



Measurement of Carbon Emissions. Documentation of the GLEN CO2 Module

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1 Introduction

1.1 General overview

This user guide provides documentation of the methodology used to calculate individual greenhouse gas emissions with the CO₂ survey module of the German Longitudinal Environmental Study (GLEN), Wave 1a, with data collection in 2025 (GLEN 2026b). Its primary objective is to describe in detail how we operationalize, compute, and aggregate individual greenhouse gas emissions across four central domains: housing, transportation, diet, and consumption, from a consumption-based life cycle perspective. This document is intended to enable users to understand, evaluate, and replicate the calculation procedures. This includes the operationalization of survey variables, transformation rules, imputation strategies, assumptions applied in the absence of detailed information, and the data sources used for parameterization. By documenting these choices, this guide aims to ensure transparency and open the survey module to critical assessment and future adaptation.

All greenhouse gas emissions are computed at the individual level. Where input data or emission factors refer to the household rather than the individual (e.g. shared housing-related emissions), we allocate the resulting estimates proportionally by dividing the household-level values by the reported number of household members. This ensures comparability across respondents while maintaining consistency with the underlying data sources. The calculation covers all greenhouse gases, including CH₄, N₂O, and fluorinated gases (F-gases) alongside CO₂, and we report all emissions throughout in CO₂ equivalents (CO₂e), meaning on the basis of the 100-year global warming potential expressed relative to CO₂. The module adopts a consumption-based, life cycle perspective on individual emissions. Emissions are attributed to the individual according to the goods and services they use. Emission factors applied are life cycle factors that capture not only direct emissions at the point of use (e.g., fuel combustion), but also the upstream emissions embodied in producing and providing these goods and services.

As GLEN is designed as a panel study, new survey data is collected annually, allowing for changes at the individual level to be analyzed. Changes in emissions can arise from (a) changes in individual behavior (e.g., driving less), (b) household investments (e.g., replacing a gas boiler with a heat pump), and (c) exogenous factors (e.g., a shift in the renewable share of the electricity mix). To allow future analyses to separate (a) and (b) from (c), all CO₂e emission variables are additionally provided using the parameterization of the first panel wave (2025) as a fixed reference.

The reference time frame for all calculations is the 12 months preceding the survey. Although we align the survey questions and resulting estimates with this temporal reference wherever possible, it is not always feasible to rely exclusively on external data sources that match this exact window. In such cases, we use the most recent and appropriate data available at the time the module was developed, and we will update the underlying sources in upcoming panel waves where possible. Detailed information on data sources, including their temporal coverage and the rationale for their selection, is provided in the respective methodological sections. Changes with respect to these data sources will be documented in the data manuals for each respective wave. The exact wording of all items relevant to the CO₂e calculation can be found under the corresponding variable name in the codebook (GLEN 2026a). Table 1 gives a compact overview of the indicators used.

Beyond the technical documentation of the calculation steps, this guide includes a section that reviews the relevant research literature and current methodological standards in individual CO₂e estimation (see Section 2). This overview contextualizes the chosen approaches, supports informed design decisions, and clarifies how the implemented procedures relate to existing scientific practice. Overall, this guide serves both as a methodological reference for researchers and as a practical manual for implementing and interpreting the CO₂e estimation framework of GLEN.

1.2 Provided variables

We supply five main estimate variables: annual CO₂e emission estimates (measured in kg CO₂e per year) for each of the four substantive domains – housing, transportation, diet and consumption – as well as a combined overall estimate given by the sum of emissions across all domains. These variables represent the primary outputs of the calculation framework and are intended for substantive analysis and reporting.

In addition to these estimates, we provide a total of five auxiliary variables in the form of imputation counters, one for each domain. These counters track the number of instances in which deviations from participants' direct responses were necessary during the calculation process. Such deviations include imputations, assumptions applied to missing data, and transformations required to derive usable numerical inputs.

Domain	Component	Indicators
Housing	Heating	Building type and age, modernization measures, usual indoor temperature, heating carriers, local weather, solar thermal system
	Electricity	Self-reported consumption, <i>or</i> number of large appliances, photovoltaic system
	Construction & maintenance	Living area, building type and age (embodied emissions)
	Second home	Indicator flag, adds 20 % of housing emissions
	Overall	Living area and household members, to scale emissions
Transportation	Private transport	Size and fuel type of cars and motorcycles, distance covered as driver or passenger, embodied emissions from vehicle construction and supply (incl. bicycles and scooters)
	Public transport	Frequency of short- and long-distance trips
	Flights	Number of private flights in four duration categories
	Cruises	Number of days on cruise ships
Diet	Energy requirement	Weight, sex, age, physical activity level
	Dietary composition	Consumption of: beef, other meat, fish, dairy and eggs, other food
Consumption	Household & individual goods	Furnishings (purchase preference, number of rooms), household appliances (count), consumer electronics (count), clothing (purchase preference)
	Pet keeping	Dogs, cats, horses, birds, aquaria and terraria, rabbits and other small animals
	Accommodation	Number of vacations in three length categories, length and type of accommodation for the longest vacation

Table 1: Overview of the indicators used in the CO₂e calculation, by domain and component

The inclusion of auxiliary variables addresses a practical methodological challenge: emission estimates rely on a large number of input variables, and restricting analyses to strictly complete cases would substantially reduce the available sample size and bias analyses. Instead, we apply carefully justified imputations where necessary. The imputation counters allow users to maintain transparency regarding these adjustments and provide flexibility in deciding how strongly imputed observations should be weighted or whether additional filtering criteria should be applied.

Examples of imputations include deriving missing data on living space from the reported number of rooms (home10). The rationale for each imputation decision is described alongside the respective calculation and operationalization steps in this document. For additional transparency, the appendix provides detailed summary tables for each domain listing all applied imputations and their corresponding conditions (see page 26ff.).

2 State of research

Individual CO₂e emissions vary widely across countries (Chancel & Piketty 2015, Ivanova & Wood 2020, Chancel 2022, Zheng et al. 2023). Within the European Union, average per-capita emissions range from roughly 6tCO₂e (Romania) to 15tCO₂e (United Kingdom) (Ivanova et al. 2017). Beyond Europe, the spread is even larger: estimates fall as low as 0.9tCO₂e in India and 1.7tCO₂e in China, while the United States have average individual emissions of about 18–20tCO₂e (Jones & Kammen 2011, Wiedenhofer et al. 2017, Feng et al. 2021).

Reported emissions diverge not only across countries but also across studies in the same national context. For Germany, published estimates of the average individual carbon footprint span roughly 6.5–14tCO₂e (Miehe et al. 2016, Kleinhückelkotten et al. 2016, Gill & Moeller 2018, Ivanova & Wood 2020, Groß et al. 2022, Brandenstein et al. 2023, Bohmann & Küçük 2024). This dispersion stems largely from methodological choices rather than from genuine differences in behavior. For example, studies differ in the consumption domains they cover: some account only for housing, transport, and diet and omit domains such as clothing and electronic devices (Schubert et al. 2013, Bohmann & Küçük 2024), others lack emissions from cruise travel or pet keeping (Miehe et al. 2016, Gill & Moeller 2018), and still others fold public (collective) emissions into the personal total (Gill & Moeller 2018). Differing system boundaries, allocation conventions, and reference years further widen the gap, making estimates difficult to compare across studies. A more fundamental divide concerns the estimation basis itself. Many studies derive emissions from household expenditure, combining reported spending with monetary emission intensities from environmentally-extended input-output models (e.g. Gough et al. (2011), Miehe et al. (2016), Ivanova et al. (2017), Gill & Moeller (2018), Ivanova & Wood (2020)). This offers a broad coverage of consumption, but it ties emissions mechanically to spending and higher prices paid for the same physical quantity are misread as higher emissions (Girod & De Haan 2010, André et al. 2024). Hence, the elasticity of emissions by expenditures is often overestimated, which is particularly problematic for investigating the influences and consequences of individual carbon emissions (Girod & De Haan 2010, André et al. 2024). To avoid these issues, we instead use self-reported quantities of individual environmental behavior, an approach that has been recently used in different forms by Bruderer Enzler & Diekmann (2019) and Gomm et al. (2023) for Switzerland, Bohmann & Küçük (2024) on the household level for Germany, and Berland & Leroutier (2025) for France.

Despite this heterogeneity, the existing literature converges on some robust patterns. First, individual emissions are highly unequally distributed and strongly structured by income within every studied country (Gough et al. 2011, Miehe et al. 2016, Ivanova et al. 2017, Gill & Moeller 2018, Bruderer Enzler & Diekmann 2019, Ivanova & Wood 2020, Brandenstein et al. 2023, Bohmann & Küçük 2024). Second, per-capita emissions tend to decrease as household size grows, reflecting economies of scale in shared dwellings and goods (Ivanova et al. 2017, Gomm et al. 2023, Bohmann & Küçük 2024). Evidence on further correlates, such as age, gender, education, or urbanity, remains mixed and has not produced consistent results (Kleinhückelkotten et al. 2016, Miehe et al. 2016, Ivanova et al. 2017, Gill & Moeller 2018, Bruderer Enzler & Diekmann 2019, Gomm et al. 2023, Bohmann & Küçük 2024). Interaction effects among these determinants and their longitudinal development over time, meanwhile, are rarely examined (Gomm et al. 2023, Lyubich 2025).

Two research needs follow from this. First, estimates are hard to compare because their methods are seldom harmonized or documented in full. Second, the determinants of individual emissions, particularly their interactions and change over time, remain underexplored. This report speaks to the first research need directly. Rather than proposing a new standard, it documents the estimation procedure in full, making every modeling choice and assumption explicit, and thereby open to scrutiny and methodological debate. As to the second research need, the GLEN survey is moreover designed as a panel, so that it will

also support individual-level analysis of various determinants as further waves accumulate.

3 Housing

The housing module quantifies the CO₂e emissions associated with a respondent’s dwelling from a life cycle perspective, spanning both the operational emissions of running the home, space heating and electricity, and the embodied emissions of constructing and maintaining it. It combines survey responses, building typologies, and life cycle emission factors that capture not only combustion or point-of-use emissions but also the upstream production of the energy carriers involved. Across the production and use phases of the dwelling, the estimate is assembled from four interconnected components:

1. A physics-informed thermal demand model estimating operational heating energy from building characteristics and climatic context
2. A survey-driven electricity demand model combining self-reported operational consumption with validation and imputation procedures
3. An embodied-emissions component assigning construction and maintenance emissions based on building age and renovation history
4. An emission accounting layer that converts energy use from heating and electricity (steps 1 and 2) into carrier-specific emissions using life cycle emission factors and aggregates operational and embodied emissions to the individual level, including an adjustment for second homes

3.1 Thermal demand model

Operational heating demand is estimated with a physics-informed building-typology model rather than self-reports. Grounding the estimate in the TABULA framework (Loga et al. 2015) yields consistent and cross-respondent comparable demand figures that follow directly from building characteristics and local climate, which also sidesteps the distortions that self-reported heating consumption tends to introduce. This design choice was corroborated by our pretest results, in which directly reported heating values were frequently implausible. TABULA supplies both the building-envelope heat need and its conversion into delivered final energy through system efficiency assumptions. The thermal demand model estimates heating-related energy use by translating survey responses into building-level physical parameters and applying standardized reference calculations. The exact calculations for each step follows Loga & Diefenbach (2013). Crucially, TABULA supplies not only the building-envelope heat demand but also its translation into delivered (final) energy through system-specific efficiency and expenditure factors, as well as calibrated default assumptions for heating systems and solar configurations typical of each reference building. We adopt these calibrated reference values and adapt their combination to our survey data; the only quantity we supply externally in the heating pathway is the carrier emission factor (see Section 3.4.1). This thermal demand estimation yields a estimate of delivered energy for each energy carrier used in *kwh/a*.

