Transportation Research Part D 49 (2016) 172–187

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Estimating changes in transport CO_2 emissions due to changes in weather and climate in Sweden

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ARTICLE INFO

Article history:
Available online 24 September 2016

Keywords:
Emission factor
CO_2 emission
Weather and climate

ABSTRACT

There is a considerable body of studies on the relationship between daily transport activities and CO_2 emissions. However, how these emissions vary in different weather conditions within and between the seasons of the year is largely unknown. Because individual activity–travel patterns are not static but vary in different weather conditions, it is immensely important to understand how CO_2 emissions vary due to the change of weather. Using Swedish National Travel Survey data, with emission factors calculated through the European emission factor model ARTEMIS, this study is a first attempt to derive the amount of CO_2 emission changes subject to the change of weather conditions. A series of econometric models was used to model travel behaviour variables that are crucial for influencing individual CO_2 emissions. The marginal effects of weather variables on travel behaviour variables were derived. The results show an increase of individual CO_2 emissions in a warmer climate and in more extreme temperature conditions, whereas increasing precipitation amounts and snow depths show limited effects on individual CO_2 emissions. It is worth noting that the change in CO_2 emissions in the scenario of a warmer climate and a more extreme temperature tends to be greater than the sum of changes in CO_2 emissions in each individual scenario. Given that a warmer climate and more extreme weather could co-occur more frequently in the future, this result suggests even greater individual CO_2 emissions than expected in such a future climate.

1. The CO_2 emissions of passenger transport and weather

The European Union has committed itself to a 20% reduction in its greenhouse gas (GHG) emissions. CO_2 emissions are the major quantity of interest, and transport is one of the main emitting sectors and the only sector that continues to grow substantially (European Commission, 2015). Overall, the transport sector produces the second largest share of CO_2 emissions among all sectors in the EU, in which road transport, mainly by passenger car, is responsible for around 70% of the total CO_2 emissions in the transport sectors (EU Transport in Figures, 2014). Measuring, modelling, and predicting CO_2 emissions from road transport are thus important and hot topics in the transportation field. Studies on CO_2 emissions from road transport have been focused on passenger transport (e.g. Barla et al., 2011; Waygood et al., 2014) and freight transport (e.g. Eng-Larsson et al., 2012; Stelling, 2014). It is well known that two major factors determine the CO_2 emissions of passenger transport, the emission factor of the vehicle and the vehicle usage (vehicle mileages travelled).

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http://dx.doi.org/10.1016/j.trd.2016.09.004
1361-9209/

The emission factor describes the amount of CO_2 emitted by a passenger car when the vehicle is being used per unit of travel. The principle sources of emissions can be categorised into three types (Boulter and McCrae, 2007): (1) 'hot' exhaust emission, the amount of CO_2 being emitted during the use of the vehicle; (2) cold start emission, the amount of CO_2 being emitted during each trip start when the engine does not reach its running temperature; and (3) evaporative emission, the amount of CO_2 emissions due to evaporative losses of volatile organic compounds. The emission factor is therefore expressed in terms of CO_2 emissions per kilometre (hot exhaust emission), per trip (cold start emission), and per hour/minute (evaporative emission). The European emission factor model ARTEMIS (Boulter and McCrae, 2007) shows that weather parameters (temperature, precipitation, etc.) affect all three types of CO_2 emission factors. In general, hot exhaust emission decreases with an increasing temperature for both petrol and diesel cars, but more so for diesel cars. Adverse weather, such as precipitation or snow, could trigger the use of in-vehicle A/C, wiper, and window defrost and thus increase the hot exhaust emissions from the auxiliary system. Cold start emissions are well known to be greater in lower temperature conditions (Andree and Joumard, 2005), whereas evaporative emissions increase with an increasing temperature (Hausberger et al., 2005). Therefore, the emission factors are strongly dependent on the weather parameters, thus leading to variations in CO_2 emissions in different weather conditions. However, existing studies on the CO_2 emissions from passenger transport usually ignore the influences of weather parameters on emission factors (e.g. Susilo and Stead, 2009; Barla et al., 2011; Waygood et al., 2014).

It has long been known that changes in weather and climate correspond to changes in travel behaviour (Koetse and Rietveld, 2009; Böcker et al., 2013a; Dijst et al., 2013). Various travel behaviour studies have examined the role of weather on changes in travel choices. Cools et al. (2010) conducted a stated preference study and proved that travel behaviour is significantly affected by weather conditions and that the impacts of weather are highly dependent on the purpose for travel. From revealed preference studies, in terms of mode choice, Sabir (2011) and Bergström and Magnusson (2003) showed a substantial increase in bicycle trip share in warmer temperatures. Saneinejad et al. (2012) also found that cycling trips were the most dependent on the change of weather. Miranda-Moreno and Nosal (2011) found that cycling flow per hour is influenced not only by the current weather but also previous weather conditions. Creemers et al. (2015) adopted meteorological measures to represent weather conditions and found that meteorological measures can better capture the impact of weather on mode choice. Liu et al. (2015a, 2015b) showed that weather effects on mode choice were different in regions with different climates and in trips with different purposes. Ahmed et al. (2013) found that weather conditions are a paramount factor influencing even commute-cycling decisions. In terms of destination choice and travel distance, Sabir (2011) found that individuals prefer closer destinations for shopping or leisure activities in adverse weather conditions. Böcker et al. (2013b) showed that a warmer and wetter future climate corresponds to an increase in travel distance. In terms of trip frequency, the number of trips conducted per individual per day decreases on windy and snowy days, whereas road traffic flow decreases significantly on rainy days (Keay and Simmonds, 2005; Kim et al., 2010).

Despite the growing knowledge on the impacts of weather on travel behaviour in general, this knowledge cannot be directly applied to the impacts of weather on CO_2 emissions. On the one hand, changes in weather and climate may lead to a modal shift and an increase/decrease of travel distance, etc., and those effects may cancel out in terms of CO_2 emissions. For instance, precipitation tends to decrease trip distance while increasing the likelihood of travelling by car. On the other hand, emission factors of vehicles vary in different weather conditions. Because the CO_2 emissions of road passenger transport are determined by both the emission factors and travel patterns of each trip/individual, the CO_2 emissions are influenced by the change of weather in a complex manner. Moreover, given that the future climate could become warmer and that weather could become more extreme, researchers and policy makers are particularly interested in knowing the change in CO_2 emissions from road passenger transport in such a future climate scenario compared to the CO_2 emissions in the current climate. However, few researchers have analysed the change in CO_2 emissions subject to the change of weather.

Thus, this paper aims to analyse and quantify the amount of CO_2 emissions from road passenger transport due to the change of weather. Using the Swedish National Travel Survey, this study first examines which weather conditions correspond to the most/least CO_2 emissions from road passenger transport. Furthermore, several econometric models are estimated in order to derive the marginal effects of weather parameters on the travel behaviour variables, including trip frequency, mode choice, destination choice, travel distance, and travel speed for car trips. Those marginal effects of weather provide the travel behaviour changes given the change of a weather variable. Those models are then used to derive the amount of CO_2 emissions per individual per day given the change of weather and climate. The results provide the changes in CO_2 emissions in various future climate scenarios compared to the current weather conditions, whereas all other factors remain unchanged.

The next section describes the details of the datasets and the emission factor models used in this paper. Then, the explanatory analysis of CO_2 emissions according to weather parameters is provided. After that, the econometric models are introduced, and the marginal effects of weather variables are presented. Furthermore, the simulation study is described, and the changes of amounts of CO_2 emissions in various future climate scenarios are presented. Finally, this paper is concluded by summarising the findings from the previous sections.

2. The Swedish National Travel Survey, the weather datasets, and the emission model

The data used in this paper stems from two data sources. The travel data come from the 2011 Swedish National Travel Survey (NTS) datasets. The NTS data are travel diary data in which a trip is defined when certain errands have been achieved at the destination (note that changing mode is not an errand). All trips a respondent took in the observed day are recorded, including the main travel mode, travel purpose, start and end points, departure and arrival times, etc., as well as individual and household characteristics (Staffan, 2001). The data also cover the vehicle information, such as the manufacture year of the vehicle and fuel type. The dataset covers all of Sweden for all days of the week and every week of the year. The respondents were selected through a stratified sampling method according to the socio-demographics and residential locations. However, one limitation of the NTS is that the departure and arrival locations of each trip are only available at the municipality level for confidential reasons.

