Nowcasting TiVA indicators

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Trade in value added (TiVA) indicators are among the key data sources used to monitor countries' integration into global supply chains. However, TiVA indicators are published with a significant lag - often two or three years long - which reduces their relevance for monitoring recent economic developments. This paper aims to provide timelier insights into the international fragmentation of production by exploring new ways of nowcasting five TiVA indicators in 2021 and 2022 for a panel of 41 economies at the economy-wide level and for 24 sectors. The analysis relies on a range on models, including machine-learning, and uses a wide range of explanatory variables capturing domestic business cycles and global economic developments. The approach selects the best model to nowcast the indicators for each country and each country-sector pair based on the out-of-sample, one-year ahead predictive performance relative to the first-order autoregressive benchmark model. Resulting nowcasting algorithms significantly improve compared to the benchmark model and exhibits relatively low prediction errors at a one and two year horizon, although model performance varies across countries and sectors.

Keywords: Nowcasting, machine learning, global value chains JEL codes: C4, C53, F17

1. Introduction

1. Integration in global value chains and related disruptions have been high on the policy agenda since the beginning of the COVID-19 crisis. Trade in value added (TiVA) indicators, published by the OECD and other international organisations are the main source of information to monitor countries' engagement in global supply chains. They are constructed by mapping out the global production network, which involves integrating many countries' Supply and Use Tables (SUTs – which show production linkages *within* countries) with trade statistics (which show exchanges *between* countries) to arrive at a globally consistent picture in the form of an inter-country input output matrix (ICIO).

2. However, SUTs and ICIOs are published with a lag of several years, resulting in TiVA indicators also being available with a long delay. For instance, the OECD published indicators for 2018 for the first time in December 2021. While the elements of the ICIOs change over time, collecting them on a timely manner is extremely costly. A more feasible alternative is to nowcast and present preliminary insights on developments integration in global value chains to inform policymakers, before the data collection takes place and provide a more complete and accurate picture.

3. Nowcasting is not new. The term is a contraction for *now* and *forecasting* and is usually used for the prediction of the present, the very near future and the very recent past. The basic principle of nowcasting is to exploit the information which is published early and possibly at higher frequencies than the variable of interest to obtain an 'early estimate' before the official figure becomes available (Bańbura Martha et al., 2013_[1]). A novel strand of the literature has moved toward the use of Big Data, which have become easier to access and handle (Bok et al., 2018_[2]).

4. An important field of research has sought to nowcast ICIOs tables using accounting relations, and techniques to impute data while ensuring data consistency at the world level. In a nutshell, these approaches apply RAS (reconciliation and adjustment of statistics) methods to national accounts and trade data to update ICIOs (see for instance Fortanier and Miao (2017_[3]), Rueda-Cantuche et al. (2018_[4]), Valderas-Jaramillo and Rueda-Cantuche (2021_[5]), OECD (2022_[6])). Following this approach, Rueda-Cantuche, Pinero and Kutlina-Dimitrova (2021_[7]) predict indicators of employment supported by exports, which are also computed based on ICIOs. An important implicit assumption underlying these approaches is that countries' industry input and output structures in extrapolated SUTs are similar to the structures of the latest available SUTs. This is a reasonable assumption in the absence of global or regional economic shocks. However, in 2020, the COVID-19 pandemic and related lockdowns hit certain activities disproportionally and the timing and the pace of recovery varied across countries and sectors. The magnitude of these changes and the extent to which they affect core TIVA indicators needs to be further investigated.

5. More recently, Metulini et al. (2022_[8]) used more advanced statistical methods to "fill in" ICIOs matrices, building on seminal work by Athey and Imbens (2019_[9]) related to matrix completion. The idea is to predict unobserved entries of a matrix using the remaining observed entries. This study has demonstrated an effective methodology for predicting missing values within the ICIO matrix. It uses data from both previous years and the current year and works well for countries that share similar characteristics with the country for which the data is not available. In contrast, the procedure is less effective if missing information is filled for countries belonging to quite different clusters.

6. A third strand of the literature nowcasts TiVA indicators using time series models (Haugh et al., 2016_[10]). Resulting estimates have proven relatively unstable, due to the small number of observations available to estimate the nowcasting models. Alternatively, trackers of global value chains (GVC) participation have been built using data on selected trade in intermediates and computed as the ratio of intermediate imports and exports as a share of total imports and exports. Those trackers are found to be relatively well correlated with GVC participation over the period 2001-2015 (Cigna, Gunnella and Quaglietti, 2022_[11]; Federal Reserve Bank of New York, 2023_[12]).

7. Against this background, the main objective of this paper is to explore new ways of nowcasting key TiVA indicators one and two years ahead. In addition to identifying models that have good nowcasting properties, the aim is also to set up a process that is for most part automatised so that nowcasts can be calculated at relatively low cost, once the best models have been selected.

8. The approach nowcasts TiVA indicators instead of ICIOs tables for two reasons. First, 'matrix completion' methods are still in their infancy, although they appear to be a promising way to get more timely indicators. Second, policymakers and analysts monitoring recent economic developments are essentially interested in key TiVA indicators. The procedure put in place could be replicated to other indicators derived from ICIOs.

9. The analysis covers 41 economies (37 OECD countries and China, India, Indonesia, South Africa) and 24 sectors and nowcasts 5 TiVA indicators for 2021 and 2022. It relies on a range of different techniques including linear regressions, penalised regressions (lasso, ridge) and gradient boosted trees (GBM). Consensus models, which average the outcomes of the penalised models and GBM, were also tested.

10. Given the relatively small sample of observations, on which models can be tested and trained, countries were pooled into a panel, with fixed effects allowing to derive country-specific outcomes. Panel settings are increasingly used in nowcasting (Fosten and Greenaway-McGrevy, 2022_[13]), including machine learning techniques (Babii et al., 2020_[14]). The use of a panel approach has been found to lead to good predictive models for GDP (Woloszko, 2020_[15]), well-being (OECD, forthcoming_[16]) or at a more disaggregated level on ICT output (OECD, forthcoming_[17]).

11. The main insights from the paper are as follows. Nowcasting models are found to outperform an autoregressive benchmark in about 75% of the cases, with generally very good performance of GBM-based models. Model performance differs across countries, sectors and target indicators. In general, models for large economies exhibit better nowcasting properties than smaller economies. Models related to economy-wide and services indicators have lower prediction errors than those related to manufacturing. Nowcasts for 2021-22 point to a decline in the share of domestic value added in export flows, albeit to a varying degree across countries and sectors. Domestic services value-added shares of exports are expected to have been broadly stable, while the foreign counterpart has increased. The share of domestic value added embodied in foreign demand is expected to have exceeded its pre-COVID crisis level in 2022.

12. The paper is organised as follows. The next section gives an overview of the empirical strategy. Section 3 details the nowcasting methods and section 4 describes the data. The approach to selecting best models is explained in Section 5, model performance is discussed in Section 6. Section 7 illustrates the results of nowcasting TiVA indicators for 2021 and 2022.

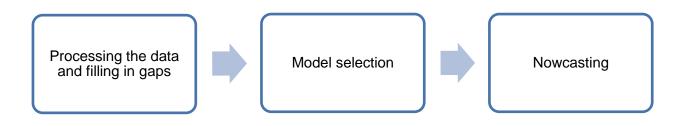
2. Overview of the empirical strategy

13. This section presents the overall strategy to nowcast TiVA indicators and describes how the different steps of the process fit together. Those steps and the methodologies underlying the different models are detailed in the subsequent sections. The logic is not different from standard nowcasting approaches (Bańbura Martha et al., 2013[1]), but the process is refined to include some of the specificities of machine-learning techniques (e.g. using cross validation to help select the best nowcasting models) (Figure 1).

14. Five TiVA indicators (target variables) were considered: domestic value-added share of exports (EXGR_DVASH), domestic services value-added share of exports (EXGR_SERV_DVASH), foreign services value-added share of exports (EXGR_SERV_FVASH) and the share of domestic value added embodied in foreign final demand (VALU_FFDDVA). Nowcasts of foreign value-added share of exports

(EXGR_FVASH) are derived from the nowcast of the domestic value-added share of exports by subtracting the latter from one, as per the definition.

Figure 1. Main steps of the empirical strategy



15. The first step is to collect and process the data that are used to predict the target variables. Predictors are related to trade development or the business cycles. This includes data from national accounts and balance of payments, but also short-term indicators such as prices, employment or financial indicators. Those data are then transformed in case they were not stationary. Indicators whose influence on predictions is expected to be large, but which are not sufficiently timely, have been prolonged with "bridges" using the same techniques and the same model selection criteria as for nowcasting the TiVA indicators. This is the case for exports, value added and production.

