030 [28]. However, battery EVs are not zero emission in our scenario since we assume the electricity generation mix remains unchanged from 2019.

For the sensitivity analysis, we estimate how much each variable contributes to the total variance of the output – thereby allowing us to rank the relative contribution of each variable to the uncertainty in emission savings. *Local* sensitivity analysis neglects the effect of correlations between each variable, while *global* sensitivity analysis includes this. We employ global sensitivity analysis because we expect these correlations to be important: for example, if the proportion of distance travelled by private vehicle is positively correlated with one-way commute distance, then the overall influence of one-way commute distance should include its association with private vehicle use. The following explains the difference between local and global sensitivity mathematically, then explains Sobol indices, a type of global sensitivity.

Mathematically, local sensitivity analysis involves changing one variable at a time from the base-case scenario [29]. If the output value is *y* and there are *n* input variables x_1, x_2,…, x_n, the local sensitivity of x_i is given by:

$$s_i = \frac{\partial y}{\partial x_i}, given\ base\ case(x_1^*, x_2^*, \dots, x_n^*) \qquad 1$$

Equation 1 measures the relative change of *y* to x_i by allowing x_i changes within its domain, but other variables remain the same as the base case $(x_1^*, x_2^*, \dots, x_n^*)$. However, Equation 1 can only accurately measure the sensitivity of *y* to *x* if there is no correlation between x_i and other variables. Otherwise, if x_i is correlated with other variables, the base case $(x_1^*, x_2^*, \dots, x_n^*)$ will no longer exist and *y* will have a different value, thus $\frac{\partial y}{\partial x_i}$ will not be accurate. Local sensitivity analysis does not consider correlations between input variables and other variables (Tian, 2013; Xu et al., 2004).

Another way to interpret local sensitivity analysis is by decomposing total variance. Each input variable $x_1, x_2, \dots, x_i, \dots, x_n$ contributes to some of the variance/uncertainty of the final output *y*. The importance of a variable is measured by how much it explains the total variance. Local sensitivity is when x_i changes its value one at a time, its contribution to the variance of output *V(y)*. Equation 1 can be rewritten as Equation 2 [30].

$$S_i = \frac{V(E(y|x_i = \widetilde{x_i}))}{V(y)} \qquad 2$$

where $\widetilde{x_i}$ is a generic value of x_i, which takes any specific value within its domain. $V(E(y|x_i = \widetilde{x_i}))$ measure the variance of the expected value of *y* given an x_i. The whole index S_i measures the share of variance in y that is dependent upon input variable x_i, ignoring the correlation between x_i and other input variables.

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

$$s_{Ti} = \frac{\partial y}{\partial x_i}, where\ values\ of\ (x_1, x_2, \dots, x_n\ )\ are\ not\ fixed \qquad 3$$

Specifically, this study uses a 'the total effect Sobol index' which captures this global sensitivity [22, 30, 31]. That is, the index measures the contribution to the variance of y from x_i taking into account x_i's correlation with other inputs. Using$x_{\sim i}$ to denote variables other than x_i, Sobol indices can be estimated in three steps.

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:

$$E_{x_{\sim i}}(y|x_i) \qquad 4$$

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

$$V_{x_i}(E_{x_{\sim i}}(y|x_i)) \qquad 5$$

Equation 5 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*:

$$S_{Ti} = \frac{V_{x_i}(E_{x_{\sim i}}(y|x_i))}{V(y)} \qquad 6$$

Equation 6 indicates the contribution to the total variance of *y* by x_i considering its correlations with other variables. In Equation 6, 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.

$$\mathrm{S_T} = \mathrm{S_1} + \mathrm{S_2} + \mathrm{S_3} + \mathrm{S_{12}} + \mathrm{S_{13}} + \mathrm{S_{23}} + \mathrm{S_{123}} = 1 \qquad 7$$

, 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_{12} and S_{12} 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}.

$$S_{T1} = S_1 + S_{12} + S_{13} + S_{123} \quad 8$$

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

3.3 Deterministic Model

This section summarizes our model for estimating the difference in carbon emissions between teleworkers (*TW*) and non-teleworkers (*N*). We run two separate models - for frequent and very frequent teleworkers respectively.

The deterministic model has three equations and thus three basic steps. Step 1 (Equation 9) calculates the baseline scenario of one non-teleworker's weekly travel carbon emission ($CO2_N$) as the sum of the emissions from commuting ($CO2_{N-com}$) and non-commute trips ($CO2_{N-non}$). Step 2 (Equation 10) calculates the corresponding emissions for teleworkers ($CO2_{TW}$), while Step 3 (Equation 11) calculates the difference between the two:

$$CO2_N = CO2_{N-com} + CO2_{N-non} \quad 9$$

$$CO2_{TW} = CO2_{TW-com} + CO2_{TW-non} \quad 10$$

$$\Delta CO2 = CO2_{TW} - CO2_N = \Delta CO2_{com} + \Delta CO2_{non} \quad 11$$

We separately estimate the difference in emissions from commute trips ($\Delta CO2_{com}$) and non-commute trips ($\Delta CO2_{non}$). Table 5 defines the relevant input variables.

Table 5 Definition and Data Source of Variables

Definition	Unit	Variable	Details of definition	Input type	Data source
Average one-way distance per trip	Miles	L_{N-com}	**Teleworkers**' average one-way **commute** distance in a week	Continuous distribution	National Travel Survey, 2017-2019
		L_{N-com}	**Non-teleworkers'** average one-way **commute** distance in a week		
		L_{TW-non}	**Teleworkers**' average one-way **non-commute** distance in a week		
		L_{N-non}	**Non-teleworkers'** average one-way **non-commute** distance in a week		
Number of trips	Integer	N_{TW-com}	**Teleworkers'** number of **commute** trips in a week	Discrete distribution	
		N_{N-com}	**Non-teleworkers'** number of **commute** trips in a week		
		N_{TW-non}	**Teleworkers'** number of **non-commute** trips in a week		
		N_{N-non}	**Non-teleworkers'** number of **non-commute** trips in a week		
Fraction of distance travelled by private vehicle transport	Fraction	$\emptyset^{pv}_{TW-com}$	fraction of **teleworkers**' distance travelled in **commute** trips	Continuous distribution	
		$\emptyset^{pv}_{N-com}$	fraction of **non-teleworkers'** distance travelled in **commute** trips		
		$\emptyset^{pv}_{TW-non}$	fraction of **teleworkers'** distance travelled in **non-commute** trips		
		$\emptyset^{pv}_{N-non}$	fraction of **non-teleworkers'** distance travelled in **non-commute** trips		
Carbon emission conversion factor	kg CO_2 /passenger mile	CF^{pv}_{com}	Carbon-dioxide emission conversion factor for **private vehicle** transport in **commute** trips	Weighted average value	2020 UK Government Greenhouse Gas Conversion Factor; 2019 Vehicle Licensing Statistics
		CF^{other}_{com}	Carbon-dioxide emission conversion factor for **other** transport in **commute** trips		
		CF^{pv}_{non}	Carbon-dioxide emission conversion factor for **private vehicle** transport in **non-commute** trips		
		CF^{other}_{non}	Carbon-dioxide emission conversion factor for **other** transport in **non-commute** trips		