The weather data come from the Swedish Meteorological and Hydrological Institute (SMHI). The weather data contain weather information measured every three hours, including average, minimum, and maximum temperatures (the average temperature is used in this paper); precipitation amounts; level of visibility (visible distance measured in km); wind speed (km/h); relative humidity; snow depth; and air pressure (SMHI, 2012).

The weather information was assigned into each trip by matching weather data from the weather station nearest to the centre of the departure municipality of that trip and by selecting the non-missing value of each weather variable with its measured time closest to the departure time. It is worth noting that the average distance from each weather station to its corresponding trip start municipality is around 10 km. One should be aware of the limitation of combining two datasets: the distance from the nearest weather station to the respondent's place of departure varies for each trip, raising questions about the degree to which weather conditions measured at the weather station are the same as those at the departure location. However, these differences are smaller for large municipalities such as Stockholm and Gothenburg, where more data were collected, while for municipalities with only a few residences, such as some in northern Sweden, that distance is greater. The spatial heterogeneity of weather effects resulting from this approach is discussed in detail by Liu et al. (2015c).

The emission factors were calculated using the European emission factor model ARTEMIS (Boulter and McCrae, 2007). For private car trips, three types of emissions were calculated: hot exhaust emissions, cold start emissions (E_c), and evaporative emissions (E_e). Hot exhaust emissions were separated into running hot exhaust emissions (E_h) and hot exhaust emissions from the auxiliary system (E_a). The corresponding emission factors were calculated accordingly: The emission factor of running hot exhaust emissions (F_h) was calculated using an average speed model. The emission factor of running hot exhaust emissions, in general, is a function of the fuel type (petrol or diesel), emission standard of the vehicle, road type of the trip (urban, rural, or motorway), ambient temperature outside the vehicle, and average speed of the trip. The emission factor of hot exhaust emissions from the auxiliary system (F_a) is dependent on the time of day, trip departure location (southern, central, or northern Sweden), ambient temperature outside the vehicle, and raining/snowing conditions. The emission factor of cold start emissions (F_c) is determined by the fuel type, emission standard of the vehicle, ambient temperature outside the vehicle, rain or snow status, average speed of the trip, trip distance, and time since last use of the vehicle. Although several types of evaporative emissions are described in the ARTEMIS model, only the emissions due to running loss are considered in this paper, as other types of evaporative emissions require detailed meteorological parameters that are not available in the data. However, given the fact that evaporative emissions are only a very small proportion of the total emissions, this simplification is still valid. The emission factor of evaporative emissions (F_e) is determined by the fuel type, road type, and ambient temperature outside the vehicle. The total emission of a given trip is then calculated by Eq. (1):

$$E_{total} = E_h + E_a + E_c + E_e = F_h \times D + F_a \times H + F_c + F_e \times D \tag{1}$$

where D denotes the travel distance of the given trip, and H denotes the travel time of the given trip. This total emission per trip, E_{total}, is then transformed into the emission per trip per individual by dividing E_{total} by the number of accompanying individuals in the given trip. Two assumptions are made for the emission standard of the vehicle and road type. Because the detailed emission standard of the vehicle is not available in the NTS but only the manufacture year of the vehicle, it is assumed in this study that vehicles manufactured before 1993 are pre-EU I standard, those between 1993 and 1996 are EU I standard, those between 1996 and 2000 are EU II standard, those between 2000 and 2005 are EU III standard, and those after 2005 are EU IV or a more recent standard (Directive 2002/51/EC, 2015). The road type—rural, urban, and motorway—is determined in this study as trips with urban road conditions are those that depart and arrive in the same municipalities and within Stockholm, Gothenburg, and Malmö municipalities, whereas trips with rural road conditions are those that depart and arrive in the same municipalities but in those other than Stockholm, Gothenburg, and Malmö. Trips with motorway road conditions are those that depart and arrive in different municipalities.

The emission factor of a bus is taken as 79 g/passenger km (Swedish public transport, 2016). The CO_2 emissions for trips by walking, cycling, metro/tram, and train are taken as 0, whereas CO_2 emissions for trips made by other modes (flight, boat, moped, coach, etc.) are not considered in this study. The zero emission assumption of trains is valid in Sweden, because the passenger trains in Sweden are all electrified, and the marginal CO_2 emission is in principal zero (Andersson and Lukaszewicz, 2006). Around 8% of trips in the NTS are made by 'other modes'.

3. The individual CO_2 emissions in Sweden

By applying emission factors on the NTS, the trip-based CO_2 emissions were then aggregated into the individual level by summing up CO_2 emissions of all trips made by the given individual. The weighted average of the individual CO_2 emissions was then calculated, with the weight used to represent the whole population of Sweden. On average, 3.87 kg of CO_2

from passenger transport are emitted per individual per day in Sweden, which is slightly more than that from a study (3.8 kg of CO_2 per person per day) that used a Dutch national travel survey in 2005 and much less than that from the same study (4.3 kg of CO_2 per person per day) (Susilo and Stead, 2009). However, given that the study mentioned above did not consider CO_2 emissions other than running hot exhaust emissions and did not consider weather in emission factors, it is plausible that the difference between individual CO_2 emissions in Sweden and those in the Netherlands/UK could be even greater.

The individual CO_2 emissions are plotted according to various weather parameters, as shown in Fig. 1.

In general, running hot exhaust emissions are the major share of total emissions (around 90%). Cold start emissions and hot emissions from the auxiliary system make up 10% of the total emissions, whereas evaporative emissions are negligible. In other words, the results indicate that ignoring cold start emissions and hot emissions from the auxiliary system, as most previous studies have done, would underestimate approximately 10% of the total emissions, which is considerable. For studies that do not include hot emissions from the auxiliary system (e.g. Waygood et al., 2014), around 5% of the total emissions are underestimated. In Fig. 1, the individual CO_2 emissions show clear variations in different seasons and regions. Individual CO_2 emissions are greater in summer and lesser in winter. Central Sweden has the lowest individual CO_2 emissions among three regions, presumably because a larger share of respondents lives in dense and urban areas such as Stockholm and Gothenburg. Previous studies (e.g. Kennedy et al., 2009) have shown that urbanisation density is inversely related to GHG emissions. It is worth noting that the individual CO_2 emissions are extremely high in the summer in northern Sweden, almost reaching 6 kg per individual per day. This is mainly due to the high vehicle mileage travelled in the summer in northern Sweden, 49 km per individual per day compared to 30 km in the other seasons in northern Sweden. However, one should be aware that only 9.3% of the total Swedish population reside in northern Sweden. Therefore, its influence on the average individual CO_2 emissions of the whole of Sweden is relatively limited. Precipitation and snow conditions seem to be positively correlated with individual CO_2 emissions. Although trip distance tends to be shorter on rainy and snowy days, private cars are more often used.

Although the above-mentioned descriptive results show clear difference in CO_2 emissions, those differences do not necessarily represent the change in CO_2 emissions due to the change of weather, because other factors such as individual socio-demographics, residential environment, etc., also play important roles in influencing individual CO_2 emissions (Susilo and Stead, 2009; Waygood et al., 2014). It is therefore of interest to know the characteristics of samples that have a high/low individual CO_2 emission. This study differentiated between five different groups (quintiles) on the basis of their individual emissions, together with the zero-emission group (the group of individuals who do not emit any CO_2 emissions in the given day). The six groups of samples and their corresponding shares of CO_2 emissions are presented in Fig. 2.

As seen in Fig. 2, 34% of the sample population did not (directly) emit any CO_2 emissions in the given day, as they used zero emission travel modes (walking, cycling, tram/metro, and train) in all their trips in the observed day. However, the last 20% emission quantile (13.1% of the total sample population) was responsible for 61.3% of the total CO_2 emissions. The characteristics of the zero emission group and the last 20% emission quantile are presented in Table 1.

It is not surprising that the last 20% emission quantile consists of more male travellers than female travellers, and almost all have a driving license. The last 20% emission quantile consists of more partnered living individuals with high income compared to the zero emission group, whereas the zero emission group consists of more young individuals and individuals who are single living without children, and with low income. Almost all individuals in the last 20% emission quantile have at least one car in the household, whereas 26% of travellers in the zero emission group do not have access to a private car. The rest of the travellers (74%) in the zero emission group, although they have access to a private car, did not use the car on the observed day, thus producing zero emissions on that particular day. A substantial proportion of individuals from the zero emission group reside in highly urbanised municipalities, such as Stockholm, Gothenburg, and Malmö. Presumably, a dense, mixed, and compact urban environment provides this particular group an opportunity to travel and carry out its daily activities without substantial need for a private car (Sun et al., 2009; Ewing and Cervero, 2010; Susilo et al., 2012).