16. The second step is to select the best model to nowcast TiVA indicators. This is the core of the approach and combines several specificities:

- First, countries have been pooled to address the issue of small sample, which would have led to estimates lacking robustness. At the same time country fixed effects allow to compute country-specific nowcasts. A similar approach was used by Woloszko (2020[15]).
- Second, five types of models have been tested: gradient boosted tree (GBM), penalised regressions (ridge and lasso), a linear regression model and a "consensus" model derived as the simple average of the GBM, ridge and lasso. Consistent with the nowcasting literature, the performance of all these models is assessed against those of an autoregressive model of order 1, as the data are annual.
- Third, a cross-validation process, splitting the data in train, validation and test set, has been implemented to prevent overfitting. In this work, cross validation is performed by combining an expanding and rolling window to ensure that sufficient observations were available to undertake standard diagnostics (e.g. test on the significance of the results). Publication lags were accounted for during the cross-validation to be as close as possible to real time conditions ("quasi real time nowcasting") (i.e. to ensure that when predicting indicators for year *t*, the models use only the information available at time *t*).
- Fourth, root mean squared errors (RMSEs) for one-year ahead predictions are computed using the outcomes of the cross-validation process and constitute the main criterion to select best models. 2-year ahead RMSEs and FDA (forecast direction accuracy, which summarises accuracy in predicting the direction - increasing or decreasing) are also computed to check the performance of the selected models.

17. The last step is to use the best models to nowcast the indicators for 2021 and 2022. Note that for each country/sector, we select the model that performs best, rather than using the model that would perform best on average across all the countries for all the countries/sectors.

18. One key specificity of the approach is to run machine-learning algorithms in a panel setting. Standard forecasting literature has focused on the use of time series methods to nowcast economic aggregates. The approach requires nonetheless sufficiently long time series. In the case where data are only available over a short time span, as is the case in this study, pooling countries, regions or sectors offers a useful alternative. For instance, Mouchart and Rombouts (2005_[18]) and Koop, McIntyre and Mitchell (2020_[19]) developed a panel approach to nowcast regional gross value added in the United Kingdom using national aggregates. Furthermore, Fosten and Greenaway-McGrevy (2022_[20]) find improvements from pooling GDP levels data across all US states compared to allowing heterogeneity of coefficients across geographical or economic sub-groups.

19. In this study, using a panel approach over 41 countries enables the deployment of machine learning algorithms while ensuring high model performance. As the target variable is annual, only a small number of time series observations is available for each country. It would have been challenging to estimate nowcasting models using traditional time series nowcasting methods, which usually rely on longer series of historical data, or more frequent data, which provide for a large sample of data points per country or sector. Country-specificity is captured through country fixed effects.

3. Methods

20. Several nowcasting approaches were tested and compared to an autoregressive model (AR), that is used as a benchmark and assumes that a given TiVA indicator is a function of its own prior values. This subsection describes those approaches briefly.

Linear regressions

21. Linear regressions model each TiVA indicator as a function of the growth rate of gross value added. Fixed effects were added to control for all variables that vary over cross-sectional units, i.e. either countries or sectors, but are constant over time. While the model is relatively simple and restricted to capturing linear effects, it is easy to compute and interpret. Under the ordinary least squares approach, the coefficients of linear regression are obtained by minimising the residual sum of squares:

$$\widehat{\beta_{OLS}} = \arg\min[\sum_{i=1}^{n} (Y_i - \beta x_i)^2],$$

where Y_i is the target indicator, x_i denotes the input variables and β stands for the vector of coefficients.

Penalised regression models: ridge and lasso

22. Ridge and lasso (least absolute shrinkage and selection operator) regressions are modified linear regression methods that constrain estimates and retain a limited number of indicators (Tibshirani, 1996_[21]; Hoerl and Kennard, 1970_[22]). Both techniques minimise the residual sum of squares and include a penalty term λ to tackle overfitting:

$$\widehat{\beta_{Penalised}} = \arg\min[\sum_{i=1}^{n} (Y_i - \beta x_i)^2 + Penalty(\lambda, \beta)].$$

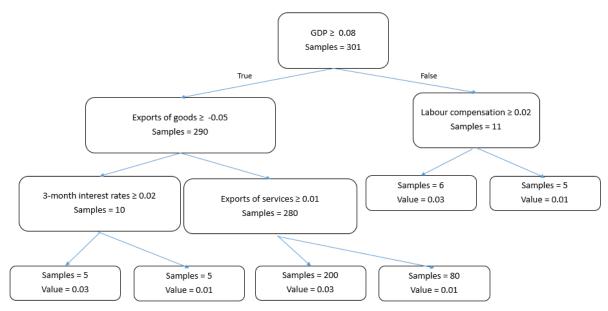
23. Ridge regression adds a penalty on the squared value of the coefficients, i.e. $Penalty(\lambda, \beta) = \lambda \sum_{j=1}^{p} (\beta_j)^2$, where *p* is the number of predictors, which has the effect of shrinking the estimated coefficients. In lasso regression, the penalty terms is the sum of the absolute value of the coefficients, i.e. $Penalty(\lambda, \beta) = \lambda \sum_{j=1}^{p} |\beta_j|$, which shrinks the coefficients towards zero, while removing the covariates whose estimated coefficients are zero from the model. Compared to a linear regression, both ridge and lasso reduce the model's variance at the expense of a slight increase in bias. Both methods rely on the assumption that explanatory variables enter the model linearly and are considered more appropriate to capture the features of dense datasets.

Decision tree ensemble methods (Gradient boosted trees)

24. Gradient boosted trees are a tree-based non-parametric ensemble learning approach, which is particularly apt to capture non-linear relationships, which can be useful in the context of macroeconomic nowcasting (Chapman and Desai, 2021_[23]). The high predictive performance of gradient boosted trees stems from the 'boosting' technique, in which trees are built sequentially to predict the error of the preceding trees. The predictions of all trees are averaged in a final step to reduce the overall prediction error (Dietterich, 2000_[24]).

25. Tree-based methods predict the value of a target variable by dividing the sample of observations into sub-groups to minimise the within group variance of the predicted variable. Figure 2 provides an example of one specific prediction path of a regression tree trained on the panel dataset to nowcast the domestic value-added share of gross exports at a country level. At first, the algorithm selects the splitting variable, GDP, and the splitting point (0.08) that minimises the variance of the target variable within the two resulting sub-groups considering all possible variables and splits. It repeats this procedure at each node, choosing from the available explanatory variables those that provide the best splits, until it reaches the final leaf.

Figure 2. Example of a prediction path in a regression tree



Note: On each branch, the value indicates the splitting point for the node. The first node (GDP) contains the full sample for that specific model (n = 301). Each node makes a split between observations that validate the condition and observations that do not. For instance, at the first node, the algorithm splits observations between years where GDP, current prices were equal to or above 0.08 (left) and below 0.08 (right). For the left path, the algorithm then subsequently picks the total value of exports above -0.05, and the interest rate above 0.02 to reach the final sample. The prediction is then a growth rate of 3% for the target variable (left bottom leaf). Source: Authors' elaborations.

Consensus model

26. While the various methods come with their strengths and weaknesses, combining them can reduce the prediction error even further, as common in the nowcasting literature (Jaax, Gonzales and Mourougane, 2021_[25]; Tiffin, 2016_[26]). In this paper, the consensus model takes the average of all predictions resulting from the machine learning models, thus creating a model with less variance in the prediction.

4. Data

Constructing the database

27. The five target variables are taken from the OECD TiVA database¹. Data were downloaded in April 2023 and available up to 2020. Table 1 reports the main statistics of the target variables.

Table 1. Basics statistics of target variables

	TiVA Codes	Average across countries	Standard deviation	Minimum	Maximum
Domestic value-added share of exports	EXGR_DVASH	-0.20	2.06	-20.23	19.54
Domestic services value- added share of exports	EXGR_SERV_DVASH	0.00	1.50	-19.01	15.08
Foreign services value- added share of exports	EXGR_SERV_FVASH	0.16	1.07	-14.32	19.18
Share of domestic value added embodied in foreign final demand	VALU_FFDDVA	0.34	3.66	-59.19	45.92

Note: Basic statistics were computed on annual percentual changes of TiVA indicators for the period 1995-2020 across the different sectors and countries analysed.

Source: Author's calculations.

28. A range of explanatory variables capturing domestic business cycles and global economic developments was collected, including measures of business activity, trade and financial indicators (Table 2). The criteria for selecting variables were relevance, coverage in terms of countries and length of the available time series.