Commute trip - $\Delta CO2_{com}$

The carbon emissions from weekly commuting is given by the product of total commute distance and the carbon intensity of the relevant mode (Equation 12 and Equation 13). We estimate weekly commute distance (passenger miles) from the product of the mean distance per trip per worker (*L*) and the number of trips (*N*) per week. We estimate weekly commuting emissions from the product of weekly commute distance, the share of each mode ($\emptyset$) and the carbon intensity of that mode (*CF*). We then calculate the difference between teleworker's and non-teleworker's emissions (Equation 14).

Difference in commute emissions - $\Delta CO2_{non}$

Non-teleworker's commute CO_2 in a week:

$$CO2_{N-com} = L_{N-com} \times N_{N-com} \times \left(CF_{com}^{pv} \times \emptyset_{N-com}^{pv} + CF_{com}^{other} \times \emptyset_{N-com}^{other}\right) \quad 12$$

Teleworker's commute CO_2 in a week:

$$CO2_{TW-com} = L_{TW-com} \times N_{TW-com} \times \left(CF_{com}^{pv} \times \emptyset_{TW-com}^{pv} + CF_{com}^{other} \times \emptyset_{TW-com}^{other}\right) \quad 13$$

Difference between the two:

$$\Delta CO2_{com} = CO2_{N-com} - CO2_{TW-com} \quad 14$$

We follow a similar process for non-commute emissions:

Difference in non-commute emissions - $\Delta CO2_{non}$

Non-teleworker's non-commute CO_2 in a week:

$$CO2_{N-non} = L_{N-non} \times N_{N-non} \times \left(CF_{non}^{pv} \times \emptyset_{N-non}^{pv} + CF_{non}^{other} \times \emptyset_{N-non}^{other}\right) \quad 15$$

Teleworker's non-commute CO_2 in a week:

$$CO2_{TW-non} = L_{TW-non} \times N_{TW-non} \times \left(CF_{non}^{pv} \times \emptyset_{TW-non}^{pv} + CF_{non}^{other} \times \emptyset_{TW-non}^{other}\right) \quad 16$$

Difference between the two:

$$\Delta CO2_{non} = CO2_{N-non} - CO2_{TW-non} \quad (17)$$

4. RESULTS

The results have two parts, Monte Carlo simulation and sensitivity analysis.

4.1 Distribution fitting and Monte Carlo simulation

The Monte Carlo simulation has two parts. First, fitting statistical distributions to each of the input variables within our model. Second, taking random samples from these distributions and using these to estimate the difference in carbon emissions between teleworkers and non-teleworkers.[2]

As described in Section 3.2, we fit separate distributions for non-teleworkers, very frequent teleworkers and frequent teleworkers. First, we look at the histogram of one-way commute distance for very frequent teleworkers (Figure 2).

Figure 2 resembles a lognormal distribution but includes including many zero values. Following Aitchison [34] we fit a zero-modified lognormal distribution that considers the proportion of zero values. If $f(t)$ denotes the probability density function of a log-normally distributed random variable t with a mean μ and variance σ^2, then the probability density function $h(x)$ of a zero-modified log-normally distributed variable x is given by:

[2] We use the R packages "fitdistrplus" 32. Delignette-Muller, M.L. and C. Dutang, *fitdistrplus: An R package for fitting distributions.* Journal of statistical software, 2015. **64**: p. 1-34. for the first stage and "sensitivity" 33. Bertrand Iooss, S.D.V., Alexandre Janon, Gilles Pujol, etc., *sensitivity: Global Sensitivity Analysis of Model Outputs*. 2021. for the second.

$$h(x) = \begin{cases} \emptyset, for\ x = 0 \\ (1-\emptyset)f(x), for\ x \neq 0 \end{cases}$$

Where $f(t) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(lnt-\mu)^2}{2\sigma^2}}$, and $\emptyset$ is the fraction of zero values.

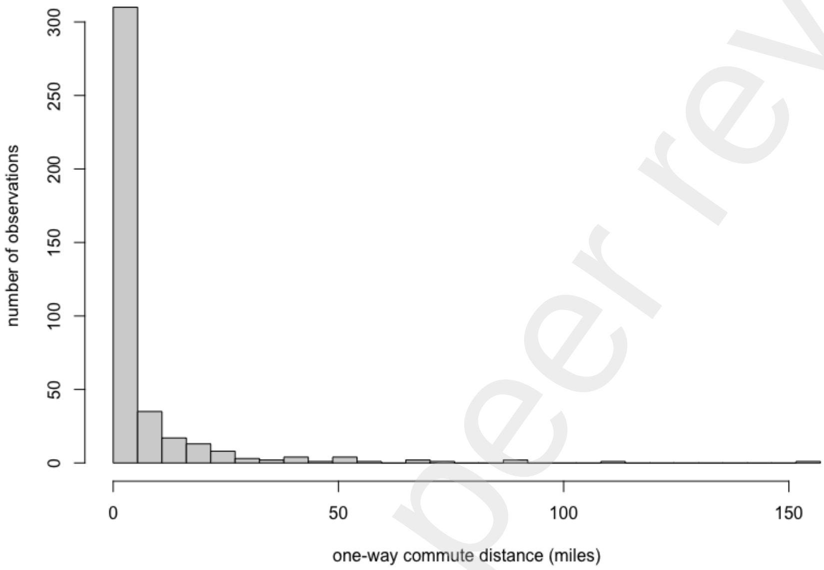


Figure 2 Histogram of One-Way Commute Distance of Very Frequent Teleworkers

We choose not to use statistical goodness of fit tests, since these "are not objective tools to decide whether a fitted distribution well describes a dataset" [32]. Instead, we test each model's goodness of fit with graphical methods recommended by Delignette-Muller and Dutang [32] – see Figure 3. These demonstrate that: a) the theoretical model (red curve) approximately follows the histogram of empirical observations; b) the quantile-quantile (Q-Q) plot approximates a straight line, except for a few extreme values; c) the empirical cumulative distribution function (CDF) observations strictly overlap with the theoretical CDF (red curve); and d) the probability-probability (P-P) plot approximately follows a straight line. We therefore conclude that a zero-modified lognormal model provides a good fit to the observed distribution of one-way commute distance for this category of workers.

