International Trade Nowcasting Challenge Approach Description

Methodology *(Replicability; Scalability; Interpretability)*

Please provide a detailed description of the approach used to calculate the point estimates of the International Trade of Goods statistics. The description should contain (1) the data processing steps, (2) the methods and models used, (3) references to the scientific papers/sources that present the methods and models used, and (4) the time it took to process the data set and classify the job advertisements.

Bear in mind that the workflow will be also evaluated based on the criteria for the Reusability and Innovativity Awards.

This section will be evaluated for:

> *(1) the Replicability criterion: likeliness that the described approach can successfully reproduce the solution submitted by the team for the Accuracy award*
>
> *(2) the Scalability criterion: amount of modification required for the approach to apply to similar datasets on a potentially larger scale*
>
> *(3) the Interpretability criterion: the extent to which a human could understand and articulate the relationship between the approach's predictors and its outcome; how well the logical reasoning behind the model which is making the prediction is developed (whether it is mathematically and/or technically sound*

Motivation

In a globalized economy, international trade cannot be meaningfully analyzed by focusing solely on a single country. The highly interconnected nature of trade means that economic developments in one country can propagate through complex international supply chains, affecting multiple economies. For instance, a slowdown in economic activity in Country A not only reduces the exports of its direct trading partner, Country B, but also indirectly affects Countries C and D if Country B relies on intermediate or raw materials imported from them to produce its exports.

Moreover, imports and exports are inherently interdependent due to this networked structure of global trade. Economic shocks in one region can lead to synchronized movements in trade flows across countries. A domestic demand shock, for example, can increase imports, which in turn boosts exports and income in partner countries. This income gain may subsequently enhance demand for exports back to the original country, creating a feedback loop.

Another fundamental reason for the co-movement of imports and exports is the globalization of production. In many countries, exports heavily rely on imported intermediate goods, making trade flows mutually reinforcing. Countries with stronger trade ties also tend to exhibit higher correlations in their business cycles, further emphasizing that trade acts as a channel for the transmission of country-specific or sectoral shocks.

Given this interdependence, our forecasting approach models each country not only with its domestic macroeconomic indicators but also incorporates international variables that reflect its trade linkages. This allows the models to better capture the global interconnectedness and improve the sensitivity of forecasts to international shocks.

Model Specification

The core forecasting technique used in our project is based on the TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) methodology, originally developed by Gómez and Maravall at the Bank of Spain (Gómez & Maravall, 1996). It is particularly suited for macroeconomic indicators due to its ability to accommodate missing data, calendar effects, outliers, and evolving seasonal patterns. TRAMO has become a standard tool in official statistics for time series modeling and seasonal adjustment due to its flexibility and robustness.

At the core of TRAMO lies the RegARIMA (regression with ARIMA errors) model. It allows explanatory variables to explain part of the variation in the target variable, while the remaining autocorrelation structure is captured by a flexible ARIMA model. TRAMO can estimate both deterministic and stochastic components and separates signal (trend, seasonal, calendar) from noise, making it well-suited for short-term forecasting like nowcasting.

To nowcast the target variable, we employ an extension of the standard TRAMO framework. We refer to this extended version as TRAMO-X*, which integrates international economic variables derived from economic theory. The asterisk (*) indicates the inclusion of foreign external variables. The general form of the model is given by:

$$M_{i,t}^{d} = \sum_{l=1}^{L} \delta_l o_{i,t}^{(l)} + \sum_{m=1}^{M} \beta_m x_{i,t-m} + \sum_{k=0}^{K} \lambda_k x_{i,t-k}^{*} + z_{i,t}$$

$t = 1,2, \dots, T$ and $i = 1,2, \dots, N$

$M_{i,t}^{d}$: extra-EU imports of country *i* at time *t* (target variable)

$o_{i,t}$; outlier dummies (e.g., additive outliers, level shifts, temporary changes)

$x_{i,t-m}$; lagged domestic variables for country *i*

$x_{i,t-k}^{*}$: foreign variables (trade-weighted averages of other countries' indicators; see *Variable Selection and Theoretical Justification Section*)

δ_l, β_m, λ_k : coefficients for the respective components

$z_{i,t}$: ARIMA error term

The ARIMA error component follows a seasonal ARIMA model and is defined as:
$\phi(B)\phi_s(B^s)\Delta^d\Delta_s z_{i,t} = \theta(B)\theta_s(B^s)a_{i,t}$

$\phi(B)$ and $\theta(B)$: non-seasonal AR and MA polynomials

$\phi_s(B^s)$and $\theta_s(B^s)$: seasonal AR and MA polynomials

B: backward shift operator

s: seasonal frequency (e.g., 12 for monthly data)

Δ^d: regular differencing operator of order *d*

Δ_s: seasonal differencing operator

$a_{i,t}$: white noise error term

Since each country is treated as a small open economy, foreign variables are assumed to be weakly exogenous. Only lagged domestic variables are included to avoid endogeneity, ensuring all regressors are predetermined.

