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Article

# Agent-Based Simulation of Long-Distance Travel: Strategies to Reduce $CO_2$ Emissions from Passenger Aviation

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**Abstract**

Every sector needs to minimize GHG emissions to limit climate change. Emissions from transport, however, have remained mostly unchanged over the past thirty years. In particular, air travel for short-haul flights is a significant contributor to transport emissions. This article identifies factors that influence the demand for domestic air travel. An agent-based model was implemented for domestic travel in Germany to test policies that could be implemented to reduce air travel and $CO_2$ emissions. The agent-based long-distance travel demand model is composed of trip generation, destination choice, mode choice and $CO_2$ emission modules. The travel demand model was estimated and calibrated with the German Household Travel Survey, including socio-demographic characteristics and area type. Long-distance trips were differentiated by trip type (daytrip, overnight trip), trip purpose (business, leisure, private) and mode (auto, air, long-distance rail and long-distance bus). Emission factors by mode were used to calculate $CO_2$ emissions. Potential strategies and policies to reduce air travel demand and its $CO_2$ emissions are tested using this model. An increase in airfares reduced the number of air trips and reduced transport emissions. Even stronger effects were found with a policy that restricts air travel to trips that are longer than a certain threshold distance. While such policies might be difficult to implement politically, restricting air travel has the potential to reduce total $CO_2$ emissions from transport by 7.5%.

**Keywords**

aviation emissions; long distance travel; mode choice modelling; transport emissions; transport modelling

**Issue**

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## 1. Introduction

According to the UN emissions gap report from 2019 (UN Environment Programme, 2019), emissions need to be reduced by 7.6% every year from 2020 to 2030 to limit global warming to 1.5°C. Otherwise, temperatures are expected to rise 3.2°C above pre-industrial levels, with severe impacts on the environment, agriculture, and human well-being. While many sectors in Germany were able to reduce greenhouse gas emissions over the past 20 years (including agriculture, manufacturing, and energy), emissions from the transport sector stagnated over the past 28 years (Umwelt Bundesamt, 2020). Aviation generated 2.4% of all $CO_2$ emissions in 2018 (Graver, Zhang, & Rutherford, 2019), with a growth rate of 32% over the past five years. In Germany alone, the amount of $CO_2$ equivalent emissions ($CO_2$eq) from international aviation increased 2.5-times over the last 30 years, while emissions from domestic aviation showed a 10% reduction in $CO_{2eg}$ (Umwelt Bundesamt, 2020). Air travel needs to be an important contributor to reduce greenhouse gas emissions to achieve climate protection goals.

At the time of writing this article, the airline industry has been decimated by an ongoing pandemic that severely restricted long-distance travel. Most airlines were only able to survive with massive governmental subsidies. Passenger air travel in Europe dropped by 89% (Nižetić, 2020), and emissions were reduced accordingly. IATA predicts, however, that air travel will recover by 2024 with an annual global growth rate of 3.7% over the next 20 years (IATA, 2020). Despite the severe impacts of the pandemic on the airline industry, the concern about growing emissions from air travel remains unchanged in the long run.

Transport studies, on the other hand, tend to focus on urban travel (Aultman-Hall, Harvey, & Jeffrey, 2015). Transport modeling in particular has a long tradition of focusing on shorter distances only (Moeckel, Fussell, & Donnelly, 2015). There is a need to study policies and regulations that help reduce emissions from long-distance travel. Long-distance transport models may help to quantify the impact on greenhouse gas emissions. Hence, this article focuses on the investigation of different policies that could be applied in the aviation sector to shift travel from air to ground modes.

## 2. Literature Review

### *2.1. Long-Distance Mode Choice Modelling*

Typically, long-distance travel demand refers to non-recurrent trips over a certain distance threshold. There is no common definition of the boundary between long-distance and short-distance travel demand. For instance, the Travel Survey of Residents of Canada (Statistics Canada, 2011) defines a long-distance trip as a trip that is an overnight trip, or a trip that is longer than 40 km, but Nordenholz, Winkler, and Knörr (2017) define long-distance travel starting at 100 km. Motivated by several references (Creemers et al., 2012; Llorca, Ji, & Molloy, 2018; Sandow & Westin, 2010), a threshold of 40 km was selected to differentiate between long and short-distance trips in this study

Although most trips are short-distance trips, long-distance trips are very relevant for the transport system. According to Shiffer (2012), 75% of all trips are shorter than 15 km, but they account for only around 30% of the vehicle-distance travelled. Moreover, the number of long-distance auto trips in Germany is expected to grow further by 13–16% by 2030, depending on the purpose of the trips. Similarly, distances are expected to grow by 12% (Federal Ministry of Transport and Digital Infrastructure, 2014).

Traditionally, most transportation studies focused on short-distance trips because of their higher frequency, better data sources, and the higher number of urban and regional planning studies. Therefore, many transport models omitted long-distance travel demand. Long-distance travel behavior is different from short-distance travel, thus the second one cannot be extrapolated from the first one (for instance, they include different transportation modes, such as bike and walk versus air and high-speed rail, respectively).

The development of statewide models was a milestone for long-distance modelling (Miller, 2004). The statewide model of Ohio (US) includes a long-distance travel demand module (Erdhardt, Freedman, & Stryker, 2007). A long-distance travel demand model for Europe was presented by Rich and Mabit (2012). This very large-scale model was (according to the authors) not accurate enough because the resolution was too coarse. Runtime issues were also reported. Lu, Zhu, Luo, and Lei (2015) developed a nested logit formulation for trip generation, destination, and mode choice that was applied for inter-city trips among a set of seven Chinese cities. In the US, Outwater, Bradley, Ferdous, Trevino, and Lin (2015) developed a national long-distance model by jointly estimating destination and mode choice. Recently, Zhang et al. (2020) applied another US-wide model to test the impact of high-speed rail at the national level. Similarly, Outwater et al. (2010) described a long-distance model for the state of California that was used to estimate the impact of new high-speed railway lines. Llorca et al. (2018) estimated trip generation, destination choice, and mode choice in multinomial logit models for the province of Ontario (Canada) based on domestic and international travel survey data. The authors added data of visitors' check-ins (Foursquare, 2017) to better characterize the variety of attractions of the destinations (e.g., to differentiate touristic ski resorts from industrial or business areas, as described in Molloy & Moeckel, 2017).