Using the same method, we find that one-way non-commute distance, the number of commute trips and the number of non-commute trips all follow zero-modified lognormal distributions for each category of worker.

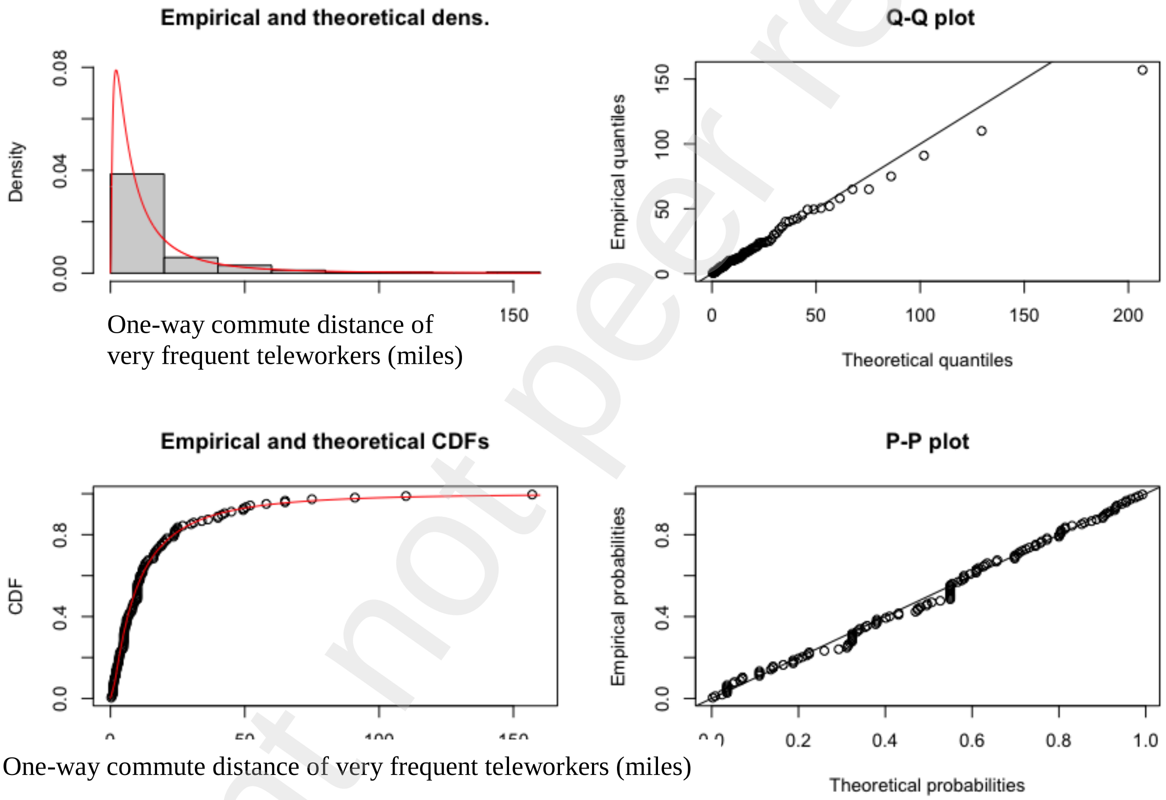


Figure 3 Goodness of Fit Graphs – (One-Way Commute Distance – Very Frequent Teleworkers)

Similarly, we examine the histogram of the proportion of distance travelled by private vehicles for commute trips (Figure 4).[3] This indicates that most workers commute entirely by car or entirely by other modes, with relatively few workers using a mix of the two. We explored a

[3] We use two categories of transport mode: private vehicles and 'other' (**Error! Reference source not found.**). The reason we classify transport modes as such is because we cannot fit any distribution if we consider all types given the condition that proportions of all transport modes should add up to 1.

number of possible distributions (Dirichlet, uniform, normal, lognormal) and found that the beta distribution provided the best fit (Figure 5). We consider our use of two categories of transport mode to be acceptable, since 70-80% of a commute distance is by private vehicles and the carbon intensity of private vehicle travel is much higher than for other modes (Table 3 and Table 4).

If variable *x* follows a beta distribution ($x \sim beta(a, b)$), then the probability density function is given by:

$$f(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{b-1}$$

Where $\Gamma(a) = (a-1)!$. For example, $\Gamma(4) = (4-1)! = 3 \times 2 \times 1 = 6$.

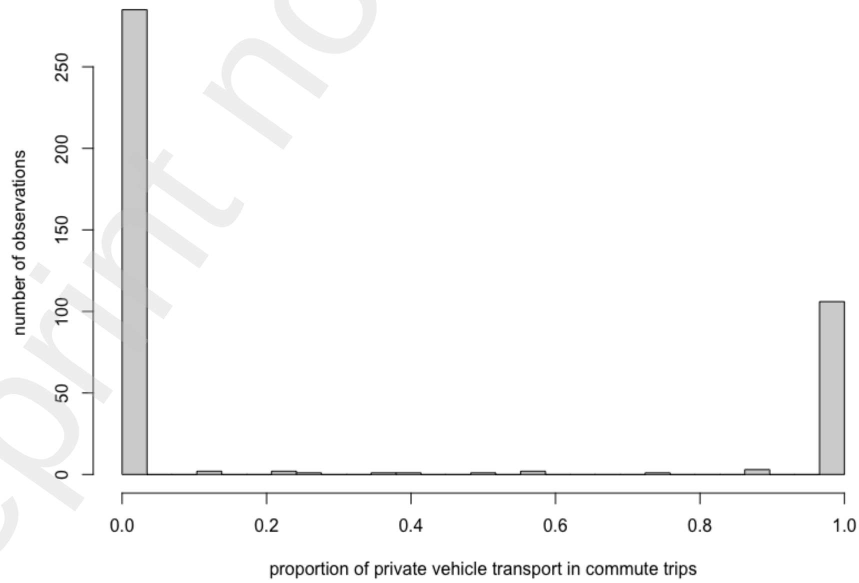


Figure 4 Histogram of Proportion of Private Vehicle Transport in Commute Trips of Very Frequent Teleworkers