Table 2. Examples of explanatory variables

	Example of variables
Activity	GDP less imports, Gross value added, Gross output by industry
International environment	Exports and Imports of intermediate goods and services Current account Global economic policy uncertainty index
Business cycles	Industrial Production Index Consumer Price Index Employment by industry
Financial and monetary indicators	Long term interest rates Real effective exchange rates

29. The dataset incorporates both country-specific variables and global indicators that either describe trends in the world's largest economies (e.g. producer price index for scheduled passenger air transportation in the United States) or measure developments beyond country borders (e.g. global

¹ OECD TiVA database website: oe.cd/tiva

economic policy uncertainty index). Sector-level models additionally include sector-specific indicators for trade, gross value added and employment.

30. Data are sourced from National Accounts, the OECD TiVA database, the Main Economic Indicators, and national sources. Table A1 provide a full description of the dataset, together with the sources.

Pre-selection and processing of the data

31. The pre-processing was done separately for the training and test samples to avoid data leakage. All data series were transformed using first differencing to ensure stationarity. In addition, all variables were standardised – a step which sets each variable's mean to zero and standard deviation to one to minimise the impact of outliers and lowers the time needed to run the models.

32. The approach to handling missing values varied depending on the extent of missing observations. The series with a starting date on or after 2010 were excluded from the data set. When a variable had more than 10 observations missing for a given country, all values for the country were replaced with the mean values computed for the rest of the sample. For sector-specific variables, observations were imputed using growth rates of the corresponding broader sector in that country (e.g. for a given country, a missing value for gross value added in manufacturing of food products and beverages is imputed using the growth rates of gross value added in manufacturing). Any missing values remaining after the imputations performed in the previous steps were filled using the median imputation for a given country or sector. This was done to ensure that all models can be tested on the panel dataset.

33. In addition, gross output, gross exports and gross value added were prolonged until 2021 using bridge models, applying the same process as for the target variables (see below). The rationale is that those variables are expected to have a large information content in predicting TiVA indicators, and even an imperfect prediction could improve the accuracy of the nowcast.

34. Finally, many variables in the dataset are highly correlated with each other, which can worsen the predictive accuracy of the penalised regressions. To address potential multicollinearity, a two-step approach was taken to select which variables to include in the estimation for ridge and lasso. First, a set of 'core' variables was obtained by running multiple random forest regressions on the full set of variables and preserving the explanatory variables that had the largest impact on predictive accuracy. Secondly, the variance inflation factor (VIF) was computed for all the remaining variables and the threshold of 10 was used to remove the highly correlated variables (James et al., 2013_[27]).

5. Selecting best models

35. The best models were selected based on the out-of-sample, one-year ahead predictive performance relative to the benchmark model, an autoregressive model with one lag. In the economy-wide analysis, one best model was identified for each country; in sector-level estimation, best models were selected for each country-sector pair.

36. Predictive performance was evaluated in terms of the relative root mean squared error (RMSE), a metric that compares the average prediction errors of a model to the benchmark. A relative RMSE below one indicates that the model outperforms the benchmark. A Diebold-Mariano test with Harvey-Leybourne-Newbold correction was used to assess whether the relative RMSE is statistically different from one, i.e. the nowcasting models had significantly higher predictive accuracy than the benchmark.

37. Additional statistics were used to assess the model quality. First, the forecasting directional accuracy (FDA) was computed – an indicator which measures the share of observations in the out-of-

sample period for which the predicted and the actual growth rates have the same sign. Secondly, two-year ahead relative RMSEs were used to evaluate the predictive power of the models over two-years periods.

38. Although this evaluation process is relatively standard in the nowcasting literature (Bańbura Martha et al., 2013_[1]; Sédillot and Pain, 2003_[28]; Mourougane, 2006_[29]), the difficulty here is to compute those metrics in quasi real time. Machine learning algorithms often encounter overfitting, which occurs when a model performs well on the training data, but poorly on new data. Cross-validation is a technique used to address this issue by testing a model's performance on unseen data. In standard cross-validation, the dataset is split into k-folds, with k-1 folds used for in-sample training and one-fold used for out-of-sample testing. This process is repeated iteratively, and the performance is calculated by averaging the test scores of the model across all sample splits (Hastie, Tibshirani and Friedman, 2009_[30]). However, in a panel setting with time series data, a random splitting of the training sample can break the order of the time series, potentially leading to inaccurate predictions (Bergmeir and Benítez, 2012_[31]).

39. To address this issue, a rolling and expanding window cross-validation approach is used (Figure 3). The data is split into in-sample and out-of-sample data, and a window is created to operate on the in-sample data, starting with a horizon of 10 years. The window is then rolled in one-year steps until it covers the full in-sample period, constantly splitting into train and test. The iterations of rolling over the in-sample period are repeated with expanding windows to create additional train and test splits. The RMSE is calculated for each sample, and the final performance of the model is calculated as the average of RMSEs on all test splits.

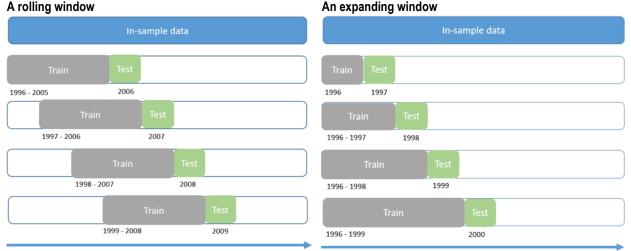


Figure 3. Example of a cross-validation strategy

Source: OECD illustration.

6. Model performance

Nowcasting models are generally found to outperform an AR benchmark

40. The nowcasting models tend to perform better than the AR1 benchmark, when performance is measured in terms of one-year ahead RMSE (Table 3). Overall, the benchmark is outperformed in nearly 76% of the instances, although to a varying degree across different indicators and sectors.

41. The GBM is selected most often as the best model (34.9% in all instances and 53% at the economy wide level), indicating that it generally has a higher predictive accuracy than the other models. Penalised

regression models (lasso and ridge) also perform relatively well and are frequently selected, notably for services. Finally, the AR1 benchmark displays good performance based on their RMSEs although it has a lower average FDA than the other models.

Table 3. Best model selection

Percentage of instances selected as best model

	Benchmark AR1	GBM	Lasso	Ridge	Consensus	OLS	Total (2-6)
EXGR_DVASH	21.4	42.0	13.0	11.0	6.6	6.0	78.6
Economy Wide	7.3	65.9	14.6	7.3	2.4	2.4	92.7
Agriculture	26.8	34.1	17.1	7.3	9.8	4.9	73.2
Manufacturing	19.5	70.7	4.9	2.4	2.4	0.00	80.5
Services	14.6	19.5	31.7	31.7	0.00	2.4	85.4
EXGR_SERV_DVASH	24.3	20.9	21.0	15.6	10.6	7.7	75.7
Economy Wide	7.3	39.0	19.5	26.8	7.3	0.00	92.7
Agriculture	19.5	29.3	34.1	0.00	4.9	12.2	80.5
Manufacturing	12.2	24.4	34.1	14.6	9.8	4.9	87.8
Services	22.0	4.9	29.3	34.1	4.9	4.9	78.0
EXGR_SERV_FVASH	18.4	36.4	15.7	8.0	12.5	8.9	81.6
Economy Wide	7.3	65.9	9.8	9.8	4.9	2.4	92.7
Agriculture	12.2	39.0	4.9	7.3	24.4	12.2	87.8
Manufacturing	17.1	58.5	12.2	0.00	12.2	0.00	82.9
Services	12.2	36.6	29.3	7.3	2.4	12.2	87.8
VALU_FFDDVA	32.8	40.1	9.6	5.7	3.5	8.3	67.2
Economy Wide	7.3	41.5	41.5	7.3	2.4	0.00	92.7
Agriculture	29.3	39.0	7.3	0.00	14.6	9.8	70.7
Manufacturing	46.3	34.1	9.8	4.9	0.00	4.9	53.7
Services	7.3	39.0	34.1	17.1	2.4	0.00	92.7
All indicator-country-sector instances	24.2	34.9	14.8	10.1	8.3	7.7	75.8

Note: Models are estimated at the indicator-sector level and one single model is selected as best for each country. The share of indicatorcountry-sector instances where selected best models correspond to one of the following statistical models: benchmark AR1, GBM, lasso, ridge, consensus and OLS.

Source: Authors' calculations.

42. On average, the performance of the best models in one-year ahead nowcasts yields a relative gain over the benchmark ranging from 3% to 31%, as measured by (1 - relative RMSE) x 100 (Table 4). Models on aggregate economy level usually outperform sectoral models. However, differences in RMSE relative to the benchmark are less stark. Gains range from 32% to 40% for economy-wide models as compared to 15% to 20% in most instances at more disaggregated sectoral levels. Better performance relative to the benchmark for more aggregated sectors is most often associated with the better quality of information.