3.1.1 Building representation using TABULA

We map each dwelling to a TABULA reference building defined by construction age, building type, and refurbishment status.

The building envelope classification is based on building type (home3), construction age (home4), and modernization measures (home14), with refurbishment captured at three levels: no modernization, partial modernization, or full modernization (“future-oriented refurbishment” Loga et al. (2015)).

In contrast to the standard TABULA implementation, we model refurbishment states for the building envelope and energy systems separately. More generally, we match the envelope and the heating system to TABULA references independently: the envelope match (home3, home4, home14) fixes the net heat demand q_h , while the reported heating system (home12) is matched to its own best-fitting TABULA system reference. This decoupling allows for realistic combinations that the vintage-typical TABULA pairing would exclude. For example, a modern heat pump in an unrefurbished 1970s dwelling: the envelope is simulated at its true age, while the heat-pump efficiency and expenditure characteristics are drawn from the nearest TABULA reference that documents such a system. As the GLEN questionnaire has fewer building-age categories than the original TABULA system (7 vs. 12), each calculation is performed for every fitting TABULA age category and averaged at the end. A mapping of categories can be found in the appendix on page 26.

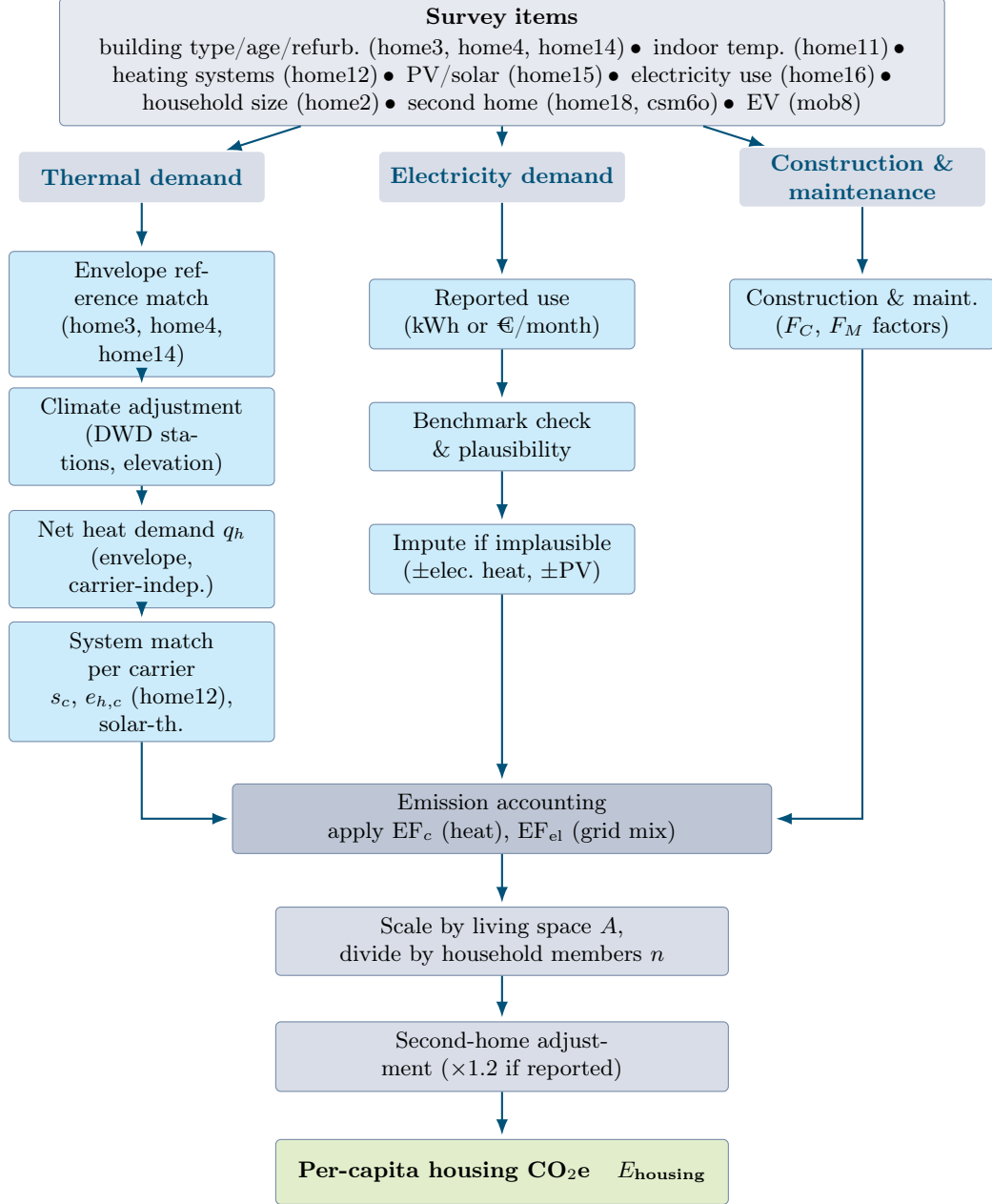


Figure 1: Overview of the housing energy and emissions modeling framework. All thermal quantities, the net envelope heat demand q_h , its conversion into delivered final energy via system efficiency/expenditure factors $e_{h,c}$, and the default heating-system and solar configurations, are taken from TABULA; the only externally supplied quantity in the heating pathway is the carrier emission factor EF_c (exceptions: district heating and grid electricity).

3.1.2 Climatic adjustment

We adjust heating demand to local weather conditions for the reference year 2024. We use daily observation data from 492 German Weather Service (DWD) stations ([Deutscher Wetterdienst 2024](#)) to derive heating-relevant indicators, including heating days (daily mean temperature below 12°C) and mean temperature during heating periods.

We generate participant-specific estimates by inverse-distance weighting of the three nearest weather stations combined with an elevation-based lapse-rate correction ($\Gamma = -0.0065$ °C/m) ([Liang et al. 2014](#)). The elevation values were extracted from the Copernicus GLO-90 DEM ([OpenTopography 2021](#)). For solar radiation, we use TABULA default values due to incomplete spatial coverage of the DWD data.

3.1.3 Heating energy demand

We define heating energy demand as the thermal output required to maintain indoor conditions given building insulation characteristics and environmental context. We obtain the net heat demand q_h (kWh/m²a) by matching each dwelling to a TABULA reference building (Section 3.1.1) and applying the standardized TABULA calculation procedure ([Loga et al. 2015](#)). The same procedure translates this net demand into delivered final energy via the system expenditure factor of the matched heating system (Section 3.1.4). Wherever possible, we use participant-reported indoor temperature (home11). If no indoor temperature is provided, we use the TABULA default value of 20°C and mark this by increasing the housing imputation counter by one. The local weather information from 3.1.2 is incorporated here to improve the precision of energy need given the climatic conditions and insolation.

3.1.4 Carrier allocation

Each reported heating system (home12) is matched to its own TABULA reference, from which the system efficiency and expenditure characteristics ($e_{h,c}$) are drawn. Because a reported system need not exist in the TABULA reference set at the dwelling’s own construction generation, we select the reference through a structured fallback search. Starting from the reported generation, we search outward to the nearest neighbouring vintages until a reference with a matching heating system is found, first requiring the reported system-refurbishment level and, if necessary, relaxing that requirement in a second pass. Coal and wood are both represented through TABULA’s biomass system reference, as the typology contains no dedicated coal system; the two therefore differ only through their carrier emission factor. If no reference can be matched, the case is flagged as a hard failure rather than silently imputed.

Following [Köhler et al. \(2018\)](#), additional heating systems increase the overall energy demand. If multiple systems are reported, each is matched as above and the energy demand is distributed according to predefined shares:

$$\text{share}_{\text{main heating system}} = \frac{1}{n_{\text{additional heating systems}} + 1} + 0.1$$

and

$$\text{share}_{\text{additional heating system}_i} = \frac{1 - \text{share}_{\text{main heating system}}}{n_{\text{additional heating systems}}} + 0.05$$

In case of missing or ambiguous heating configurations, or where several plausible references remain (eg. central gas heating as well as individual gas heating plausible matches), we average across the plausible matches and record this in the imputation counter.

3.1.5 Solar thermal systems

We integrate solar thermal systems into the estimation by reducing the energy required from conventional heating carriers for domestic hot water preparation. If the TABULA reference configuration already includes solar thermal support for the matched building, we retain existing values; otherwise, we apply a simplified approximation by reducing hot-water energy demand by 65% to represent solar heat input ([Mauthner et al. 2016](#)).

3.2 Electricity demand model

3.2.1 Estimation of benchmark values

While electricity consumption is primarily based on participant responses (home16), which we validate against expected benchmark values and standardized conversion procedures, we calculate an expected

annual consumption value using a publicly available reference formula provided by [EnBW \(2025\)](#) to contextualize reported electricity consumption:

$$\text{kWh/year} = 9 \cdot \text{living space} + 200 \cdot \text{household members} + 200 \cdot \text{no. of large electronic devices}$$

3.2.2 Photovoltaic systems

We incorporate photovoltaic (PV) and solar systems as adjustments to reference energy flows based on participant responses (home15). The calculation distinguishes between five possible situations: (a) no solar use, (b) a small plug-in balcony photovoltaic system (“Balkonkraftwerk”), (c) a conventional roof-mounted photovoltaic installation (“standard PV system”), (d) a solar thermal system for domestic hot water, and (e) the respondent has a system but does not know which one.

For conventional photovoltaic systems, we estimate annual electricity generation using standardized reference values derived from the TABULA building typology dataset by matching the reported building type to a comparable reference building. If no direct match is available, we use a comparable multi-family building reference as a proxy to ensure consistency across cases.

We model “Balkonkraftwerke” separately using a fixed annual electricity generation value of 1,750 kWh/year, which represents a typical small plug-in PV system. For both photovoltaic options, we assume that 30% of generated electricity is self-consumed within the household ([Verbraucherzentrale 2026](#)). This share offsets electricity demand and associated emissions.