The following issues are commonly reported by the above-mentioned studies. Firstly, the quality of the long-distance travel demand data is lower compared to the detailed travel dairies used for short-distance travel. In Germany, the German Household Travel Survey (*Mobilität in Deutschland* in German; see Federal Ministry of Transport and Digital Infrastructure, 2017) only reports up to three overnight trips for the last three months and does not even identify their destination. For short-distance travel, on the other hand, all respondents report a full-detail travel diary for one day. Zhang et al. (2020) used data from the largest US long-distance travel survey from 1995, which was already 25 years old. Secondly, transport supply data limited the model development as well, especially with regard to public transport schedules. The use of General Transit Feed Specification (GTFS) has partially solved these data issues, although these data are not available everywhere. The supply data of air travel is not provided in most cases. Moreover, the data of destination attractions, relevant for discrete choice models for destination choice, is limited as well (Van Nostrand, Sivaraman, & Pinjari, 2013) and needs to be more specific than population or number of jobs of alternative zones. Nordenholz et al. (2017) evaluated modal shifts for long-distance passengers in Germany. With an aggregated model of about 400 zones, the authors modelled changes in modal share due to changes in cost or travel times. Changes were described to be very moderate. Third, due to the large scale of the models, the resolution is often too coarse to evaluate local changes (Llorca et al., 2018; Rich & Mabit, 2012), where the importance of access and egress trips would be more relevant (i.e., the model zones are too large to differentiate travel patterns of travelers who live close to public transport facilities from others). Lastly, travel demand models are rarely used to evaluate the impact of transport policies and investments on emissions.

### *2.2. Greenhouse Gas Emission Estimation*

Previous studies show many alternative methods to estimate transport-related emissions, from complete life-cycle analyses to only tailpipe emissions. In this section, we summarize methods for emission estimation for ground and air transport.

The emissions produced by ground transportation are usually calculated as the product of a vehicle emission factor and the distance travelled. The energy consumption of a vehicle depends on the age of the vehicle, its engine, type of fuel, but also on external factors such as road type and homogeneity of the road segments, the road surface, slope, idling, congestion, or weather conditions (Brand & Preston, 2010; Llopis-Castello, Camacho-Torregrosa, & Garcia, 2019; Reichert, Holz-Rau, & Scheiner, 2016).

Thanks to a microscopic simulation it is possible to assign different emission factors to different vehicles and different driving situations. The Multi-Agent Transport Simulation (MATSim) emission extension implements this approach (Hülsmann, Gerike, Kickhöfer, Nagel, & Luz, 2011). Simpler large-scale emission estimations are based only on the product of emission factors and the total amount of fuel used or the total number of kilometers travelled by mode. The emission calculation for public modes follows a similar approach but additionally considers the number of seats and the average occupancy on the public transport vehicle (Reichert et al., 2016). Such emission factors allowed nationwide emission calculations, based on distances travelled as reported by household survey data (Brand & Preston, 2010; Heinen & Mattoili, 2019; Hoyer & Holden, 2003; Pagoni & Psaraki-Kalouptsidi, 2016; Reichert et al., 2016).

In aviation, the emissions are typically separated into two parts: (1) landing/take-off emissions (LTO), including all activities around the airport and (2) climb-cruise-descent emissions (CCD or non-LTO) for activities above 1,000 m. This is done to account for the high difference in energy consumption and related fuel burn during the LTO part of the flight compared to the CCD part. After the cruise altitude has been reached, the aircraft's engines burn less fuel per kilometer due to the thinner atmosphere and flying at a stable altitude (Miyoshi & Mason, 2009; Pagoni & Psaraki-Kalouptsidi, 2018; Pejovic, Noland, & Williams, 2008). This division follows the Tier 2 methodology provided by the Intergovernmental Panel on Climate Change (IPCC, 2019). As an example, Mayor and Tol (2008) used the emission factor of 6.5 kg of $CO_2$ per passenger during LTO and 0.02 kg of $CO_2$ per passenger-kilometer during CCD.

Due to the difference in emissions in the LTO and CCD parts of the flight, the amount of emissions per km on long and short distance flights varies as well. Therefore, some studies define separate emission factors for short or domestic flights and for international (long-distance) flights (Brand & Preston, 2010; Miyoshi & Mason, 2009; Pejovic et al., 2008; Reichert et al., 2016). The distance threshold for this separation varies. It is difficult to argue which flight length is more harmful in terms of emissions released because short flights spend a smaller part of the flight in high altitudes where contrails can occur, but they consume more fuel per passenger and km (Aamaas, Borken-Kleefeld, & Peters, 2013; Hofer, Dresner, & Windle, 2010; Reichert et al., 2016). The short-haul flights $CO_2$ emissions are so high compared to ground modes that, in general, the shift from short-haul aviation to ground transportation results in reductions of $CO_2$ emissions (Hofer et al., 2010).