In terms of experiencing different weather conditions, there is no considerable difference in the shares of individuals from the zero emission group and the last 20% emission quantile observed in each season. Individuals from the zero emission group are more likely to be observed in a warmer than normal day (temperature on the given day is higher than its monthly historical mean in the given municipality) than those from the last 20% emission quantile. A larger proportion, 38.3%, of individuals from the last 20% emission quantile is observed travelling on rainy days compared to those from the zero emission group (the corresponding proportion is 26%). However, that difference in terms of snow is less considerable compared to that in terms of precipitation.

4. Deriving the marginal effects of weather on travel behaviour variables

4.1. The travel behaviour models

The difference in individual CO_2 emissions shown in Fig. 1 does not necessarily represent the impacts of weather, since other factors may vary significantly in different groups of weather condition classifications. Therefore, estimates that represent the changes in travel behaviour variables solely due to the change of weather are required. Travel behaviour variables,

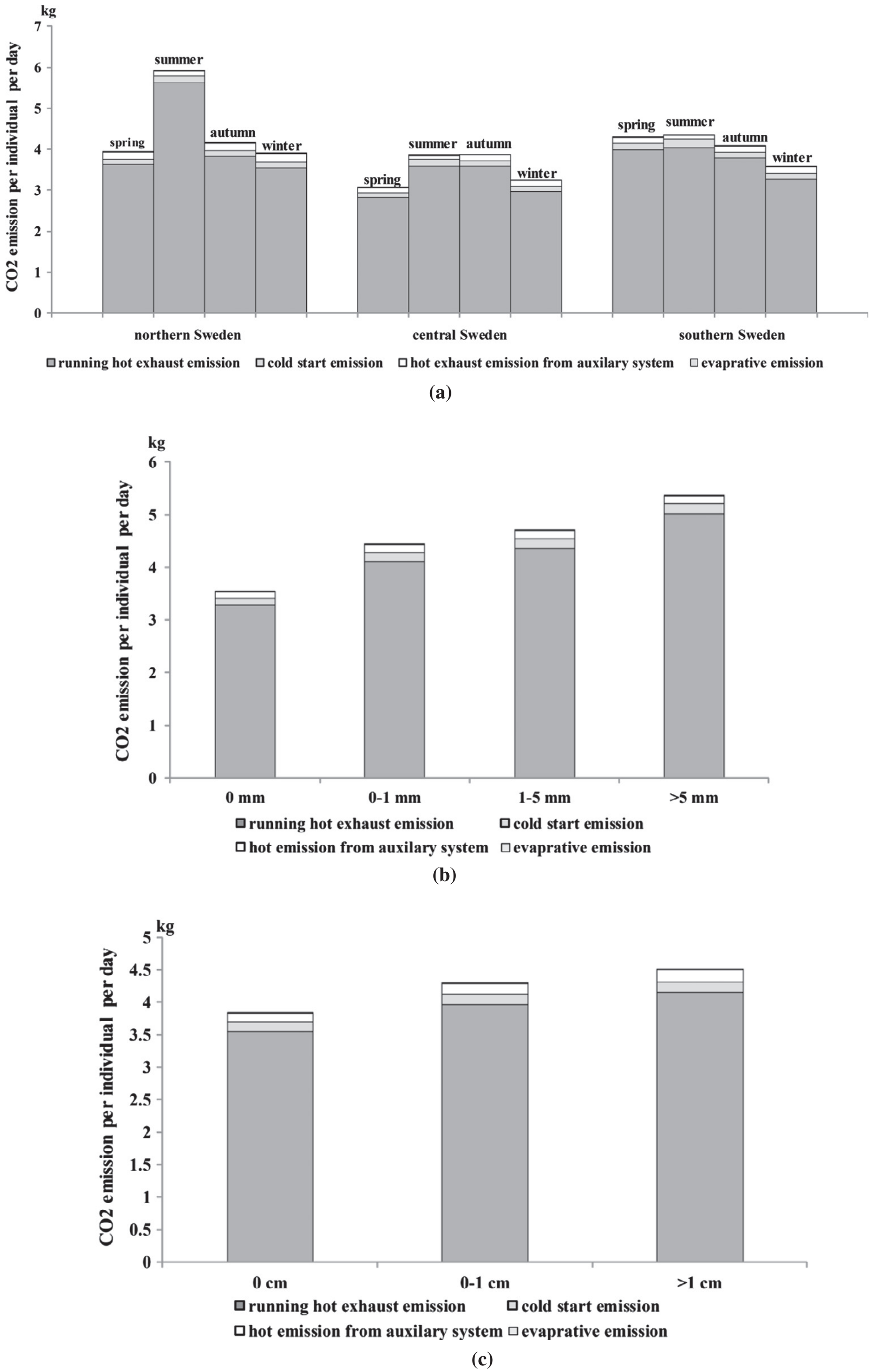

Fig. 1. Individual CO_2 emissions (kg/day) under different weather conditions. (a) Individual CO_2 emissions (kg/day) in different seasons and regions of Sweden. (The geographical classification of Sweden is based on Nomenclature of Territorial Units for Statistics. The counties of northern Sweden refer to Härjedalen, Medelpad, Jämtland, Ångermanland, Västerbotten Norrbotten, and Lappland. The counties of central Sweden refer to Hälsingland, Dalarna, Cästrikland, Uppland, Värmland, Västmanland, Narke, and Södermänland. The counties of southern Sweden refer to Dalsland, Bohus Iän, Västergötland, Östergötland, Småland, Öland, Gotland, Blekinge, Skäne, and Halland.) (b) Individual CO_2 emissions (kg/day) in different precipitation categories. (c) Individual CO_2 emissions (kg/day) in different snow-depth categories.

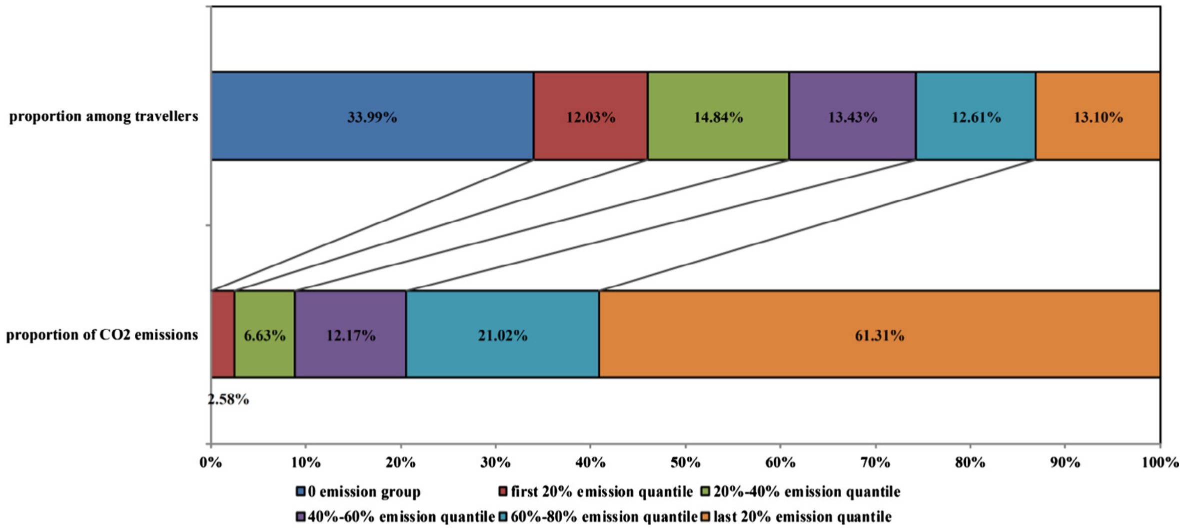

Fig. 2. Proportion of individuals against their CO_2 emissions.

including trip frequency, travel mode choice, destination choice, travel distance, and average speed, were well known to affect the CO_2 emissions. Therefore, a series of models was constructed to obtain the marginal effects of weather variables on these five travel behaviour variables. Those marginal effects denote the amount of changes in each travel behaviour variable given the change of a weather variable while other factors remain invariant. Therefore, those marginal effects represent the changes in each travel behaviour variable solely due to the change of weather.

