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E.2 – Environmental statistics and accounts; sustainable development

Eurostat's estimates of quarterly greenhouse gas emissions accounts

Methodological note

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CONTENTS

1. INTRODUCTION

This note provides an overview on the methodology used to compute, quality assess and publish Eurostat's estimates of quarterly greenhouse gas emissions accounts.

Greenhouse gases (GHG) are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and fluorinated gases (F-gases), and their emissions are expressed in a common unit, tonnes of CO_2 equivalents.

The technique to produce the quarterly estimates can be characterised as an econometric-statistical approach, commonly applied for quarterly national accounts. It is widely based on IMF's Quarterly National Accounts Manual (2017 Edition) ([1]). Eurostat work on quarterly estimates of greenhouse gas emissions is internationally coordinated with IMF, OECD, IEA and UNSD through a joint task team.

Eurostat's estimates of quarterly greenhouse gas emissions build on the *annual* air emissions accounts (AEA) that Eurostat collects from European national statistical institutes. AEA record flows of greenhouse gases emitted into the atmosphere as a result of economic activities of resident units (businesses, households and government). The AEA are compiled according to the international System of Environmental-Economic Accounting (SEEA) and the ESS manual for air emission accounts ([2]). European national statistical institutes calculate AEA and report annual estimates to Eurostat 21 months after the reference year, according to Regulation (EU) No 691/2011 ([3]).

The basic methodological principle for the quarterly estimates is to temporally disaggregate the annual air emissions accounts (AEA) time series into quarterly values and to extrapolate for those quarters for which annual AEA are not available yet. Both steps, temporal disaggregation and extrapolation, are performed with auxiliary information from sub-annual 'predictor' variables ('indicators') suited to approximate the quarterly behaviour of the 'target' variable (i.e. the greenhouse gases emissions). Potential sub-annual 'predictor' variables are e.g. monthly energy statistics, short-term production volume indices, or quarterly national accounts.

2. IDENTIFICATION OF THE TARGET VARIABLES (AEA DATA POINTS OF GREENHOUSE GAS EMISSIONS)

The first step is to identify the 'target' variables, i.e. AEA data points of greenhouse gas emissions, for which quarterly emissions are to be estimated.

Eurostat's annual AEA are multi-dimensional data cubes including several hundreds of data points per time period and geographical entity. Eurostat's annual AEA have the following five dimensions:

- GEO – geopolitical entity (reporting)
- TIME – reference year

([1]) https://www.imf.org/external/pubs/ft/qna/

([2]) https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/KS-GQ-15-009

([3]) https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1416221752426&uri=CELEX:02011R0691-20140616

- AIRPOL – 7 air pollutants and 6 greenhouse gases (13 substances plus groupings) – the six greenhouse gases, all expressed in CO2-equivalents, are CO_2, N_2O, CH_4, HFC, PFC, and NF_3_SF_6. In addition, the gases N_2O and CH_4 are also available in their simple mass weight, i.e. not converted into CO2-equivalents.

- NACE_R2 – classification of economic activities NACE Rev. 2 (including households' activities) – NACE A*64 plus three classes of households' activities – this leads in total to 67 distinct classes at the most detailed level; in addition several sub-totals and totals.

- UNIT – unit of measure – tonnes and thousand tonnes

The most characteristic dimension of the AEA data cube is the economic activity. The second most relevant dimension is the greenhouse gas. For six greenhouse gases, the AEA data set has 402 data points for one geographical entity, reference year, and unit of measure (67 economic activities x 6 greenhouse gases = 402). This needs to be aggregated to a manageable number. Here, one may distinguish two levels of aggregation:

(1) **estimation level**, i.e. the number of aggregated AEA data points for which the actual estimation procedure is performed (see this chapter 2);

(2) **dissemination level**, i.e. the number of aggregated AEA data points for which estimation results are published by Eurostat (see chapter 5).

Obviously, the estimation level (1) is more detailed than the dissemination level (2).

