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Eurostat's estimates of quarterly greenhouse gas emissions accounts

Methodological note

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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). AEA are compiled according to the international System of Environmental-Economic Accounting (SEEA). 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[2].

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)

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.elibrary.imf.org/view/books/069/24171-9781475589870-en/24171-9781475589870-en-book.xml?rskey=JxaaMY&result=8

[2] 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 CO2, N2O, CH4, HFC, PFC, and NF3_SF6. In addition, the gases N2O and CH4 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 (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) **<u>estimation level</u>**, i.e. the number of aggregated AEA data points for which the actual estimation procedure is performed (see this chapter 2);

(2) **<u>dissemination level</u>**, 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[3], 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[4] uses 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).

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3 Publishing on 15 February 2022 estimates for Q3-2021

4 https://climatedata.imf.org/pages/re-indicators#re1

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)[5]. 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 actually unknown because only annual data are available. This 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

[5] https://www.elibrary.imf.org/view/books/069/24171-9781475589870-en/24171-9781475589870-en-book.xml?rskey=JxaaMY&result=8

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, in chain linked volumes (2015)	B1G_B-F	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	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
Gross value added in service industries, in chain linked volumes (2015)	B1G_G-U	Eurostat	Gross value added and income A*10 industry breakdowns	namq_10_a10
Heating degree days	HDD_IEA	IEA	Heating degree days (reference temperature 18°C and threshold temperature 15°C.	HDDThold18
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 deflated turnover in wholesale and retail trade (2021) [6]	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

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.

6 When data were not available, 'Index of turnover – Total' was applied.

4.2. Standard methods

The standard methodology is actually a bunch of 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 minimize 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).

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.

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. Instead, the additional quarters beyond the available annual air emissions accounts are estimated using the following formula, which is a weighted average for the quarter-on-quarter change rates of the three last observations (IMF 2017):

$$I_T = I_{T-1}\left[\frac{3}{6}\frac{I_{T-1}}{I_{T-2}} + \frac{2}{6}\frac{I_{T-2}}{I_{T-3}} + \frac{1}{6}\frac{I_{T-3}}{I_{T-4}}\right]$$

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

For these data points, no sub-annual predictor has been identified.

For the estimate of Q3 and Q4 the standard methodology for cases where no predictor is available is applied (same as for methane emissions from waste management, see previous section).

For the estimate of Q1 and Q2 the time series of the annual data points is extrapolated by one additional year using annual change rates of livestock statistics, before the standard methodology for cases where no predictor is available is applied (same as for methane emissions from waste management, see previous section).

4.3.3. 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). However, the temporal disaggregation step is undertaken manually by using two data sources:

- For the period 2010-2018: the annual air emissions accounts are used, whereby each annual data points is decomposed into four equal quarterly parts.

- For the period 2019 onwards: quarterly OECD data on CO2-emissions by air transport are used.

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

Unlike to other data points, no country-specific predictor is used. For water transport, the predictor selected is the EU-27 aggregate for fuel delivered to international marine bunkers. It reflects the overall activity levels of marine transport in European harbours.

4.4. Gap filling and inconsistencies

All predictors are checked for data gaps and inconsistency.

In some cases, missing values appear in the predictors' data sets. These are gap-filled using the following methods:

- Missing values for a country over the complete time series: data are imputed from a similar country (similarity is considered taking into account the specific economic sector).

- Isolated missing values: the quarter-on-quarter growth rate from the previous or next year is applied to the quarter just before the missing value.
- Longer series of missing values (more than 4 quarters): data from previous or next year is assigned to the gap.

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 and Spain. For quarter 4 of 2024, Sweden could not provide data, and therefore the data for Sweden were estimated by Eurostat.

Three aggregations are done before publication.

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

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

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 three measurement units: thousand tonnes in CO2 equivalents (THS_T), tonnes per capita, and percentage change compared to the same quarter of the previous year (PCH_SM). 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.

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 2022. The metric is therefore computed as follows:

$$Estimation\ error = \frac{AEA_{2022}^{estimated}}{AEA_{2022}^{actual}} - 1$$

To obtain the $\mathrm{AEA}_{2022}^{\mathrm{estimated}}$, the quarterly estimates are computed using a shortened annual air emissions accounts time series that only go up to 2021. This then allows to simulate the estimation of reference year 2022 and compare it to the actual 2022 value (outturn). The results of this simulation are presented and compared in Table 2, the estimation error $AEA_{2022}^{estimated}$ 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]	3 605 559	3 685 367	79 808	6 300	2.21
AT	72 061	73 899	1 838	245	2.55
BE	105 741	110 107	4 366	529	4.13
BG	60 042	60 789	746	289	1.24
CY	8 803	8 947	144	18	1.64
CZ	109 631	109 838	207	308	0.19
DE	794 472	792 405	- 2 067	1 803	- 0.26
DK	82 607	93 025	10 418	1 539	12.61
EE	14 988	14 555	- 432	67	- 2.88
EL	87 623	90 066	2 443	684	2.79
ES [1]	304 355	305 866	1 511	1 165	0.50
FI	48 420	48 171	- 249	176	- 0.52
FR	427 291	444 317	17 026	1 106	3.98
HR	24 848	25 449	601	66	2.42
HU	65 547	68 000	2 454	222	3.74
IE	73 844	77 818	3 974	265	5.38
IT	424 374	428 762	4 389	662	1.03
LT	25 564	26 004	440	96	1.72
LU	9 277	9 425	148	47	1.59
LV	11 619	12 279	660	153	5.68
MT	3 880	3 729	- 150	20	- 3.87
NL [1]	174 172	182 651	8 479	738	4.87
PL	402 753	418 563	15 810	1 017	3.93
PT	60 187	60 764	576	101	0.96
RO	112 100	114 390	2 291	367	2.04
SE	49 090	51 222	2 132	157	4.34
SI	15 180	15 873	693	56	4.56
SK	37 091	38 454	1 362	287	3.67