Table 4. Relative RMSEs one-year ahead by sector and indicator

	Domestic value- added share of exports	Domestic services value-added share of exports	Foreign services value-added share of exports	Share of domestic value added embodied in foreign final demand
Economy Wide	0.69	0.74	0.78	0.70
Mining and quarrying	0.91	0.92	0.91	0.93
Agriculture	0.84	0.85	0.87	0.90
Manufacturing	0.75	0.86	0.82	0.90
Food products, beverages and tobacco	0.77	0.90	0.82	0.89
Textiles, leather and footwear	0.83	0.90	0.83	0.96
Wood and products of wood and cork; Paper	0.79	0.91	0.88	0.90
Basic metals; Fabricated metal products	0.85	0.88	0.92	0.92
Coke and refined petroleum; Chemical; Pharmaceuticals; Rubber and plastics; Other non-metallic minerals	0.81	0.86	0.85	0.90
Computer, electronic and optical equipment; Electrical equipment	0.91	0.94	0.89	0.97
Motor vehicles; Other transport equipment	0.87	0.93	0.88	0.97
Machinery and equipment, nec	0.87	0.91	0.90	0.96
Services	0.77	0.79	0.86	0.74
Wholesale and retail trade; Transport activities; Accommodation and food and service activities	0.75	0.80	0.89	0.85
Financial and insurance	0.91	0.92	0.91	0.89
Telecommunications; IT and other information services	0.89	0.91	0.89	0.87
Professional, scientific and technical activities; Administrative and support services	0.88	0.89	0.88	0.88
Other service activities	0.83	0.92	0.88	0.91
All indicator-country-sector instances	0.83	0.88	0.87	0.89

Best model RMSE relative to benchmark AR1, average across countries

Note: Relative RMSEs for one-year ahead predictions with respect to the benchmark AR1, average across the countries. Since more aggregated sectors like Manufacturing and Services were estimated independently of their corresponding disaggregated sectors, the relative RMSEs of the former do not represent the average of the latter.

Source: Authors' calculations.

43. The Diebold-Mariano tests, adjusted for small samples, confirm that for most indicator-countrysector instances the difference with respect to the benchmark is statistically different from zero, although less markedly so for disaggregated sectors. Some examples are shown in the Annex for a selection of countries where nowcasting performance is relatively high (United States, China), medium (Portugal) and low (Slovak Republic) (Table A.2. 2 - Table A.2. 5). Overall, the RMSE corresponding to the best model is significantly lower than the benchmark in 74% of the instances for the share of domestic value added embodied in foreign final demand and up to 82% of them for the domestic value-added share of exports. 12 |

44. Performances are slightly worse for two-years ahead than one-year ahead models. Two-years ahead models showed an overall 5% decrease in performance based on their average RMSEs due to longer publication lags. This result holds across most of the indicators and sectors.

45. Nevertheless, when analysing relative RMSEs (Table 4 vs Table A.2. 1), the performance of the models is quite similar for one and two-years ahead predictions, as the AR1 benchmark RMSEs decline to a similar degree as the other models.

46. This masks, however, some differences across indicators and sectors. For example, there is an increase in relative RMSEs when increasing the prediction horizon for all indicators associated with services. However, these differences are not significant in most cases.

47. An additional metric, the FDA, also suggests that nowcasting models manage to predict the direction of annual developments in TiVA indicators in most cases. Indeed, in more than 85% of instances, the share one-year ahead models for which actual and predicted annual changes have the same sign is found to be greater than 60% (Figure 4). The two-years ahead predictions appear to be equally effective as the one-year ahead in predicting the directions of annual changes in the TiVA indicators.

Figure 4. Distribution of forecasting directional accuracy estimates

1 v ear ahead 2 years ahead 800 600 nstances 400 200 0 0.6 0.7 0.3 0.5 0.6 0.7 0.8 0.9 0.4 0.5 0.8 0.9 1.0 0.4 1 0 0.3

Per cent, across all indicator-country-sector instances

Note: Forecasting directional accuracy (FDA) measures the share of observations in the out-of-sample periods for which the predicted and actual growth rates have the same sign. Source: Authors' calculations.

Performance is generally better for larger than for smaller economies

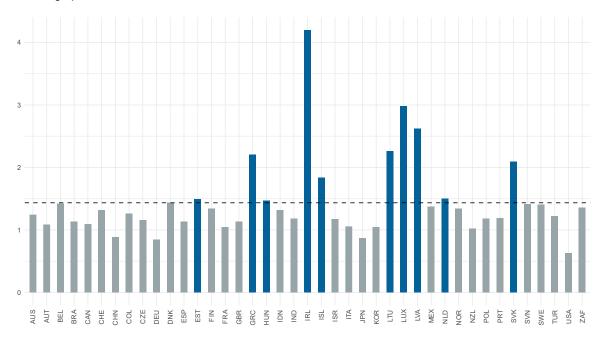
48. Performance, measured in terms of RMSEs, varies widely across countries, with some countries performing on average across indicator-sector instances much better than other (Figure 5). This is the case of largest economies, in particular United States, Japan, Germany, and China, whose RMSEs are on average 0.6 to 0.9 percentage point lower than the average of countries. Other large economies, such as France, Italy, the United Kingdom, Canada, India, Indonesia, Brazil also display relatively lower RMSEs (0.5 percentage point or less than the average).

49. By contrast a group of small economies has been found harder to nowcast. Ireland, Iceland, Greece, Lithuania, Luxembourg, Latvia, Slovak Republic and, to a lesser extent, Estonia, Hungary and the

Netherlands present higher errors across all TiVA indicators considered (country average RMSE is equivalent to 1.5).

Figure 5. RMSEs are lower in largest economies

Percentage points



Note: Country-average RMSEs were estimated for one-year ahead predictions and for all indicator-sector instances. The horizontal dashed line corresponds to the overall average RMSE (1.5).

Source: Authors' calculations.

50. Several factors may explain this relatively bad performance. First, the target variables (annual changes of TIVA indicators) have a larger standard deviation for those economies than for the rest. This could reflect a higher volatility of the target variable or important structural changes in the country's engagement in global value chains.

51. Ireland, whose performance is estimated to be the worst in the group of countries considered, is a clear example where those two explanations compound each other. On the one hand, the volatility of the target is more pronounced than in other countries. For instance, the standard errors of domestic valueadded shares are, on average, more than 2 times higher than those of the other countries. On the other hand, the country underwent significant changes in the nature and the depth of its global value chains. For instance, the domestic value-added shares in the information technology and other informational services industry were close to 80% in 1995 but dropped to only 30% in 2020.

52. Poorer performance is also sometimes associated with specific episodes, such as the 2008 global financial crisis. Eight out of ten countries with large nowcasting errors exhibited larger errors during the financial crisis than in normal time, explaining their overall worse performance. Bad performer countries were characterised by RMSEs 26% higher during the global financial crisis than in normal times (as compared to 20% in the other countries). The exception is Ireland whose RMSE was lower during the global financial crisis than in normal times (Figure 6).

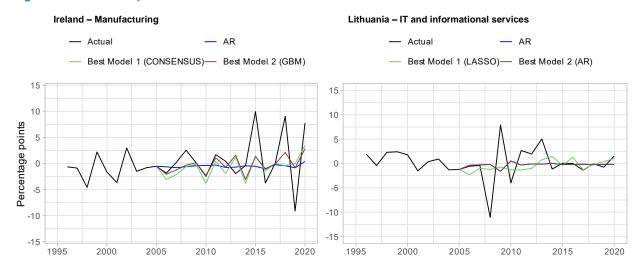


Figure 6. Predictive performance for domestic value-added shares

Note: Domestic value-added shares are measured using EXGR_DVASH in the TiVA dataset. Source: Author's calculations.

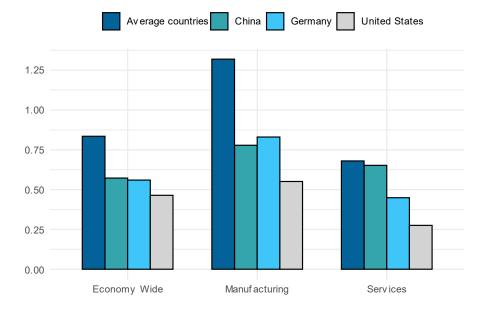
Prediction errors are found to be smaller at the economy wide and for services than for manufacturing

53. Performance across sectors also differs. Indeed, predictions errors for services and the aggregate economy are found to be lower than those for manufacturing. This is true on average across countries and for three reference economies, United States, China, and Germany, which display the lowest RMSEs overall (Figure 7). Differences between country averages and reference countries are also larger in manufacturing than in services and in the economy as a whole. This reflects large errors in a handful of countries (Ireland, Luxembourg, Australia, Greece, Republic Slovak, Mexico, and Lithuania) which drive the average RMSEs in the manufacturing upwards. Once excluding these countries, the difference between manufacturing on one hand and services and economy-wide on the other hand is significantly reduced, both in terms of overall errors but also in terms of the gap between the RMSE on average across countries and in the three reference countries.