In order to identify appropriate levels of aggregation several steps were undertaken.

a) the quantitative most important AEA data points of greenhouse gas emissions were identified;

b) a range of available sub-annual predictors was investigated with regards to its suitability for the quantitative most important data points identified in step a);

c) criteria for the choice of the eventual dissemination level were anticipated, including their possible interrelation with a) and b).

Starting with the Q3-2021 production cycle ([4]), Eurostat implemented 46 data points for the estimation level (see Annex 1) and a NACE based classification with 10 data points was chosen for the dissemination level (see Annex 2). The latter can be 'mapped' to the classification that IMF ([5]) and the OECD ([6]) use for their quarterly GHG emissions.

Each of the 46 annual AEA data points of greenhouse gas emissions (target variables) is temporally disaggregated using the methodology outlined in chapter 3. Those calculations are performed at Member State level, i.e. 46 time series are produced for each Member State. Those are afterwards aggregated for dissemination (see chapter 5).

([4]) Publishing on 15 February 2022 estimates for Q3-2021

([5]) https://climatedata.imf.org/pages/economic-activity-indicators#id2

([6]) https://data-explorer.oecd.org/vis?df[ds]=DisseminateFinalDMZ&df[id]=DSD_AEA@DF_AEA&df[ag]=OECD.SDD.NAD.SEEA f

3. OVERVIEW OF THE ESTIMATION METHODOLOGY

Eurostat applies a standard method for the majority of 46 AEA data points of greenhouse gas emissions to produce the quarterly estimates. The standard method can be characterised as an econometric-statistical approach, commonly applied for quarterly national accounts. It is widely based on IMF's Quarterly National Accounts Manual (2017 Edition) ([7]). It consists of two-methodological steps:

- Temporal disaggregation: Annual time series of the target variables (i.e. AEA data points of greenhouse gas emissions) is temporally disaggregated into quarterly time series. The process ensures that the sum of the four quarters is equal to the annual value ('benchmarked') for the reference years for which annual data is available.

- Extrapolation (early estimates): The quarterly time series of the target variables obtained from previous step is extrapolated up to the most recent quarter for which an estimation is wanted and feasible.

Predictor variables are used for the temporal disaggregation and the extrapolation. A predictor variable is a sub-annual (monthly or quarterly) indicator that aims at providing the (unknown) quarterly behaviour of the target variable. When assessing the suitability of a predictor, two features are relevant: correlation with the target-variable and data availability/coverage (both in terms of geographical and time dimensions).

Section 4.1 provides detailed information on the predictor variables identified for the standard method cases.

There are a few AEA data points of greenhouse gas emissions for which the standard method is not applied. Section 4.3 explains the methods applied for these specific cases.

For both, standard and specific methods, the temporal additivity constraint holds: i.e. the sum of the estimated quarters must equal the annual value (i.e. quarterly estimates are 'benchmarked' to annual values).

4. ESTIMATION PROCEDURE

4.1. Selection and assignment of sub-annual predictor variables

In a first step, Eurostat identified potentially suitable sub-annual predictor variables (see Table 1). In a second step, Eurostat selected sub-annual predictors and assigned them to the 46 AEA data points of greenhouse gas emissions (see Annex 3).

The sub-annual predictor to be selected and assigned to a given AEA data point of greenhouse gas emissions should ideally show the same quarterly trend as the emissions; in other words, both time series should be correlated in their development over time. There are two main constraints here. First, the quarterly trends of AEA data points of greenhouse gas emissions are unknown, because only annual data are available. This

([7]) https://www.imf.org/external/pubs/ft/qna/

makes it difficult to assess the closeness to the quarterly trends of potential predictors. Secondly, the range of timely available sub-annual predictors is limited. In the end, the sub-annual predictors are chosen on plausible assumptions about their correlation over time with the respective AEA data point of greenhouse gas emissions.

Eurostat identified a number of sub-annual predictors (see Table 1). These come from different statistical sources. Most of them come from Eurostat.