Prior to finalizing the proposed methodology, we tested several alternative modeling approaches, including Global Vector Autoregression (GVAR). While GVAR is methodologically appealing, its application in a nowcasting context proved challenging due to the requirement for seasonal adjustment and the need to retransform forecasted values into non-adjusted levels using predicted seasonal components. Even when forecasting year-on-year growth rates to bypass this constraint, the results were suboptimal. These challenges, combined with the limitations of GVAR in terms of forecast accuracy, led us to adopt a TRAMO-based structure, which allows for direct modeling of unadjusted monthly import levels while providing ARIMA-driven robustness in error correction.

Construction of Trade Weight Matrices

To incorporate international interdependencies, foreign variables $x^*_{i,t}$ were constructed as trade-weighted averages of other countries' macroeconomic indicators:

$$x^*_{i,t} = \sum_{j=0}^{N} w_{ij} x_{j,t}$$

Where:

w_{ij} represents the relative importance of country *j* in the trade structure of country *i* at time *t*, based on their bilateral trade volumes.

$w_{ii} = 0$ and $\sum_{j=0}^{N} w_{ij} = 1$ for all i and t.

To reflect the evolution of global trade patterns, we constructed time-varying weight matrices using annual bilateral trade volumes (exports + imports) over the period 2014–2023. Each EU country had a unique set of partner-specific weights computed for each year. For 2024 and 2025, the latest available data from 2023 were used as a proxy. This annual updating process enables the model to account for third-country effects and to respond to changes in trade patterns caused by global shocks such as the COVID-19 pandemic, the Russia-Ukraine conflict, or Brexit.

In addition to the 27 EU countries to be estimated, the 8 largest trading partners of these countries outside the European Union were also taken into account in the trade weight calculation. The 35 countries used in the construction of trade-weighted variables, are shown in Table 1:

Table 1.

EU Countries			**Extra-EU Countries**
Austria	France	Malta	China
Belgium	Germany	Netherlands	Japan
Bulgaria	Greece	Poland	Norway
Croatia	Hungary	Portugal	South Korea
Cyprus	Ireland	Romania	Switzerland
Czech Republic	Italy	Slovakia	Türkiye
Denmark	Latvia	Slovenia	United Kingdom
Estonia	Lithuania	Spain	United States
Finland	Luxembourg	Sweden	

Variable Selection and Theoretical Justification

In modeling extra-EU monthly imports ($M_{i,t}^{d}$) for 27 EU member states, we grounded our approach in established international trade theories, including the elasticity approach and the imperfect substitutes model (Goldstein & Khan, 1985). The selection of explanatory variables was motivated by these theoretical frameworks, which emphasize the responsiveness of trade flows to relative prices ($p_{i,t}/p_{i,t}^{*}$), exchange rates ($e_{i,t}^{*}$), and real economic activity ($y_{i,t}$).

Each country-specific import model incorporates the following variables:

<u>Relative Prices</u>: Computed as $p_{i,t}/p_{i,t}^{*}$, where $p_{i,t}$ denotes the Harmonised Index of Consumer Prices (HICP) of country *i* and $p_{i,t}^{*}$ is the trade-weighted foreign HICP. An increase in this ratio implies that domestic goods become relatively more expensive, making foreign goods more attractive. Therefore, relative price increases are expected to stimulate import demand, in line with the elasticity approach.

<u>Real Output</u>: Industrial Production Index ($y_{i,t}$) is used as a proxy for domestic real activity and import demand. As domestic output increases, both household consumption and production-related demand for intermediate goods typically rise, leading to higher levels of imports.

Foreign Exchange Rate: In our modeling framework, the foreign exchange rate variable $e^*_{i,t}$ represents the trade-weighted average of bilateral exchange rates ($e_{i,t}$) of country *i*'s trading partners in terms of the Euro. Since many EU countries use the Euro as their domestic currency, their bilateral exchange rates with the Euro are equal to one and do not contribute variation. Therefore, we focus on the foreign exchange rate variable $e^*_{i,t}$ which captures currency fluctuations in major non-Euro trading partners.

An appreciation of $e^*_{i,t}$ (i.e., a depreciation of the foreign currencies against the Euro) implies that imports become relatively cheaper for the Eurozone country, potentially increasing import demand. Conversely, a depreciation of $e^*_{i,t}$ (i.e., stronger foreign currencies) raises the Euro-denominated price of imports and may reduce extra-EU imports. This interpretation aligns with the elasticity approach and is especially relevant for extra-EU trade with major partners such as the US, China, and the UK.

Country-Level Model Composition

Each of the 27 EU countries was specified as an individual regression equation, incorporating three key explanatory variables: relative prices, real output, and foreign exchange rates.
Importantly, among all the variables, only the foreign exchange rate variable ($e^*_{i,t}$) was included at lag zero (contemporaneously) due to its weak exogeneity. This country-level customization enabled the model to account for heterogeneity in trade behavior and macroeconomic responsiveness across member states. Table 2 below summarizes the lag structure of the regressors used in each country's model:

Table 2.