54. Disaggregating by sectors, the relatively worse performance for manufacturing is driven by motor vehicles, computers and electrical equipment, machinery and equipment, and coke and refined petroleum, plastics; pharmaceuticals and others, which show relatively higher RMSEs on average across countries and a more significant difference with respect to the United States (Figure 8). By contrast, manufacturing sectors such as wood and paper, and food products, beverages, and tobacco, show relatively good performance across indicators while the difference with respect to the United States is less significant.

Figure 7. RMSE economy-wide, manufacturing and services, selected economies

Percentage points



Note: RMSEs were averaged for the 41 countries at economy wide, manufacturing and services level. Source: Author's calculations.

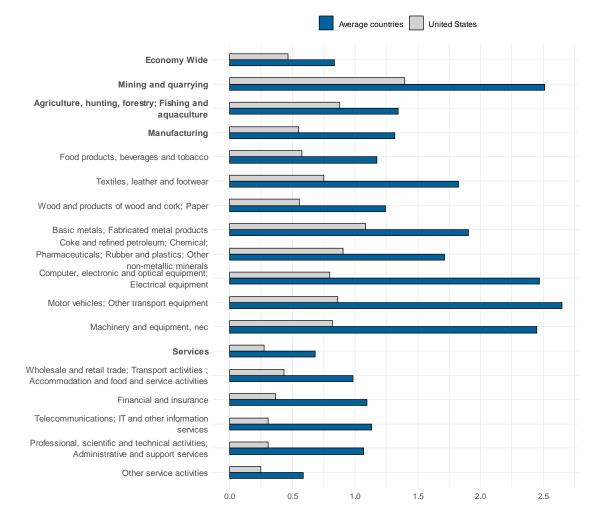
55. Finally, services exhibit the lowest country average RMSEs and the difference with respect to reference countries is the least. Within services, wholesale and retail trade, transport activities; accommodation and food and service activities, financial and insurance, and professional, scientific, and technical activities; administrative and support services show good performance and the lowest difference with respect to United States.

Export-related indicators exhibit on average better nowcasting performance than the foreign demand-based indicators

56. The basic TiVA indicators seek to capture the origin of the value added of industries based on different flows, either exports (e.g. the domestic value-added share of exports) or final demand for goods and services in foreign countries (e.g. the share of domestic value added embodied in foreign final demand). Other indicators such as the domestic or foreign services value-added share of exports capture the increasing importance of services inputs in the production processes of manufacturing firms (Miroudot and Cadestin, 2017_[32]).

Figure 8. RMSEs by sectors

Percentage points

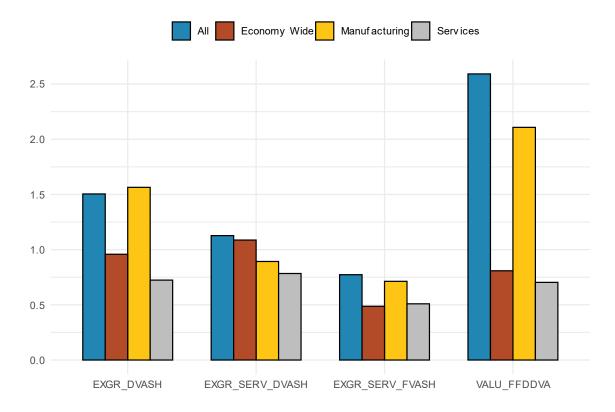


Source: Author's calculations.

57. Export-based indicators exhibit lower RMSEs than foreign demand-based indicators (Figure 9). RMSEs are close to 2.5% for the share of domestic value added embodied in foreign final demand on average across countries, as opposed to slightly less to 1.5% for the domestic content of exports and close or lower than 1% for domestic and foreign services contents of exports. The difference is essentially due to relatively worse nowcasting performance for this indicator in the manufacturing sector (above 2% on average across countries, while it is close to 1-1.5% for the other indicators), which itself stems from a relatively higher volatility of the indicator in this sector (Table 5). Errors related to this indicator in manufacturing are particularly marked for in Ireland, Lithuania, Luxembourg, Sweden. At the economy-wide and for services, the performance of the models related to this indicator appear to be close or even sometimes slightly better than those of the other indicators.

Figure 9. RMSE by indicators, selected sectors

Percentage points



Source: Author's calculations

58. Within export-based indicators, RMSEs are found to be relatively lower for the foreign services value-added share in exports. This holds at the economy-wide but also manufacturing and services levels. A lower volatility of this indicator explains this better performance (Table 5).

Table 5. Volatility of target variables

		Standard deviation (average 1995-2020)			
	TiVA Codes	All instances	Economy- wide	Manufacturing	Services
Domestic value-added share of exports	EXGR_DVASH	2.06	1.56	2.07	1.21
Domestic services value-added share of exports	EXGR_SERV_DVASH	1.50	1.61	1.09	1.27
Foreign services value-added share of exports	EXGR_SERV_FVASH	1.07	0.77	0.99	0.82
Share of domestic value added embodied in foreign final demand	VALU_FFDDVA	3.66	1.63	2.64	1.33

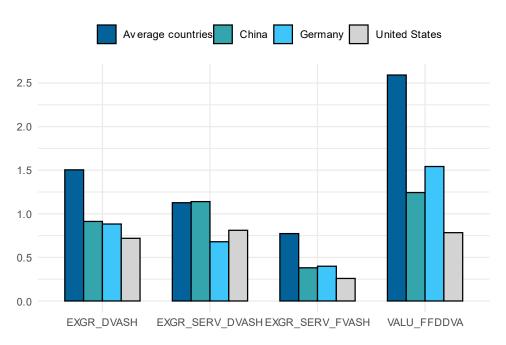
Source: Author's calculations

59. The difference between the country average and the reference countries appears to be largest for the share of domestic value added embodied in foreign final demand. This is essentially explained by much worse performance of Latvia, and to a lesser extent, Ireland, Lithuania and Luxembourg, for this indicator, and in the case of the manufacturing sector, a larger number of countries for which errors are relatively

elevated. Excluding those countries from the analysis, the gap between the average of countries and the United States, where errors are the smallest, would be reduced by 13%.

Figure 10. One-year ahead RMSE by indicators, selected economies

Percentage points



Source: Author's calculations.

7. Nowcasting 2021 and 2022

60. This section reports the nowcast for 2021 and 2022 produced with the models discussed in the previous sections.

The share of domestic value-added in exports is estimated to have fallen in 2021-22

61. At the economy-wide level, the share of domestic value added in exports declined from 1995 up until the global financial crisis, as countries across the globe engaged in global value chains and substituted domestic value added with imported intermediates to produce exportable goods and services (Figure 11). This is consistent with (Antras and Chor, 2022_[33]). Since the financial crisis, the indicator has been broadly stable, a phenomenon often called de- or slow-balisation (Jaax, Miroudot and van Lieshout, 2023_[34]).

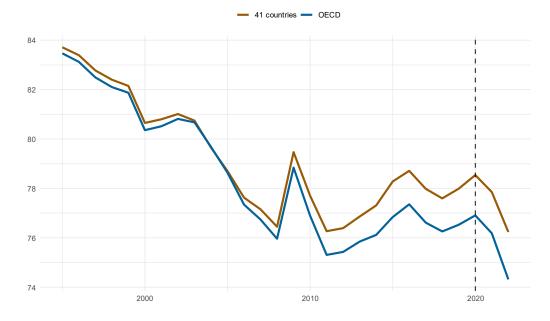


Figure 11. Evolution of the share of domestic value-added in exports at the economy-wide level Per cent

Note: Average over the corresponding country's domestic value-added shares of exports weighted with exports, not corrected from intra-trade. This differs from estimates reported in the OECD TiVA database (Guilhoto, 2022_[35]). Source: Authors' calculations

62. Nowcasts for 2021-22, using the models described in the preceding sections suggest that the content of domestic value added in export has been falling in 2021 and 2022, both on average across OECD countries, and at a more global level, when large emerging-market economies are included. The fall was widespread, with all the regions and the vast majority of the 41 countries covered in the analysis experiencing a drop in the domestic value-added content of exports (Figure 12).

63. The magnitude of the fall in 2021-22 is comparable to the one triggered by the global financial crisis in 2008, although there are differences across countries. Both crises led to declines in export flows and aggregate demand, combined with a strong volatility of commodity prices, which affected trade related to global value chains (Lebastard, 2023_[36]).