The most common fuel used in civil aviation is kerosene (Lee, Pirati, & Penner, 2009). Nevertheless, the emission factor depends not only on the amount of fuel burned but also on aircraft and engine type and the distance of the flight. The carbon dioxide emission has been usually calculated based on the amount of fuel burned multiplied by a factor of 3.157 kg $CO_2$ per kg of fuel (International Civil Aviation Organization [ICAO], 2016). This emission factor is used in various studies (ICAO, 2016; Larsson, Kamb, & Akerman, 2018; Pagoni & Psaraki-Kalouptsidi, 2016, 2018; Pejovic et al., 2008). Some studies introduce additionally a factor of 1.9 while calculating $CO_2$ emissions to include the magnitude of radiative forcing effect (Boussauw & Vanoutrive, 2019; Caset, Boussaw, & Storme, 2018; DEFRA, 2016, 2020; Larsson & Kamb, 2019). Due to high uncertainty, this factor may vary (Foster, Berntsen, & Betts, 2007; Lee, Fahey, & Skowron, 2020; Rädel & Shine, 2008).

## **3. Methodology**

This research applied an agent-based model to simulate long-distance travel behavior during an average weekday day in Germany. The approach follows the trip-based travel demand model framework and includes the first three steps: trip generation, destination choice, mode choice. Travel demand is simulated at the agent-based (microscopic) scale, thus the individual behavior of travelers is explicitly represented. The model structure is shown in Figure 1.

Our study area covers all of Germany. It is divided into 11,717 number of zones to allocate structural data, such as population, employment, schools and shops. Zones correspond to municipalities (*Gemeinde* in German) and the boroughs of the 14 most populated cities (Hamburg, Hanover, Bremen, Dortmund, Düsseldorf,

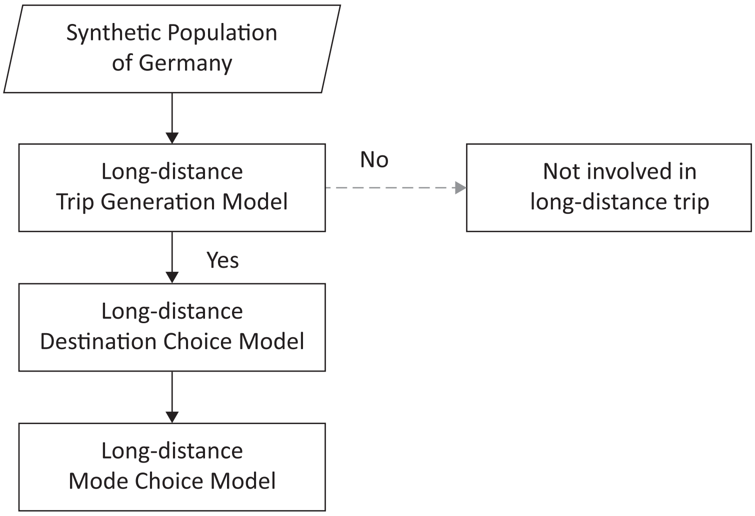


**Figure 1.** Model framework.

Duisburg, Essen, Cologne, Frankfurt, Stuttgart, Munich, Berlin, Dresden, and Leipzig), shown in Figure 2. The number of zones is substantially larger than in previous Germany-wide models. Winkler and Mocanu (2017), for example, included 412 zones corresponding to the counties (*Landkreis* in German) for their Germany model.

A synthetic population of persons and households was generated. This synthetic population matches sociodemographic attributes at the aggregate as reported by census data. During the generation of the synthetic population, census microdata records are selected to match the control totals of the study area. We used Iterative Proportional Updating (Konduri, You, & Garikapati, 2016) with three geographical levels (borough, municipality and county) and two personal levels (person, household), as described by Moreno and Moeckel (2018). The synthetic population has around 80 million persons in 53 million households. The information of socio-demographic data (control totals) is obtained from the German Household Census and the GENESIS online database (for municipalities and counties; see Statistische Ämter des Bundes und der Länder, 2011; Statistisches Bundesamt, 2019). Additionally, census data at the borough level were collected from the websites of the 14 most populated cities. These include, for example, persons by gender and age, employment by sector or households by size. As an example, Table 1 shows the average of the absolute error of all controlled attributes by municipalities. The average error