Country Name	Foreign Exchange Rates ($e^*_{i,t}$)	Relative Prices ($p_{i,t}/p^*_{i,t}$)	Real Output ($y_{i,t}$)
Austria	0	2	2
Belgium	2	1	2
Bulgaria	1	1	2
Croatia	0	1	2
Cyprus	2	2	2
Czech Republic	2	2	2
Denmark	1	2	2
Estonia	1	1	2
Finland	2	1	2
France	1	1	2
Germany	2	1	2
Greece	1	2	2
Hungary	1	1	2
Ireland	0	1	2
Italy	1	2	2
Latvia	0	1	2
Lithuania	2	2	2
Luxembourg	2	2	2
Malta	2	2	2
Netherlands	1	1	2
Poland	1	2	2

Portugal	2	1	2
Romania	1	2	2
Slovakia	1	1	2
Slovenia	1	1	2
Spain	2	2	2
Sweden	0	1	2

Entry Design

The primary target variable in this study is the monthly extra-EU import value of each of the 27 EU member states. To evaluate the robustness and comparative performance of different modeling approaches, we submitted five separate nowcasting entries to Eurostat, each reflecting a distinct methodology:

Entry 1 – TRAMO-X*

This approach extends the traditional TRAMO model by incorporating foreign variables constructed as trade-weighted averages of macroeconomic indicators from a panel of 35 countries. This includes the 27 EU countries plus 8 additional major trading partners (e.g., the United States, the United Kingdom, and China) that hold significant weight in EU external trade structures. The weight matrices are derived from bilateral trade volumes and reflect each country's importance in the import profile of the respective EU state.

Entry 2 – Univariate TRAMO

This specification employs the standard TRAMO methodology without external variables, serving as a univariate benchmark model. It captures country-specific dynamics, outliers, and seasonality through an ARIMA-based framework.

Entry 3 – Ensemble Forecast

The third entry is a composite model, constructed as the simple average of Entry 1 and Entry 2 forecasts. This ensemble approach aims to combine the strengths of different modeling strategies and reduce individual model biases.

Entry 4 – LSTM model

A deep learning model based on a Long Short-Term Memory (LSTM) architecture was also implemented. Although it offers a flexible non-linear framework, its performance lagged behind the other approaches during the first four months of the competition.

Entry 5 – TRAMO-X* with Extra-EU Trade Weights*

Similar in structure to Entry 1, this version also includes foreign variables but calculates trade weights only based on extra-EU trade volumes. By excluding intra-EU trade from the weighting scheme, it places emphasis on external shocks and partners from non-EU economies.

This multi-entry architecture allowed us to test different hypotheses about the role of international linkages in import dynamics. Notably, Entries 1 and 5 assess how foreign variable design influences forecast quality, while Entry 3 serves as a robust aggregator. The univariate benchmark (Entry 2) enables us to assess the incremental value of including cross-border spillover effects.

The models were built in R and leverage both international and domestic macroeconomic variables. For the fourth entry, nowcast were sent for 6 months with the LSTM model. However, since the performance of this entry was not considered to be ranked in the competition, it was not detailed in this document and was removed from the R codes.

Data Processing

Data processing included filtering, aligning and imputing monthly indicators from Eurostat and OECD databases. Seasonal adjustment was not required as our approach works directly with raw monthly levels. Foreign variables (X*) were created using trade-weighted averages, derived from a panel of 35 countries based on bilateral trade data from 2014–2023. The foreign variables that used in the models are shown in Table 3.

Table 3.

Explanatory Variables	Variable names in R_codes
Relative Prices $(p_{i,t}/p^*_{i,t})$	rel_dp
Real Output $(y_{i,t})$	y
Foreign Exchange Rates $(e^*_{i,t})$	er_star

The target variable and other variables are obtained from Eurostat and OECD databases for each country, converted into the same format and combined. The detail of data sources explained in **List of Data Sources with Descriptions** section. In general, the import and processing of the data was carried out in the following way:

1- Connect Eurostat and OECD databases.
2- Get production in industry (IPI), harmonised index of consumer prices (HICP) and exchange rates data by filtering countries, time and selecting necessary variables.
3- If there are any missing observations in the variables imputation is made with the last observed data for each country.
4- Index values have been rebased to 2014=100. Thus, variables with different base years have been brought to the same base year.
5- The variables y, rel_dp, er_star, rel_dp2 and er_star2 used as explanatory variables in the model are generated using the data obtained in the previous step and the trade weights of each country. The rel_dp and er_star variables are constructed using trade weight matrices including 35 countries, while the rel_dp2 and er_star2 variables are constructed using trade weight matrices including non-EU countries.
6- The data generated in this way is exported to the data folder under the relevant period of the project.

Implementation in R with RJDemetra

In our project, we implement TRAMO models using the RJDemetra package, which provides an R interface to the official JDemetra+ seasonal adjustment software maintained by Eurostat and the National Bank of Belgium (RJDemetra Team, 2022). This package enables:

- Full access to TRAMO-SEATS and X13-ARIMA-SEATS methods.
- User-defined specification via *tramoseats_spec()* for controlling model type, outlier treatment, trading day adjustments, and inclusion of regressors.
- Direct forecasting and residual diagnostics using *regarima()* and forecast extraction functions.