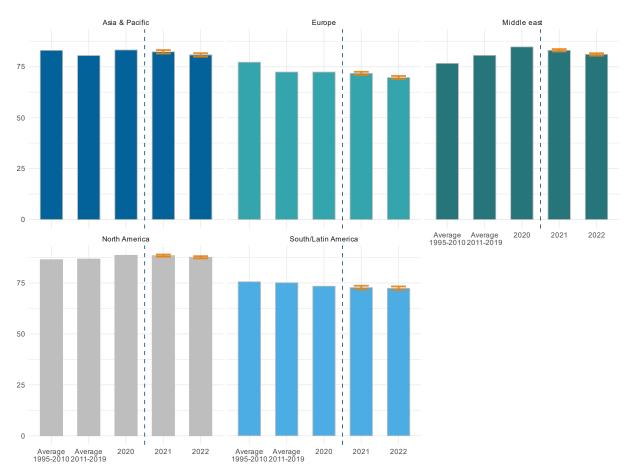


Figure 12. Share of domestic value-added in exports at the economy-wide level by region

Per cent

Note: Regional averages over the corresponding country's domestic value-added shares of exports weighted with exports, not corrected from intra-trade. This differs from estimates reported in the OECD TiVA database (Guilhoto, 2022_[35]). Error bands correspond to the nowcasted value -/+ the correspondent RMSE. Source: Authors' calculations.

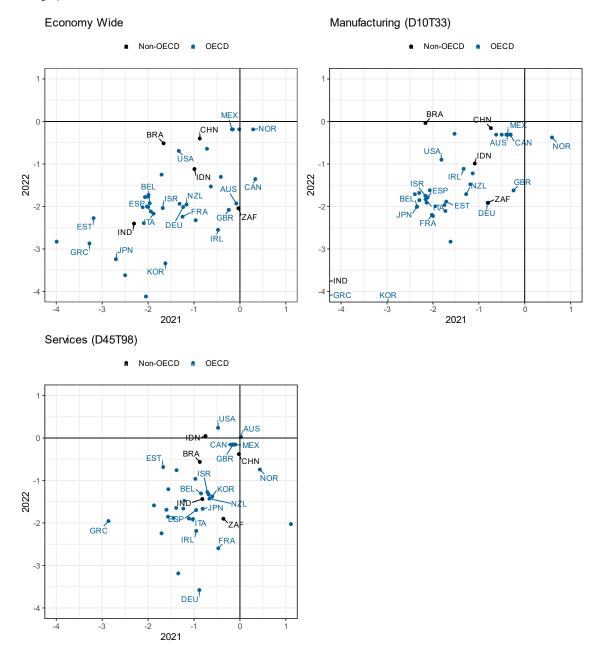
64. Aggregates at the economy-wide level are mirrored by developments at the sectoral level. Most countries experienced a decline in the domestic value-added share in exports in 2021 and 2022 in manufacturing and services (Figure 13).

65. The intensity of the decline differs across sectors and appear stronger in manufacturing than in services for most economies. the contraction in manufacturing is particularly marked in Greece, India and Korea. Germany stands out with a more pronounced fall predicted in services rather than in manufacturing.

66. A group of countries, most notably China, Mexico, and Australia, experienced only very light negative changes in the domestic value-added share in exports at both economy and sectoral level. Norway is the only country that recorded an increase in both years, at the economy-wide manufacturing and services levels. In Canada, the indicator is nowcast to decrease in 2022 after a very small increase in 2021. But those moves are marginal with the confidence bands.

Figure 13. Change in the domestic value-added share of exports by sector

Percentage point



Note: Differences between developments at the economy-wide level on the one hand and manufacturing and services at the other hand may be explained by developments in sectors which are not shown. Source: Authors' calculations.

Domestic services value-added shares of exports are expected to have been broadly stable, while the foreign counterpart has increased

67. Nowcasts point to little movement in the domestic services content of export in 2021 and 2022 in all the regions (

68. Figure 14). This stability masks a wide disparity in the direction of the nowcast across

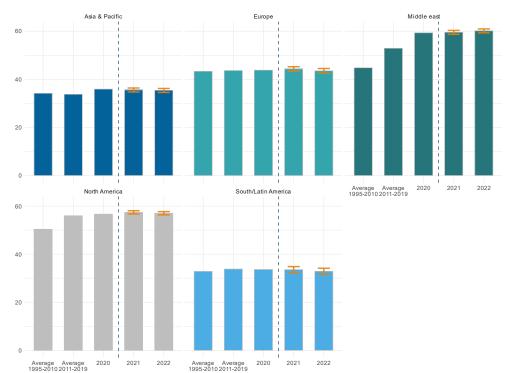
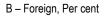
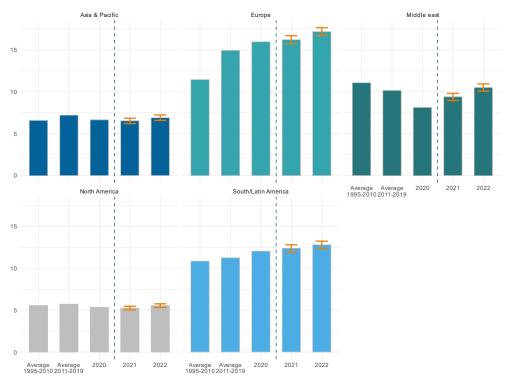


Figure 14. Services content of exports by region

A - Domestic, Per cent





Note: Regional averages over the corresponding country's domestic value-added shares of exports weighted with exports, not corrected from intra-trade. This differs from estimates reported in the OECD TiVA database (Guilhoto, 2022[35]). Error bands correspond to the nowcasted value -/+ the correspondent RMSE. Source: Authors' calculations.

countries, but also across sectors (Annex 4). While most countries experienced declined in the indicator related to the manufacturing sector in 2021-22 and an increase in the agriculture sectors, outcomes were much diverse in the services sector.

69. By contrast, the foreign services content of exports is found to have increased during the period, notable in Europe (from 16 in 2020 to 17.9 in 2022) and the Middle East (from 9.4 in 2020 to 10.5 in 2022). This increase was also broad-based when looking at sectoral developments.

The share of domestic value added embodied in foreign demand is nowcast to have exceeded its pre-COVID crisis level in 2022

70. The share of domestic value added embodied in foreign final demand declined in most regions in 2020. But the fall is nowcast to have been short-lived, and the share is estimated to have recovered steadily in 2021 and 2022 (Figure 15). Marked increases in the share can be observed in Europe (from 27.5% in 2020 to 31% in 2022), the Middle East (from 23.8% in 2020 to 27.1% in 2022) and South and Latin America (from 19.4% in 2020 to 21.5% in 2022). In all regions but North America, the indicator is expected to have exceed in 2022 its pre-crisis level.

71. The increase is estimated to have occurred in most sectors and countries, with different magnitude (Annex 4). In the manufacturing sector, large increases are observed for the United Kingdom, Canada, China and Mexico. In the services sectors, the rise in more homogenous across countries.

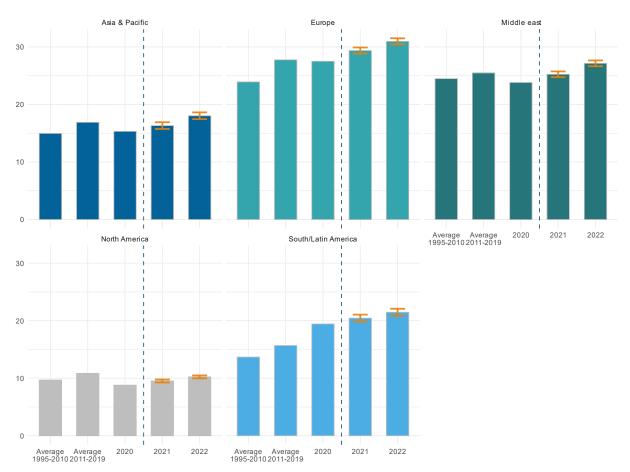


Figure 15. Share of domestic value added embodied in foreign final demand by region

Per cent

Note: Regional averages over the corresponding country's domestic value-added shares of exports weighted with exports, not corrected from intra-trade. This differs from estimates reported in the OECD TiVA database (Guilhoto, 2022_[35]). Error bands correspond to the nowcasted value -/+ the correspondent RMSE. Source: Authors' calculations

8. Conclusion

72. This paper put forward a new approach to nowcast five TiVA indicators, at economy-wide level and for 24 sectors and 41 countries. It relies on a range of machine-learning approaches together with more simple linear regression-based models in a panel setting. Models are tested in close to real time and appear to bring significant gains in nowcasting performances compared to a standard auto-regressive benchmark.

73. But there is variation in performance across countries, sectors and indicators. Model predictions appear to be much better for larger economies than for small economies (in particular Ireland, Lithuania and Greece). Predictions errors appear to be also lower at the economy-wide and services sector levels than for manufacturing. Export-related indicators exhibit on average better nowcasting performance than the foreign demand-based indicators.