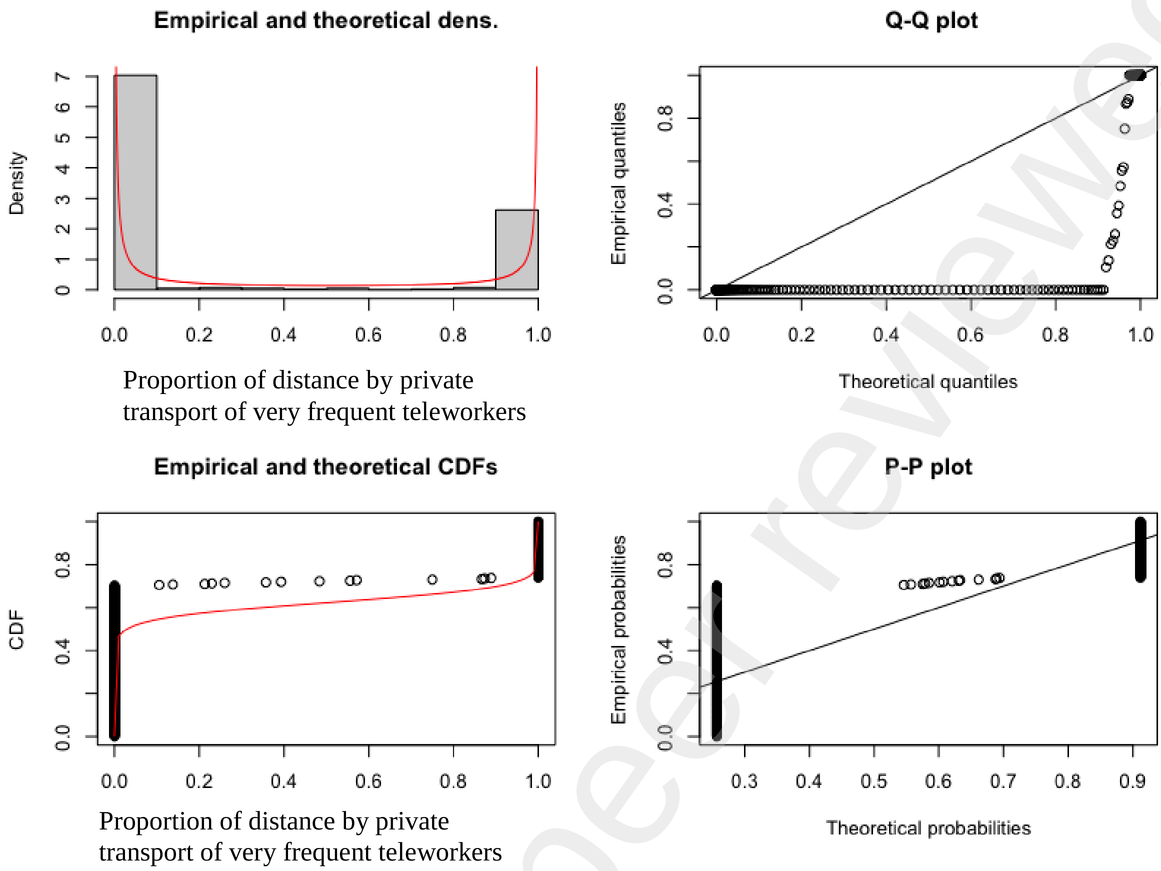


Figure 5 Goodness of Fit Graphs (Proportion of Distance by Private Transport - Very Frequent Teleworkers)

With the same method, we find that the proportion of non-commute distance by private transport follows a beta distribution for each category of worker.

Table 6 compares the mean, standard deviation and parameter values of the fitted distributions. We can see that, on average, very frequent and frequent teleworkers take 32-34% fewer commute trips in a week compared to non-teleworkers. Very frequent teleworkers also have a significantly higher proportion of zero commute trips, presumably because many of the former work at home all week and do not commute at all. However, the mean one-way commute distance for very frequent teleworkers is 17% longer than that for frequent teleworkers and 90%

Table 6 Mean, standard deviation and parameter values of the fitted distributions – comparing teleworkers with non-teleworkers

		Non-teleworkers	Very frequent teleworkers	Frequent teleworkers
Number of commute trips in a week	mean	7.1	4.7	4.8
	standard deviation	1.8	2.2	2.0
	proportion of *0* trip	23%	63%	29%
One-way commute distance (miles)	mean	7.1	8.3	13.5
	standard deviation	2.8	3.3	3.2
Number of non-commute trips in a week	mean	10.6	13.0	11.9
	standard deviation	2.4	2.3	2.3
	proportion of *0* trip	5%	3%	2%
One-way non-commute distance (miles)	mean	5.8	6.2	6.6
	standard deviation	2.4	2.3	2.4
Private vehicle proportion in commute trips	*a*	0.10	0.06	0.08
	b	0.07	0.11	0.08
Private vehicle proportion in non-commute trips	*a*	0.24	0.29	0.30
	b	0.09	0.10	0.10

Note: one-way commute distance, number of commute trips, one-way non-commute distance and number of non-commute trips follow zero-modified lognormal distributions. The proportion of private vehicles in commute and non-commute trips both follow beta distributions. Higher values of the 'a' parameters and lower values of the 'b' parameters value indicate higher proportion of distance travelled by private vehicle.

longer than that of non-teleworkers'. This difference will offset the carbon emission savings from fewer commute trips.

Table 6 also shows that very frequent teleworkers and frequent teleworkers take 23% and 12% more non-commute trips than non-teleworkers. These additional trips will further offset the emission savings from fewer commutes. Furthermore, the mean distance of these trips is longer than those for non-teleworkers - by 7% and 14% respectively.

However, both types of teleworkers are less likely to use private vehicles when commuting. As private vehicles have higher carbon intensity than other transport (Table 3 and Table 4), this may reduce teleworkers' emissions. Nevertheless, teleworkers are more likely to use private vehicle in non-commute trips, which could again offset the emission savings.