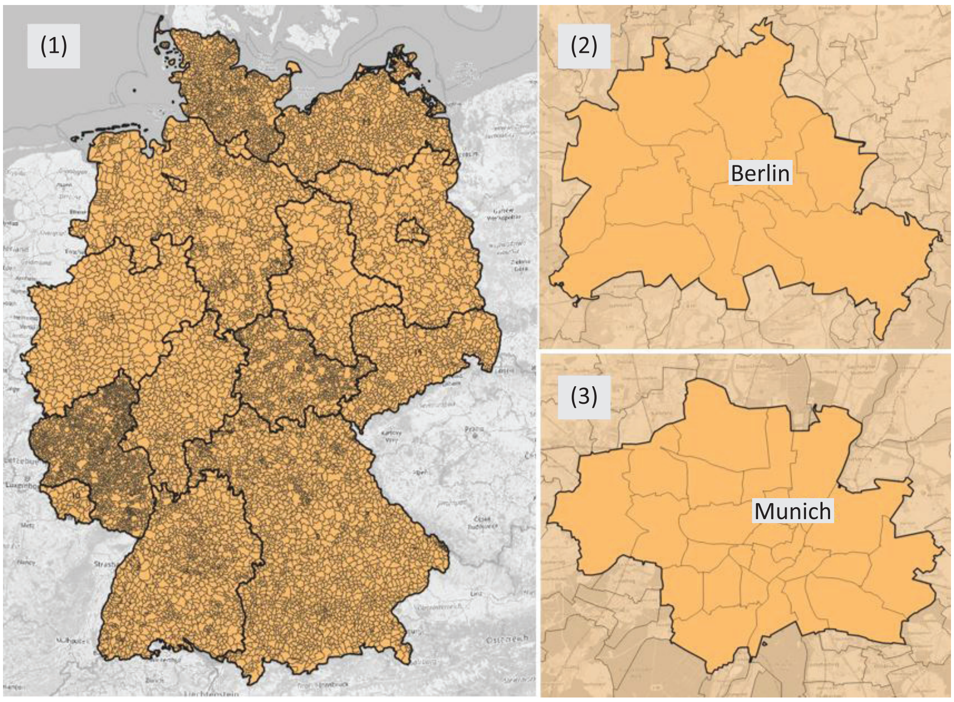


**Figure 2.** Zone system: (1) Germany, (2) Berlin, (3) Munich.

**Table 1.** Average absolute error of controlled attributes by municipalities.

| Average error | Number and share of municipalities | Average population by municipalities |
|---|---|---|
| 0%—5% | 9,689 (85.47%) | 7,617.03 |
| 5%—10% | 1,135 (10.01%) | 4,778.17 |
| 10%—15% | 282 (2.49%) | 2,580.20 |
| 15%—20% | 126 (1.11%) | 737.55 |
| 20%—30% | 104 (0.92%) | 521.96 |
| Total | 11,336 (100%) | 7,065.94 |

by municipalities ranges between 0% and 30%. Smaller municipalities tend to be more difficult to match.

The synthetic population was used as input for the long-distance travel demand model. First, the long-distance trip generation module simulates whether a person makes a long-distance trip or not on a given day using multinominal logit model. Among those individuals who make a long-distance trip, we distinguish individuals making daytrips (outbound and inbound trips on the same day), overnight trips (either the outbound or the inbound trip is made during the observed day), and individuals who are away on the simulated day (since they started an overnight trip before and return after the simulated day). A threshold value of 40 km was chosen to distinguish short- and long-distance trip for all non-work trip purposes (Llorca et al., 2018). Commute trips of any length are treated as habitual travel and not included as long-distance trips. Long-distance trips distinguish three purposes: business, leisure and private. Business trips are trips to see customers or business partners and conference visits (travel costs are commonly paid by the employer). Leisure trips contain trips for recreational purposes. Private trips cover long-distance trips to visits family and friends, shopping, seeing a doctor, and others.

The second module is the long-distance destination choice model, which selects the destination for the long-distance trips with a multi-nominal logit model. The 11,717 zones described above form the choice set. The last component is the long-distance mode choice model. Four modes are considered by a multinomial logit model: auto, air, rail, and long-distance bus. For long-distance bus and rail, local transit is considered for access and egress trips, while auto was chosen for airport access and egress.

These models are estimated and calibrated based on the household travel survey described in Section 4.1. The multinomial logit model calculates the utility for a traveler to select a given alternative. In the case of trip generation, the alternatives are, for example, no long-distance travel, long-distance daytrip, long-distance overnight trip, or being away on a long-distance trip. The main assumption of the multinomial logit model is that the alternatives are irrelevant and independent from each other and that people can make rational choices by differentiating the utility of each alternative (Ortuzar, Hensher, & Jara-Diaz, 1999). The probability of choosing an alternative is shown in Equation 1 and Equation 2:

$$P_{pj} = \frac{e^{V_{pj}}}{\sum_{k=1}^{k=K} V\, e^{V_{pk}}} \tag{1}$$

Here, the following applies:

- $P_{pj}$ is the probability for individual $p$ to select alternative $j$.
- $V_{pj}$ is the utility for individual $p$ to select the alternative $j$, as described in Equation 2.
- $k = 1, 2, \ldots K$ is the set of alternatives.

$$V_{pj} = \sum_{s=1}^{s=S} \beta_s x_s \tag{2}$$

Here, the following applies:

- $s = 1, 2, \ldots S$ is a set of explanatory variables for the number of trips.
- $\beta_s$ is the coefficient of the explanatory variables $s$.
- $x_s$ is the value of the explanatory variables $s$.

Explanatory variables that were highly correlated were excluded from the models. If two variables correlated by more than $R^2 = 0.5$, only one of the two was retained.

## 4. Data

In the following paragraphs, household travel survey, transportation networks, and attraction data are presented.

### 4.1. Household Travel Survey

We used the latest household travel survey available in Germany—the German Household Travel Survey—which is a nationwide survey conducted by the German Federal Ministry of Transport and Digital Infrastructure (2017). The survey includes household and person characteristics, as well as daily travel diaries during one day. The surveyed days are distributed equally across seasons, months, and days of week, allowing to analyze the behavior in relation to weekdays/weekends, vacation/non-vacation days and seasons. In total, 156,420 households (around 0.38% of all households in Germany) participated. Every household member was invited to answer this survey regardless of their age, gender, or occupation status. This survey included 316,361 people (0.38% of the population) and 960,619 trip records. The survey includes a second dataset of overnight trips in the last three months. This dataset, however, does not specify trip origins or destinations and includes a maximum of three overnight trips per person.

We use the daily travel diary dataset of the survey for our model estimation. This dataset provides trip origin, destination, mode, time of day, and purpose of every trip made on the surveyed day.