If participants report having a solar system but do not specify the system type, the model defaults to a standard photovoltaic system. We record the application of this default classification by increasing the housing imputation counter by one.

We implement no detailed yield simulations or regional differentiation from TABULA; all solar calculations rely on the standardized reference assumptions.

3.2.3 Processing of reported electricity consumption values

Participants are asked to report electricity consumption either directly in annual kWh or as monthly electricity expenditure in euros. If only monthly costs are provided, these are converted into annual kWh using the mean electricity price of the previous year:

$$\text{kWh/year} = 12 \cdot \frac{\text{euro/month}}{\bar{p}_{\text{euro/kWh}}}$$

The mean electricity price is derived from the national average from 2024 ([Bundesnetzagentur für Elektrizität Gas Telekommunikation Post Eisenbahnen 2025](#)). We evaluate the reported electricity consumption against the expected benchmark value (see Section 3.2.1) using a relative deviation measure:

$$\Delta_{\text{rel}} = \frac{\text{reported power consumption} - \text{expected power consumption}}{\text{expected power consumption}}$$

We classify a reported value as implausible if one of the following conditions applies:

- Excessively high power consumption without structural explanation: $\Delta_{\text{rel}} > 2.0$ (i.e., more than 200% above the expected value) and neither an electric heating system nor an electric vehicle (mob8) is reported.
- Unusually low power consumption without on-site generation: $\Delta_{\text{rel}} < -0.5$ (i.e., less than half of the expected value) and no photovoltaic system is reported.
- Extreme deviations: Reported consumption is more than ten times higher or lower than the expected value, irrespective of the heating configuration.

If a value is missing or we classify it as implausible, we impute electricity consumption using the expected benchmark value. The imputed value is adjusted by:

- Adding estimated electric heating demand in case of electricity-based heating (see Section 3.1.4),
- Subtracting self-consumed solar electricity production estimated for present solar systems (see Section 3.2.2).

Otherwise, we assume that the adjustments are already included in the values reported by participants. We record all applied imputations in the housing imputation counter.

3.3 Construction and maintenance

Following the approach in the CO₂ emission calculation of the German Environment Agency (Paar et al. 2025), we assign each building construction and maintenance emissions. The base emission values for construction (C) and maintenance (M) of each building are derived from Mahler et al. (2019). The base estimation is as follows:

$$E_{\text{construction and maintenance}} = \text{Emissions}_C \cdot F_C + \text{Emissions}_M \cdot \min(F_{M,\text{hist}} + F_{M,\text{survey}}; 1)$$

Buildings older than 50 years are not assigned any construction emissions; newer buildings are assigned more emissions to account for higher building standards (see Appendix A3 for F_C). For maintenance, a historic factor is estimated to account for repairs and updates that happened before the 15-year window the survey captures (see Appendix A5 for $F_{M,\text{hist}}$). To account for the measures captured in the survey, we count the number of renovations indicated by variable home14 (see Table A4 for $F_{M,\text{survey}}$). The combined maintenance factor cannot exceed 100%. Both for maintenance and construction the emission estimates are provided in kg of CO₂e per year and m², meaning a full 100% assignment does not compile all construction and maintenance emissions into one year.

3.4 Emission accounting and aggregation

The consolidated energy use from the heating and electricity models at the building level are used as input factors for emission accounting.

3.4.1 Emission factors

CO₂e emission factors for individual energy carriers are primarily derived from an official information sheet published by the Bundesamt für Wirtschaft und Ausfuhrkontrolle (BAWA 2025). These carrier emission factors are the only externally supplied quantity in the heating pathway; all preceding thermal quantities (envelope demand, system conversion, default configurations) originate from TABULA. Two exceptions apply. For district heating, no suitable emission factor is provided in the referenced BAWA document, so district-heating emission values are used from the standardized TABULA reference assumptions. Electricity emissions are calculated using the German national electricity generation mix for the reference year 2024 (Icha & Lauf 2025), ensuring that electricity emissions reflect the contemporaneous average carbon intensity of grid electricity rather than technology-specific assumptions.

3.4.2 Scaling and allocation

We initially calculate heating emissions in units of CO₂/m²/year. The total dwelling-level heating emissions is obtained by multiplying these by the estimated living space. We allocate both heating and electricity emissions to the individual by dividing the household-level emissions by the number of household members (home2).

3.4.3 Second-home adjustment

If a second home is reported (home18) or if the accommodation of the longest vacation is a respondent's own vacation home (csm60), we add emissions equal to 20% of main-residence emissions (heating + electricity + construction). This flat-rate adjustment reflects the absence of detailed information on secondary dwelling characteristics while ensuring consistent inclusion of additional housing-related emissions. If the answer for home18 is missing, we assume that there is no second home and increase the housing imputation counter by one.

3.4.4 Stylized summary

The full housing estimate can be summarized as a per-capita accounting identity over four emission components. The simulated building physics enter only through the envelope heat demand $q_h^{(\text{env})}$ and the system conversion factor $e_{h,c}^{(\text{sys})}$, which are matched to the TABULA references *independently* (Section 3.1.4); only the carrier emission factor EF_c is supplied externally:

$$E_{\text{housing}} = \frac{(1 + 0.2 \delta_{2\text{nd}}) (E_{\text{heat}} + E_{\text{el}} + E_{\text{C\&M}})}{n_{\text{members}}}, \quad \delta_{2\text{nd}} \in \{0, 1\}$$

with the dwelling-level components

$$E_{\text{heat}} = A \sum_c s_c \underbrace{q_h^{(\text{env})}}_{\text{envelope ref.}} \underbrace{e_{h,c}^{(\text{sys})}}_{\text{system ref.}} \underbrace{\text{EF}_c}_{\text{external}}$$

$$E_{\text{el}} = \text{EF}_{\text{el}} \cdot D_{\text{el}},$$

$$D_{\text{el}} = \begin{cases} \hat{D}_{\text{el}} & \text{if self-report plausible} \\ B + D_{\text{el}}^{\text{heat}} - D_{\text{self}}^{\text{PV}} & \text{if imputed} \end{cases}$$

$$E_{\text{C\&M}} = E_C F_C + E_M \cdot \min(F_{M,\text{hist}} + F_{M,\text{survey}}, 1)$$

where A is living space, s_c the carrier shares (Section 3.1.4), EF_c the carrier emission factors, B the electricity benchmark (Section 3.2.1), and $\delta_{2\text{nd}}$ flags a reported second home. Because $q_h^{(\text{env})}$ is carrier-independent, the effect of the reported heating system on emissions reduces to a swap of $e_{h,c}^{(\text{sys})} \text{EF}_c$ for an otherwise identical building; for two dwellings with the same envelope this is simply $(e_{h,\text{coal}} \text{EF}_{\text{coal}}) / (e_{h,\text{gas}} \text{EF}_{\text{gas}})$.

4 Transportation

To estimate emissions from transportation, we use four measurement concepts:

- Private transport,
- Public transport,
- Flights,
- Cruise trips.

We consider both direct emissions from transportation (tank-to-wheel) and indirect emissions from extraction, production and supply of fuel (well-to-tank) in all measurement concepts. In addition, we consider emissions from construction and vehicle maintenance in the calculation of emissions from private transport, public transport and flights. As so far there are no data available on the emissions of construction and maintenance of cruise ships, these emissions are missing. A list of the used emission factors in the domain of transportation can be found in the appendix on page 30.

4.1 Private transport

4.1.1 Use of private vehicles

The first concept measures the emissions of private transport, summarizing the emissions from the use and construction of private vehicles. First, we calculate the emissions from the use of private vehicles by multiplying the self-reported personal mileage from the last 12 months with the most frequently used private vehicles (max. 3 cars and 2 motorcycles or motor scooters in the CAWI version / max. 3 vehicles in the PAPI version; mob9) with the average emissions of the vehicle per vehicle kilometer, which we derive from the reported vehicle's class (mob7) and fuel type (mob8). We measure personal mileage in the last 12 months in seven categories, which we designed based on the distribution of personal mileage in the representative population survey 'Mobility in Germany 2023' conducted by the German Federal Ministry of Transport (Follmer 2025). We take both riding as a passenger and driving into account to allocate emissions not only to the driver. For the sake of simplicity, we use an average occupancy of 1.5 people/car and 1 person/motorcycle or motor scooter (Follmer 2025). If respondents use more than the maximum number of vehicles for which we ask for detailed information, they can indicate this (mob6), and we add an average car (mid-size gasoline-powered car) or motorcycle/motor scooter with low mileage (2,500 km/year) in that case (max. 6 each). If respondents do not provide the number of cars or motorcycles in the PAPI questionnaire, but report vehicle class, fuel type, and personal mileage for one or more vehicles in the follow-up questions due to misinterpretation, we impute the number of cars/motorcycles according to their answers. We consider each of the imputations in the imputation counter for transportation. As regular use of vehicles from other households is quite rare, we restrict our estimation to vehicles from the respondent's own household. This further enables the use of the data for estimating the embodied emissions from the construction of private vehicles. Furthermore, we consider neither bicycle and electric scooters due to their marginal emissions ($<5 \text{ g CO}_2\text{e/km}$; Allekotte et al. (2020)) nor the use of car-sharing services and taxis, as these transport modes are used to a very limited extent compared to private cars and motorcycles in Germany (Follmer 2025).

$$E_{prtuse} = \sum_{i=1}^{\text{no. of vehicles}} \frac{\text{mileage with vehicle } i \cdot \text{average emissions per vkm by class and fuel of vehicle } i}{\text{average occupancy of vehicle } i \text{ (1 or 1.5)}}$$

4.1.2 Construction of private vehicles

We derive emissions from vehicle construction and supply by using the individual number of used cars, motorcycles, and motor scooters (mob6), their respective class (mob7), and fuel type (mob8). Besides private cars, motorcycles, and motor scooters, we also consider the emissions from construction and supply of an electric bicycle, bicycle, and/or electric scooter, respectively, if a person uses these vehicles at least once per month (mob1). We weight all emissions according to the average life cycle in the case of cars and motorcycles/motor scooters also according to the number of adults in the household (home2, home7), as they are most often in possession of all adults in the household. We assume an average life cycle of 15 years for cars, motorcycles and motor scooters, 10 years for bicycles and 5 years for electric scooters according to (Allekkotte et al. 2020).

$$E_{prtconstruction} = \sum_{i=1}^{\text{no. of vehicles}} \frac{\text{average production emissions of vehicle } i \text{ by its class and fuel}}{\text{average life cycle of vehicle } i \cdot \text{no. of adults in HH (car and motorcycle)}}$$

4.1.3 Emission factors

For the use of private vehicles, the values for well-to-tank (WTT), tank-to-wheel (TTW) and maintenance emissions per vehicle kilometer (vkm) for mid-size cars (all fuels besides gasoline) are from a report by the German Environment Agency on CO₂e emissions of cars with conventional and alternative fuels (Biemann et al. 2024). For mid-sized gasoline-powered cars, we calculate the TTW emissions as an average of compressed natural gas (CNG) (Biemann et al. 2024) and liquified petroleum gas (LPG), for which we assume 90% of TTW emissions of a petrol car (Allgemeiner Deutscher Automobilclub 2022), as LPG cars are not included in Biemann et al. (2024). With the exception of plug-in-hybrids, hybrid cars are considered gasoline cars due to their marginal proportion of driving with an electric motor (Biemann et al. 2024). For the other three car classes besides mid-size (small, large, and SUV/Van), we weighted the emission values for all fuel types for WTT, TTW, and maintenance of mid-size cars according to the average weight of all new registered cars in the respective car classes in 2024 (Kraftfahrt-Bundesamt 2025). For motorcycles and motor scooters, all emission values are obtained from (Allekkotte et al. 2020).