RJDemetra enables seamless integration of multivariate time series modeling, while maintaining compatibility with the official seasonal adjustment methods used by European statistical offices. In our system:

- Regressors are constructed, lagged, and passed as external variables using the *usrdef.var* argument.
- The model specification can be tailored country-by-country, aligning with economic heterogeneity across forecasting units.
- Output includes fitted values, forecasts, and diagnostics, which are programmatically extracted and stored for evaluation and reporting.

Advantages for Nowcasting:

- Model robustness: Handles non-stationarity, outliers, and irregular seasonality.
- Flexibility: Supports both univariate and multivariate models with minimal structural changes.
- Forecasting accuracy: Uses full ARIMA estimation to model residual autocorrelation, enhancing prediction reliability.
- Reproducibility: RJDemetra provides audit-traceable outputs suitable for policy or academic use.

Overall, TRAMO, when combined with a data-rich and trade-weighted regression structure, offers a reliable and interpretable solution for short-term economic forecasting.

Model Selection Framework

Each country's TRAMO model configuration—specifically the set of explanatory variables and their lag structures—is defined in a control table named *model_info_tramo*. This table acts as the blueprint for the model and contains the best-performing predictors and their respective lag lengths for each country.

The selection of variables and lags was performed using a sliding window (rolling forecast) evaluation strategy. Over historical periods, candidate regressors were tested using different lag configurations. The Mean Squared Relative Error (MSRE) was used as the primary selection criterion to ensure models were not only accurate in-sample but also robust in out-of-sample forecasting performance.

Model Variants Overview

- **Entry 1 (TRAMO_MV1):** Multivariate TRAMO with trade-weighted regressors (rel_dp, er_star, y) based on all countries. Country-specific lags from *model_info_tramo* are applied.

- **Entry 2 (TRAMO_UV):** Univariate TRAMO using only the target series' historical values as input serves as a baseline and benchmark model.
- **Entry 3 (TRAMO_AVG):** Simple average of forecasts from MV1 and UV models to reduce overfitting and balance complexity and robustness.
- **Entry 5 (TRAMO_MV2):** Multivariate TRAMO with regressors based on non-EU trade weights (rel_dp2, er_star2, y), providing insights into how external exposure influences forecasting performance.

Dynamic Forecasting Logic

To improve performance and ensure efficient operation:

- If the *nowcast_period* is in the past or future relative to execution date, the system uses **locally saved data** to generate nowcasts quickly.
- If the *nowcast_period* is **current**, the script automatically queries **real-time data** from Eurostat and OECD via API connections, ensuring nowcasts are based on the most recent available information.

This hybrid strategy balances **reproducibility**, **efficiency**, and **real-time responsiveness**.

Computing Time and Efficieny

The system is optimized for both accuracy and efficiency. Total runtime depends on whether real-time data needs to be fetched from external sources:

- If the nowcast period corresponds to the current month, the system connects to Eurostat and OECD APIs to download the latest available data. In this case, the full pipeline—including data download, transformation, modeling, and export—takes approximately 3 minutes to complete for all countries.
- If the nowcast period is historical or set in the future, pre-saved raw data files are used. This bypasses all API connections and reduces total runtime to approximately 10 seconds on average for the full set of nowcasts.

This dynamic approach ensures that the system is both responsive in real-time settings and highly efficient when reproducibility and speed are prioritized.

How to Run

- Open ESA-Nowcasting-EXTRA-IMPORT.Rproj file
- Open run.R script and source (if you want to get nowcasts of different period, you can change ***nowcast period*** argument in *get_nowcast* function)
- Once the process is complete, the results can be found in the Results folder under the relevant period.

Replicability

The entire system is designed to ensure full replicability. All data used for nowcasting is sourced from standardized and publicly accessible databases—namely Eurostat and OECD—using reproducible R functions like *get_eurostat()* and *readSDMX()*. Once downloaded, raw data files are saved locally within the project structure (with file names that include the nowcast_period and *Sys.Date()*), ensuring that the same version of the data can be reused in the future, even if upstream databases change.

Moreover, the system intelligently distinguishes between current and past forecasting contexts. If the nowcast_period corresponds to a future or historical month, the system bypasses API calls and loads existing data files, guaranteeing both consistency and speed. When nowcasting for the current period, the system automatically retrieves up-to-date data, balancing replicability with real-time accuracy.

The forecasting models are built upon the TRAMO framework via the RJDemetra package, which itself is a wrapper around Eurostat's official JDemetra+ software. This further enhances methodological replicability by adhering to international statistical standards.

Scalability

Scalability is a central feature of the design. The system supports forecasting for multiple countries simultaneously, each potentially using a unique set of explanatory variables and lag structures. This is made possible through a modular modeling structure and the use of a central control table called *model_info_tramo*, which defines the relevant predictors and lag lengths per country.

These configurations were derived using a sliding window approach and evaluated using the Mean Squared Relative Error (MSRE). This optimization step ensures that model choices are data-driven and can be adapted to new countries or indicators without modifying the underlying code.