Panel mixed binary logit models were used to model the destination choice of non-work trips. The model is simplified as each individual chooses between two destination choices for his or her non-work trips: the destination is located in the same municipality of departure or the destination is located outside the municipality of departure. The model has the following general form:

$$U_{i,j,k} = \alpha_k + X_{i,j}\beta_k + \mu_{i,k} + \varepsilon_{i,j,k} \tag{2}$$

$$P_{i,j,k} = \int_{-\infty}^{+\infty} \frac{e^{U_{i,j,k}}}{\sum_{k=1}^{2} e^{U_{i,j,k}}} f(\mu_{i,k}) d\mu_{i,k} \tag{3}$$

where $U_{i,j,k}$ represents the utility of choosing choice k {the destination is located in the same municipality of departure, the destination is located outside the municipality of departure} for individual i and his/her non-work trip j. α_k is the alternative specific constant. $X_{i,j}$ represents the explanatory variable set that influences the destination choice, which includes weather variables. β_k represents the corresponding parameters. $\mu_{i,k}$ is the individual level error term that captures the panel effect, which is assumed to be normally distributed. $f(\mu_{i,k})$ denotes the probability density function of $\mu_{i,k}$. $P_{i,j,k}$ is evaluated through simulation. The panel effect is considered to take into account the fact that several trips were made by the same individual. $\varepsilon_{i,j,k}$ is the independent and identically distributed (iid) error term that is assumed to be Gumbel distributed and leads to the logit probability expression shown in Eq. (3). The marginal effect of a given weather variable $X_{i,j}$ is then expressed as $\partial P_{i,j,k}/\partial X_{i,j}$. The marginal effect is calculated by the following equation:

$$M_{i,j,k} = \partial P_{i,j,k}/\partial X_{i,j} = \frac{P_{i,j,k}(X_{i,j} + \Delta X_{i,j}) - P_{i,j,k}(X_{i,j})}{\Delta X_{i,j}} = \frac{\int_{-\infty}^{+\infty} \frac{e^{U_{i,j,k}(X_{i,j}+\Delta X_{i,j})}}{\sum_{k=1}^{2} e^{U_{i,j,k}(X_{i,j}+\Delta X_{i,j})}} f(\mu_{i,k}) d\mu_{i,k} - \int_{-\infty}^{+\infty} \frac{e^{U_{i,j,k}(X_{i,j})}}{\sum_{k=1}^{2} e^{U_{i,j,k}(X_{i,j})}} f(\mu_{i,k}) d\mu_{i,k}}{\Delta X_{i,j}} \tag{4}$$

In Eq. (4), $\Delta X_{i,j}$ denotes a small change of the given weather variable $X_{i,j}$. In this study, $\Delta X_{i,j}$ takes the value of 1% of the mean of $X_{i,j}$ over all samples. The integral in Eq. (4) is handled by simulation technique. The marginal effect at the sample mean is reported, which takes the mean of all $M_{i,j,k}$ for all individuals and their trips. The marginal effect then represents the probability change in the dependent variable due to unit change of a given weather variable $X_{i,j}$.

Two sub-models were estimated for the non-work trips departure in urban areas (Stockholm, Gothenburg, and Malmö) and rural areas (other municipalities). It is assumed that the destination of the work trip does not change for the given individual on the given day given the change of weather conditions.

Panel mixed multinomial logit models were used to model travel mode choice. Four sub-models were estimated: (1) work trips made by individuals with at least one car in the household, (2) non-work trips made by individuals with at least one car in the household, (3) work trips made by individuals with no car in the household, and (4) non-work trips made by

Table 1
Profile of the zero emission group and the last 20% emission quantile.

	The zero emission group	The last 20% emission quantile
Socio-demographics		
Gender		
Male	47.4%	60.6%
Female	52.6%	39.4%
Age		
Average age	40.8	46.3
Driving license		
Younger than 17	17.6%	3.1%
Having driving license	65.4%	96.1%
Not having driving license but older than 17	17.0%	0.8%
Household type		
Younger than 24	29.5%	8.8%
24–64 & single living without children	13.2%	16.4%
24–64 & single living with youngest child 0–6 years old	1.0%	1.3%
24–64 & single living with youngest child 7–18 years old	1.8%	2.2%
24–64 & partnered living without children	18.7%	39.2%
24–64 & partnered living with youngest child 0–6 years old	9.3%	15.3%
24–64 & partnered living with youngest child 7–18 years old	8.8%	22.6%
Over 64	17.2%	8.8%
Missing data	0.6%	0.9%
Household income		
Household income <150,000 SEK	6.3%	1.5%
Household income 150,000–400,000 SEK	24.2%	20.2%
Household income >400,000 SEK	39.6%	55.6%
Missing data	29.8%	22.8%
Household size		
Average household size	2.72	2.77
Household car ownership		
Household with no car	26.1%	0.4%
Household with one car	51.0%	43.2%
Household with two cars	18.9%	43.3%
Household with more than two cars	3.7%	13.1%
Missing data	0.2%	/
Residential municipality		
Stockholm	18.8%	8.2%
Gothenburg	6.4%	3.3%
Malmö	2.4%	1.8%
Other municipalities	72.5%	86.7%
Weather conditions		
Season		
Observed in spring	26.1%	23.7%
Observed in summer	24.1%	27.2%
Observed in autumn	25.5%	27.3%
Observed in winter	24.3%	21.7%
Temperature		
Average temperature deviation against its monthly mean value	0.43	0.35
Precipitation		
No precipitation in the observed day	74.0%	61.7%
Precipitation in the observed day 0–1 mm	16.6%	23.2%
Precipitation in the observed day 1–5 mm	7.3%	11.1%
Precipitation in the observed day >5 mm	2.1%	4.0%
Snow		
Snow depth in the observed day is 0 cm	93.2%	91.3%
Snow depth in the observed day 0–1 cm	1.4%	1.8%
Snow depth in the observed day >1 cm	5.4%	6.9%

Note: data are weighted in order to represent the whole population of Sweden.

individuals with no car in the household. The choice set was simplified into {physically active modes (walking and cycling), bus, tram/metro, others} for those with no car in the household and {physically active modes, car, bus, tram/metro, others} for those with at least one car in the household. Both the car drivers and car passengers were counted as car users. Although people from households without a car can potentially still use a car by a car sharing system, this is not included in this study since only 2% of all observed trips made by respondents in households without a car are trips with rented or borrowed cars.

Panel log-linear models were used to model the trip distance of non-work trips:

$$\log(D_{i,j}) = \alpha + X_{i,j}\beta + \mu_i + \varepsilon_{i,j} \tag{5}$$

where $D_{i,j}$ is the trip distance of non-work trip j made by individual i. α is the intercept. μ_i is the individual level error term and $\varepsilon_{i,j}$ is the iid error term, which are both assumed to be normally distributed. Three sub-models were estimated for (1) the non-work trips of which the departure and arrival locations are in an urban area and in the same municipality (urban local trips), (2) the non-work trips of which the departure and arrival locations are in a rural area and in the same municipality (rural local trips), and (3) the non-work trips of which the departure and arrival locations are in different municipalities (long-distance trips). It is also assumed that the travel distance for the work trip does not change for the given individual on the given day given the change of weather conditions.

Panel linear models were used to model the average speed of car trips. Similar to the models for trip distance, three sub-models were estimated for urban local trips, rural local trips, and long-distance trips. The models have a similar form as those for trip distance:

$$V_{i,j} = \alpha + X_{i,j}\beta + \mu_i + \varepsilon_{i,j} \tag{6}$$

where $V_{i,j}$ is the average speed for the non-work trip j made by individual i.

Finally, a negative binomial model was used to model the number of non-work trips made per individual per day. Again, it is also assumed that the number of work trips made by the given individual on a given day would not vary given the change of weather.

A list of explanatory variables used in those models is presented in Table 2. Observed temperature was separated into measures of monthly variation and daily variation in order to differentiate the impact of variation of 'normal'/'as expected' weather conditions between municipalities with the impact of variation of 'un-usual'/'unpredictable' weather conditions from a local perspective (Liu et al., 2015b). The 'normal' value here is the average monthly temperature during the 10 years prior to the analysed year in each municipality where the trip took place. This measure of 'normal' temperature represents the local climate of each month in the given municipality. The corresponding coefficients may reveal differences in travel patterns between summer (warmer months) and winter (colder months). The daily variation measure was represented by a Z score, showing the deviation of that value on the given day when the trip took place from its corresponding 'normal' temperature. This measure of 'abnormal' temperature represents the degree of warmer/colder than the normal temperature. The corresponding coefficients denote the individuals' behavioural response to an extremely cold/warm day (temperature being much lower/higher than the mean temperature in the municipality in that month). This daily variation measure represented by a Z score was then separated into two intervals—'Z score < 0' and 'Z score > 0'—since both large positive and large negative Z scores indicate an extreme temperature. An interaction effect between the temperature measures of monthly variation and daily variation was also introduced, as the effects of this daily variation measure may differ in municipalities in warmer or colder months.