1 Eurostat estimates for NL and ES 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 2022, annual data (estimation error (%) = (estimate/outturn-1)*100)*

The estimation error for the EU is 2.21%, i.e. the reference year 2022 is overestimated. The estimation error varies across countries in a range from approximately -4% to +13%.

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, implemented in 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, implemented in 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 of greenhouse gas emissions	Predictor code
Target	Predictor code
CO2_A	B1G_A
CH4_A	-
N2O_A	-
FGAS_A	namq_10_gdp
CO2_B	B1G_B-F
CH4_B	B1G_TOTXA
N2O_B	B1G_TOTXA
FGAS_B	namq_10_gdp
CO2_C23	IIP_C23
CO2_C24	IIP_C24
CO2_CXC23_C24	B1G_B-F
CH4_C	B1G_TOTXA
N2O_C	B1G_TOTXA
FGAS_C	namq_10_gdp
CO2_D	NELE_CF
CH4_D	B1G_TOTXA
N2O_D	B1G_TOTXA
FGAS_D	namq_10_gdp
CO2_E	B1G_B-F
CH4_E	-
N2O_E	B1G_TOTXA
FGAS_E	namq_10_gdp
CO2_F	B1G_B-F
CH4_F	B1G_TOTXA
N2O_F	B1G_TOTXA
FGAS_F	namq_10_gdp
CO2_G	B1G_G-U
CH4_G	B1G_TOTXA
N2O_G	B1G_TOTXA
FGAS_G	sts_trtu_q
CO2_H49	GID_ROADFUEL
CO2_H50	FUELGDOIL_INTMAR_EU
CO2_H51	AIRTRANS_CO2
CO2_HXH49-H51	B1G_G-U
CH4_H	B1G_TOTXA
N2O_H	B1G_TOTXA
FGAS_H	namq_10_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	namq_10_gdp

Annex 4: Methods for temporal disaggregation implemented in R-package 'tempdisagg'

The R package ***tempdisagg*** implements the following standard methods for temporal disaggregation: Denton, Denton-Cholette, Chow-Lin, Fernandez and Litterman.
On the one hand, Denton (Denton, 1971) and Denton-Cholette (e.g. Dagum and Cholette, 2006) are primarily concerned with movement preservation, generating a series that is similar to the indicator series whether or not the indicator is correlated with the low frequency series. Alternatively, these methods can disaggregate a series without an indicator.
On the other hand, Chow-Lin, Fernandez and Litterman use one or several indicators and perform a regression on the low frequency series. Chow-Lin (Chow and Lin, 1971) is suited for stationary or cointegrated series, while Fernandez (Fernández, 1981) and Litterman (Litterman, 1983) deal with non-cointegrated series.

<table>
<tr><th>Method</th><th>Description</th></tr>
<tr><td>denton-cholette</td><td rowspan="2">The Denton methods "denton" and "denton-cholette" can be specified with one or without an indicator. The parameter h can be set equal to 0, 1, or 2. Depending on the value, the denton procedure minimizes the sum of squares of the deviations between the levels (0), the first differences (1) or the second differences (2) of the indicator and the resulting series</td></tr>
<tr><td>denton</td></tr>
<tr><td>chow-lin-maxlog</td><td rowspan="6">Generalized least squares (GLS) methods, where an autoregressive parameter ρ is estimated. Default (and recommended) method is chow-lin-maxlog. With truncated.rho=0 (default), it produces good results for a wide range of applications.
There are two variants of the chow-lin-minrss approach that lead to different results: Ecotrim by Barcellan (2003) uses a correlation matrix instead of the variance covariance matrix (implemented in "chow-lin-minrss-ecotrim"), the Matlab library by Quilis (2009) multiplies the correlation matrix with 1/(1 − ρ2) (implemented in "chow-lin-minrss-quilis").</td></tr>
<tr><td>chow-lin-minrss-ecotrim</td></tr>
<tr><td>chow-lin-minrss-quilis</td></tr>
<tr><td>litterman-maxlog</td></tr>
<tr><td>litterman-minrss</td></tr>
<tr><td>chow-lin-fixed</td></tr>
<tr><td>dynamic-maxlog"</td><td rowspan="3">(experimental) Dynamic extensions of Chow-Lin (Santos Silva and Cardoso, 2001). If the autoregressive parameter ρ is equal to 0, no truncation remainder is added.</td></tr>
<tr><td>dynamic-minrss"</td></tr>
<tr><td>dynamic-fixed"</td></tr>
<tr><td>fernandez</td><td></td></tr>
<tr><td>litterman-fixed</td><td></td></tr>
</table>

Source: Sax & Steiner, 2013, Sax & Steiner 2020