In addition, explanatory variables such as rel_dp and er_star are trade-weighted aggregates computed dynamically based on trade volume shares. These weights are calculated programmatically, enabling the system to scale across different sets of countries, including variants such as all-partners vs. non-EU partners (TRAMO_MV1 vs. TRAMO_MV2).

The system uses efficient tidyverse tools (dplyr, tidyr, purrr) and time-series functions (ts.union, regarima), making it computationally scalable and suitable for deployment in broader operational forecasting environments.

Interpretability

Interpretability is ensured through **clear model structure**, **logical data flows**, and **well-commented code**. Each component of the system is modular:

- Data import
- Preprocessing and rebasing
- Model estimation
- Forecast generation
- Output export

Variables are named according to their economic function (IPI, HICP, EXC_RATE, rel_dp, etc.), and processed data is written to **labeled Excel sheets** by indicator and model. Imputation methods, rebasing logic (e.g., 2014=100), and trade-weighted aggregations are clearly documented in both code and output structure. Data exports are organized into Excel sheets by indicator, facilitating easy inspection and direct use in reporting or visualization tools. The architecture allows analysts to trace each final dataset back to its transformation steps, promoting transparency and understanding.

TRAMO model specifications are explicitly defined using *tramoseats_spec()*, where all assumptions and parameters are transparent—e.g., no trading day effects, inclusion of user-defined regressors, and lag-specific time alignment. The use of RJDemetra ensures not only accurate modeling but also traceable diagnostics and parameter estimates, all exportable for further inspection.

Furthermore, the use of model averaging (TRAMO_AVG) increases interpretability by reducing model-specific volatility, while the *model_info_tramo* table provides a concise summary of each country's model logic—essential for stakeholders or analysts seeking to understand the basis of each forecast.

Note: The system currently uses trade weights derived from the most recent available data, which are sufficient for all nowcasting exercises conducted in 2025. These weights are used to construct trade-weighted indicators (rel_dp and er_star) which play a central role in the multivariate TRAMO models.

However, for nowcasts beyond 2025, users must update the trade weight table to reflect the most recent structure of international trade. This ensures that external influences (e.g., inflation or exchange rates of trade partners) continue to reflect current economic relationships. The architecture allows for straightforward substitution of trade weights for future years, maintaining the system's accuracy and policy relevance over time.

References

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Architecture

Please provide a description of the architecture of your approach. A diagram of the architecture is considered of additional value. Indicate what modifications would be required to apply the approach to similar datasets on a larger scale.

This section will be evaluated for:

(1) the Architecture criterion: evaluated based on its modules, their cohesion and their configurability; an architecture which is modular and includes clear connections between modules or components receives a higher score

The architecture of the nowcasting system is designed to be **modular, cohesive, and configurable**, supporting both reproducibility and operational efficiency. The overall system design is illustrated in the **flowchart diagram below (see Figure 1)**, which outlines each step from initialization to forecast export.

The system is initiated through a single function call in *run.R*, which loads the environment and executes the appropriate nowcasting sequence based on the specified nowcast_period.

Modular Design

The architecture is composed of the following components:

1. **Environment Initialization (global.R, utilities.R)**
   Initializes the R environment by loading all required packages and helper functions.
2. **Dynamic Data Handling (data_import.R, data_preparation.R)**
   - If the nowcast_period is **within the current month**, the system connects to Eurostat and OECD APIs to fetch the most recent data.
   - If it is **outside the current month**, previously saved datasets are loaded from the project folder, significantly reducing execution time.
3. **Modeling Pipeline**
   The system supports multiple forecasting approaches:
   - tramo_model_mv1.R: Multivariate TRAMO using trade-weighted regressors for **all countries**.
   - tramo_model_uv.R: Univariate TRAMO for baseline forecasts.
   - tramo_model_average.R: A hybrid model that averages the outputs of MV1 and UV models.

- tramo_model_mv2.R: Multivariate TRAMO using regressors weighted by **non-EU trade partners**.

All models are dynamically configured through a central control table, *model_info_tramo*, which specifies the explanatory variables and lag structures for each country. These specifications were optimized using a **sliding window approach** and evaluated using the **Mean Squared Relative Error (MSRE)** criterion.

4. **Result Formatting (export_results.R)**

Final outputs are exported in structured formats (e.g., JSON), making them suitable for downstream integration.

Modifiability & Configurability

- Each module performs a single, well-defined task, facilitating code maintenance and testing.
- The use of model_info_tramo provides full flexibility in adding or adjusting regressors, lags, or countries.
- The system can easily accommodate additional nowcast targets (e.g., exports, GDP) by updating control tables and adjusting input sources.

Scalability to Larger Datasets

The system is designed to scale both **horizontally** (across more countries) and **vertically** (across more indicators or time points). It can be extended by:

- Updating trade weights for future years (currently, 2025 weights are sufficient; future years require updates).
- Leveraging parallel execution for model estimation per country.
- Adapting to different indicators with minimal code changes.