We have insufficient data to fit statistical distributions for the carbon intensity of private vehicles and other modes. We therefore estimate a mean value of carbon emissions per passenger mile for each category of travel (Section 3.1) and assume a truncated normal distribution of emission factors, with a lower bound of zero and a standard deviation of 10% [35]. Table 7 shows the relevant parameters for two vehicle modes (private vehicles and other), two travel purposes (commute and non-commute) and two assumptions for private vehicles (current carbon intensity and carbon intensity after replacement with battery-electric vehicles) (see Section 3.2). The carbon intensity is higher for commute trips than for non-commute trips because the former have a lower average vehicle occupancy. Private vehicle transport has a much higher carbon intensity than other modes. Assuming that modal share, average vehicle occupancy and electricity generation mix remain unchanged, shifting from the current mix of cars and vans to battery-electric cars and vans will reduce carbon emissions for private vehicle transport by 69%.

Table 7 Parameters of Carbon Intensity under Truncated Normal Distribution

		mean (kg CO_2/passenger miles)
Current scenario - commute:		
	Private vehicle transport	0.246
	Other transport	0.041
Current scenario - non-commute:		
	Private vehicle transport	0.170
	Other transport	0.020
No fossil fuel cars/vans scenario - commute:		
	Private vehicle transport	0.077
	Other transport	0.041
No fossil fuel cars/vans scenario - non-commute:		
	Private vehicle transport	0.053
	Other transport	0.020

Note: We assume a standard deviation of 0.10 for both modes, and a lower bound of the distribution of 0. The no fossil fuel cars/vans scenario assumes the replacement of conventional cars and vans with EVs, with the other modes remaining unchanged.

Next, we use the probability distribution results from Table 6 and Table 7 to run Monte Carlo simulations. Table 8 summarizes the simulation results for our three categories of worker. Each section shows a separate simulation for commute trips and total travel, and for both current vehicles and battery-electric vehicles. We present the first quartile, mean, median, 3rd quartile and standard deviation estimates of weekly transport carbon emissions for non-teleworkers, together with the percentage difference in weekly carbon emissions for frequent and very frequent teleworkers. The Welch t-tests indicate whether the difference in mean carbon emissions is statistically significant.

Table 8 Difference between Teleworkers and Non-teleworker in Transport CO_2

Unit: kg CO_2/week	1st Qu.	Median	Mean	3rd Qu.	s.d.	T test
Commute CO_2 under current scenario						
non-teleworkers	2.9	7.7	19.0	20.2	37.9	
very frequent teleworkers	-100%	-100%	-66%	-90%	-9%	Less****
frequent teleworkers	-100%	-51%	6%	-20%	71%	Uncertain
Total transport CO_2 under current scenario						
non-teleworkers	7.1	17.6	33.3	39.3	53.3	
very frequent teleworkers	-27%	-20%	-6%	-11%	8%	Less**
frequent teleworkers	25%	26%	39%	29%	66%	More****
Commute CO_2 assuming no fossil fuel cars/vans						
non-teleworkers	1.5	4.4	11.4	11.3	28.3	
very frequent teleworkers	-100%	-100%	-62%	-87%	-22%	Less****
frequent teleworkers	-100%	-50%	2%	-13%	13%	Uncertain
Total transport CO_2 assuming no fossil fuel cars/vans						
non-teleworkers	4.2	10.5	20.7	23.6	38.2	
very frequent teleworkers	-32%	-20%	-4%	-10%	0.3%	Less*
frequent teleworkers	21%	25%	39%	31%	73%	More****

Note: very frequent teleworkers work from home 3-5 days a week; frequent teleworkers work from home 1-2 days a week; "-100%" denotes that the original carbon emissions is 0; * , **, *** and **** represent 10%, 5%, 1% and 0.1% significance level respectively when testing mean values with Welch T test.

We can see from Table 8 that very frequent teleworkers have much lower carbon emissions for commuting than non-teleworkers. The "-100%" values for the first quantile and median means that the original values are zero, which can be explained by the fact that very frequent teleworkers have much higher proportion of zero commute trips (see also Table 6), which results in significantly lower carbon emissions. Frequent teleworkers, however, have slightly higher mean values of commute emissions than non-teleworkers, but lower median and third quantile values. This indicates that most frequent teleworkers have lower emissions than non-teleworkers, but a few have very high commute emissions. The high standard deviation indicates the presence of extreme values. Hence, it is uncertain whether the average commute emissions from teleworkers are higher than those of non-teleworkers. We can infer from Table 6 that the longer one-way commute distance of teleworkers mitigates the emission savings from fewer commute trips.

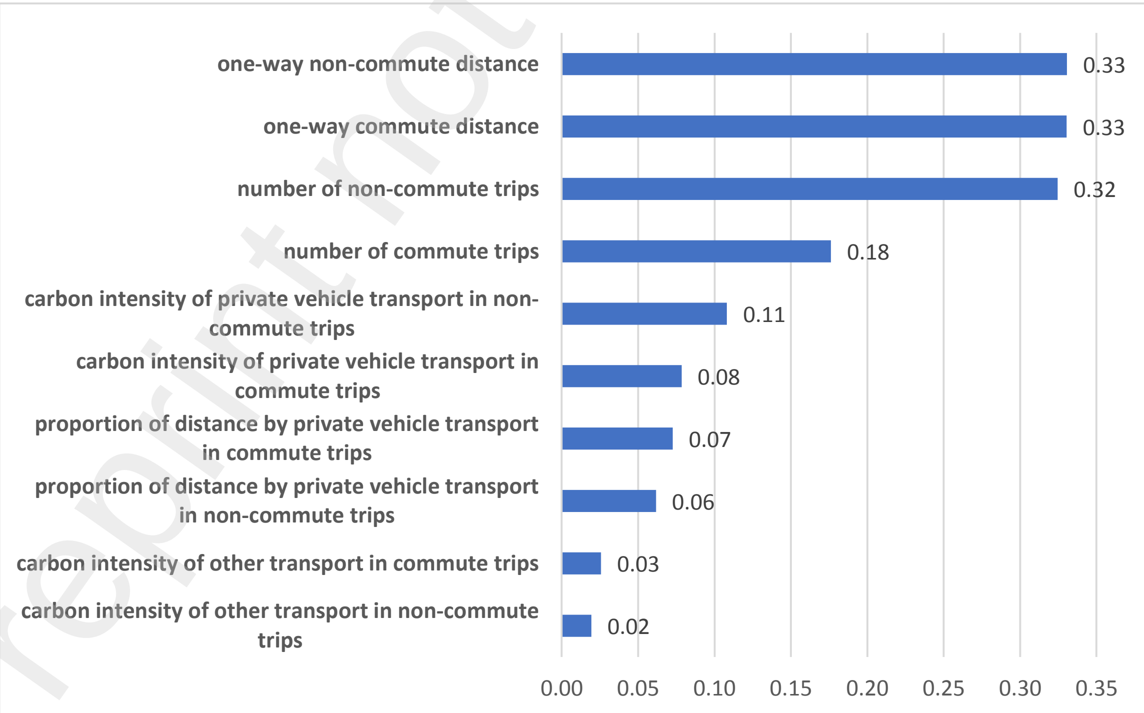
Very frequent teleworkers also have lower total (commute + non-commute) carbon emissions than non-teleworkers (Table 8). However, the difference is smaller than for commute emissions alone. This is because very frequent teleworkers have longer one-way commute distance, more non-commute trips and longer one-way non-commute distance (Table 6). All three factors offset the emission savings from fewer commute trips. In comparison, frequent teleworkers have significantly higher total transport carbon emissions than non-teleworkers. Since their average commute emissions are similar, this means frequent teleworkers have much higher non-commute carbon emissions than non-teleworkers. We can see from Table 6 that this is because frequent teleworkers have more non-commute trips, as well as having longer one-way non-commute distances.