For the construction of private vehicles, we use emission values from a study of the Austrian Environment Agency on the CO₂e emissions of car production and supply (David et al. 2021) and from the ecological comparison of different transport modes by Allekkotte et al. (2020) for all other vehicles. Due to a lack of data, we estimate the emissions for SUV/vans and small plug-in-hybrid or hydrogen cars by weighting the emissions from mid-size cars according to the average weight of new registered cars in 2024 (Kraftfahrt-Bundesamt 2025). As before, we consider other hybrid cars aside from plug-in-hybrid cars to be gasoline cars.

4.2 Public transport

The second measurement concept of transportation addresses the CO₂e emissions from the use of public transport. These are calculated by multiplying the individual distance traveled with public transport over the last 12 months by the average emissions per passenger kilometer with public transport. We estimate the mileage by using the self-reported current frequency of using public transport (mob1), as pretests showed that reporting annual mileage was very complex for respondents, in particular for long-distance public transport. We assume an average length of 25.4 km for a short-distance public transport trip and 321.6 km for a long-distance public transport trip (twice the average trip length according to Follmer (2025)) and multiply these values with the specified frequency ("almost" daily=300, "multiple times per week"=150, "once per week"=50, "multiple times per month"=30, "less often"=12, "(almost) never"=0). We differentiate between long-distance and short-distance public transport, as long-distance public transport generates only around half the emissions per passenger kilometer (Allekkotte et al. 2020). In contrast, we do not differentiate between bus and train transportation, as both transport modes have very similar CO₂e emissions per passenger kilometer when considering the differentiation in long- and short-distance transport (Allekkotte et al. 2020).

$$E_{publictr.} = 25.4 \cdot \text{frequency of using short-distance pt} \cdot \text{average emissions per pkm with short-distance pt} \\ + 321.6 \cdot \text{frequency of using long-distance pt} \cdot \text{average emissions per pkm with long-distance pt}$$

4.2.1 Emission factors

All emissions values are from [Allekotte et al. \(2020\)](#). As this study reports emission values separately for trams and metros, regional busses, regional trains, long-distance busses, long-distance trains and coaches, we use average emission values for short-distance and long-distance public transport weighted by the given total annual passenger kilometers per transport mode ([Allekotte et al. 2020](#)).

4.3 Flights

In the third section, we measure the CO₂e emissions from the use of airplanes. We decided against asking respondents to report the total flight distance or flight time in the last 12 months, as the required knowledge for this is, similar as for public transport, very complex. Instead, respondents reported the number of short, medium, long and ultra-long-haul flights in the last 12 months (mob11), which we multiply with the average individual emissions per flight according to the length category. This differentiation is necessary for three reasons: First, the emissions of flying are higher for the take-off and landing phase. Second, longer flights need extra fuel for fuel transportation. Third, emissions cause a stronger climate response at higher altitudes, which are used more often in longer flights ([Dahlmann et al. 2024](#)). We use flight duration instead of flight distance to differentiate between flight categories, as this is more familiar to the respondents. We consider a short-haul flight 0-2 hours in duration, a medium-haul flight 2-3.5 hours, a long-haul flight 3.5-7 hours, and an ultra-long-haul flight more than 7 hours, as this is a common differentiation in the field of aviation research ([Mensen 2013](#)). Outbound and return flights were counted as one flight as, to our pretest results, this is much closer to the respondents' perspective.

$$E_{flights} = \sum_{i=1}^4 \text{no. of flights of duration } i \cdot \text{average emissions of a flight of duration } i \text{ per person}$$

Due to several inconsistencies and missing values, we apply some data cleaning steps and imputations for this measurement concept. First, if the response to the question "Did you fly privately last year?" (mob10) deviates from the reported number of flights (mob11), we use the number of flights and ignore the former response. Furthermore, we exclude individuals with an exceptionally high number of flights (more than one flight per two days). Finally, we impute missing responses for the number of flights in a flight duration category with "no flight" if the respondent answered in no other flight duration category "no flight" and reported at least one flight in another flight duration category, otherwise, we exclude the respondent from the analyses. For each variable where we apply this imputation, we increase the imputation counter for transportation by one.

4.3.1 Emission factors

We use the average emissions of one outbound and return flight to the 20 most popular flight destinations from Germany in the respective flight duration category in 2024 for each reported flight, employing the most frequently used departure airport for the respective destination as the location of departure ([Statistisches Bundesamt 2025](#)). Most often, this is Frankfurt, and in some cases Düsseldorf, Munich, Berlin, or Hamburg. To calculate total emissions, we use the "software for a simplified estimation of CO₂ equivalents of individual flights" developed by the German Aerospace Center (DLR) for the German Environment Agency ([Dahlmann et al. 2024](#)). This calculator estimates the CO₂e emissions of flights as precisely as possible and is based on a global historic set of detailed flight trajectories, flight emissions, and respective climate responses. It considers distance and airplane size (5 categories) to estimate fuel consumption and NO_x emissions, and start and destination of the flight to estimate the non-CO₂ emissions according to the average latitude (in three clusters), but does not require information about the actual flight route, fuel consumption, or weather conditions. To evaluate the typical airplane size for each flight, we use the average number of seats according to the summer flight plan of 2025, accessed from the travel portal wego.com ([Wego Pte Ltd. 2025](#)). In order to weight the emissions of each flight by the number of passengers, we divide the total emissions of the flight by the average occupancy rate of national/international flights ([Allekotte et al. 2020](#)) and the number of seats. Finally, we calculate the

average of the individual emissions from all 20 example flights in a flight duration category, weighted by the total number of passengers who flew to the respective destinations in 2024 ([Statistisches Bundesamt 2025](#)).

4.4 Cruise trips

The fourth measurement concept of transportation deals with the CO₂e emissions from cruises. For this purpose, respondents reported whether their longest vacation in the last 12 months was a cruise (csm6) and its duration (csm5). If the longest vacation was not a cruise trip, but the respondent reported at least one cruise trip in the last 12 months (csm3i4/csm3i9o), we assume an average trip length based on all specified vacation length categories and their frequencies (csm4; 1-3 overnight stays=3 travel days, 4-7 overnight stays=6.5 travel days, more than 8 overnight stays=11.5 travel days).

Therefore, the calculation of emissions from cruises is either

$E_{cruisetrips} = \text{duration of longest vacation} \cdot \text{av. emissions per person and travel day with a cruise ship}$
if the longest vacation was a cruise trip, or

$E_{cruisetrips} = \text{average vacation length by specified length categories (without longest vacation)}$
 $\cdot \text{average emissions per person and travel day with a cruise ship}$

if the person took a cruise trip, but it was not the longest vacation, or $E_{cruisetrips}$ is 0.

In this way, we cover the largest part of emissions from cruise trips without asking for the exact distance traveled or the total number of overnight stays in the last 12 months, which would require more knowledge from respondents. We made no distinction between sea and river cruise trips, as these differ only slightly in terms of emissions per passenger kilometer ([Schulz et al. 2020](#)). Furthermore, we do not consider cruise trips without overnight stays or private boat trips due to their minor significance for the average annual emissions ([Schulz et al. 2020](#)).

In the data preparation of this subdomain, we also apply some data cleaning steps and imputations. First, if the respondent reported no cruise trip in the last year but specified a cruise ship as the accommodation of their longest vacation, we assume that the answer for the longest vacation is correct. Second, we impute missing answers for the number of vacations in a vacation length category with "no vacation" if the respondent answered in no other length category "no vacation" but reported at least one vacation in another length category, otherwise we exclude the person from the analyses. For each of these imputations, we increase the imputation counter for transportation by one. Moreover, if there are inconsistent answers for the length of the longest vacation and the number of vacations in the vacation length categories, we subtract the length of longest vacation from the sum of medium lengths of the specified length categories (min. 0) in the estimation of the cruise trip's duration. Finally, if information for the length or the accommodation category of the longest vacation are missing, we impute the medium length of the longest specified vacation length category, respectively, and impute that it was not a cruise. These changes are also recorded in the imputation counter variable.

4.4.1 Emission factors

All emissions values are obtained from a report of the German Environment Agency on the CO₂e emissions of German tourist mobility ([Schulz et al. 2020](#)). As this study reports the emission values separately for sea and river cruise trips, we use an average emission value weighted by the total number of passenger travel days in the categories in 2024 ([Deutscher Reiseverein 2025](#)). To convert the emission values from CO₂e/pkm to CO₂e/travel day, we collected information from several German cruise lines and calculated an average distance traveled per travel day of their sea and river cruises in 2024.