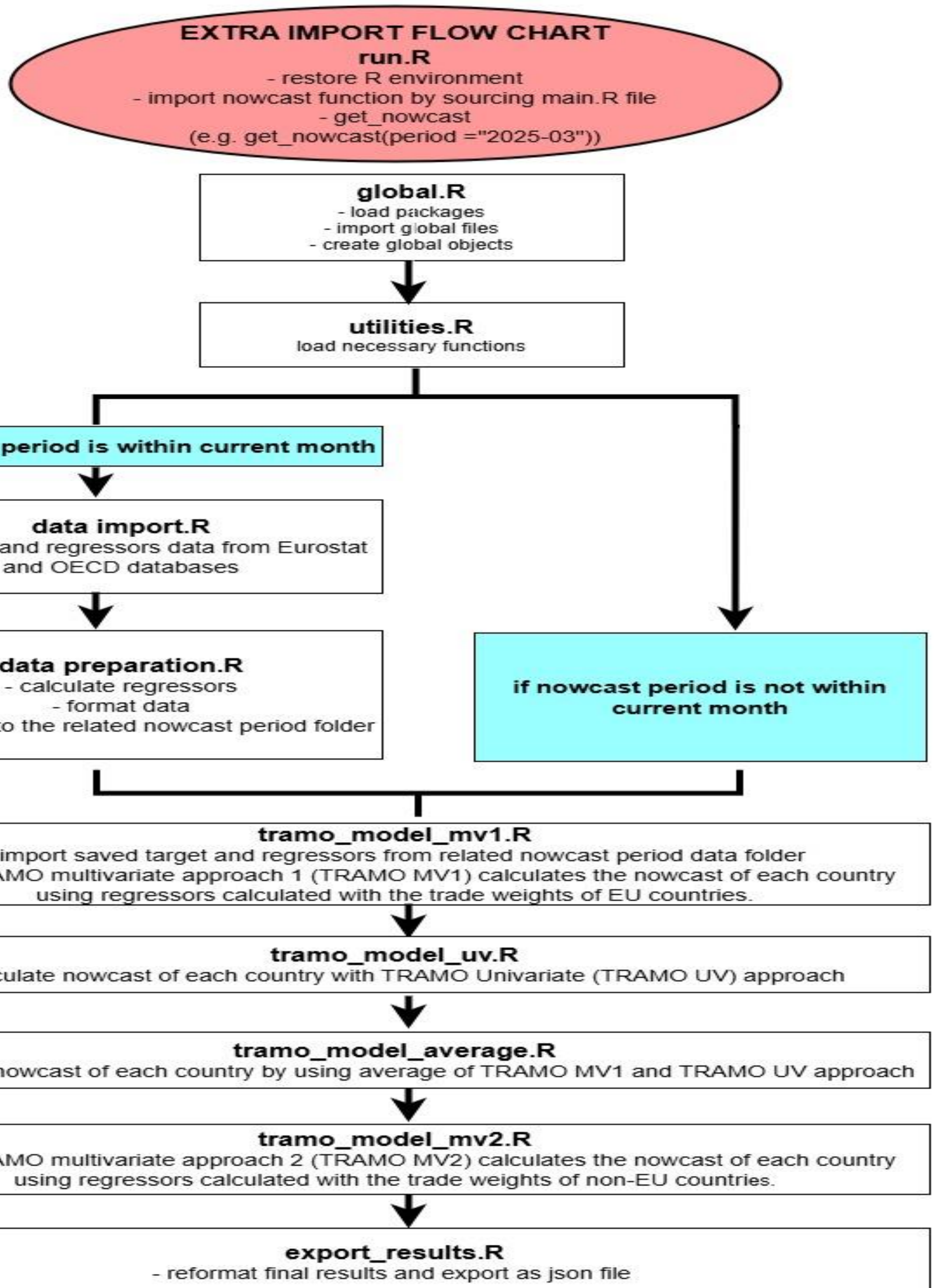
Execution Time & Performance

Runtime varies depending on data freshness:

- **~3 minutes** when fetching live data from Eurostat and OECD APIs (i.e., for current month nowcasting).
- **~10 seconds** when using pre-saved datasets for past or future periods.

This dual-mode execution provides both **speed** and **up-to-date accuracy**, depending on the analytical context.

Figure 1 Extra Import Flow Chart



List of Data Sources with Descriptions

For each country, list the data sources (and their description) that were used to calculate the point estimates for the selected country. Please use the template below to provide the information for each source. If multiple data sources were used, please copy paste the template below and fill it in.

Bear in mind that the data sources will also be evaluated based on its openness, availability, coverage and consistency.

Introduction

In order to ensure reproducibility, we took care to use open source data. For this reason, we extracted all the variables from Eurostat and OECD databases using the relevant R packages. Since the data was extracted for all countries, the following tables are not made by each country. The figures in the 1st table include all country data points extracted from the relevant databases. Furthermore, we used "UN Comtrade Database" to construct the trade weights. We downloaded the total trade (import+ export) values of EU countries from other countries year by year.