Replacing conventional cars and vans with EVs leads to similar results to the current scenario: namely, with very frequent teleworkers having lower commuting and total emissions than non-teleworkers, and with frequent teleworkers have higher total emissions. The mean emissions are 38-40% lower when assuming no fossil fuel cars and vans compared to the current scenario for all types of workers. However, the percentage differences of emissions are similar between both types of teleworkers and non-teleworkers.

4.2 Global sensitivity analysis

Figure 6 shows the global sensitivity of the modelled variation of total transport carbon emissions to each input variable. In other words, it indicates the relative contribution of different variables to the variance in total emissions. The global sensitivity is measured by the Sobol indices (Section 3.2), with a higher index indicating a larger contribution to total carbon emissions. We can see from Figure 6 that the three most important variables are one-way commute distance, one-way non-commute distance and the number of non-commute trips. As we are analysing 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, such as modal choice and the number of non-commute trips. For example, if people have shorter commute and non-commute distances, they are more likely to walk and cycle for those trips. Therefore, considering correlations between variables, two key strategies

Figure 6 Global Sensitivity of Total Transport Carbon Emissions of All Workers



Note: the numbers are the original Sobol indices.

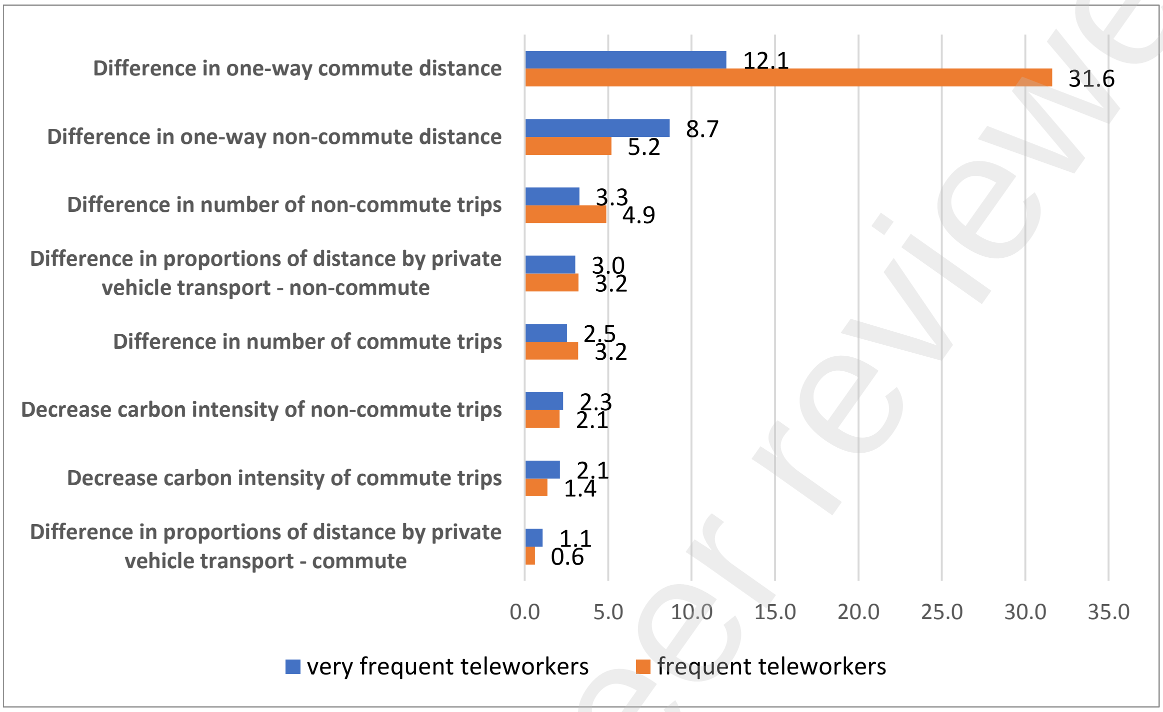
for reducing carbon emissions are to encourage workers to live closer to their workplaces and to ensure easy access to local facilities (i.e., shops, pharmacies, etc.).

In comparison, variations in the carbon intensity of household vehicles explains a much smaller proportion of the variance in total emissions. At present, differences in the carbon intensity of private vehicles largely result from differences in the size and fuel efficiency of those vehicles; as fossil fuel cars are prevalent in most households currently, these differences are not substantial enough to heavily influence emissions. However, in the intermediate stage when households are replacing fossil fuel vehicles with EVs, this variable could become more important. Once all households have EVs, there will be little or no variation in the carbon intensity of private vehicles, so this variable again will not contribute much to the variance in total emissions.