### 4.2. Network

The network provides travel time and distances by mode for both selected and non-selected destinations and modes. Travel times and distances by mode between all zones are stored in skim matrices. The following data sources were used to generate the skim matrices:

- Road network: The road network was downloaded from OpenStreetMap (wiki.openstreetmap.org). For Germany, it includes freeways, trunk roads, as well as primary, secondary and tertiary roads. For each link, length, speed limit, number of lanes and capacity are provided by OpenStreetMap (2021). In exceptional cases where these attributes were missing, default values were used. To obtain the travel time by auto for each trip of the German Household Travel Survey, we used the simulation model MATSim (Axhausen, Nagel, & Horni, 2016). MATSim was also used to calculate skim matrices.
- Ground public transport network: Networks for all public transport modes were obtained from GTFS (Brosi, 2019). Stop locations, lines (in the sequence of stops) and journeys (individual services of each line on a selected day) were available for download. Timetable information represents a complete all-day timetable. We distinguished between long-distance rail (intercity rail, interregional rail) and long-distance bus services, covered by the Deutsche Bahn and by Flixbus or BlaBlaBus, respectively. Local public transportation such as commuter rail, subway, tram, interregional bus, and local bus were used as access/egress modes to long-distance travel modes. Using GTFS data, travel times from point to point were calculated using the SBB router within MATSim (Swiss Federal Railways, 2018).
- Air network: flight data from before the COVID-19 pandemic were used to construct the air network. The data were downloaded from OpenFlights (github.com/jpatokal/openflights) and contain flight connections between airports, including departure and destination, airline and aircraft type. Connections that are not covered by a direct flight were calculated in a second step by calculating the route from the starting point to the destination via all possible hubs. Access and egress time by car were added to the total trip duration. To obtain the total travel time by air, we also added an average pre-boarding waiting time (90 minutes), post-landing processing time (15 minutes), and transfer time (between 30 and 100 minutes depending on the hub).

### 4.3. Trip Attraction

To estimate the long-distance destination choice model, information about destinations was required. Apart from population and employment, and to better reflect the attractiveness of places for leisure trips, we also included the number of hotels in each potential destination (Statistische Ämter des Bundes und der Länder, 2020).

## 5. Model Estimation

This section summarizes the model estimation results for trip generation, destination choice and mode choice.

### 5.1. Trip Generation Model

German Household Travel Survey provides 316,361 person records. After removing records with missing or non-plausible values (7.32% removed), there were 293,216 records available for model estimation. The results for long-distance trip generation are summarized in the Supplementary File (Table A1). In this model, there are four alternatives: not to conduct long-distance travel, long-distance daytrip, long-distance overnight trip and being away.

Car ownership has a positive impact on the generation of long-distance daytrips of all trip purposes, but it has a negative impact on private overnight trips and no impacts on other overnight trips. People living in households with a higher economic status are more likely to make any forms of long-distance trips, especially for private and leisure purposes. Employed people tend to be less likely to conduct long-distance private and leisure trips than non-employed, but more likely to make long-distance business trips. Presumably, this is related to the availability of time for long-distance travel.

After the model was estimated, it was implemented with the synthetic population for Germany and calibrated to match the share of alternatives observed in the German Household Travel Survey. The calibration factors were added to the utility function. In Table 2, the modeled and observed (in the survey) shares of the different trip types are compared, showing a close match after calibration. The majority of the population (around 94%) does not make long-distance trips on a given day.

### 5.2. Destination Choice Models

While the German Household Travel Survey has 960,619 trip records (including short- and long-distance), only 12,451 records describe long-distance trips with

**Table 2.** Long-distance trip generation results.

| | No long-distance trip | | Daytrip | | Overnight trip | | Being away | |
|---|---|---|---|---|---|---|---|---|
| Trip purpose | Model | Survey 2017 | Model | Survey 2017 | Model | Survey 2017 | Model | Survey 2017 |
| Private | 98.14% | 98.16% | 1.11% | 1.11% | 0.68% | 0.70% | 0.07% | 0.04% |
| Business | 97.93% | 97.96% | 1.65% | 1.65% | 0.35% | 0.35% | 0.07% | 0.04% |
| Leisure | 98.11% | 98.12% | 0.88% | 0.89% | 0.89% | 0.88% | 0.12% | 0.11% |
| Total | 94.18% | 94.23% | 3.64% | 3.65% | 1.92% | 1.93% | 0.26% | 0.19% |

complete origin and destination information (applying the 40 km threshold for non-commute trips, as described above). The distance by car is assigned for each trip record using the MATSim model for estimating and calibrating the destination choice model. The model estimation result of long-distance destination choice is shown in the Supplementary File (Table A2). Three attributes were included in this model: the logarithm with base 10 of car distance, total population and employment at destination, and the number of hotels at the destination. Ideally, the model should be estimated with the full choice set of 11,717 alternatives. Due to the computational limitations, we selected 500 random alternatives and the actually chosen alternative for each trip to conduct model estimation.

The results show, as expected, that the probability of a destination decreases as the distance increases. Total population and employment and the number of hotels have a positive impact on the utility, which means destinations with more population, employment and hotels are more likely to be chosen. The model was implemented and calibrated to match the average one-way distance between survey and model. The calibration factors of the destination choice model, as shown in the Supplementary File (Table A2), are multiplied with the distance parameter. The calibrated results are summarized in Table 3. Overall, the model matches the average one-way travelled distance, as it should be expected from a calibrated model. The modeled standard deviation is slightly smaller than observed, which indicates that the model has a tendency to slightly underestimate rather short and very long long-distance trips.

### *5.3. Mode Choice Model Estimation*

The mode choice model considers four modes: auto, air, long-distance bus, and long-distance rail. The complete data set for mode choice model estimation consists of 7,098 records, with 5,125 records for day trips and 1,973 records for overnight trips. Two separate mode choice models were estimated for domestic day and overnight trips, assuming that a decision of choosing a mode is influenced by the duration of the trip. The results of the multinomial logit model estimation are presented in the Supplementary File (Tables A3 and A4). To include the sensitivity to travel time and cost, and to avoid the strong correlation between the two, we convert both terms into generalized travel time, as described in Equation 3:

$$gTime = time + \frac{cost}{VOT} \times 60 \qquad (3)$$

Here, the following applies:

- *time* is the travel time in hours;
- *cost* is the cost of the trip in euro;
- *VOT* is the value of time (65 EUR/h for business trip, 32 EUR/h for private and leisure trips; see Llorca et al., 2018)

According to Equation 3, business trips are less sensitive to price increases than leisure or private trips, where the value of time is smaller. This reflects that business trips are commonly paid by the employer, making those trips less price sensitive. Generalized travel cost and socio-economic attributes are included in the utility calculation for each mode and purpose.