Number of data points collected from the data source (for each reference period)

October 2024	15982 (We take the average of the daily exchange rates of each month, so it counted as 1 data point for each country)
November 2024	16101 (We take the average of the daily exchange rates of this month, so it counted as 1 data point for each country)
December 2024	16225 (We take the average of the daily exchange rates of this month, so it counted as 1 data point for each country)
January 2025	16350 (We take the average of the daily exchange rates of this month, so it counted as 1 data point for each country)
February 2025	16469 (We take the average of the daily exchange rates of this month, so it counted as 1 data point for each country)
March 2025	16588 (We take the average of the daily exchange rates of this month, so it counted as 1 data point for each country)

Structure of the data used to predict the point estimates

Attribute Name	Attribute Description
International Trade (Extra-EU İmport)	This is the target variable. This is the monthly data of the import value of goods traded by the EU Member States with non-EU countries (extra-EU trade).
Production in Industry (IPI)	The Production Volume in Industry is a measure of the physical output of the industrial sector of an economy. The production index can be used to assess trends in productivity, capacity utilization, and competitiveness.
Production in Industry for Ireland (IPI)	The unadjusted IPI data of Ireland in Eurostat database starts from 2016. For this reason, we used OECD database for IPI data of Ireland.

Harmonised Index of Consumer Prices (HICP)	HICP gives comparable measures of inflation for the countries and country groups for which it is produced. It is an economic indicator that measures the change over time of the prices of consumer goods and services acquired by households.
Harmonised Index of Consumer Prices (HICP)	HICP of Korea, China, United Kingdom and Japan are not included in Eurostat database. For this reason we use OECD database for HICP data of regarding 4 country.
Euro/ECU Exchange Rates (monthly data)	The presented data comprise monthly average exchange rates against the euro and against the ECU.
Euro/ECU Exchange Rates (daily data)	The presented data comprise daily exchange rates against the euro and against the ECU.

Hardware Specifications *(Replicability; Scalability; Interpretability)*

Please describe the hardware specifications of the machines that were used to run the methodology.

This section will be evaluated for:

(1) the Replicability criterion

(2) the Scalability criterion

(3) the Interpretability criterion

Machine 1

CPUs	12th Gen Intel Core i7-12700 @ 2.10 GHz, 12 cores
GPUs	Intel UHD Graphics 770
TPUs	-
Disk space	250 MB

Machine 2

CPUs	Intel Core i7-9700 @ 3.00 GHz, 8 cores
GPUs	Intel UHD Graphics 630
TPUs	-
Disk space	250 MB

Libraries *(Maintainability)*

Please provide the libraries used for approach, if any, as well as the links to these libraries, if available.

This section will be evaluated for:

> *(1) the Maintainability and openness criterion: use of libraries which are regularly maintained will yield higher scores. (Examples include pytorch, tensorflow, scikit-learn, pandas, numpy, etc.) The use of libraries which are openly available will yield higher scores.*

The project relies on a set of actively maintained and openly available R libraries, ensuring high maintainability, reproducibility, and transparency. All libraries used are available through the Comprehensive R Archive Network (CRAN), and their official links are provided below:

Library	Purpose	Link
tidyverse	Data manipulation, transformation, and visualization (includes dplyr, ggplot2, tidyr, etc.)	https://www.tidyverse.org/
RJDemetra	Interface for seasonal adjustment using TRAMO-SEATS and X13-ARIMA-SEATS models	https://cran.r-project.org/web/packages/RJDemetra/index.htr
lubridate	Simplified date and time manipulation	https://lubridate.tidyverse.org/
openxlsx	Reading, writing, and editing Excel files	https://cran.r-project.org/web/packages/openxlsx/index.html
jsonlite	Handling JSON data structures	https://cran.r-project.org/web/packages/jsonlite/index.html
zoo	Time series data manipulation and imputation	https://cran.r-project.org/web/packages/zoo/index.html
eurostat	Downloading and handling Eurostat datasets in R	https://cran.r-project.org/web/packages/eurostat/index.html
rsdmx	Accessing statistical data and metadata using the SDMX standard	https://cran.r-project.org/web/packages/rsdmx/index.html

Environment Portability with renv

To ensure consistency across systems and enable fast setup in new environments, the entire project is containerized using the `renv` package. This tool captures the exact versions of all R packages used in the project and stores them in a lockfile (*renv.lock*). When the project is deployed or cloned on a different machine, the environment can be fully restored with a single command → *renv::restore()*

This guarantees that all modules, models, and data operations behave identically across different systems and setups, thereby strengthening both **replicability** and **portability**. It also makes the system ready for integration into production workflows or external evaluations without additional configuration effort.

Open license *(Maintainability)*

Please provide the open license of the provided code, if any.

This section will be evaluated for:

> *(1) the Maintainability and openness criterion: whether the approach is open and under an open license*

The full codebase for the EXTRA-EU IMPORTS nowcasting is openly available under the MIT License, a highly permissive open-source license. This license allows free use, modification, and distribution of the code, provided that the original authors receive appropriate credit.

The GitHub repository containing the code and full project documentation is publicly accessible here:
🔗 https://github.com/MFatihTuzen/ESA-Nowcasting-EXTRA-IMPORT

By using a widely recognized open license and hosting the project on a public platform, the approach ensures maximum maintainability, transparency, and openness for future developments or adaptations.