Predictor label	Predictor code	Provider	Data set name	Data set code
Gross value added in agriculture, forestry and fishing, in chain linked volumes (2015)	B1G_A	Eurostat	Gross value added and income A*10 industry breakdowns	namq_10_a10
Gross value added in industry (except construction), in chain linked volumes (2015)	B1G_B-E	Eurostat	Gross value added and income A*10 industry breakdowns	namq_10_a10
Gross value added in manufacturing, in chain linked volumes (2015)	B1G_C	Eurostat	Gross value added and income A*10 industry breakdowns	namq_10_a10
Gross value added in construction, in chain linked volumes (2015)	B1G_F	Eurostat	Gross value added and income A*10 industry breakdowns	namq_10_a10
Gross value added in wholesale and retail trade, transport, accommodation and food service activities, in chain linked volumes (2015)	B1G_G-I	Eurostat	Gross value added and income A*10 industry breakdowns	namq_10_a10
Gross value added in all NACE activities (excl. NACE A), in chain linked volumes (2015)	B1G_TOTXA	Eurostat	Gross value added and income A*10 industry breakdowns	namq_10_a10
Index of industrial production (volume) in other non-metallic mineral products (ISIC: C23)	IIP_C23	UNIDO	UNIDO Quarterly Index of Industrial Production	quarterly_iip
Index of industrial production (volume) in basic metals (ISIC: C24)	IIP_C24	UNIDO	UNIDO Quarterly Index of Industrial Production	quarterly_iip
Net electricity generation from combustible fuels (excluding renewable combustible fuels) ([8])	NELE_CF	Eurostat	Net electricity generation by type of fuel	nrg_cb_pem
Gross inland deliveries – observed - of motor gasoline and road diesel (excluding blended biofuels)	GID_ROADFUEL	Eurostat	Supply and transformation of oil and petroleum products - monthly data	nrg_cb_oilm
International marine bunkers and final consumption transport sector of oil products (EU27 aggregate)	FUELGDOIL_INTMAR_EU	Eurostat	Supply and transformation of oil and petroleum products - monthly data	nrg_cb_oilm
CO2 emissions air transport	OECD_AIR	OECD	Air transport CO2 emissions	airtrans_CO2
CO2 emissions maritime transport	OECD_MARITIME	OECD	Maritime transport CO2 emissions	maritime_CO2
Heating degree days	HDD_IEA	IEA	Heating degree days (reference temperature 18°C and threshold	HDDThold18

([8]) Starting from the publication in August 2026, this predictor has a dedicated treatment – see chapter 4.3.3.

			temperature 15°C.	
Index of deflated turnover in wholesale and retail trade (2021)	TOVV_G	Eurostat	Turnover and volume of sales in wholesale and retail trade - quarterly data	sts_trtu_q
Gross domestic product at market prices, in chain linked volumes (2015), million euro	GDP	Eurostat	GDP and main components (output, expenditure and income)	namq_10_gdp
Live bovine animals, thousand heads (animals)	APRO_A	Eurostat	Bovine population – annual data	apro_mt_lscatl

Table 1: List of sub-annual predictors potentially suited for temporal disaggregation and extrapolation of AEA data points of greenhouse gas emissions

Annex 3 presents the detailed assignment of above predictor variables to the 46 AEA data points of greenhouse gas emissions.

4.2. Standard methods

The standard methodology is composed of sub-methods which all have in common that they employ sub-annual predictor variables to estimate the sub-annual time series of an annual target variable. Further, these standard methods have in common that they conduct two steps, temporal disaggregation and extrapolation, in one go.

The standard methods can be placed in two groups:

- Denton's variants: this is a benchmarking method aiming at minimising previously specified changes in the quarterly estimates while ensuring that the benchmarking constraint (i.e. the sum of the four quarters is equal to the annual value) is respected (Eurostat 2013) (Eurostat 2018).

- Static Regression methods: including Chow-Lin, Fernandez and Litterman (Eurostat 2013) (Eurostat 2018).

To choose the most suitable standard method, several aspects are considered such as:

- Plausibility of the resulting quarterly estimates;

- Quality of the forecast: based on the simulation of an historical year for which annual AEA data is already available. Chapter 6 provides more information on this quality assessment.