All of the models were estimated through a backward elimination method, where all explanatory variables were initially entered into the model, and then those that turned out to be insignificant in each step were sequentially removed. The full estimation results of the parameters are not shown in the paper due to the limitation in the length of the paper. However, the estimated marginal effects of each weather variable are presented in Table 3. As discussed above, those marginal effects represent the changes of a travel behaviour variable given a unit change of a weather variable while other explanatory variables remain invariant. For instance, as shown in Table 3a, a one degree increase in monthly mean temperature corresponds to a 0.42 percentage point increase in the probability of choosing the destination of a non-work trip other than the municipality of departure (a long-distance trip).

4.2. The impacts of weather on the travel behaviour variables

As shown in Table 3, although some travel behaviour variables are relatively invariant to the change of weather, all models exhibit at least one weather variable that has a significant marginal effect. Those changes in travel behaviour variables surely lead to the change in the amount of CO_2 emissions subject to the change of weather. Those marginal effects also indicate the direction of the change in amount of CO_2 emissions subject to the change of weather, as an increase/decrease of a particular travel behaviour variable has an intuitive interpretation to the direction of change of CO_2 emissions. Moreover, the individual level error terms of all models are highly significant even with individual socio-demographic variables being considered. It indicates a strong between-individual variation, and ignoring this panel effect would likely lead to biased marginal effect estimates. In many models, the magnitude of between-individual variation is even larger than that of iid error terms.

As shown in Table 3, the probability of choosing a destination of a non-work trip outside the municipality of departure would increase in warm months. This indicates an increase in travel distance in warm months, which echoes the finding of Sabir (2011). For those who depart in rural areas, a warmer-than-normal day would indicate a decreasing probability of having the destination outside the municipality of departure, thus potentially leading to a decrease in trip distance and CO_2 emissions. Moreover, this effect tends to be more substantial in cold months. As expected, snow corresponds to a decreasing probability of having the destination outside the municipality of departure, although this effect becomes insignificant for those who depart in urban areas.

As the use of private car is the major source of CO_2 emissions, Table 3 only presents the marginal effects of weather variables on the probability of choosing car as the main travel mode in individuals' work/non-work trips. For those who do not have a car in the household (note that only a few individuals in the sample do not have a car in the household), the marginal

Table 2
Explanatory variables used in each model.

	Destination choice	Mode choice	Trip distance	Average speed for car trips	Number of non-work trips
Socio-demographics					
Male (reference)					
Female (D)	√	√	√	√	√
Number of children under 6 years old in the trip (C)	√	√	√	√	
Age under 25 (D)	√	√	√	√	√
Age between 25 to 64 (reference)					
Age over 64 (D)	√	√	√	√	√
Single living (reference)					
Partnered living (D)	√	√	√		√
Living type missing (D)	√	√	√		√
Low income (D)	√	√	√		√
Medium income (reference)					
High income (D)	√	√	√		√
Income missing (D)	√	√	√		√
Home location in Stockholm (reference)					
Home location in Gothenburg (D)					√
Home location in Malmö (D)					√
Home location in other municipalities (D)					√
Trip information					
Departure location in Stockholm (reference)					
Departure location in Gothenburg (D)	√	√	√	√	
Departure location in Malmö (D)	√	√	√	√	
Departure location in other municipalities (D)	√	√	√	√	
Departure at morning peak 6:00–9:00 (D)	√	√	√	√	
Departure at daytime 9:00–16:00 (reference)					
Departure at afternoon peak 16:00–19:00(D)	√	√	√	√	
Departure at night time19:00–6:00 (D)	√	√	√	√	
Trip takes place on Monday to Thursday (D)	√	√	√	√	√
Trip takes place on Friday (D)	√	√	√	√	√
Trip takes place on weekend (reference)					
Trip distance (C)		√			
Square of trip distance (C)		√			
Vehicle model before 2000 (D)				√	
Vehicle model 2000–2005 (D)				√	
Vehicle model after 2005 (reference)					
Weather condition					
Historical monthly mean temperature in the given municipality (C)	√	√	√	√	√
Temperature Z score < 0 (C)	√	√	√	√	√
Temperature Z score > 0 (C)	√	√	√	√	√
Monthly mean × Z score < 0 (C)	√	√	√	√	√
Monthly mean × Z score > 0 (C)	√	√	√	√	√
Precipitation amount (C)	√	√	√	√	√
Square of precipitation amount (C)	√	√	√	√	√
Snow depth (C)	√	√	√	√	√
Snow depth missing (D)	√	√	√	√	√

Note: The variables 'Living type missing', 'Income missing', and 'Snow depth missing' are dummy variables indicating the corresponding measures are missing for the given observation. The purpose of using 'missing dummy' instead of pairwise elimination is to keep as many observations as possible for estimation.
C in parentheses denotes that the corresponding variable is a continuous variable, whereas D in parentheses denotes that the corresponding variable is a dummy variable.

effects of weather variables on the probability of choosing bus as the main mode were presented. For those who have at least one car in the household, the probability of choosing car for their work trips is relatively invariant to the changes of weather compared to their mode choices for non-work trips, which is expected. Only the interaction effect between 'monthly mean temperature' and 'temperature Z score > 0' is significant among all weather variables considered. For their non-work trips, the probability of choosing car tends to increase on a warmer-than-normal day, especially in cold months, which indicates a substantial increase in CO_2 emissions in that weather condition in winter. Moreover, a thick snow depth on the ground corresponds to a decreasing probability of choosing car in their non-work trips (Liu et al., 2015a), thus contributing to the reduction of CO_2 emissions.

For trip distance, a warm month and a warmer-than-normal day, in general, correspond to a longer trip distance. Precipitation is related to a decreasing trend of trip distance of urban local trips but shows no significant effect on that of rural local trips. Although intuitively precipitation and snow may influence the average speed of car trips, the corresponding variables

Table 3a
Marginal effects of weather variables in each travel behaviour model.

	Destination choice for non-work trips (Probability of travelling across)		Mode choice model (Panel mixed multinomial logit)			
	Departure in urban area $P_{accross}$	Departure in rural area $P_{accross}$	For work and with car P_{car}	For non-work and with car P_{car}	For work and no car P_{bus}	For non-work and no car P_{bus}
Weather variables						
Historical monthly mean temperature in the given municipality (C)	**0.42** **(4.91)**	**0.23** **(2.68)**	0.03 (0.28)	−0.01 (−0.24)	**−0.34** **(1.67)**	−0.10 (−0.82)
Temperature Z score < 0 (C)	/	/	1.41 (1.23)	0.31 (0.94)	−1.55 (−1.26)	/
Temperature Z score > 0 (C)	/	**−1.34** **(1.73)**	/	**0.47** **(4.70)**	**−3.41** **(−3.34)**	/
Monthly mean × Z score < 0 (C)	/	/	−0.13 (−1.04)	**−0.09** **(−2.28)**	**0.32** **(1.70)**	**0.32** **(1.78)**
Monthly mean × Z score > 0 (C)	/	**0.23** **(2.85)**	**0.14** **(2.99)**	**−0.07** **(−3.52)**	**0.16** **(1.89)**	−0.10 (−1.49)
Precipitation amount (C)	/	0.44 (1.53)	0.08 (0.38)	0.08 (0.56)	**0.86** **(2.16)**	−0.16 (−1.43)
Square of precipitation amount (C)	/	/	/	/	−0.01 (−1.01)	−0.01 (−0.63)
Snow depth (C)	/	**−0.15** **(2.84)**	0.02 (0.22)	**−0.09** **(−1.67)**	0.70 (1.11)	/
Model information						
Number of observations (trips)	12,543	20,575	11,352	27,013	1275	3577
Number of individuals	5011	7898	5172	9386	611	1363
Log-likelihood	−4653.5	−9697.5	−9659.7	−19904.8	−907.9	−2435.2
Log-likelihood at zero beta	−8694.1	−14261.5	−18270.3	−43475.7	−1767.5	−4958.8
McFadden's rho	0.465	0.320	0.471	0.542	0.486	0.509
Standard deviation of individual level error term	**2.193** **(20.38)**	**2.156** **(32.91)**	**3.12** **(37.60)**	**4.01** **(55.97)**	**5.23** **(8.54)**	**2.70** **(18.92)**
Standard deviation of iid error term (standard Gumbel distribution)	1.283 (fixed)	1.283 (fixed)	1.283 (fixed)	1.283 (fixed)	1.283 (fixed)	1.283 (fixed)