The proportion of distance travelled by private vehicles makes a relatively small contribution to the variance in carbon emissions (Figure 6). This is because we are sampling from the current distribution of modal choice, and private vehicles overwhelmingly dominate personal travel, together with the associated emissions. However, the proportion of distance accounted for by other modes could change in the future, e.g., if everyone cycled to work, then commute emissions would be eliminated.

Figure 7 shows the sensitivity of the difference of total transport carbon emissions between very frequent teleworkers and non-teleworkers, and between frequent teleworkers and non-teleworkers. The figure shows which factors are the most important in explaining the difference of the total transport emissions. One-way commute distance is the most important variable for both types of teleworkers, especially for frequent teleworkers because they still commute 3-4

Figure 7 Global sensitivity of the difference in total transport emissions between teleworkers and non-teleworkers



Note: the sensitivity scores are the original Sobol indices times 1000. Very frequent teleworkers work from home 3-5 times/week, frequent teleworkers work from home 1-2 times a week.

times a week. This can be explained not only by the fact that one-way commute distance is a key driver of commuting emissions, but also the influence of one-way commute distance on other variables. For instance, people who live further from their workplaces are more likely to live in rural areas, further from local facilities; thus, they tend to travel further for non-commute purposes and to use private vehicles more often when travelling. These correlated effects from longer one-way commute distance leads to much higher emissions.

One-way non-commute distance is the second most important factor in explaining the difference in carbon emissions between teleworkers and non-teleworkers (Figure 7). This indicates the importance of encouraging high-density, mixed-use developments that provide easy access to non-work destinations such as shopping, leisure and restaurants. Absent such developments, non-commuting travel will be dominated by long-distance trips in private cars.

The remaining variables have similar importance (Figure 7), which does not mean they are unimportant in reducing emissions, but from the current probability distributions they are less likely to vary in the direction of emission savings for teleworkers. For example, the difference in number of non-commute trips makes a relatively small contribution to the difference in emissions between teleworkers and non-teleworkers, probably because from the distributions in our sample, it is less likely that teleworkers could radically reduce their number of non-commute trips to have much less emissions than non-teleworkers. Similarly, reducing carbon intensity of private vehicles probably would work the same for both teleworkers and non-teleworkers; thus, reducing carbon intensity is less likely to make teleworkers have less emissions than non-teleworkers. This does not understate the importance of reducing the carbon intensity of private travel, but progress in that direction would make little contribution to the emission savings from teleworking.

5. Conclusion

The literature on the environmental benefits of teleworking has tended to employ proxies for environmental impact such as distance travelled rather than more direct measures such as carbon emissions. It is also paid insufficient attention to the sensitivity of those benefits to variations in key variables, such as one-way commute distance. Focusing upon English teleworkers, this paper has addressed these limitations with the help of Monte Carlo simulation techniques combined with 'total effect Sobel indices'. The latter indicates the contribution of variables to the variance in travel-related emissions, taking into account their correlation with other variables. The assumed distribution of each variable was based upon the observed distribution from over 10,000 workers during the period of years 2017-2019, but we also explored a comparative static scenario in which conventional vehicles were replaced by EVs.

The results indicate that people who telework 3-5 times a week have *lower* emissions for both commuter travel and total travel than non-teleworkers. However, people who telework 1-2 times a week have *higher* travel-related emissions than non-teleworkers. This is explained by the fact that teleworkers tend to live further from their workplace than non-teleworkers (so they have longer one-way commute distances), tend to live further from amenities than non-teleworkers (so they have longer one-way non-commute distances), and tend to take more non-commute trips than non-teleworkers. Hence, if teleworkers are only working from home a couple of days a week, the emission savings from fewer commuting trips may be more than offset by the additional emissions from longer travel distances and more non-commute trips. Hence, if low-frequency teleworking is associated with low-density living patterns, the net result may be *higher* travel-related emissions.

The global sensitivity analysis results show that the difference of one-way commute distance between teleworkers and non-teleworkers has the highest overall importance in explaining their transport carbon emission difference. This is not only because that one-way commute distance itself heavily influences commute emissions, but also because its correlations with other variables largely affects emissions, e.g., people who live further from their workplaces tend to use private vehicles more often and are more likely to live in more rural areas further from local facilities. The second and the third most important variables are one-way non-commute distance and the number of non-commute trips. These variables further confirm the significance of a good built environment to enable environmental benefits from teleworking. A good built environment facilitates people to live closer to their workplaces and local facilities, and to travel fewer trips to access their daily needs, e.g., groceries, medications, and social activities.

One important limitation of our study is our use of historical data within our simulations. Our estimates of the relative importance of different variables are based upon the range of variation in those variables over the two-year period prior to the Covid pandemic. Future technical and policy changes could lead to much larger variations in these variables, such as a much greater use of active travel modes and a much wider range of households engaging in teleworking. However, changes that affect both teleworkers and non-teleworkers to a similar degree may not have a significant influence on the environment benefits of teleworking - as demonstrated by our EVs scenario.

A key implication from our study is the need to ensure that the increased popularity of teleworking does not encourage people to relocate to areas that are further from their workplace, and/or further from retail, leisure and other destinations, and/or poorly served by public transport ('telesprawl'). Unfortunately, there are early signs of trends in this direction. For example, the Resolution Foundation [36] found that house prices in the least-populated English local authorities increased by more than 10% between February 2020 and June 2021, compared to only 6% in the most populated authorities. These 'telesprawl' trends are not encouraging, but if more teleworkers become full-time teleworkers, i.e., those who only work from home and do not commute at all, then the environmental benefits of teleworking can still be maximized.

Another important implication is the importance of urban planning on the environmental effects of teleworking. Good urban planning enables teleworkers to travel less to access essential facilities, such as schools and shops. In the UK, home builders are required to set funding for building local infrastructure, but there have been debates on the amount of funding and problems on the effectiveness of the regulation [37]. To create a clean and green environment, it is fundamental to ensure that such regulations come into effect so that residents could settle in a well-designed neighborhood without the need to travel too far for their daily activities.

CRediT authorship contribution statement

Yao Shi: Methodology, Software, Validation, Formal analysis, Visualization, Conceptualization, Writing – original draft, Writing – review & editing.

Steven Sorrell: Supervision, Conceptualization, Writing – review & editing.