The default standard method chosen by Eurostat is the Denton proportional first difference variant method. The estimates for the quarters beyond the last available annual data point are extrapolated using the timelier predictors' data. The Denton proportional first difference variant method aims at assigning to the quarterly estimate the same period-to-period growth rate by minimizing the following penalty function (IMF 2017):

$$P(x,z) = \sum_{t=2}^{T} \left[\left(\frac{x_t}{z_t} - \frac{x_{t-1}}{z_{t-1}} \right) \right]^2$$

Where x is the quarterly estimate, z is the predictor value and t the considered quarter.

The quarterly estimates are the values that minimize the penalty function $P(x, z)$ while fulfilling the temporal disaggregation constraint (the sum of the four quarters need to be equal to the annual value).

Eurostat uses the R package rjd3bench to perform the temporal disaggregation and extrapolation (see also **Annex 4**).

4.3. Specific methods for selected AEA data points of greenhouse gas emissions

For some target variables (i.e. AEA data points of greenhouse gas emissions), no predictor is selected either because of the specificities of the target variable, or because of unavailability of suitable predictors.

In other cases, the treatment of the predictor differs from the generic approach. Such cases are described below.

4.3.1. Methane emissions from waste management (CH4_E)

Methane emissions from waste management show a stable downwards trend and it is reasonable to extrapolate this trend. This is applied by the standard methodology for cases where no predictor is available.

The annual air emission accounts data is temporally disaggregated using the Boot, Feibes and Lisman (1967) method. In practical terms, this method can be implemented by applying the Denton's proportional first variant method with a constant as a predictor (IMF 2017).

Since there is no predictor, forecasting cannot be performed directly with the disaggregation method. For this reason, forward ARIMA (Autoregressive Integrated Moving Average) forecasting is applied.

4.3.2. Emissions of methane and nitrous oxide from agriculture (CH4_A, N20_A)

For these data points, the bi-annual predictor 'bovine population – annual data' is used. Bovine population is available from two surveys: May/June and November/December. These figures are used to temporally disaggregate the annual emissions into two. Then, the Denton method is applied to temporally disaggregate the series into quarters.

4.3.3. Emissions of carbon dioxide from electricity, gas, steam and air conditioning supply (CO2_D)

The monthly predictor net electricity production from combustible fuels (*nrg_cb_pem*) is only available at the aggregated product level. To fully account for changes in the energy mix used as input to electricity generation, the monthly information is complemented with information from Eurostat's annual energy statistics (*nrg_bal_peh*).

For fuel categories reported only in aggregated form, quarterly values are disaggregated into detailed fuel products using annual fuel shares derived from the annual dataset. When annual data for the latest year are unavailable, the most recent fuel shares are carried forward.

The electricity generation is then converted from GWh to TJ (conversion factor 3.6), adjusted for efficiency to estimate the fuel input, and finally multiplied by the corresponding emission factor (see **Annex 5**). The resulting sub-annual emissions are then aggregated for all the combustible fuels (excluding renewables) and used as a predictor for the temporal disaggregation and extrapolation. Whenever emissions cannot be estimated (due to missing monthly energy statistics data) the general gap-filling approach is applied, as for the remaining predictors (see 4.4)

4.3.4. Emissions of carbon dioxide from air transport (CO2_H51)

For this data point the standard method is applied (Denton proportional first variant method, see section 4.2). The temporal disaggregation is based on OECD data on CO_2 emissions by air transport as a predictor. Since this dataset only has data from reference year 2019 onwards, the following gap-filling procedure is applied:

- for the period 2010-2018, gross value added of wholesale and retail trade, transport, accommodation and food service activities (NACE G-I) is used to backcast the missing years in the OECD dataset.

- for the period 2019 onwards: quarterly OECD data on CO_2-emissions from air transport are used.

4.3.5. Emissions of carbon dioxide from water transport (CO2_H50)

The predictor used for the temporal disaggregation and extrapolation is the quarterly OECD CO_2 emissions from maritime transport.

In terms of estimation method, the same procedure as for air transport is applied.