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74. Looking forward, a number of improvements could be made. First further investigation would be warranted to better capture the engagement in global value chains of small, open and fast-growing economies such as Ireland. Second, the approach could be extended to nowcast bilateral indicators of TiVA, or more generally other indicators derived from ICIOs such as employment or carbon footprints.

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Annex 1. Data Sources

Table A1. Information on data used in the analysis

Category	Variable	Source	Dimension
Balance of Payments	Capital account Balance	Main Economic Indicators, OECD	Country
Balance of Payments	Capital account Credits	Main Economic Indicators, OECD	Country
Balance of Payments	Capital account Debits	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Balance, Total Balance of Goods	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Balance, Total Balance of Primary Income	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Balance, Secondary Income	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Balance, Services	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Balance, Total Balance	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Balance, Total Balance as % of GDP	Main Economic Indicators, OECD	Country
alance of Payments	Current account Credits, Total Credits in Goods	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Credits, Primary Income	Main Economic Indicators, OECD	Country
alance of Payments	Current account Credits, Secondary Income	Main Economic Indicators, OECD	Country
alance of Payments	Current account Credits, Services	Main Economic Indicators, OECD	Country
alance of Payments	Current account Credits, Total as % of Current account	Main Economic Indicators, OECD	Country
alance of Payments	Total Credits as % of Goods and Services	Main Economic Indicators, OECD	Country
alance of Payments	Current account Credits, Total Credits	Main Economic Indicators, OECD	Country
Balance of Payments	Current account Debits, Goods	Main Economic Indicators, OECD	Country
alance of Payments	Current account, Primary Income Debits	Main Economic Indicators, OECD	Country
alance of Payments	Current account, Secondary Income Debits	Main Economic Indicators, OECD	Country
alance of Payments	Current account Debits, Services	Main Economic Indicators, OECD	Country
alance of Payments	Total Debits as % of Current account	Main Economic Indicators, OECD	Country
alance of Payments	Current account, Services Total Debits as % of Goods and Services	Main Economic Indicators, OECD	Country
	Current account, Total Debits	Main Economic Indicators, OECD	Country
alance of Payments alance of Payments			
	Financial account, Direct investment Net	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Direct investment Net acquisition of financial assets	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Direct Investments	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Balance	Main Economic Indicators, OECD	Country
alance of Payments	Financial accout, Net acquisition of financial assets	Main Economic Indicators, OECD	Country
alance of Payments	Financial account Net incurrence of liabilities	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Financial derivatives Net	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Other investment Net	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Other investment Net acquisition of financial assets	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Other investment Net incurrence of liabilities	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Portfolio investment Net	Main Economic Indicators, OECD	Country
alance of Payments	Financial account, Portfolio investment Net acquisition of financial assets	Main Economic Indicators, OECD	Country
Balance of Payments	Financial account, Portfolio Investments	Main Economic Indicators, OECD	Country
Balance of Payments	Financial account, Reserve Assets	Main Economic Indicators, OECD	Country
Balance of Payments	Net errors and omissions Balance	Main Economic Indicators, OECD	Country
Business tendency surveys	Rate of capacity utilization in manufacturing	Main Economic Indicators, OECD	Country
Business tendency surveys	Confidence indicators in manufacturing	Main Economic Indicators, OECD	Country
Business tendency surveys	Confidence indicators in manufacturing	Main Economic Indicators, OECD	Country
Susiness tendency surveys	Future tendency of employment in manufacturing	Main Economic Indicators, OECD	Country
Business tendency surveys	Stocks of finished goods in manufacturing	Main Economic Indicators, OECD	Country
Business tendency surveys	Future tendency of selling prices in manufacturing	Main Economic Indicators, OECD	Country
Consumer opinion surveys	Consumer Confidence Indicator	Main Economic Indicators, OECD	Country
Consumer opinion surveys	Confidence indicators (from Consumer opinion surveys)	Main Economic Indicators, OECD	Country
rice Index	Consumer Price Index (All items)	Main Economic Indicators, OECD	Country
rice Index	Consumer Price of Food and non-Alcoholic beverages	Main Economic Indicators, OECD	Country
rice Index	Consumer Price Index (All items non-food non-energy)	Main Economic Indicators, OECD	Country
rice Index	Consumer Prince Index (Energy: Fuel, electricity & gasoline)	Main Economic Indicators, OECD	Country
xchange rates	Real effective exchange rates, CPI based	Main Economic Indicators, OECD	Country
xchange rates	Real effective exchange rates, ULC based	Main Economic Indicators, OECD	Country
xchange rates	Average of daily exchange rates between national currency and USD	Main Economic Indicators, OECD	Country
iterest rates	Interbank rates (90-day)	Main Economic Indicators, OECD	Country
terest rates	Interbank rates (< 24 hrs)	Main Economic Indicators, OECD	Country
ternational Trade	Total value of Exports of goods	Main Economic Indicators, OECD	Country
Iternational Trade	Total value of Imports of goods	Main Economic Indicators, OECD	Country
Iternational Trade	Trade Balance, goods	Main Economic Indicators, OECD	Country
mployment	Active population aged 15-64 (Labor Force Survey)	Main Economic Indicators, OECD	Country
mployment	Inactivity rate (all persons aged 25-54)	Main Economic Indicators, OECD	Country
		Main Economic Indicators, OECD	
eading indicators	CLI (Amplitude adjusted)		Country
eading indicators	CLI (Normalised)	Main Economic Indicators, OECD	Country
eading indicators	CLI (Trend restored)	Main Economic Indicators, OECD	Country
eading indicators	GDP (Normalised)	Main Economic Indicators, OECD	Country
eading indicators	GDP (Original series)	Main Economic Indicators, OECD	Country
eading indicators	GDP (Ratio to trend)	Main Economic Indicators, OECD	Country
eading indicators	GDP Trend	Main Economic Indicators, OECD	Country
lational Accounts	Exports of Goods and Services (Constant prices)	Main Economic Indicators, OECD	Country
lational Accounts	Government Final Consumption Expenditure (Constant prices)	Main Economic Indicators, OECD	Country
lational Accounts	GDP (Constant prices)	Main Economic Indicators, OECD	Country
lational Accounts	Gross Fixed Capital Formation (Constant prices)	Main Economic Indicators, OECD	Country
lational Accounts	GDP minus Imports of Goods and Services (Constant prices)	Main Economic Indicators, OECD	Country
lational Accounts	Private Final Consumption Expenditure (Constant prices)	Main Economic Indicators, OECD	Country
	i maio i mai obnoumption Experiatare (obnotant prices)	Main Economic Indicators, OECD	Country