Tim Foxon: Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

1. Cerqueira, E.D.V., et al., *Does working from home reduce CO2 emissions? An analysis of travel patterns as dictated by workplaces.* Transportation Research Part D: Transport and Environment, 2020. **83**: p. 102338.
2. e Silva, J.d.A. and P.C. Melo, *Does home-based telework reduce household total travel? A path analysis using single and two worker British households.* Journal of Transport Geography, 2018. **73**: p. 148-162.
3. Zhu, P., *Telecommuting, household commute and location choice.* Urban Studies, 2013. **50**(12): p. 2441-2459.
4. Zhu, P. and S.G. Mason, *The impact of telecommuting on personal vehicle usage and environmental sustainability.* International Journal of Environmental Science and Technology, 2014. **11**(8): p. 2185-2200.
5. Mokhtarian, P.L., G.O. Collantes, and C. Gertz, *Telecommuting, residential location, and commute-distance traveled: evidence from State of California employees.* Environment and Planning A, 2004. **36**(10): p. 1877-1897.
6. Henderson, D.K., B.E. Koenig, and P.L. Mokhtarian, *Using travel diary data to estimate the emissions impacts of transportation strategies: The Puget Sound Telecommuting Demonstration Project.* Journal of the Air & Waste Management Association, 1996. **46**(1): p. 47-57.
7. Helminen, V. and M. Ristimäki, *Relationships between commuting distance, frequency and telework in Finland.* Journal of Transport Geography, 2007. **15**(5): p. 331-342.
8. Ravalet, E. and P. Rérat, *Teleworking: decreasing mobility or increasing tolerance of commuting distances?* Built Environment, 2019. **45**(4): p. 582-602.
9. Caldarola, B. and S. Sorrell, *Do teleworkers travel less? Evidence from the English National Travel Survey.* Transportation Research Part A: Policy and Practice, 2022. **159**: p. 282-303.
10. Koenig, B.E., D.K. Henderson, and P.L. Mokhtarian, *The travel and emissions impacts of telecommuting for the State of California Telecommuting Pilot Project.* Transportation Research Part C: Emerging Technologies, 1996. **4**(1): p. 13-32.
11. Stiles, J. and M.J. Smart, *Working at home and elsewhere: daily work location, telework, and travel among United States knowledge workers.* Transportation, 2020: p. 1-31.
12. Hook, A., B.K. Sovacool, and S. Sorrell, *A systematic review of the energy and climate impacts of teleworking.* Environmental Research Letters, 2020. **15**(9): p. 093003.
13. O'Brien, W. and F.Y. Aliabadi, *Does telecommuting save energy? A critical review of quantitative studies and their research methods.* Energy and Buildings, 2020: p. 110298.
14. Kim, S.-N., S. Choo, and P.L. Mokhtarian, *Home-based telecommuting and intra-household interactions in work and non-work travel: A seemingly unrelated censored regression approach.* Transportation Research Part A: Policy and Practice, 2015. **80**: p. 197-214.
15. Lachapelle, U., G.A. Tanguay, and L. Neumark-Gaudet, *Telecommuting and sustainable travel: reduction of overall travel time, increases in non-motorised travel and congestion relief?* Urban Studies, 2018. **55**(10): p. 2226-2244.

16. Wang, K. and B. Ozbilen, *Synergistic and threshold effects of telework and residential location choice on travel time allocation.* Sustainable Cities and Society, 2020. **63**: p. 102468.
17. Chakrabarti, S., *Does telecommuting promote sustainable travel and physical activity?* Journal of Transport & Health, 2018. **9**: p. 19-33.
18. Van Lier, T., A. de Witte, and C. Macharis, *How worthwhile is teleworking from a sustainable mobility perspective? The case of Brussels Capital region.* European Journal of Transport and Infrastructure Research, 2014. **14**(3).
19. Elldér, E., *Telework and daily travel: New evidence from Sweden.* Journal of Transport Geography, 2020. **86**: p. 102777.
20. O'keefe, P., et al., *The impacts of telecommuting in Dublin.* Research in Transportation Economics, 2016. **57**: p. 13-20.
21. Kitou, E. and A. Horvath, *Energy-related emissions from telework*. 2003, ACS Publications.
22. Craglia, M. and J. Cullen, *Modelling transport emissions in an uncertain future: What actions make a difference?* Transportation Research Part D: Transport and Environment, 2020. **89**: p. 102614.
23. Smith, C.J., et al., *Current fossil fuel infrastructure does not yet commit us to 1.5 C warming.* Nature communications, 2019. **10**(1): p. 1-10.
24. Guerin, T.F., *Policies to minimise environmental and rebound effects from telework: A study for Australia.* Environmental Innovation and Societal Transitions, 2021. **39**: p. 18-33.
25. Department for Transport, *National Travel Survey, 2002-2019*, U.D. Service, Editor. 2020.
26. BEIS, *Greenhouse gas reporting: conversion factors 2020*. 2020.
27. Department for Transport and DVLA, *Vehicle licensing statistics data tables*. 2019.
28. Department for Transport and Office for Zero Emission Vehicles, *Consulting on ending the sale of new petrol, diesel and hybrid cars and vans*. 2020.
29. Razavi, S. and H.V. Gupta, *What do we mean by sensitivity analysis? The need for comprehensive characterization of "global" sensitivity in E arth and E nvironmental systems models.* Water Resources Research, 2015. **51**(5): p. 3070-3092.
30. Saltelli, A., et al., *Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index.* Computer physics communications, 2010. **181**(2): p. 259-270.
31. Sobol, I.M., *Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates.* Mathematics and computers in simulation, 2001. **55**(1-3): p. 271-280.
32. Delignette-Muller, M.L. and C. Dutang, *fitdistrplus: An R package for fitting distributions.* Journal of statistical software, 2015. **64**: p. 1-34.
33. Bertrand Iooss, S.D.V., Alexandre Janon, Gilles Pujol, etc., *sensitivity: Global Sensitivity Analysis of Model Outputs*. 2021.
34. Aitchison, J., *On the distribution of a positive random variable having a discrete probability mass at the origin.* Journal of the american statistical association, 1955. **50**(271): p. 901-908.
35. Brand, C., M. Tran, and J. Anable, *The UK transport carbon model: An integrated life cycle approach to explore low carbon futures.* Energy Policy, 2012. **41**: p. 107-124.
36. Judge, L. and C. Pacitti, *The Resolution Foundation Housing Outlook*, in *Quarterly Briefing: Q2 2021*. 2021, Resolution Foundation.
37. Grimwood, G.G. *When new housing is built, can communities get the infrastructure to go with it?* 2019.