4.4. Gap filling and inconsistencies

All predictors are checked for data gaps and inconsistency. Time series are split by country (geo) and frequency (monthly or quarterly), being verified if all expected time points are present for each country. Zeros are treated as missing (NA), except for heating degree days where real zeros exist and are converted to 0.001.

In some cases, missing values appear in the predictors' data sets. If gaps exist, the gap-filling approach depends on its relative position in the time series:

- When the gap is at the end of the time series, backcasting is performed using reverse ARIMA forecasting, where the observed part of the series is reversed, an ARIMA model is fitted. Forecasts are generated in reverse and then flipped back to original order.

- For interior gaps, the interpolation is done using state-space smoothing.

- If the gap is at the end of the time series, the estimation is done using forward ARIMA forecasting, where an ARIMA model is fitted to the observed part and forecasts are generated to fill the trailing gaps.

- If a country's time series is entirely missing or exceeds a defined threshold of missingness, the EU average — computed from complete country series — is imputed.

This approach ensures consistency, transparency, and reproducibility across all EU countries and variables.

4.5. Seasonal adjustment

With the release of Q2 2025, Eurostat started performing a seasonal adjustment of the quarterly air emission estimates.

Two main groups of seasonal adjustment methods can be distinguished: methods based on moving averages and model-based methods (Handbook of Quarterly National Accounts, 7.29). Eurostat applies the X13 ARIMA-SEATS using the R package rjd3x13 (Seasonal Adjustment with X-13 in 'JDemetra+ 3.x').

Seasonal adjustment is applied indirectly, i.e. Eurostat seasonally adjusts the predictor variables used for the temporal disaggregation.

Once the seasonally adjusted series are produced, the same temporal disaggregation and extrapolation is applied as to the non-adjusted equivalents. This ensures that both raw and seasonally adjusted estimates of quarterly indicators are available, enhancing analytical robustness and comparability across countries and time periods.

Member States report non-seasonally adjusted quarterly estimates (see section 5). Here, Eurostat applies the direct method and seasonally adjusts the quarterly air emission estimates which are reported. The original Eurostat estimates (both seasonally and non-seasonally adjusted) are then adjusted to fit to the totals reported by the countries, ensuring consistency at all levels across the different dimensions.

Quarterly estimates (seasonally and non-seasonally adjusted) for the EU are calculated based on the aggregation of quarterly figures for the individual Member States.

Like the non-seasonally adjusted series, the seasonally adjusted estimates are benchmarked to the published annual AEA.

For quarters for which no annual AEA is published:

- If four quarters are available to derive an annual estimate, the four seasonally adjusted quarters are constrained by the total of the four unadjusted quarters.

- If less than four quarters are available for one year, seasonally adjusted figures are not constrained, unless if unadjusted figures are reported by Member States.

No weather or calendar adjustment is performed.

More information can be found in this technical note.

5. AGGREGATION FOR DISSEMINATION

The estimates are produced for each Member State, according to the method explained above. In each quarterly estimation cycle, the complete time series starting from 2010Q1 are re-calculated. This means that 46 time series are produced for each Member State.

The EU Member States also have the possibility to report their own quarterly greenhouse gas emissions at the most aggregated level (all industries and households, i.e. one figure per quarter). This is done through a dedicated questionnaire which is submitted to Eurostat on a quarterly basis. So far, this was the case for Sweden, the Netherlands, Slovenia and Spain.

Three aggregations are done before publication.

1. First, the six greenhouse gases are summed up to one greenhouse gas aggregate expressed in CO2-equivalents using global warming potential factors.

2. Secondly, the EU-27 aggregate is calculated bottom-up from the 27 Member States' data.

3. Thirdly, the 46 time series built from the data points outlined in Annex 1 are aggregated into 10 groupings of economic activities and a total. This aggregation level for dissemination is applied for the EU-27 aggregate and presented in Annex 2. Country data are further aggregated to one single national total for dissemination.