The model was calibrated to match the observed modal shares in the survey (Federal Ministry of Transport and Digital Infrastructure, 2017). As shown in Table 4, auto is the predominant mode for long-distance travel. The model estimation results for day and overnight trips are summarized in the Supplementary File (Tables A3 and A4) and consist of 18 attributes. Auto was selected as the base alternative (with an alternative specific constant set

**Table 3.** Long-distance destination choice model results.

| One-way average travelled distance and standard deviation (in parenthesis) by car (km) | Daytrip | | | Overnight trip | | |
|---|---|---|---|---|---|---|
| | Private | Business | Leisure | Private | Business | Leisure |
| Model | 204.97 (162.35) | 180.50 (147.48) | 174.56 (146.07) | 226.78 (171.37) | 257.13 (179.09) | 229.79 (173.07) |
| Survey 2017 | 206.94 (187.13) | 179.78 (154.60) | 176.09 (172.71) | 226.69 (187.50) | 258.21 (193.18) | 229.18 (189.32) |

**Table 4.** Summary of the choice results.

| | Daytrip | | Overnight trip | | Total | |
|---|---|---|---|---|---|---|
| Travel Mode | Model | Survey 2017 | Model | Survey 2017 | Model | Survey 2017 |
| Auto | 86.05% | 87.53% | 81.19% | 74.69% | 83.54% | 81.11% |
| Air | 0.39% | 0.80% | 3.96% | 5.71% | 2.23% | 3.26% |
| Bus | 3.13% | 2.34% | 3.13% | 4.63% | 3.13% | 3.49% |
| Train | 10.44% | 9.32% | 11.71% | 14.96% | 11.10% | 12.14% |

to zero). Although the coefficients vary slightly among purposes and trip types, we generally observed that females and persons of single-person households are more likely to choose rail. This is also observed for both young and elderly travelers. Bus and train tend to be preferred by low-income households. As expected, generalized time negatively affect the utility, making closer destinations more attractive.

## 6. Calculation of Greenhouse Gas Emissions

This study focuses on calculating $CO_2$ emissions of all considered long-distance modes. Unfortunately, it was not feasible to work with $CO_2$ equivalent emissions ($CO_2$eq), as $CO_2$eq takes into account the commonly-known GWP (global warming potential) of $CO_2$, $CH_{4,}$ and $N_2O$ gases (Brander, 2012). In this study, we estimate emission factors for the air mode based on the distance flown, and information about the amounts of $CH_4$ and $N_2O$ emitted per km depending on the flight distance was not found.

The emission factor for auto was taken from HBEFA for the year 2020 for diesel and gasoline light-duty vehicles (HBEFA, 2020). The share of gasoline and diesel-powered vehicles was 65.9% and 31.7%, respectively (Kraftfahrt-Bundesamt, 2020). The emission factor for auto trips used for this study is 170.89 g$CO_2$/km travelled. This emission factor does not account for start emissions. To account for the presence of multiple passengers in the car, the amount of $CO_2$ emissions released by auto was divided by 2.25 (Federal Ministry of Transport and Digital Infrastructure, 2017). The coefficient 2.25 represents the average occupancy rate for domestic auto long-distance trips in Germany. The emission factor for a long-distance bus was taken from HBEFA as well for the year 2020 and it is equal to 1,291.847 g$CO_2$/km travelled (HBEFA, 2020). Considering the average occupancy of long-distance buses of 60% and the average number of available seats of 49, a long-distance bus carries 29 passengers on the average. Therefore, the emission factor per passenger on a long-distance bus is 44.55 g$CO_2$/km. In Germany, there are several types of trains operating long-distance travel and the energy consumption varies for each train type. Most trains are electrically powered and the average energy consumption per passenger is 28.33 Wh/km (DeutscheBahn, 2010). Considering Germany´s federal electricity mix, the emission factor per passenger travelling by train is 14 g$CO_2$/km (DeutscheBahn, 2010).

As mentioned earlier the emission factor for air travel depends on the distance travelled. The shorter the travelled distance, the higher the emission factor per km. The ICAO carbon emission calculator was used to calculate flight $CO_2$ emissions for almost 800 city pairs (ICAO, 2016). Based on the data collected, we estimated the amount of $CO_2$ emissions released per passenger per kilometer travelled subject to the total travelled trip distance. For flights that require a transfer, emission factors were derived for each leg. Table 5 shows the emission factor for each air trip based on trip distance. The estimated $CO_2$ emission factor was multiplied by 1.9 to account for the radiative forcing effect (DEFRA, 2016, 2020; Larsson & Kamb, 2019). We recognize that this factor of 1.9 is an overestimate for short-distance air trips and an underestimate for the long-distance trips. However, to the authors' knowledge, there is no method to take into account the trip length and adjust the 1.9 factor accordingly (Larsson & Kamb, 2019). As explained earlier (Section 4.2), auto was set as the access and egress mode to and from airports and the emission factor by auto was used to account for access and egress emissions. Flight emissions and auto emissions were added to calculate total emissions. All the presented emission factors are summarized in Table 5 and were used for emission calculations in this study.

## 7. Scenario Analysis

We tested different scenarios with policies that aim at reducing air travel. We studied restrictions of air trips below a distance threshold and increases of the airfare. We considered four different thresholds for air trips: 300, 500, 700, and 900 km, below which the air mode was made unavailable. Regarding the airfare increase, we considered three scenarios with 100%, 300%, and 500% increase.