5 Diet

Unlike other components of the CO₂-module that rely on bottom-up aggregation of detailed behavioral responses, the diet component follows a structured top-down estimation strategy that combines a national baseline with relative survey adjustments. Accurately measuring individual food quantities in surveys is highly challenging due to recall bias, systematic under-reporting, and the cognitive difficulty of tracking heterogeneous food types ([Salvini et al. 1989](#), [Betim Cazarin 2022](#)). We estimate individual dietary emissions in four analytical steps:

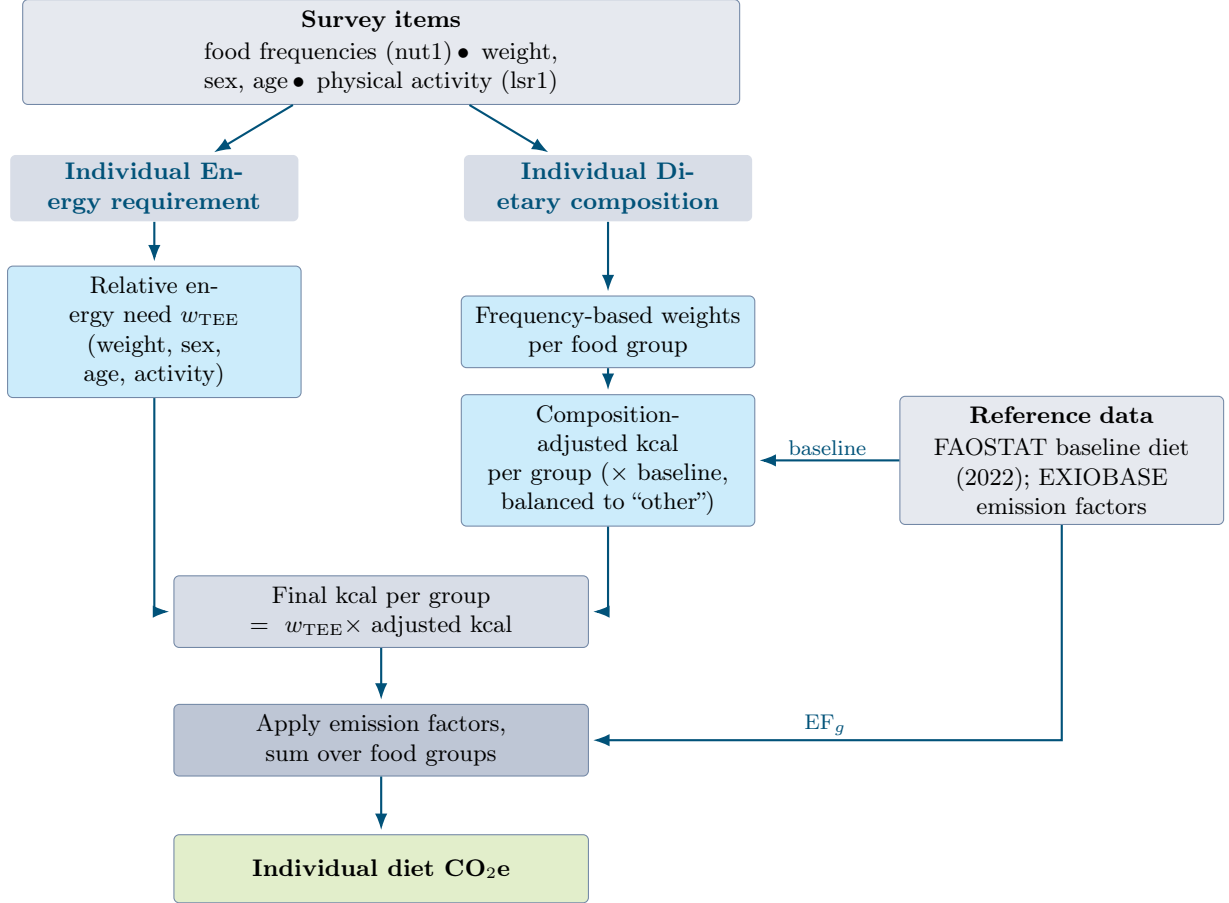


Figure 2: Overview of the diet emissions modelling framework. Individual estimates adjust a national dietary baseline along two dimensions: dietary composition, derived from reported food frequencies, and total volume, scaled by an individual’s relative energy need w_{TEE} . The FAOSTAT food balance sheets supply the per-capita baseline diet and EXIOBASE the food-group emission factors EF_g ; the survey enters only through the relative composition and volume adjustments.

1. Deriving a national baseline diet using FAOSTAT consumption data,
2. Adjusting the composition of this baseline using individual survey-reported eating habits,
3. Scaling total intake according to estimated individual energy requirements,
4. Translating adjusted caloric intake into CO₂e emissions using emission intensities from EXIOBASE [Stadler et al. \(2018\)](#).

This approach preserves macro-level consistency while allowing meaningful individual-level variation in dietary composition and total energy intake. It is based on four assumptions and principles. First, we assume that FAOSTAT food balance sheets provide a suitable anchor for average dietary composition at the population level. Second, we treat ordinal frequency categories as monotonic proxies of relative consumption intensity within each food group. Third, we separate dietary composition (identified from reported frequencies) from dietary volume (scaled using estimated individual energy requirements via total energy expenditure (TEE)). Fourth, to maintain energy balance after adjusting the four focal categories (i.e., beef, other meat, fish, dairy & eggs), we apply a caloric closure rule that reallocates the net difference to a residual category ("other"), interpreted as the set of remaining foods that plausibly substitutes for differences to animal-based intake.

5.1 Data sources and baseline construction

5.1.1 National dietary baseline

The national dietary baseline is based on the food balance sheets of the Food and Agriculture Organization of the United Nations (FAOSTAT, [2022](#)). We use the most recent data release available at the time

of analysis (reference year 2022), which provides harmonized estimates of per capita food availability in Germany, reported in both kilograms and kilocalories per capita per day. Although the data base deviates from the period specified in GLEN (last 12 months before the survey), the FAOSTAT release represents the most recent fully validated and internationally harmonized dataset. As short-term fluctuations in national-level food consumption are typically modest relative to structural dietary patterns, the temporal gap is unlikely to materially affect estimated emission intensities or relative dietary composition.

For the present analysis, we use kilocalorie values as the central metric, ensuring comparability across food groups and facilitating subsequent scaling to individual energy requirements. We harmonize the classifications of FAOSTAT and EXIOBASE by aggregating them into a common set of food groups: beef, fish, other meat, dairy and eggs, and other food (see table A14 in the appendix). We apply a correction for eggs using external data (Meier 2011), as EXIOBASE does not provide sufficient disaggregation for this category. This harmonization ensures consistent linkage between consumption data and environmental intensities.

5.1.2 Emission factors

The emission factors are obtained from the EXIOBASE version 3 (Stadler et al. 2018), the most recent fully documented release available at the time of module construction. EXIOBASE links economic sectors to detailed environmental extensions, including greenhouse gas emissions, within a multi-regional input-output framework. As with FAOSTAT, the EXIOBASE reference year precedes the survey time frame. However, emission intensities at the aggregated food-group level typically evolve gradually, and short-term changes are small relative to structural differences between food categories (e.g., ruminant meat versus plant-based products). The use of the latest harmonized release therefore provides a stable and internally consistent basis for estimating dietary emissions.

For each food group g , we divide total CO₂e emissions by total caloric output to derive emission intensities in kilograms of CO₂e equivalents per kilocalorie, which we later apply to individual consumption estimates.

$$EF_g = \frac{\text{total CO}_2 \text{ emissions}_g}{\text{total kcal}_g}.$$

5.2 Construction of individual consumption profiles

We derive individual dietary estimates by adjusting the national caloric baseline along two dimensions:

1. Relative dietary composition (based on reported consumption frequencies),
2. Total intake level (based on estimated energy requirements).

5.2.1 Frequency-based adjustment of dietary composition

Respondents report food consumption using ordered frequency categories (nut1; "(almost) daily", "multiple times per week", "once per week", "multiple times per month", "less often", "(almost) never"). As these responses are ordinal rather than quantitative, we approximate relative consumption intensities using a distribution-sensitive weighting procedure. The weighting function follows a power-law distribution in which reported consumption frequency serves as a proxy for relative intake. Higher-frequency categories receive progressively larger weights, while lower-frequency categories receive progressively smaller weights. The slope of this relationship is allowed to vary across food groups based on the position of the modal frequency category. Consequently, foods that are typically consumed infrequently (e.g. beef products) exhibit a stronger differentiation between high- and low-frequency consumers than foods that are more commonly consumed (e.g. dairy products).

Each frequency category c_j (ordered from 1 = "(almost) daily" to 6 = "(almost) never") is mapped according to a baseline intensity score:

$$r_j = \begin{cases} 0, & \text{if category } i \text{ corresponds to "never",} \\ (\frac{6-c_j}{5}), & \text{otherwise.} \end{cases}$$

To reflect empirical consumption patterns, the slope of the weighting curve varies by food group (g). γ_g denotes a food-group-specific parameter derived from the modal category of responses.

$$\gamma_g = 1 + \alpha * (\frac{c_{\text{modal}} - 1}{4})$$

The scaling parameter α was set to 2. This value produced a clear differentiation between frequency categories while avoiding excessively extreme weights for commonly consumed food groups.

We define raw weights as:

$$\tilde{w}_{ig} = \begin{cases} 0, & \text{if category } i \text{ corresponds to "never",} \\ r_j^{\gamma_g}, & \text{otherwise.} \end{cases}$$

To preserve the average caloric intake of each food group, the raw weights are normalized so that their weighted average equals one under the observed distribution of responses. In practice, each raw weight is divided by the weighted mean of all raw weights within the respective food group:

$$w_{jg} = \frac{\tilde{w}_i}{\sum_c s_c \tilde{w}_c},$$

where (s_c) denotes the observed share of respondents in frequency category (c) . This normalization ensures that the overall per-capita caloric intake of a food group remains unchanged after applying the frequency adjustment. This normalization ensures that average caloric intake at the population level remains unchanged. The adjusted caloric intake for individual i and food group g is therefore:

$$\text{caloric intake}_{ig}^{\text{adj}} = w_{ig} \cdot \text{population kcal}_g.$$

If any response in a food category is missing, we impute the estimated intake with the average population value. Each replacement increases the imputation in the domain of diet by one.

5.2.2 Caloric redistribution across food groups

Adjustments based on reported consumption frequencies modify the caloric allocation of the focal food categories (i.e., beef, other meat, fish, dairy and eggs). To maintain physiologically plausible energy balance, total caloric intake must remain internally consistent after these adjustments.

Following a similar approach to Bird et al. (2019), we apply an energy-balance closure rule that reallocates deviations from the baseline allocation to the residual category ("other"). Importantly, this food group contains exclusively non-animal food products (see Appendix Table A14), and thus represents plant-based and mixed foods that plausibly substitute for changes in animal-based intake.

Formally, the net caloric difference for each respondent is calculated as:

$$\Delta_{\text{kcal}_i} = \sum_{gi} \left(\text{population kcal}_g - \text{caloric intake}_{ig}^{\text{adj}} \right).$$

This difference is added to (or subtracted from) the "other" category. Conceptually, this corresponds to a substitution assumption whereby reductions in animal-based consumption are compensated by increased intake of plant-based foods, while increases in animal-based consumption reduce caloric intake from the residual plant-based category. This procedure preserves total caloric intake while allowing for meaningful variation in dietary composition.

5.3 Adjustment for individual energy requirements

While frequency weighting determines dietary composition, we scale total consumption volume using estimated individual energy requirements. We define the total energy expenditure (TEE) as the product of the resting energy expenditure (REE) and the physical activity level (PAL).

We calculate the REE in MJ following Braun et al. (2019):

$$REE_{\text{MJ}} = 0.047 \times \text{weight} + 1.009 \times \text{male} - 0.01452 \times \text{age}_{\text{years}} + 3.21$$

and convert the result to kilocalories by multiplying by 239. Accordingly, per definition, gender and age are correlated with CO₂ emissions from the diet.

The PAL, in contrast, is derived from two survey items capturing self-reported frequency of physical activity performed indoors and outdoors (lsr1). We interpret these items as proxies for overall activity intensity in the absence of detailed time-use information.