Note: '/' means the corresponding variable was eliminated through the backward elimination method. Numbers in parenthesis are corresponding *t*-values calculated through the delta method. Numbers in bold characters are significant at 10% level. Note that it is possible that the given marginal effect is insignificant while the corresponding parameter is significant and kept in the model. For models of destination choice, the marginal effects on the probability of travelling across municipality are presented. For models of mode choice, the marginal effects on the probability of choosing car are presented for those households with a car. The marginal effects on the probability of choosing bus are presented for those without a car in household.

show no significant effects. However, precipitation and snow influence the destination choice, which serves as a selection mechanism for the trip distance and average models. In other words, changes in precipitation amount and snow depth may lead to a shift in the selection of trip distance and average models (e.g. shift from an urban local trip to long-distance trip given the change in precipitation amount and snow depth), resulting in the change of average speed in different rainy and snowy conditions. Moreover, monthly mean temperature shows positive effects on the average speed of all types of trips, whereas the effects of temperature Z score variables and the interaction variables differ in different types of trips. For the trip frequency of non-work trips, only the interaction effect between monthly mean temperature and temperature Z score > 0 shows a significant effect.

It is worth noting that the study builds upon the one-day travel diary data, not a long-term panel database. Thus, the estimated marginal effects of weather variables represent how the entire sample would have different travel behaviour in different weather conditions rather than that one given individual would have different travel behaviour in different weather conditions. The latter may infer the long-term travel behaviour of individuals, such that a given individual may choose to allocate more leisure travel on warm and sunny days while taking fewer trips on cold and rainy days. Capturing this long-term travel budget (trade-off) may require longitudinal travel diary data for a long time period.

5. Changes in CO_2 emissions due to the change of weather

Although the marginal effects of weather variables on travel behaviour variables give intuitive interpretations on the changes in CO_2 emissions due to the change of weather, the overall picture of the effects of weather is still unclear. For instance, from the discussion above, trip distance tends to increase in warm months (an increase in monthly mean temperature). However, the emission factor of car is generally smaller in warmer months, raising questions on the changes in amount of CO_2 emissions given the change in monthly mean temperature. Therefore, the marginal effects of weather variables on CO_2 emissions were derived based on the travel behaviour models presented in Section 4. Those marginal effects

Table 3b
Marginal effects of weather variables in each travel behaviour model.

	Trip distance for non-work trips (panel log-linear)			Average speed of car trips (panel linear)			Number of non-work trips per individual per day (Negative binomial)
	Urban local trips Log(*D*)	Rural local trips Log(*D*)	Long distance trips Log(*D*)	Urban local trips *V*	Rural local trips *V*	Long distance trips *V*	Non-work trips E(*N*)
Weather variables							
Historical monthly mean temperature in the given municipality (C)	**0.007 (2.18)**	**0.009 (3.59)**	**0.021 (5.16)**	0.091 (1.63)	**0.116 (2.93)**	**0.169 (2.72)**	/
Temperature Z score < 0 (C)	/	/	/	**−2.345 (−3.36)**	/	**1.730 (1.96)**	/
Temperature Z score > 0 (C)	/	**0.086 (2.95)**	**0.129 (2.98)**	/	**0.462 (1.72)**	/	/
Monthly mean × Z score < 0 (C)	/	/	**−0.009 (−2.61)**	/	/	**−0.187 (−2.22)**	/
Monthly mean × Z score > 0 (C)	/	−0.004 (−1.64)	**−0.012 (−3.28)**	/	/	/	**0.003 (4.19)**
Precipitation amount (C)	**−0.069 (−4.00)**	/	/	/	/	/	/
Square of precipitation amount (C)	**0.004 (3.41)**	/	**−0.001 (−1.85)**	/	/	/	/
Snow depth (C)	/	/	/	/	/	/	/
Model information							
Number of observations (trips)	9619	15,903	5894	4989	9980	6715	/
Number of individuals	3640	5863	3173	1889	3851	3324	14,026
Adjust R square	0.029	0.035	0.229	0.072	0.066	0.099	/
Standard deviation of individual level error term	0.94	0.94	1.14	10.99	13.83	17.93	/
Standard deviation of iid error term	1.03	0.92	0.67	14.95	14.11	16.97	/
Dispersion parameter	/	/	/	/	/	/	**3.996 (28.96)**
Log-likelihood	/	/	/	/	/	/	−27182.4
AIC	/	/	/	/	/	/	54,393

Note: '/' means the corresponding variable was eliminated through the backward elimination method. Numbers in parenthesis are corresponding *t*-values calculated through the delta method. Numbers in bold characters are significant at 10% level. Note that it is possible that the given marginal effect is insignificant while the corresponding parameter is significant and kept in the model. For models of destination choice, the marginal effects on the probability of travelling across municipality are presented. For models of mode choice, the marginal effects on the probability of choosing car are presented for those households with a car. The marginal effects on the probability of choosing bus are presented for those without a car in household.

represent the changes in CO_2 emissions, expressed in terms of individual CO_2 emissions, given a new scenario of weather conditions (a new set of values of weather variables).

In order to derive such changes in CO_2 emissions, the changes of travel behaviour variables in the new scenario of weather conditions were first derived through the travel behaviour models described in Section 4. In general, the derivation of the changes of travel behaviour variables in the new scenario of weather conditions is identical to the derivation of the marginal effects of weather variables presented in Table 3, as shown below:

$$M_w^i = E\left(Y^i|X^i_{w\_new},\beta\right) - E\left(Y^i|X^i_{w\_old},\beta\right) \tag{7}$$

where M_w^i denotes the change of a particular travel behaviour variable for observation i given a new scenario of weather conditions. $X^i_{w\_new}$ denotes the explanatory variable set where the original weather variables are substituted by a new set of weather variables given a particular weather scenario. $X^i_{w\_old}$ denotes the explanatory variable set with the original weather variables. β denotes the estimated parameters of a given model. $E(Y^i|X^i_w,\beta)$ denotes the expected outcome of the travel behaviour variable Y^i, given the explanatory variable set X^i_w and corresponding parameters β. For the models of average speed of car trips (panel linear model), the expected outcome is $E(Y^i|X^i\beta) = X^i\beta$. For the models of trip distance (panel log-normal linear model) and number of non-work trips per day (negative binomial model), the expected outcome is $E(Y^i|X^i\beta) = e^{X^i\beta}$. For the models of destination choice and mode choice (panel mixed logit models), the change of share of each alternative in the whole sample was first determined. For a given alternative k, the change of number of observations choosing alternative k due to the change of weather variables is:

$$N_k = \sum_i P^{w\_new}_{i,k} - \sum_i P^{w\_old}_{i,k} \tag{8}$$

where $P_{i,k}^{w\_new}$ is the predicted probability of choosing alternative k for observation i given the new set of weather variables. $P_{i,k}^{w\_old}$ is the predicted probability of choosing alternative k for observation i given the weather variables in the data. The expression of $P_{i,k}^{w\_new}$ and $P_{i,k}^{w\_old}$ is presented in Eq. (3). If N_k is positive, which means that N_k observations were shifting from other alternatives to alternative k due to the change of weather variables, N_k observations with the highest values of $P_{i,k}^{w\_new}$ among the observations that do not choose alternative k were selected to shift from other alternatives to alternative k. If N_k is negative, those with the lowest values of $P_{i,k}^{w\_new}$ among the observations that choose alternative k were selected to shift from alternative k to other alternatives. Those N_k observations then denote M_w^i.