Quarterly data are disseminated employing four measurement units: thousand tonnes in CO2 equivalents (THS_T), tonnes per capita, percentage change compared to the same quarter of the previous year (PCH_SM) and percentage change on previous period (PCH_PRE). Comparison with the same quarter of the previous year is the most adequate one for data not seasonally adjusted. Comparison of non-seasonally adjusted data for consecutive quarters gives volatile results. For seasonally adjusted figures, comparison with the previous quarter is possible.

6. ASSESSMENT OF ESTIMATION ERRORS

The main metric computed to assess the quality of these results is the estimation error between the annual sums of the quarterly air emission estimates with the actual annual air emissions accounts. As of this writing, the latest official annual air emission accounts data based on Regulation (EU) No 691/2011 is for the reference year 2023. The metric is therefore computed as follows:

$$Estimation\ error = \frac{AEA_{2023}^{estimated}}{AEA_{2023}^{actual}} - 1$$

To obtain the $\mathrm{AEA}_{2023}^{\mathrm{estimated}}$, the quarterly estimates are computed using a shortened annual air emissions accounts time series that only go up to 2022. This then allows to simulate the estimation of reference year 2023 and compare it to the actual 2023 value (outturn). The results of this simulation are presented and compared in Table 2, the estimation error $AEA_{2023}^{estimated}$ is presented in the last column to the right.

Country	Outturn (actual)	Simulated estimate	Difference (estimate-outturn)	Root-mean-square deviation (RMSD)	Difference in percentage
EU [1]	3 341 205	3 387 111	45 906	3 735	1.37
AT	68 813	69 901	1 088	141	1.58
BE	101 325	100 076	- 1 248	152	- 1.23
BG	46 932	47 158	225	192	0.48
CY	8 943	8 808	- 136	17	- 1.52
CZ	94 838	97 376	2 538	261	2.68
DE	710 349	724 688	14 339	1 418	2.02
DK	81 205	79 062	- 2 142	441	- 2.64
EE	11 803	10 683	- 1 120	149	- 9.49
EL	82 001	83 524	1 524	273	1.86
ES [1]	280 456	291 182	10 726	525	3.82
FI	44 532	44 346	- 186	102	- 0.42
FR	408 224	425 968	17 744	976	4.35
HR	25 926	24 854	- 1 072	83	- 4.13
HU	59 630	62 263	2 633	262	4.42
IE	72 935	73 637	702	134	0.96
IT	397 086	398 311	1 225	1 014	0.31
LT	25 141	25 136	- 4	83	- 0.02
LU	9 422	9 709	288	39	3.05
LV	11 575	11 905	330	51	2.85
MT	5 383	5 213	- 170	27	- 3.15
NL [1]	165 633	166 409	776	395	0.47
PL	370 624	364 320	- 6 305	1 231	- 1.70
PT	52 726	55 619	2 893	264	5.49
RO	106 303	107 720	1 417	342	1.33
SE [1]	48 754	48 695	- 59	166	- 0.12
SI [1]	14 514	14 191	- 323	73	- 2.22
SK	36 133	36 355	222	110	0.61

1 Eurostat estimates for the Netherlands, Spain, Slovenia and Sweden are not disseminated, since these countries report their own figures to Eurostat. Such figures also change the EU aggregated total which is disseminated.

*Table 2: Estimation error of quarterly GHG: Simulation of reference year 2023, annual data (estimation error (%) = (estimate/outturn-1)*100)*

The estimation error for the EU is 1.37%, i.e. the reference year 2023 is overestimated. The estimation error varies across countries in a range from approximately -9% to +5%.

7. Conclusions

With this note Eurostat provides information on the methodology used to estimate quarterly greenhouse gas emission accounts. The methodology described in this note may be subject to changes in the future, which may imply data revisions of previously published data.

The release dates are pre-announced in Eurostat's release calendar. Each quarter, Eurostat intends to publish the complete time series starting in the first quarter of 2010. Data previously published may be revised. Further information on the data publication and dissemination can be found in the metadata accompanying the data.

8. References

Eurostat. "ESS guidelines on temporal disaggregation, benchmarking and reconciliation." 2018.