We convert the reported frequency categories into approximate monthly activity days by combining indoor and outdoor activities to obtain an overall activity indicator. Based on this measure, we assign PAL categories following general ranges suggested by the DGE guidelines Deutsche Gesellschaft für Ernährung e.V. (nd). A PAL of 1.2-1.3 would relate to frail, immobile, bedridden individuals (who are confined to a sitting or lying position), whereas a PAL of over 2 would refer to highly active individuals such as

construction workers, farmers, forest workers, miners, and competitive athletes (physically demanding occupational work or very active leisure activities). We assign a minimum PAL between 1.5 and 2.0 depending on the reported physical activities assuming at least a very moderate level of physical activity above absolute immobility and below the highest values of extreme athletes, avoiding very low or high values given the survey’s level of detail. Occupational activity and active travel are not included in the current operationalization.

As FAOSTAT food balance sheets represent food supply rather than actual physiological intake, reported caloric availability includes losses such as household waste, preparation losses, and other non-consumed fractions. Consequently, the average per capita kilocalorie values derived from FAOSTAT exceed the estimated physiological energy requirements based on TEE. Rather than attempting to remove these components, we retain the FAOSTAT baseline to preserve consistency with supply-based accounting and associated emission intensities. Therefore, we adjust individual consumption relative to average energy requirements by scaling intake proportionally to each respondent’s TEE:

$$wTEE_i = \frac{TEE_i}{mean(TEE_i)}.$$

We obtain the final individual caloric intake per food group by multiplying composition-adjusted intake by this scaling factor. In case of missing values for age, weight, or PAL, we use the population mean instead. Each replacement is recorded in the imputation counter.

The final caloric intake estimation for each food group is then calculated as:

$$caloric\ intake_{ig}^{final} = wTEE_i \cdot caloric\ intake_{ig}^{adj}$$

5.4 Combination of adjusted caloric intake and emission factors

We combine adjusted caloric intake with food-group-specific (g) emission factors (EF) to individual dietary emissions by applying the following formula:

$$CO_{2,i}Diet = \sum_g caloric\ intake_{ig}^{final} \cdot EF_g$$

6 Consumption

We use six measurement concepts to measure emissions from consumption. Although consumption is strongly associated with income, we do not derive consumption emissions directly from household or individual income (as do, for instance, Paar et al. (2025)). As we are especially interested in enabling analyses of factors explaining individual CO_{2e} emissions, we capture consumption more explicitly considering self-reported differences in lifestyle and consumption patterns. We consider four types of consumer goods: furnishings, household appliances, consumer electronics, and clothing, alongside two widespread forms of leisure activities: pet keeping and using accommodation facilities for vacations. Other areas of consumption, such as postal services, telecommunications, healthcare facilities, waste and disposal management, sports, reading, housework, garden work, and other forms of leisure activities, that are partially included in other studies on individual or household CO_{2e} emissions, are not considered here due to their marginal significance for total individual CO_{2e} emissions.

To calculate consumption emissions for consumer goods, we use a cradle-to-customer framework. We consider all CO_{2e} emissions that occur in the consumption process, from the extraction of raw materials, the production and processing of goods, to distribution to stores and consumers. For furnishings, household appliances, consumer electronics and clothing, all emission values are from the carbon emission database of the French Environment Agency (Lhotellier et al. 2017, Agence de la Transition Écologique 2024) as the German Environment Agency does not provide detailed emission values for many consumer goods. Furthermore, we draw on results from specific studies on emissions from keeping pets (Annaheim et al. 2024) and the use of accommodation facilities (Scott et al. 2008, Ratjen 2016). A detailed list of the utilized emission values can be found in the appendix on page 33.

6.1 Furnishings

To record the emissions of furnishings, a complete list of furnishings in the respondent’s home and their acquisition year would be optimal, but too extensive for respondents. Therefore, we assume an average of one cupboard, one table, and one shelf per room (incl. kitchen, but excl. bathroom) in the respondent’s home. We also include an additional sofa for the entire apartment and one bed per person. We use an

average life cycle of 15 years for cupboards, shelves, and beds, and 10 years for tables and sofas (Lhotellier et al. 2017). Other furnishings are not considered due to their marginal emissions (<50 kg CO₂e/piece) (Agence de la Transition Écologique 2024) or low prevalence. Furthermore, we adjust the assumed amount of furnishings in possession by the self-reported individual purchase preference for furnishings (csm2i2). If a respondent enjoys buying furniture, we assume double frequency of consumption. If the respondent does not like to buy furniture at all, we assume half frequency of consumption. The three other intermediate categories are in-between (option 2 (“true”): 0.75; option 3 (“neutral”): 1; option 4 (“not true”): 1.5). In a final step, we divide the emissions by the number of household members (home2).

$$E_{furnishings} = \left(\frac{\text{no. of rooms} \cdot \text{av. emissions of furnishings in an av. room} + \text{av. emissions of a sofa}}{\text{no. of HH members} \cdot \text{average life cycle of respective furnishings}} + \frac{\text{average emissions of a bed}}{\text{average life cycle of a bed}} \right) \cdot \text{frequency of purchasing furnishings}$$

6.2 Household appliances

Second, we estimate the CO₂e emissions caused by the consumption of household appliances. Here, we focus on the stock of devices in the respondent’s household (home19), as household appliances are bought quite rarely and more regularly (Lhotellier et al. 2017). We consider only electronic devices that have emissions of at least 50 kg CO₂e/device (Agence de la Transition Écologique 2024) and do not record fridges, stoves, or ovens, as almost all households in Germany have these devices and multiple ownership is rare (Statistisches Bundesamt 2023). For all other devices, there are almost no households that have more than one of each category (Statistisches Bundesamt 2023); therefore, we simplify the items, asking whether the respondent’s household owns the respective device or not. As typically all household members share household appliances, we weight the emissions according to the number of household members (home2). In addition, we also weight the emissions according to the devices’ average life cycle and therefore assume, for the sake of simplicity, a comparable life cycle across the population. Starting in wave 2a, we will survey whether respondents have bought a new appliance and assume previously reported appliances to still be in the household. For the new appliance, we start the life cycle counter from one, whereas we maintain the average duration for other devices.

$$E_{householdappliances} = \sum_{i=1}^9 \frac{\text{average emissions of appliance } i}{\text{average or personal life cycle of appliance } i \cdot \text{no. of HH members}}$$

6.3 Consumer electronics

For the consumption of consumer electronics, we use a similar approach as for the household appliances, but account for the greater variance in the consumption behavior of the population (home20). We focus on the most common devices with an emission of at least 50 kg CO₂e/device (Statistisches Bundesamt 2023, Agence de la Transition Écologique 2024). Often, people use more than one device of the same category, for example smartphones or TVs. Thus, we include an additional response option for several devices, which we record as two devices for the sake of simplicity. The question is limited to devices currently in use, as individuals often keep an old device after buying a new one but do not use it anymore, meaning the device’s life cycle is already over. Moreover, we only refer to individual use as we do not want to consider devices that are exclusively used by respondents’ household members. Furthermore, in contrast to the measurement for household devices, we account for more heterogeneous consumption frequencies in the population by asking about the preference for purchasing electronic devices (csm2i3). As with furnishings, we measure the purchase frequency in a range from double to half life cycle duration. If the response to the number of devices is missing in a device category, and in no other device category "no device" is reported, while at least one device is reported in total, we impute the missing answer as "no device" and increase the imputation counter for consumption by one. Otherwise, we exclude the respondent from the analyses.

$$E_{consumerelectronics} = \sum_{i=1}^4 \frac{\text{average emissions of device } i \cdot \text{frequency of purchasing electr. devices}}{\text{average life cycle duration of device } i}$$

6.4 Clothing

To measure emissions from the consumption of clothing, it would be optimal to have a complete list of clothing that a respondent has bought in the last 12 months. As this information is difficult to remember and burdensome to report, we instead use the self-reported preference for buying clothes and shoes in general (csm2i1) to infer the personal average frequency of purchasing clothing. A pretest showed that shopping preference predicts purchase frequency well. As in the previous sections, we use a range from double to half frequency to record purchase preferences. The average amount of clothing per year originates from a report by the German Trade Association on the clothing consumption behavior of the German population ([Handelsverband Deutschland 2021](#)) and focuses on the six most common types of clothing: dresses, dress shirts, jackets, jeans and trousers, pullover and sweatshirts, shirts, and shoes. Emission values are obtained from the French Environment Agency ([Lhotellier et al. 2017](#), [Agence de la Transition Écologique 2024](#)), but the average life cycle durations of the clothing stem from a summary by the German Textile Cleaning Association ([Deutscher Textilreinigungsverband 2021](#)).

$$E_{\text{clothing}} = \sum_{i=1}^6 \frac{\text{average emissions of purchasing clothing } i \cdot \text{freq. of purchasing clothing } i}{\text{average life cycle duration of clothing } i}$$

6.5 Pet keeping

For emissions from pet keeping, we record the number and type of pets that a respondent owns (home8) to calculate the average emissions caused by pet keeping in one year. This includes food, equipment, accommodation, care, and medical products, but not car rides as these are already included in private transport. We draw on results from a study by [Annaheim et al. \(2024\)](#), which analyzed the annual CO₂e emissions of keeping six different kinds of pets in Switzerland (i.e., dog, cat, horse, rabbit, bird, and fish). As pets are usually kept by everyone in the household, we weight the emissions according to the number of household members (home2). In contrast, we do not consider the pet's weight, as this information may not be known and is not central for the estimation of emissions ([Annaheim et al. 2024](#)).

$$E_{\text{petkeeping}} = \sum_{i=1}^6 \frac{\text{average emissions of keeping a pet of type } i}{\text{no. of persons in household}}$$

6.6 Accommodation

To measure emissions from using accommodation facilities, we analyze how often respondents have stayed in different types of accommodation facilities in the last 12 months. As the total number of overnight stays in accommodation facilities is difficult to report, we survey the exact vacation length and the accommodation category only for the longest vacation in the last 12 months (csm5, csm6). For other vacations, we record whether respondents made none, one, or several vacations in three duration categories (csm4) and assume the average emissions out of all accommodation categories per overnight stay. For each duration category, we calculate emissions using the midpoint of the category (short vacations=2, middle vacations=5.5, long vacations=10.5) and assume two vacations per category if the respondent answered "several vacations". Lastly, we subtract the overnight stays that have already been considered in the cruise trips section of transportation.