Therefore, the predicted travel behaviour variable given the change of weather is expressed as:

$$Y_{new}^i = Y_{old}^i + M_w^i \tag{9}$$

where Y_{new}^i denotes the new travel behaviour variable given the change of weather. Y_{old}^i denotes the travel behaviour variable observed in the data. It is important to note that the predicted travel behaviour variable builds upon the observed data Y_{old}^i rather than the predicted values from the model. The influence of the change of weather variables is expressed in the marginal effect M_w^i. Given that some models show poor model fit (e.g. the adjust R square of trip distance model of urban local trips is 0.02), the predicted value from the model may differ substantial from the observed data, which is due to the large estimated standard deviation of the iid error term. However, the marginal effect M_w^i takes the difference of expected outcomes of the model given the changes of weather (see Eq. (8)). It is therefore more stable and reliable compared to directly using the predicted values as Y_{new}^i, since the impact of this large standard deviation of the iid error term is cancelled out when deriving M_w^i, as the standard deviation of the iid error term appears in both the terms $E\left(Y^i|X_{w\_new}^i, \beta\right)$ and $E\left(Y^i|X_{w\_old}^i, \beta\right)$, as shown in Eq. (7).

The predicted travel behaviour variables according to Eq. (9) were then used to calculate the individual CO_2 emissions in the new weather scenario. A general flowchart of the calculation is shown in Fig. 3.

As shown in Fig. 3, the predicted changes of destination choice given the change of weather were first calculated, in which certain observations shifted from local trips to long-distance trips and vice versa given the new weather scenario. Given those changes in destination choices, the changes of average speed profile and trip distance profile were then determined. For those observations that shifted destination choices, $E\left(Y^i|X_{w\_new}^i, \beta\right)$ of average speed and trip distance were calculated using the function of the new model according to the new destination choice (local trips or long-distance trips). For instance, a given trip shifted from an urban local trip to a long-distance trip. Therefore, $E\left(Y^i|X_{w\_old}^i, \beta\right)$ of the trip distance model was calculated through the estimated function of urban local trips. However, $E\left(Y^i|X_{w\_new}^i, \beta\right)$ of the trip distance model was calculated through the estimated function of long-distance trips, because the destination choice has changed given the new weather scenario. The changes in model choice were then determined given the change in trip distance. Those changes in travel behaviour variables and the new emission factors given the new weather scenario were then used to calculate the CO_2 emissions of each trip. The CO_2 emissions at trip level were then aggregated into individual level by considering the changes in the number of non-work trips per individual per day.

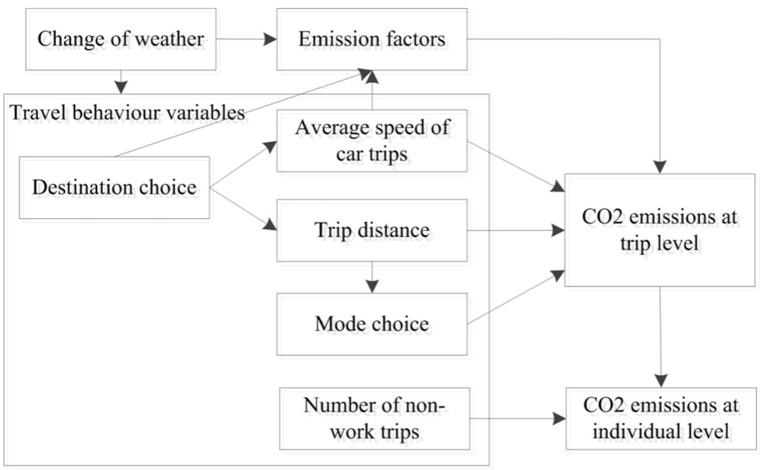

Fig. 3. Flowchart of the prediction of CO_2 emissions under new weather scenario.

Given the fact that the future climate will become warmer and weather will become more extreme and unpredictable, a series of scenarios is considered: (1) the monthly mean temperature increases by 1–5 °C (a warmer climate), (2) the daily temperature Z score is 10–50% more extreme (a more extreme temperature), (3) a combination of scenario 1 and scenario 2 (a warmer climate and a more extreme temperature), (4) precipitation amount is 10–50% more (more extreme rainy conditions), and (5) snow depth are 10–50% more (more extreme snowy conditions).

The predicted change in CO_2 emissions in these five scenarios are presented in Table 4.

As shown in Table 4, individual CO_2 emissions tend to increase in the scenario of a warmer climate. Given that the monthly mean temperature increases by 5 °C, the corresponding individual CO_2 emissions would increase by 6.8% with all else being equal. As seen in Table 3, an increase in monthly mean temperature corresponds to an increase in trip distance, which therefore increases the likelihood of choosing a private car. Although the emission factor of a private car decreases with the increase of temperature, this part of reduction in CO_2 emissions does not surpass the CO_2 emissions from the increased use of a private car and vehicle kilometres travelled. By looking into different sources of emissions, hot emissions from the auxiliary system increase dramatically by 37.0% given a 5 °C rise in monthly mean temperature, whereas cold start emissions decrease slightly in a warmer climate by 9.7%. A more extreme temperature also corresponds to the increase of individual CO_2 emissions, although the magnitude is much smaller than that of the scenario of a warmer climate. Increasing the daily temperature Z score by 50% only leads to a 2.3% increase in individual CO_2 emissions. Contrary to the scenario of a warmer climate, cold start CO_2 emissions remain relatively unchanged in a more extreme temperature condition. In the scenario of both a warmer climate and a more extreme temperature, the change in individual CO_2 emissions becomes more dramatic. It is worth noting that the change in CO_2 emissions in the scenario of a warmer climate and a more extreme temperature tends to be larger than the sum of changes in CO_2 emissions in each individual scenario. For instance, the individual CO_2 emissions increase by 382 g in the scenario of ‘increasing monthly mean temperature by 5 °C and increasing daily temperature Z score by 50%’, whereas the sum of the changes in individual CO_2 emissions in each scenario is only 356 g (265 g + 91 g). This indicates that the CO_2 emissions from passenger transport are likely to increase more than expected in such a joint scenario, which is more likely to occur in the future.

In the scenarios of heavier rain situations, the individual CO_2 emissions do not vary substantially. Although the precipitation amount is negatively related to the trip distance of urban local trips (see Table 4), its influence on CO_2 emissions is absorbed by the slightly more preferable usage of car mode on rainy days as well as the increase in emission factors on rainy days, mainly the factor of emissions from the auxiliary system. Moreover, the individual CO_2 emissions drop slightly in a much thicker snow scenario, although the magnitude is small. It is worth noting that only 30% of all sampled trips are under rainy conditions, whereas only 8% are under snowy conditions. Therefore, changes in precipitation amount and snow depth would only affect the CO_2 emissions of those trips. However, it is plausible that the individual CO_2 emissions may increase/decrease more substantially if the heavy rain and thick snow situations become more frequent, which this study does not consider.

According to the future climate prediction from Intergovernmental Panel on Climate Change (IPCC) (Collins et al., 2013), the global mean temperature will increase from 0.5 °C to 4 °C in the years 2081–2100 compared to the reference years (1981–2000), depending on the scenario. Precipitation change would be between 0% and 20%. The annual minimum daily temperature would be 11 °C colder and the annual maximum daily temperature 4 °C warmer in Sweden. Therefore, the emission of a possible scenario ‘mean temperature +4 °C, Z score +50%, and precipitation +20%’ is calculated, which results in 4184.7 g per individual per day (108.1% of the base scenario). This means that CO_2 emissions will increase by 8% due to the changes in weather and climate in a pessimistic future climate scenario. This indicates that if a large-scale transport demand–supply model does not take into account weather elements, its prediction of CO_2 emissions in the future scenario can be significantly underestimated. Transport policies related to climate mitigation should either focus on market penetration of green vehicles (e.g. electric vehicle) in order to lower emission factors or cope with an increased travel demand, especially for long-distance car trips in Sweden, to decrease vehicle kilometres travelled.

6. Discussions and conclusion

Although there is growing knowledge of the impacts of weather on the change of travel behaviour, the impacts of weather on CO_2 emissions from passenger transport still receive little attention. However, the impacts of weather on CO_2 emissions from passenger transport are not directly transferrable from the knowledge of weather impacts on travel behaviour, due to the dual role of weather in travel behaviour change and emission factor change. Therefore, this paper explored the relationship between the changes of weather conditions and the change in CO_2 emissions from passenger transport by considering the influences of weather on both travel behaviour and emission factors. This study is a first attempt to get a plausible estimate of the change in individual CO_2 emissions given the change of weather conditions. Using NTS data and weather data from SMHI, the individual CO_2 emissions were calculated by using the emission factors derived from the European emission model ARTEMIS. The individual CO_2 emissions showed clear variations in different seasons and weather conditions. A series of econometric models was used to model the travel behaviour variables that are relevant to individual CO_2 emissions. The marginal effects of each weather variable on those travel behaviour variables were presented. The results in general correspond to the existing knowledge on the impacts of weather on travel behaviour. A warmer climate corresponds to an increasing trip distance, which thus increases the probability of choosing a private car, whereas precipitation and snow conditions discourage individuals from conducting long-distance trips.