Eurostat. "Handbook on quarterly national accounts." 2013.

IMF. "Quarterly National Accounts Manual." 2017.

Sax, Christoph, and Peter Steiner. *Package 'tempdisagg' - Methods for Temporal Disaggregation and Interpolation of Time.* 2020.

—. *Temporal Disaggregation of Time Series.* The R Journal Vol. 5/2, December 2013, pp. 80ff., 2013.

Annex 1: Eurostat estimation level of 46 AEA data points, as implemented since February 2022

		A	B	C	C23	C24	D	E	F	G	H49	H50	H51	H52	H53	I	J	K	L	M	N	O	P	Q	R	S	T	U	HH_ HEAT	HH_ TRA	HH_ OTH	TOTAL_ HH
1	CO2_A	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	CH4_A	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	N2O_A	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	FGAS_A	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	CO2_B	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	CH4_B	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	N2O_B	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	FGAS_B	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	CO2_C23	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	CO2_C24	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	CO2_CXC23_C24	0	0	1	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	CH4_C	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	N2O_C	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	FGAS_C	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	CO2_D	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	CH4_D	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	N2O_D	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	FGAS_D	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	CO2_E	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	CH4_E	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	N2O_E	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	FGAS_E	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	CO2_F	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	CH4_F	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	N2O_F	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	FGAS_F	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	CO2_G	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	CH4_G	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	N2O_G	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	FGAS_G	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	CO2_H49	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	CO2_H50	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	CO2_H51	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	CO2_HXH49-H51	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	CH4_H	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	N2O_H	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	FGAS_H	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	CO2_I-U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
39	CH4_I-U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
40	N2O_I-U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
41	FGAS_I-U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
42	CO2_HH_TRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
43	CO2_HH_HEAT_OTH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
44	CH4_HH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
45	N2O_HH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
46	FGAS_HH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0

Annex 2: Eurostat dissemination level

NACE based classification of economic activities for which quarterly emissions (all GHG gases expressed as CO_2-equivalents) are presented, as implemented since February 2022.

	NACE_R2 as in [env_ac_ainah]	A	B	C	D	E	F	G	H49	H50	H51	H52	H53	I	J	K	L	M	N	O	P	Q	R	S	T	U	HH_HEAT	HH_TRA	HH_OTH	TOTAL_HH
1	TOTAL_HH - All NACE activities plus households	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	A - Agriculture, forestry and fishing	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	B - Mining and quarrying	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	C - Manufacturing	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	D - Electricity, gas, steam and air conditioning supply	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	E - Water supply; sewerage, waste management and remediation activitie	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	F - Construction	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	H - Transportation and storage	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	G-U_X_H - Services (except transport and storage)	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
10	HH - Total activities by households	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0

Annex 3: Assignment of predictors to 46 AEA data points of greenhouse gas emissions

AEA data point	Predictor code
CO2_A	B1G_A
CH4_A	APRO_A
N2O_A	APRO_A
FGAS_A	GDP
CO2_B	B1G_B-E
CH4_B	B1G_TOTXA
N2O_B	B1G_TOTXA
FGAS_B	GDP
CO2_C23	IIP_C23
CO2_C24	IIP_C24
CO2_CXC23_C24	B1G_C
CH4_C	B1G_TOTXA
N2O_C	B1G_TOTXA
FGAS_C	GDP
CO2_D	NELEG
CH4_D	B1G_TOTXA
N2O_D	B1G_TOTXA
FGAS_D	GDP
CO2_E	B1G_B-E
CH4_E	-
N2O_E	B1G_TOTXA
FGAS_E	GDP
CO2_F	B1G_F
CH4_F	B1G_TOTXA
N2O_F	B1G_TOTXA
FGAS_F	GDP
CO2_G	B1G_G-I
CH4_G	B1G_TOTXA
N2O_G	B1G_TOTXA
FGAS_G	TOVV_G
CO2_H49	GID_ROADFUEL
CO2_H50	OECD_MARITIME
CO2_H51	OECD_AIR
CO2_HXH49-H51	B1G_G-I
CH4_H	B1G_TOTXA
N2O_H	B1G_TOTXA
FGAS_H	GDP
CO2_I-U	B1G_G-U
CH4_I-U	B1G_G-U
N2O_I-U	B1G_G-U
FGAS_I-U	B1G_G-U
CO2_HH_TRA	GID_ROADFUEL
CO2_HH_HEAT_OTH	HDD_IEA
CH4_HH	B1G_TOTXA
N2O_HH	B1G_TOTXA
FGAS_HH	GDP