In this subdomain, we again apply some data cleaning steps and imputations due to missing values and inconsistencies. As already mentioned in Section 4.4 (cruise trips), we impute missing answers for the number of vacations in a vacation length category with "no vacation" if the respondent answered in no other length category "no vacation" but reported at least one vacation in another length category. Otherwise, we exclude the person from the analyses. Each imputation is included in the imputation counter for consumption. In addition, if the response for the question "Did you take a vacation last year?" (csm3i1) deviates from the answers for the vacation length categories (csm4) or the longest vacation (csm5), we assume that the information about the vacation length is correct. Moreover, if there are inconsistent responses for the length of the longest vacation and the number of vacations in the vacation length categories, we subtract the length of longest vacation from the sum of medium lengths of the specified length categories (min. 0) in the estimation of the total number of nights spent in accommodation. Lastly, if information for the length or accommodation category of the longest vacation are missing, we impute the medium length of the longest specified vacation length category or, respectively, the average emission value of all accommodation categories. Both imputations increase the imputation counter for consumption by one.

$$\begin{aligned}
E_{accommodation} = & \sum_{i=1}^3 \text{no. of vacations of length } i \text{ (without longest vacation)} \\
& \cdot \text{medium length of a vacation of length } i \cdot \text{average emissions of one overnight stay} \\
& + \text{number of overnight stays on the longest vacation} \\
& \cdot \text{average emissions of one overnight stay in the used accommodation category (longest vacation)}
\end{aligned}$$

6.6.1 Emission factors

Our emission values draw on results from two reports on CO₂e emissions from using accommodation facilities (pension, vacation homes, and campsites: [Scott et al. \(2008\)](#), hotels: [Ratjen \(2016\)](#)). As the emission values for hotels with less than 5 stars are presented separately, we summarize them to one category, weighted by the number of hotels per category ([Deutscher Hotellerie- und Gaststättenverband 2025](#)).

7 Infrastructure

We have not considered public CO₂e emissions. However, individuals also make use of infrastructure such as public buildings, services provided by the education, and healthcare systems. According to [Paar et al. \(2025\)](#), this results in an average amount of 1.13 t of CO₂e emissions per person and year. Therefore, adding a constant base amount would be possible and would increase the absolute value of emissions, but would not affect multivariate results.

8 Distribution of CO₂e emissions

As expected, the four sectors (i.e., housing, transportation, diet, and consumption) and total emissions exhibit right-skewed distributions; consequently, the median is always lower than the mean. Total CO₂ emissions exceed the territorial, production-based figures from official statistics. Housing and transportation contribute the most to emissions, followed by diet and consumption. When Gini coefficients are calculated as a measure of inequality, the highest level of inequality in emissions is found in the transportation sector, followed by housing, consumption, and diet. [Figure 3](#) shows the distribution of total emissions and [Figure 4](#) shows emissions across the four sectors.

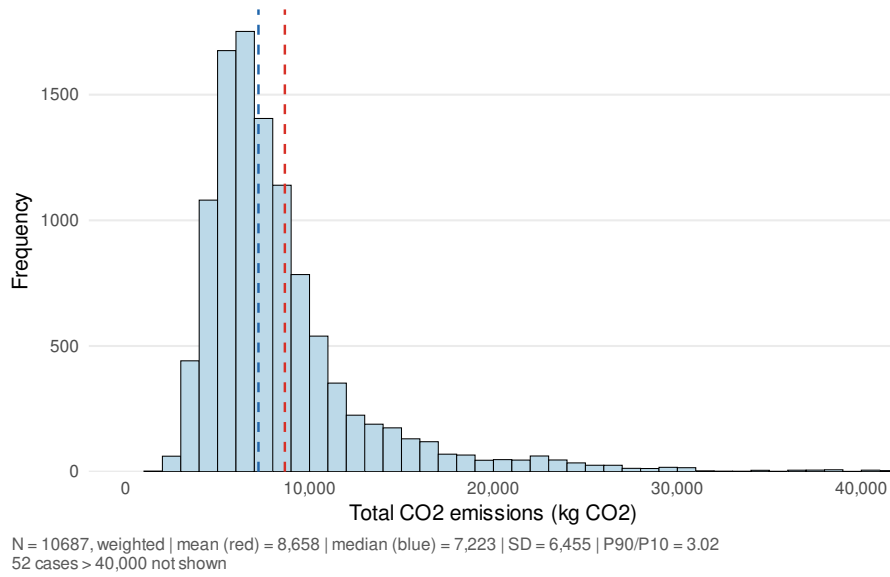


Figure 3: Distribution of overall CO₂e emissions in wave w1a. Complete cases with all imputations.

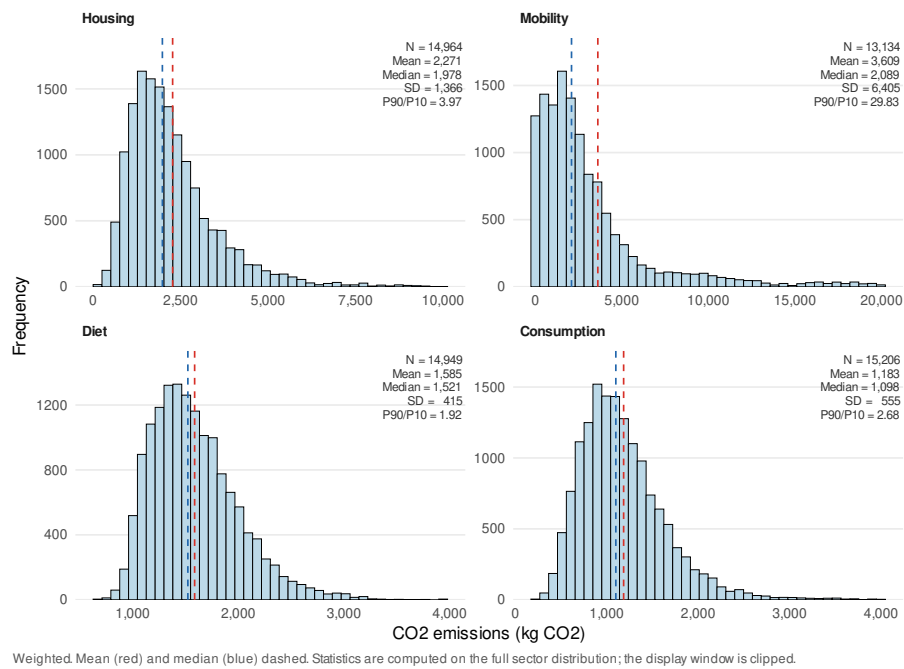


Figure 4: Distribution of CO₂e sector emissions in wave w1a. Sector complete cases with all imputations.

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Appendix

Table A2: Mapping of Building Age Categories on TABULA Categories

New Code	New Category (Survey)	Original Categories (TABULA)
01	before 1918	before 1859; 1860–1918
02	1919–1948	1919–1948
03	1949–1969	1949–1957; 1958–1968
04	1970–1994	1969–1978; 1979–1983; 1984–1994
05	1995–2009	1995–2001; 2002–2009
06	2010–2015	2010–2015
07	After 2015	After 2015

Table A3: Factors used to account for embodied emissions by building age category

Construction period	Factor F_C	Rationale
Up to 1918	0%	More than 50 years old; construction-related emissions assumed to be fully depreciated.
1919–1948	0%	More than 50 years old; same rationale as above.
1949–1969	0%	Predominantly more than 50 years old; even the newest buildings in this category (1969) are older than 55 years.
1970–1994	40%	Transitional category: the first German Thermal Insulation Ordinance (1978) lies approximately in the middle of this period; around 40% of the period falls after 1978, following the logic applied in the UBA methodology.
1995–2009	75%	Entirely post-1978; includes buildings constructed under earlier energy-efficiency regulations (EnEV 2002/2007).
2010–2015	90%	Newer efficiency standards (EnEV 2009/2014) associated with increased material requirements.
Since 2016	100%	Current building standard (EnEV 2016 / GEG 2020).

Table A4: Renovation depth factors based on the number of reported renovation measures

Number of measures	Typical combination	Renovation depth	Factor $F_{M,survey}$
0	No measures	None	0%
1–2	e.g., windows only or heating system only	Partial renovation	25%
3–4	e.g., windows + external wall insulation + heating system	Substantial renovation	50%
5–6	All major measures: insulation, windows, heating system, and ventilation	Comprehensive renovation	100%

Table A14: Mapping of FAOSTAT Items and EXIOBASE Sectors to Grouped Categories

FAOSTAT Item	EXIOBASE Sector	Grouped Category
Bovine Meat	Cattle	Cattle and products
Mutton & Goat Meat	Cattle	Cattle and products
Offals, Edible	Products of meat cattle	Cattle and products
Fish, Liver Oil	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products

FAOSTAT Item	EXIOBASE Sector	Grouped Category
Freshwater Fish	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Demersal Fish	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Pelagic Fish	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Marine Fish, Other	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Crustaceans	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Cephalopods	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Molluscs, Other	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Aquatic Animals, Others	Fish and other fishing products; services incidental of fishing (05)	Fish and other fishing products
Wheat and products	Wheat	Other
Rice and products	Paddy rice	Other
Barley and products	Cereal grains nec	Other
Maize and products	Cereal grains nec	Other
Rye and products	Cereal grains nec	Other
Oats	Cereal grains nec	Other
Millet and products	Cereal grains nec	Other
Cereals, other	Cereal grains nec	Other
Potatoes and products	Vegetables, fruit, nuts	Other
Yams	Vegetables, fruit, nuts	Other
Roots, Other	Vegetables, fruit, nuts	Other
Sugar beet	Sugar cane, sugar beet	Other
Sugar (Raw Equivalent)	Sugar	Other
Sweeteners, Other	Food products nec	Other
Honey	Food products nec	Other
Beans	Vegetables, fruit, nuts	Other
Peas	Vegetables, fruit, nuts	Other
Pulses, Other and products	Vegetables, fruit, nuts	Other
Nuts and products	Vegetables, fruit, nuts	Other
Soyabeans	Oil seeds	Other
Groundnuts	Oil seeds	Other
Sunflower seed	Oil seeds	Other
Rape and Mustardseed	Oil seeds	Other
Coconuts – Incl Copra	Oil seeds	Other
Olives (including preserved)	Oil seeds	Other
Oilcrops, Other	Oil seeds	Other
Soyabean Oil	Products of Vegetable oils and fats	Other
Groundnut Oil	Products of Vegetable oils and fats	Other
Sunflowerseed Oil	Products of Vegetable oils and fats	Other
Rape and Mustard Oil	Products of Vegetable oils and fats	Other
Olive Oil	Products of Vegetable oils and fats	Other
Maize Germ Oil	Products of Vegetable oils and fats	Other
Oilcrops Oil, Other	Products of Vegetable oils and fats	Other
Tomatoes and products	Vegetables, fruit, nuts	Other
Onions	Vegetables, fruit, nuts	Other
Vegetables, other	Vegetables, fruit, nuts	Other
Oranges, Mandarines	Vegetables, fruit, nuts	Other
Lemons, Limes and products	Vegetables, fruit, nuts	Other
Grapefruit and products	Vegetables, fruit, nuts	Other
Citrus, Other	Vegetables, fruit, nuts	Other
Bananas	Vegetables, fruit, nuts	Other
Plantains	Vegetables, fruit, nuts	Other