**Table 5.** Emission factors for long-distance modes.

| Mode | Auto | Air | Bus | Rail |
|---|---|---|---|---|
| Emission factor, kg/passenger-km | 0.171 | $1.8453 \times$ air traveled distance$^{-0.401} \times 1.9$ | 0.045 | 0.014 |

As the model is agent-based, a random number is needed to select a discrete travel choice for each agent. Therefore, every model run is slightly different. We run the model 8 times with different random seeds and calculated the average to obtain more reliable results. The results of the base scenario are presented in Table 6. A total of 4,512,610 domestic long-distance trips were simulated for an average day for Germany. Air trips accounted for 0.39% of daytrips in Germany and for 3.96% of overnight trips. However, the total amount of $CO_2$ emissions released by aviation was significantly larger: 8.54% of daytrip $CO_2$ emissions and 43.30% of overnight trip emissions. Long-distance bus and rail, on the other hand, produced lower shares of $CO_2$ compared to their shares in the number of trips.

After analyzing the base scenario, we run the above-mentioned policy scenarios and calculated $CO_2$ emissions by air and ground modes. The results of scenarios that restrict air travel below a certain distance are summarized in Figure 3. The amount of air emission steadily decreases as the threshold is increased. When the distance threshold is 900 km, air travel is strongly reduced and emissions drop by 93.1% with the number of air trips dropping to 4,917 trips. At the same time, the emissions of the remaining long-distance ground modes increase due to the shift from the air mode, with the highest increase of 3.6% in the 900 km scenario. Overall, emissions are reduced by 24.2% in this scenario. In reality, some travel might be suppressed by this scenario, which could reduce emissions even further but is not accounted for by the model.

With respect to the scenarios with higher airfares, an increase of 100% already reduced $CO_2$ emissions from aviation by 28.42% compared to the base scenario (11,086.95 tons of $CO_2$ per day), as seen in Figure 4. As airfare was increased by 500%, the reduction in $CO_2$ emissions was 53.2% (equivalent to 20,745.64 tons of $CO_2$). The emissions from ground transportation increased due to the shift from air mode (up to a 2.1%, when air fares increase by 500%). The total emissions are reduced by up to 13.8% with the highest airfare increase.

**Table 6.** Base scenario modal share of domestic long-distance trips and $CO_2$ emissions by mode.

| | Travel Mode | | | | Total |
|---|---|---|---|---|---|
| | Auto | Air | Bus | Train | |
| | Number of trips | | | | |
| Day Trip | 1,879,515 (86.05%) | 8,449 (0.39%) | 68,315 (3.13%) | 227,990 (10.44%) | 2,184,269 (100%) |
| Overnight Trip | 1,890,301 (81.19%) | 92,304 (3.96%) | 72,950 (3.13%) | 272,748 (11.71%) | 2,328,303 (100%) |
| Total | 3,769,815 (83.54%) | 100,793 (2.23%) | 141,264 (3.13%) | 500,737 (11.10%) | 4,512,610 (100%) |
| | $CO_2$ emissions, tons | | | | |
| Day Trip | 49,134.10 (87.34%) | 4,762.05 (8.46%) | 1,226.62 (2.18%) | 1,133.54 (2.01%) | 56,256.31 (100%) |
| Overnight Trip | 42,969.60 (54.01%) | 34,253.56 (43.06%) | 1,080.48 (1.36%) | 1,249.39 (1.57%) | 79,553.02 (100%) |
| Total | 92,103.70 (67.01%) | 39,015.61 (28.39%) | 3,937.06 (2.86%) | 2,382.93 (1.73%) | 137,439.30(100%) |