Annex 4: Methods implemented in R-package ‘rjd3bench’

The R package ***rjd3bench*** provides an interface to the 'JDemetra+ 3.x' time series analysis software. It gives a variety of methods for temporal disaggregation and interpolation, benchmarking, reconciliation and calendarization.

Temporal disaggregation & interpolation:

- Chow-Lin, Fernandez and Litterman
- Model-Based Denton
- Autoregressive Distributed Lag (ADL) models

Benchmarking:

- Denton
- GRP (Growth Rate Preservation)
- Cubic Splines
- Cholette

Reconciliation and multivariate temporal disaggregation:

- Multivariate Cholette

Annex 5: Emission factors and efficiencies in electricity production

Product code	Product label	Emission factor * (kg CO2/TJ)	Efficiency ** (%)
C0110	Anthracite	98 300	37
C0121	Coking coal	94 600	34
C0129	Other bituminous coal	94 600	40.5
C0210	Sub-bituminous coal	96 100	33
C0220	Lignite	101 000	34
C0311	Coke oven coke	107 000	38
C0312	Gas coke	107 000	38
C0320	Patent fuel	97 500	85
C0330	Brown coal briquettes	97 500	80
C0340	Coal tar	80 700	81
C0350	Coke oven gas	44 400	39
C0360	Gas works gas	44 400	45
C0371	Blast furnace gas	260 000	39.5
C0379	Other recovered gases [1]	182 000	46
P1100	Peat	106 000	38
P1200	Peat products [2]	106 000	51.5
S2000	Oil shale and oil sands	107 000	34
W6100	Industrial waste (non-renewable)	143 000	37.5
W6220	Non-renewable municipal waste	91 700	24
G3000	Natural gas	56 100	43
O4100_TOT	Crude oil	73 300	54.5
O4200	Natural gas liquids	64 200	54.5
O4300	Refinery feedstocks	73 300	54.5
O4400X4410	Additives and oxygenates (excluding biofuel portion) [3 4]	73 300	34.5
O4500	Other hydrocarbons [3 4]	73 300	34.5
O4610	Refinery gas	57 600	48
O4620	Ethane	61 600	34.5
O4630	Liquefied petroleum gases	63 100	37
O4640	Naphtha	73 300	34
O4651	Aviation gasoline [4]	70 000	34.5
O4652XR5210B	Motor gasoline (excluding biofuel portion) [4]	69 300	34.5
O4653	Gasoline-type jet fuel [4]	70 000	34.5
O4661XR5230B	Kerosene-type jet fuel (excluding biofuel portion) [4]	71 500	55
O4669	Other kerosene	71 900	33
O4671XR5220B	Gas oil and diesel oil (excluding biofuel portion)	74 100	35
O4680	Fuel oil	77 400	35
O4691	White spirit and special boiling point industrial spirits [4]	73 300	34.5
O4692	Lubricants [4]	73 300	34.5
O4693	Paraffin waxes [4]	73 300	34.5
O4694	Petroleum coke	97 500	39
O4695	Bitumen	80 700	39.5
O4699	Other oil products n.e.c. [3]	73 300	34.5

* 2006 IPCC Guidelines for National Greenhouse Gas Inventories, chapter 2: Stationary combustion, Table 2.2
** ESS validation manual, Energy statistics on quantities & prices, average efficiency for 'electricity only' by 'main activity producer'

[1] Emission factor taken from oxygen steel furnace gas

[2] Emission factor taken from peat

[3] Emission factor taken from other petroleum products

[4] Efficiency taken from other oil products