FAOSTAT Item	EXIOBASE Sector	Grouped Category
Apples and products	Vegetables, fruit, nuts	Other
Pineapples and products	Vegetables, fruit, nuts	Other
Dates	Vegetables, fruit, nuts	Other
Grapes and products (excl wine)	Vegetables, fruit, nuts	Other
Fruits, other	Vegetables, fruit, nuts	Other
Coffee and products	Food products nec	Other
Cocoa Beans and products	Food products nec	Other
Tea (including mate)	Food products nec	Other
Pepper	Food products nec	Other
Pimento	Food products nec	Other
Cloves	Food products nec	Other
Spices, Other	Food products nec	Other
Wine	Beverages	Other
Beer	Beverages	Other
Beverages, Fermented	Beverages	Other
Beverages, Alcoholic	Beverages	Other
Infant food	Food products nec	Other
Miscellaneous	Food products nec	Other
Pigmeat	Pigs	Pigs, Poultry and other Animal products
Poultry Meat	Poultry	Pigs, Poultry and other Animal products
Meat, Other	Meat animals nec	Pigs, Poultry and other Animal products
Fats, Animals, Raw	Animal products nec	Pigs, Poultry and other Animal products
Butter, Ghee	Dairy products	Raw Milk, Dairy products and Eggs
Cream	Dairy products	Raw Milk, Dairy products and Eggs
Eggs	Eggs	Raw Milk, Dairy products and Eggs
Milk – Excluding Butter	Raw milk	Raw Milk, Dairy products and Eggs

Table A5: Historical renovation factors by building age category

Construction period	Factor $F_{M,hist}$	Rationale (based on UBA methodology)
Up to 1918	50%	Very old buildings; at least one major renovation is assumed to have occurred outside the 15-year observation window.
1919–1948	50%	Old buildings; at least one renovation is likely to have taken place outside the observation window.
1949–1969	40%	Following the UBA approach: approximately 40% of buildings were constructed after 1979, implying a proportional probability of earlier renovations not captured by the survey.
1970–1994	35%	A portion of renovations is expected to have occurred before the observation window; more recent renovations are captured by the survey.
1995–2009	10%	Few renovations are expected to have occurred before the 15-year observation window.
2010–2015	0%	Renovation activities are assumed to be fully covered by the survey period.
Since 2016	0%	Buildings are too new for major renovation activities to be expected.

Table A6: Overview of imputations applied in the domain of transportation

Input variable	Imputation trigger	Imputation rule	Page
Number of flights	Missing answer for number of flights in a flight length category	Replace with "no flight" if in no flight length category "no flight" is reported and in at least one flight length category at least one flight is reported, else "NA"	p. 12
Number and length of cruise trips	Missing answer for number of vacations in a vacation length category	Replace with "no vacation" if in no vacation length category "no vacation" is reported and in at least one vacation at least one vacation is reported, else "NA"	p. 13
Length of longest vacation	Missing answer for length of longest vacation	Use medium length of longest specified vacation length category	p. 13
Accommodation category of longest vacation	Missing answer for accommodation category of longest vacation	Treat the longest vacation as no cruise trip	p. 13

Table A7: CO₂e values for use of private vehicles

Class	Diesel	Petrol	PHEV	Electro	Gas	Hydrogen
Small car	0.162 kg	0.163 kg	0.116 kg	0.064 kg	0.139 kg	0.109 kg
Mid-size car	0.206 kg	0.208 kg	0.148 kg	0.081 kg	0.177 kg	0.139 kg
Large car	0.267 kg	0.268 kg	0.190 kg	0.103 kg	0.229 kg	0.179 kg
SUV/Van	0.233 kg	0.234 kg	0.166 kg	0.090 kg	0.200 kg	0.156 kg
Motorcycle (all fuels)	0.175 kg					
Motor scooter (all fuels)	0.103 kg					

Table A8: CO₂e values for construction and supply of private vehicles

Class	Diesel	Petrol	PHEV	Electro	Gas	Hydrogen	Life cycle
Small car	9380.0 kg	8658.0 kg	10086.2 kg	10865.0 kg	8658.0 kg	12735.3 kg	15
Mid-size car	10823.0 kg	10101.0 kg	13200.0 kg	17429.0 kg	10101.0 kg	16667.0 kg	15
Large car	14430.0 kg	12987.0 kg	15292.0 kg	21459.0 kg	12987.0 kg	19475.0 kg	15
SUV/Van	12099.4 kg	11292.3 kg	14756.7 kg	19484.5 kg	11292.3 kg	18632.6 kg	15
Motorcycle (all fuels)	1302.5 kg						15
Motor scooter (all fuels)	658.8 kg						15
E-bike	265.0 kg						10
E-scooter	178.1 kg						5
Bicycle	130.5 kg						10

Table A9: CO₂e values for public transport, flights and cruise trips

Category	CO ₂ e
Public transport	
Short-distance public transport (per pkm)	0.080 kg
Long-distance public transport (per pkm)	0.043 kg
Flights	
Short-haul flight	362.396 kg
Medium-haul flight	718.670 kg
Long-haul flight	1612.460 kg
Ultra-long-haul flight	7605.452 kg
Short-haul flight (per pkm)	0.230 kg
Medium-haul flight (per pkm)	0.223 kg
Long-haul flight (per pkm)	0.261 kg
Ultra-long-haul flight (per pkm)	0.470 kg
Cruise trips	
Per travel day	142.082 kg
Per pkm	0.433 kg

Table A10: Imputations applied in the domain of housing

Input variable	Imputation trigger	Imputation rule	Page
Building type	Missing response	Case excluded from CO ₂ estimation	p. 5
Building age	Missing response	Case excluded from CO ₂ estimation	p. 5
Living area	Missing or refused response	Replace with Destatis average floor area by number of rooms	p. 9
Indoor temperature	Missing response	Replace with TABULA standard indoor temperature (20°C)	p. 7
Local heating climate (heating days, outdoor temperature)	Local weather data not available	Replace with TABULA standard climate: 222 heating days, mean outdoor temperature of 4.4°C on those days	p. 7
Main heating source	“Don’t know” response	Average over all TABULA heating systems matching building type, age, and heating refurbishment level	p. 7
Building modernization items (roof/wall/basement insulation, windows, heating unit, ventilation)	Refused or “don’t know” on an individual item	Treat each unanswered item as “measure not carried out”; answered items are kept as given	p. 5
Solar equipment items (balcony PV, roof PV, solar thermal)	Refused or “don’t know” on an individual item	Treat each unanswered item as “system not present”; answered items are kept as given	p. 8
Solar equipment type	Solar system present, but type unknown	Treat as photovoltaic system (most common type)	p. 8
Second home	No answer	Treat as no second home	p. 9
Electricity consumption	Missing or implausible response	Replace with expected benchmark value (ENBW formula: floor area, household size, appliance stock); add electric heating demand for electricity-based heating; subtract self-consumed solar production	p. 8

Table A11: Imputations applied in the domain of diet

Input variable	Imputation trigger	Imputation rule	Page
Beef consumption frequency	Missing or invalid response	Replace with population average frequency	p. 15
Fish consumption frequency	Missing or invalid response	Replace with population average frequency	p. 15
Other meat consumption frequency	Missing or invalid response	Replace with population average frequency	p. 15
Dairy consumption frequency	Missing or invalid response	Replace with population average frequency	p. 15
Egg consumption frequency	Missing or invalid response	Replace with population average frequency	p. 15
Height, age, weight	One or more variables missing	Replace with population average	p. 15

Table A12: Imputations applied in the domain of consumption

Input variable	Imputation trigger	Imputation rule	Page
Number of consumer electronics	Missing answer for number of devices in a device category	Replace with "no device" if "no device" is not reported in any other device category and at least one device is specified in another device category, else "NA"	p. 18
Number and length of vacations	Missing answer for number of vacations in a vacation length category	Replace with "no vacation" if "no vacation" is not reported in any other vacation length category and at least one vacation is specified in another vacation length category, else "NA"	p. 19
Length of longest vacation	Missing answer for length of longest vacation	Use medium length of longest specified vacation length category	p. 19
Accommodation category of longest vacation	Missing answer for accommodation category of longest vacation	Use average emission value of all accommodation categories	p. 19

Table A13: CO₂e values for consumption

Category	CO ₂ e	Life cycle	Specifications
Furnishings			
Bed	346.9 kg	15	Bed frame, slat frame, mattress 1.4m*1.9m (foam / spring)
Cupboard	906.9 kg	15	Solid wood / fiberboard
Shelf	544.1 kg	15	60% emissions of cupboard (estimation)
Sofa	186.4 kg	10	Leather / textile, 2 places
Table	70.2 kg	10	Solid wood / fiberboard, 4 places
Household appliances			
Dishwasher	271.2 kg	11	For 12 covers
Freezer	358.5 kg	15	205 l / 261 l
Microwave	98.3 kg	8	Without oven function, 18 l
Mobile air conditioner	238.9 kg	6	2500 Watt
Oven	217.6 kg	19	Electric, 54 l
Refrigerator	278.4 kg	11	247 l / 294 l
Stove	163.2 kg	19	Electric, 4 hotplates
Tumble dryer	301.9 kg	13	Condensation dryer / heat pump, 6 kg / 8 kg
Washing machine	341.1 kg	11	7 kg
Consumer electronics			
Desktop-PC (incl. monitor)	417.2 kg	6	For office use, 23.8 inches
Laptop	156.2 kg	4	14.5 inches
Smartphone, tablet	51.2 kg	2.5	5.5 inches / 10 inches
TV	404.1 kg	8	35 inches / 45 inches / 55 inches
Clothing			
Dress	48.9 kg	3	Cotton / viscose / polyester
Dress shirt	10.7 kg	2.5	Cotton / viscose
Jacket	49.2 kg	3.5	Acrylic / polyester / faux leather
Jeans	23.2 kg	2.5	Cotton
Pullover, Sweatshirt	33.3 kg	2.5	Wool / acrylic / cotton
Shirt	6.3 kg	2	Cotton / polyester
Shoes	16.5 kg	3	Plastic / leather / textile
Average amount per year	328.4 kg		
Pet keeping			
Dog	788.5 kg		29 kg
Cat	390.0 kg		4.2 kg
Horse	2356.0 kg		550 kg
Rabbit	120.0 kg		4 kg
Bird	60.0 kg		Budgerigars
Fishes	90.0 kg		Aquarium (350 l), 50 fishes
Accommodation (per night)			
Hotel (5 stars)	47.6 kg		
Hotel (1-4 stars)	18.8 kg		
Pension, hostel, guest house	7.9 kg		
Vacation home	15.9 kg		
Campsite	4.0 kg		
Average accommodation	18.8 kg		