Table 4
Individual CO_2 emissions in the new scenarios of weather conditions.

	Total emissions (g)		Hot exhaust emissions (g)		Hot emissions from auxiliary system (g)		Cold start emissions (g)		Evaporative emissions (g)	
	Value	Percentage (%)	Value	Percentage	Value	Percentage (%)	Value	Percentage (%)	Value	Percentage (%)
Scenario 1										
Current weather conditions	3871.1	100	3593.2	100	144.7	100	132.9	100	0.3	100
Monthly mean temperature + 1 °C	3922.7	101.3	3640.0	101.3	151.8	104.9	130.5	98.2	0.3	101.9
Monthly mean temperature + 2 °C	3978.3	102.8	3689.4	102.7	160.2	110.7	128.2	96.5	0.4	135.8
Monthly mean temperature + 3 °C	4025.2	104.0	3728.3	103.8	170.9	118.1	125.5	94.4	0.5	169.8
Monthly mean temperature + 4 °C	4077.7	105.3	3771.1	104.9	183.2	126.7	122.9	92.5	0.5	169.8
Monthly mean temperature + 5 °C	4136.0	106.8	3817.2	106.2	198.2	137.0	120.0	90.3	0.6	203.8
Scenario 2										
Current weather conditions	3871.1	100	3593.2	100	144.7	100	132.9	100	0.3	100
Daily temperature Z score + 10%	3893.5	100.6	3612.5	100.5	147.9	102.2	132.8	99.9	0.3	101.9
Daily temperature Z score + 20%	3914.8	101.1	3630.0	101.0	151.6	104.8	132.8	99.9	0.3	101.9
Daily temperature Z score + 30%	3932.6	101.6	3644.1	101.4	155.6	107.5	132.6	99.8	0.3	101.9
Daily temperature Z score + 40%	3947.6	102.0	3653.6	101.7	161.4	111.6	132.3	99.6	0.4	135.8
Daily temperature Z score + 50%	3961.7	102.3	3666.8	102.0	162.5	112.3	132.0	99.3	0.4	135.8
Scenario 3										
Current weather conditions	3871.1	100	3593.2	100	144.7	100	132.9	100	0.3	100
Temperature + 1 °C and Z score + 10%	3941.9	101.8	3655.6	101.7	155.6	107.5	130.4	98.1	0.4	135.8
Temperature + 2 °C and Z score + 20%	4010.2	103.6	3712.7	103.3	169.2	116.9	127.9	96.3	0.4	135.8
Temperature + 3 °C and Z score + 30%	4083.8	105.5	3772.3	105.0	185.9	128.5	125.0	94.1	0.6	203.8
Temperature + 4 °C and Z score + 40%	4168.9	107.7	3839.2	106.8	206.9	143.0	122.2	92.0	0.7	237.8
Temperature + 5 °C and Z score + 50%	4252.7	109.9	3900.8	108.6	230.9	159.6	120.1	90.4	0.9	305.7
Scenario 4										
Current weather conditions	3871.1	100	3593.2	100	144.7	100	132.9	100	0.3	100
Precipitation amount + 10%	3871.2	100.0	3593.4	100.0	144.7	100.0	135.7	102.1	0.3	101.9
Precipitation amount + 20%	3872.2	100.0	3594.3	100.0	144.8	100.1	135.7	102.1	0.3	101.9
Precipitation amount + 30%	3872.0	100.0	3594.1	100.0	144.8	100.1	135.7	102.1	0.3	101.9
Precipitation amount + 40%	3870.0	100.0	3592.2	100.0	144.8	100.1	135.6	102.0	0.3	101.9
Precipitation amount + 50%	3873.5	100.1	3595.7	100.1	145.1	100.3	135.5	101.9	0.3	101.9
Scenario 5										
Current weather conditions	3871.1	100	3593.2	100	144.7	100	132.9	100	0.3	100
Snow depth + 10%	3864.7	99.8	3587.0	99.8	144.6	99.9	132.8	99.9	0.3	101.9
Snow depth + 20%	3858.0	99.7	3580.4	99.6	144.5	99.9	132.8	99.9	0.3	101.9
Snow depth + 30%	3856.1	99.6	3578.5	99.6	144.5	99.9	132.8	99.9	0.3	101.9
Snow depth + 40%	3855.6	99.6	3578.1	99.6	144.4	99.8	132.8	99.9	0.3	101.9
Snow depth + 50%	3855.3	99.6	3577.8	99.6	144.4	99.8	132.8	99.9	0.3	101.9

These models were then used in a simulation study to derive the changes in individual CO_2 emissions due to the changes of weather conditions. The marginal effects of weather variables on each travel behaviour variable were derived and used to calculate the travel behaviour changes under the new weather scenario. Those travel behaviour changes together with the changes in emission factors were then used to derive the changes in individual CO_2 emissions. A series of scenarios was considered given that the future climate will become warmer and that weather will become more extreme and unpredictable. The scenario analysis showed an increase in individual CO_2 emissions in a warmer climate and in more extreme temperature conditions, whereas increasing intensity of precipitation and snow corresponds to a slight decrease in individual CO_2 emissions, although it may be due to the fact that only a few trips were sampled in those weather conditions. It is worth noting that the change in CO_2 emissions in the scenario of a warmer climate and a more extreme temperature tends to be larger than the sum of changes in CO_2 emissions in each individual scenario. Given that a warmer climate and more extreme weather would co-occur more frequently, this result suggests even greater individual CO_2 emissions in such a future climate than in either a warmer climate or more extreme weather conditions. Furthermore, the weather scenarios considered in this study can be combined with other scenarios regarding the change of land use patterns, socio-demographical profiles, and vehicle fleet profiles to derive a more comprehensive picture of CO_2 emissions in various possible future scenarios.

The results presented in this study indicate the importance of considering weather and climate change in the evaluation of CO_2 emissions. Given that most large-scale transport demand–supply interaction models do not consider the impacts of weather variability, using the estimated CO_2 emissions from those models as the estimates of future external effects may considerably underestimate the actual future CO_2 emissions. With global warming and more frequent adverse weather, such an underestimation may reach 8% or more. In cost–benefit analysis, the underestimated external cost of CO_2 emissions would lead to a higher rank for projects with considerable environmental impacts. Possible abatement could be to set up a higher marginal external cost for CO_2 emissions—higher than the shadow price for CO_2 emissions—in order to give a higher weight of CO_2 emissions per capital. For traffic management, the efforts then must not only cope with the seasonal and local weather pattern of activity–travel behaviour. For instance, more congestion on a warm summer day is expected. Therefore, appropriate congestion mitigation measurements are needed. Moreover, long-distance car trips are more preferred in warm months. Freeway management is needed in warm months to cope with the increasing demand.

Nevertheless, one should also be aware of the limitations of this study. First, this study used national survey data in which detailed departure and arrival locations are not available. Therefore, detailed land use and accessibility variables were not used in the econometric model. Second, this study derived the marginal effects of weather from econometric models, while some of which showed low model fit. However, a transport model with demand–supply interaction would provide more accurate marginal effects of weather, since certain travel behaviour variables such as average speed are more suitably described in the supply model with a detailed speed–density relationship in each link rather than any regression models. However, given that the travel route of each trip is not available in the NTS and few transport demand–supply models consider weather as a factor, econometric models were used in this study. Third, the results from this study are also exploratory and need to be validated, preferably with the results from large-scale demand–supply models if weather elements are considered. Fourth, the marginal effects of weather variables are likely to vary among regions and countries with a different climate (Liu et al., 2015b). A meta-analysis comparing the CO_2 emissions subject to the change of weather would give a comprehensive picture of the influence of weather on a global scale. It was also assumed in this study that the individual activity–travel engagement behaviour would follow the patterns that were exhibited in the NTS. There is no guarantee that the individual activity–travel engagement behaviour would remain the same when the weather characteristics change in the future. The study also only focuses on direct in-use CO_2 emissions, not the carbon footprint. All of these issues would be possible future research directions of this study.

Acknowledgement

An earlier version of this paper has been presented at the 95th Annual Meeting of the US Transportation Research Board at Washington, D.C., January 2016.

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