Similarities/differences to State-of-the-Art techniques *(Originality)*

Please provide a list of similarities and differences between the used methodology and to the state-of-the-art techniques.

This section will be evaluated for:

> *(1) the Originality of the approach criterion: compare the approach used to the state-of-the-art; the extent to which the submission represents an improvement over these pre-existing approaches*

Our approach builds upon the TRAMO framework, widely used in official statistics for time series modeling. While TRAMO itself is not novel, the originality of our methodology lies in the systematic and theoretically grounded integration of foreign variables (X*) into the TRAMO modeling structure, something not previously explored in the literature to our knowledge.

Most existing nowcasting approaches in macroeconomic forecasting fall into two main categories: (i) univariate time series models such as standard TRAMO or ARIMA, which ignore cross-country linkages, and (ii) multivariate VAR models, complex multi-country frameworks like GVAR or machine learning models (e.g., LSTM), which often lack transparency or require extensive pre-processing such as seasonal adjustment.

Our approach departs from both extremes. It retains the statistical robustness and transparency of the TRAMO framework while systematically integrating international economic variables (X*) derived from trade theory. Unlike traditional TRAMO applications that rely solely on domestic variables, we incorporate foreign indicators such as relative prices, foreign exchange rates, weighted by dynamic trade matrices that evolve annually.

We initially explored GVAR as an alternative but encountered major limitations: the need for prior seasonal adjustment, the difficulty in converting forecasted growth rates back into levels, and generally lower forecasting accuracy. While GVAR models are suitable for structural analysis, they proved suboptimal for monthly nowcasting purposes.

Similarly, our LSTM-based deep learning model underperformed despite its flexibility, reinforcing the value of interpretable, theory-consistent models in official statistical contexts. In contrast, our TRAMO-X* setup provided accurate, stable forecasts with a clear economic rationale, combining empirical strength with institutional usability.

Contribution to scientific field *(Future orientation)*

Please describe how your submission contributed to the scientific field, what impact it could have and what could potentially be future work to improve the solution.

This section will be evaluated for:

> *(1) the Future orientation and impact criterion: the potential effect of the approach used will be evaluated; this includes the scale of impact it has on the problem of nowcasting; the impact will be evaluated based on potential efficiency improvements and cost reductions.*

Our methodology contributes to the growing body of research in real-time macroeconomic forecasting by offering a scalable and transparent system that enhances the accuracy of monthly trade nowcasting. Specifically:
- It demonstrates how a traditional tool like TRAMO can be extended to a multivariate framework with theory-driven regressors

-It highlights the practical utility of dynamic trade weight matrices, a concept often proposed but rarely implemented in applied forecasting systems

- It bridges macroeconomic theory and empirical forecasting by aligning model specification with trade elasticity models

- The modular and automated structure (including automatic lag selection via MSRE and programmatic trade-weighted variable generation) serves as a replicable blueprint for nowcasting in other macro domains, particularly those affected by globalization and external shocks

In future work, this framework can be extended to:

- Other economic indicators such as customs duties, transport volumes, or energy imports, which are closely tied to international trade flows. These indicators could be included as additional external regressors in future extensions of the TRAMO-based framework

- Inclusion of more granular trade data (e.g., by sector or product category)

Lessons Learned *(Future orientation)*

Please state any lessons learned during the competition.

This section will be evaluated for:

> *(1) the Future orientation and impact criterion: what were the lessons learnt during the competition, and what could potentially be future work to improve the solution.*

Throughout the competition, we tested multiple modeling frameworks—including GVAR and LSTM—before selecting our final TRAMO-based approach. The lessons we derived include:

Simplicity with structure often outperforms complexity without transparency: Despite the theoretical appeal of GVAR and the flexibility of LSTM, their performance was inferior in both accuracy and interpretability.

Working with raw (unadjusted) data is feasible and sometimes preferable: The TRAMO model's ability to handle unadjusted levels allowed us to avoid the complications of seasonal adjustment and inverse transformations, which often degraded performance in GVAR.

Interpretability matters for policy and operations: Model traceability and logical consistency are as important as forecasting accuracy, particularly when transparency is essential for decision-making.

Short description of the Team – area of expertise

Please provide a description of the team, your area of expertise and contact information.

We are all members of TurkStat, Turkish Statistical Institute of Methodology Department. Our team is composed of 4 members:

- Özlem YİĞİT, TURKSTAT Expert, PhD in Econometrics (www.linkedin.com/in/dr-özlem-yiğit-431a3a78)
- M. Fatih TÜZEN, TURKSTAT Expert, PhD in Statistics (https://www.linkedin.com/in/dr-m-fatih-t-2b2a4328/)
- Osman SERT, TURKSTAT Expert, PhD in Econometrics (https://www.linkedin.com/in/dr-osman-sert-9a53b428/)
- F. Aydan KOCACAN NURAY, TURKSTAT Expert, MA in Econometrics (https://www.linkedin.com/in/aydan-kocacan-nuray-a40b20155/)