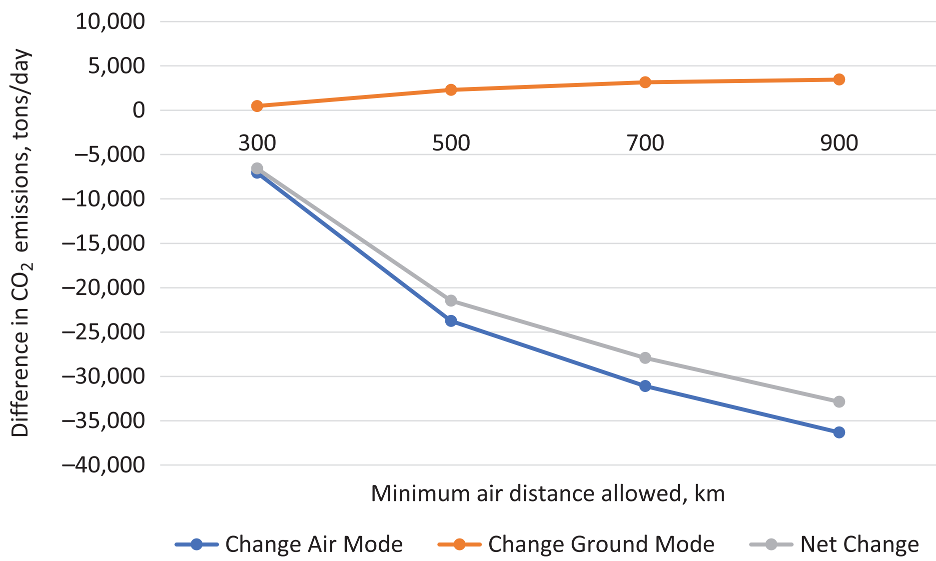


**Figure 3.** Change in $CO_2$ emissions due to minimum distance restriction for air travel.

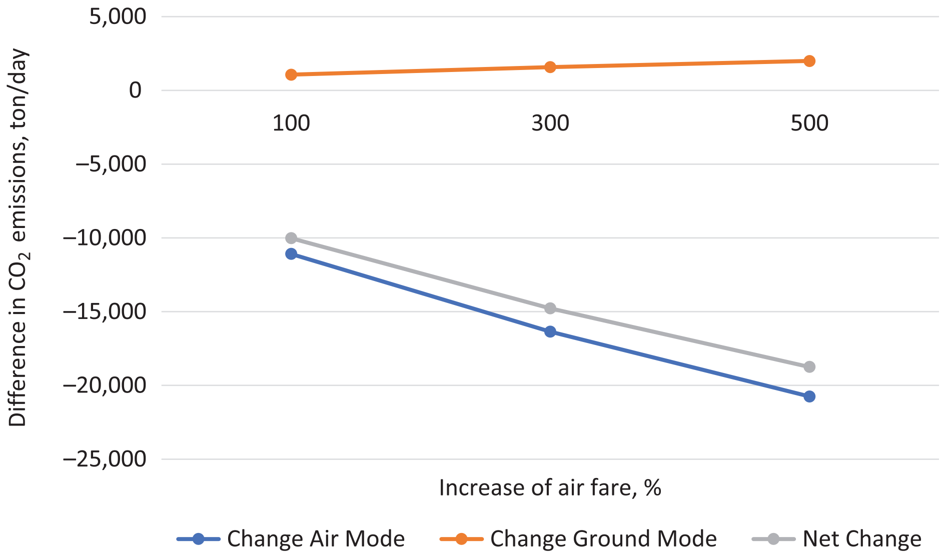


**Figure 4.** Change in $CO_2$ emissions based on air fare increase.

## 8. Conclusion

This research evaluated the potential of policies to reduce $CO_2$ emissions produced by long-distance travel. Specifically, we used an agent-based travel demand model to estimate the demand for long-distance travel and coupled the model with a $CO_2$ emissions calculator. It was shown that policies that restrict air travel below a defined threshold distance were more effective in $CO_2$ emissions reduction than increasing airfares. Compared to urban travel, air travelers are less sensitive to price increases due to higher values of time in long-distance travel. Also, many domestic air trips in Germany are business trips for which the employer covers the travel costs, which tends to reduce price sensitivity.

Another important aspect of this study is to quantify the shift from air mode to ground modes, and the corresponding levels of emissions. Traveling by auto is often more economical than other public ground modes, particularly when traveling with more than one person. Overall, the best $CO_2$ emission reduction with almost 33,000 tons per day was achieved with the scenario that restricted air travel to trips above 900 km. While politically difficult to implement, the strict air travel restrictions are most powerful in reducing the number of air trips and associated $CO_2$ emissions.

One aspect that sets this model apart from most other existing long-distance models is that it is built as an agent-based model. Agent-based models introduce a lot of flexibility to design scenarios (Donnelly, Erhardt, Moeckel, & Davidson, 2010). If someone wanted to test the impact of increasing eligibility for telework on long-distance travel, it is simple to add the attribute "eligible for telework" to each agent and adjust the choice models accordingly. However, agent-based modeling comes at a price. Such models require a random number generator to simulate choices of individual agents. Depending on the random numbers chosen, every model run produces slightly different results. The differences between model runs are marginal if a large number of agents is simulated or if a lot of choices of these agents are simulated, as a large number of events averages out. Whenever a small number of agents or rare events are studied, agent-based models need to be run many times and the average across many model runs needs to be calculated (Wegener, 2011).

Long-distance travel is not as rare that it would be difficult to study it with an agent-based model, at least not for common destinations and modes. In this application, however, agent-based models proofed to be challenging. Some scenarios tested to limit air travel to trips above a certain threshold distance only. While the number of air trips eliminated by these policies was stable across different model runs, the alternative modes chosen were not. If 100 air travelers with trips under 300 km switch to ground modes due to this policy, it makes a large difference in terms of $CO_2$ emissions if 30 of them chose bus in one model run and 35 in another model run. While both results might be perfectly plausible outcomes, it would be invalid to assess this policy based on a single model run. Therefore, the model had to be run multiple times to calculate the average of every scenario presented in this article.

A limitation is that the effects of congestion of the road network were not considered. If congestion on the network was considered, travelers shifting from air to car could impact the congestion of the road network and affect travel times and emissions. The selected trip-based sequential travel model does not take into account the interaction between the steps. The application of copula models could better account for this issue, but a study area with 11,717 zones makes a joint destination and mode choice unfeasible. An improvement could be to include mode choice logsums as terms of the utility of destinations in the destination choice model. This would affect destination of trips after modal restrictions are introduced (e.g., if flights under 500 km are prohibited, former air travelers may decide to travel to closer destinations). Last but not least, induced demand due to new modes or dampened travel demand due to restrictive scenarios are not considered in this model, as they are difficult to quantify.

It is planned to test more policies to reduce total $CO_2$ emissions including tolls on freeways and ride-sharing solutions. International travel will be added. This would allow to implement additional policies that promote more local travel and penalize short-duration overseas trips. More detailed emission factors for cars and buses that account for traffic conditions are planned to be used to account for the negative impacts of road congestion.

The policies analyzed in this article explored the potential to reduce $CO_2$ emissions of long-distance travel. It was shown that certain policies would significantly reduce long-distance emissions. The most impactful scenario tested was to limit air travel to destinations with a distance of 900 km or more, which led to a reduction of 32,900 tons of $CO_2$ per day. In a country like Germany where decent rail connections are available between all major cities, this might not be too much of a burden for travelers (even though travel times would increase for many trips). This policy would reduce the total emissions from the transport sector in Germany (160 million tons $CO_2$ per year in 2018; see Statista, 2018) by 7.5%. Given that the emissions of the transport sector were rather constant over the past 30 years, such a policy could be an important start to reduce transport emissions.

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### Conflict of Interests

The authors declare no conflict of interests.

### Supplementary Material

Supplementary material for this article is available online in the format provided by the authors (unedited).

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