National Accounts	Exports of Goods and Services (Current prices)	Main Economic Indicators, OECD	Country
National Accounts	Government Final Consumption Expenditure (Current prices)	Main Economic Indicators, OECD	Country
National Accounts	GDP (Current prices)	Main Economic Indicators, OECD	Country
		,	
National Accounts	Gross Fixed Capital Formation (Current prices)	Main Economic Indicators, OECD	Country
National Accounts	GDP minus Imports of Goods and Services (Current prices)	Main Economic Indicators, OECD	Country
National Accounts	Private Final Consumption Expenditure (Current prices)	Main Economic Indicators, OECD	Country
National Accounts	GDP Deflator	Main Economic Indicators, OECD	Country
National Accounts	Private Consumption Expenditure Deflator	Main Economic Indicators, OECD	Country
Real Indicators	Domestic Producer Price Index (Manufacturing)	Main Economic Indicators, OECD	Country
Real Indicators	Production in Construction, index	Main Economic Indicators, OECD	Country
Real Indicators	Industrial Production, index	Main Economic Indicators, OECD	Country
Real Indicators	Manufacturing Production, index	Main Economic Indicators, OECD	Country
Real Indicators	New passenger car registrations	Main Economic Indicators, OECD	Country
		Main Economic Indicators, OECD	
Real Indicators	Retail trade volume, index		Country
Share Prices	Share Prices, Index	Main Economic Indicators, OECD	Country
Real Indicators	Total international receipts, US Dollars	Tourism Statistics, OECD	Country
Real Indicators	Total international expenditure, US Dollars	Tourism Statistics, OECD	Country
Real Indicators	Total international arrivals	Tourism Statistics, OECD	Country
Real Indicators	Nights in all types of accommodation	Tourism Statistics, OECD	Country
Real Indicators	Total international departures	Tourism Statistics, OECD	Country
National Accounts	Gross Value Added, current prices	Detailed National Accounts, OECD, UNSD	Country-sector
National Accounts	Gross Output, current prices	Detailed National Accounts, OECD, UNSD	Country-sector
Employment	Employment by industry	Detailed National Accounts OECD	Country-sector
International Trade	Exports of Services in USD, EBOPS 2010	ITSS OECD, EBOPS 2010	Country-sector
International Trade	Imports of Services in USD, EBOPS 2010	ITSS OECD, EBOPS 2010	Country-sector
International Trade	Exports of Other Goods in USD	Bilateral Trade by Industry and End Use, OECD	Country-sector
International Trade	Exports of Intermediate Goods in USD	Bilateral Trade by Industry and End Use, OECD	Country-sector
International Trade	Imports of Other Goods in USD	Bilateral Trade by Industry and End Use, OECD	Country-sector
International Trade	Imports of Intermediate Goods in USD	Bilateral Trade by Industry and End Use, OECD	Country-sector
Interest rates	Yields on medium-term bonds. Brazil	Datastream	Global
Leading indicators	Purchasing Managers Index New Export Orders, Brazil	Datastream	Global
	5 5 1 7		
Share Prices	Share Prices Index, Brazil	Datastream	Global
Interest rates	Yields on medium-term bonds, China	Datastream	Global
Share Prices	Share Prices Index, China	Datastream	Global
Interest rates	Yields on medium-term bonds, Emerging Markets	Datastream	Global
Leading indicators	Purchasing Managers Index New Export Orders, Emerging Markets	Datastream	Global
Share Prices	Share Prices Index, Emerging Markets	Datastream	Global
Interest rates	Yields on medium-term bonds, France	Datastream	Global
			Global
Leading indicators	Purchasing Managers Index New Export Orders, France	Datastream	
Share Prices	Share Prices Index, France	Datastream	Global
Interest rates	Yields on medium-term bonds, Indonesia	Datastream	Global
Share Prices	Share Prices Index, Indonesia	Datastream	Global
Interest rates	Yields on medium-term bonds, India	Datastream	Global
Share Prices	Share Prices Index, India	Datastream	Global
Interest rates	Yields on medium-term bonds, Italy	Datastream	Global
	Purchasing Managers Index New Export Orders, Italy	Datastream	Global
Leading indicators			
Share Prices	Share Prices Index, Italy	Datastream	Global
Interest rates	Yields on medium-term bonds, Japan	Datastream	Global
Leading indicators	Purchasing Managers Index New Export Orders, Japan	Datastream	Global
Share Prices	Share Prices Index, Japan	Datastream	Global
Interest rates	Yields on medium-term bonds, USA	Datastream	Global
Leading indicators	Purchasing Managers Index New Export Orders, USA	Datastream	Global
Share Prices	Share Prices Index, USA	Datastream	Global
Others		ECB	Global
	Systemic Stress Composite Indicator (Europe)		
Price Index	Services Import Price Index: Import Air Freight (USA)	FRED	Global
Price Index	Services Export Price Index: Export Air Passenger Fares (GBR)	FRED	Global
Price Index	Services Export Price Index: Export Air Passenger Fares (JPN)	FRED	Global
Price Index	Services Import Price Index: Import Air Passenger Fares - United Kingdom (GBR)	FRED	Global
Others	All Employees, Air Transportation (USA)	FactSet	Global
Others	Weekly Initial Claims (ICSA) (USA)	FRED	Global
Others	All Employees, Leisure and Hospitality (USA)	FRED	Global
Real Indicators	Industrial Production: Manufacturing (NAICS) (IPMAN) (USA)	FRED	Global
Real Indicators	Capacity Utilization: Manufacturing (NAICS) (MCUMFN) (USA)	FRED	Global
Price Index	Producer Price Index by Industry: Scheduled Passenger Air	FRED	Global
	Transportation: International (USA)		
Price Index	Producer Price Index by Industry: Scheduled Freight Air Transportation: Scheduled Freight Air Transportation Services (USA)	FRED	Global
Leading indicators	Economic policy uncertainty index	Policyuncertainty.com	Global
Leading indicators	Global Economic policy uncertainty index (GDP weighted)	Policyuncertainty.com	Global
Price Index	Beverage Price Index, 2016 = 100, includes Coffee, Tea, and Cocoa	IMF Primary Commodity Prices	Global
Price Index	Coal Price Index, 2016 = 100, includes Australian and South African Coal	IMF Primary Commodity Prices	Global
Price Index	Precious Metals Price Index, 2016 = 100, includes Gold, Silver, Palladium and Platinum Price Indices	IMF Primary Commodity Prices	Global
Price Index	Agricultural Raw Materials Index, 2016 = 100, includes Timber, Cotton, Wool, Rubber, and Hides Price Indices	IMF Primary Commodity Prices	Global
Price Index	Crude Oil (petroleum), Price index, 2016 = 100, simple average of three	IMF Primary Commodity Prices	Global
	spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh		

Price Index	Agriculture Price Index, 2016 = 100, includes Food and Beverages and Agriculture Raw Materials Price Indices	IMF Primary Commodity Prices	Global
Price Index	All Metals Index, 2016 = 100: includes Metal Price Index (Base Metals) and Precious Metals Index	IMF Primary Commodity Prices	Global
Price Index	All Metals EX GOLD Index, 2016 = 100: includes Metal Price Index (Base Metals) and ONLY Silver, Palladium, Platinum	IMF Primary Commodity Prices	Global
Price Index	Food and Beverage Price Index, 2016 = 100, includes Food and Beverage Price Indices	IMF Primary Commodity Prices	Global
Price Index	Food Price Index, 2016 = 100, includes Cereal, Vegetable Oils, Meat, Seafood, Sugar, and Other Food (Apple (non-citrus fruit), Bananas, Chana (legumes), Fishmeal, Groundnuts, Milk (dairy), Tomato (veg)) Price Indices	IMF Primary Commodity Prices	Global
Price Index	Industrial Inputs Price Index, 2016 = 100, includes Agricultural Raw Materials and Base Metals Price Indices	IMF Primary Commodity Prices	Global
Price Index	Base Metals Price Index, 2016 = 100, includes Aluminum, Cobalt, Copper, Iron Ore, Lead, Molybdenum, Nickel, Tin, Uranium and Zinc Price Indices	IMF Primary Commodity Prices	Global
Price Index	Natural Gas Price Index, 2016 = 100, includes European, Japanese, and American Natural Gas Price Indices	IMF Primary Commodity Prices	Global
Price Index	Fuel (Energy) Index, 2016 = 100, includes Crude oil (petroleum), Natural Gas, Coal Price and Propane Indices	IMF Primary Commodity Prices	Global
Price Index	All Commodity Price Index, 2016 = 100, includes both Fuel and Non-Fuel Price Indices	IMF Primary Commodity Prices	Global
Price Index	Commodities for Index: All, excluding Gold, 2016 = 100	IMF Primary Commodity Prices	Global
Price Index	Fertilizer Index, 2016 = 100, includes DAP, Potash, UREA	IMF Primary Commodity Prices	Global
Price Index	Non-Fuel Price Index, 2016 = 100, includes Precious Metal, Food and Beverages and Industrial Inputs Price Indices	IMF Primary Commodity Prices	Global
Price Index	Producer Price Index, Manufacturing, Food, USA	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, CAN	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, DEU	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, FRA	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, USA	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, DEU	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, FRA	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, DEU	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, FRA	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Manufacturing, USA	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Industrial Activities, DEU	Main Economic Indicators, OECD	Global
Price Index	Producer Price Index, Industrial Activities, FRA	Main Economic Indicators, OECD	Global
Stock index	MSCI World Automobiles Index	MSCI	Global

Annex 2. Additional results on model performance

Keys to variables

EXGR_DVASH: domestic value-added share of exports EXGR_SERV_DVASH: domestic services value-added share of exports EXGR_SERV_FVASH: foreign services value-added share of exports VALU_FFDDVA: share of domestic value added embodied in foreign final demand

Table A.2. 1: Relative RMSEs two-years ahead by sector and indicator

Best model RMSE relative to benchmark AR1, average across countries

	Domestic value- added share of exports	Domestic services value-added share of exports	Foreign services value-added share of exports	Share of domestic value added embodied in foreign final demand
Economy Wide	0.74	0.84	0.82	0.61
Mining and quarrying	0.90	0.91	0.91	0.90
Agriculture	0.85	0.91	0.90	0.88
Manufacturing	0.76	0.78	0.85	0.67
Food products, beverages and tobacco	0.74	0.85	0.83	0.89
Textiles, leather and footwear	0.73	0.89	0.77	0.85
Wood and products of wood and cork; Paper	0.83	0.89	0.82	0.93
Basic metals; Fabricated metal products	0.76	0.91	0.85	0.91
Coke and refined petroleum; Chemical; Pharmaceuticals; Rubber and plastics; Other non-metallic minerals	0.85	0.89	0.91	0.91
Computer, electronic and optical equipment; Electrical equipment	0.78	0.84	0.87	0.91
Motor vehicles; Other transport equipment	0.92	0.93	0.89	0.97
Machinery and equipment, nec	0.88	0.93	0.88	0.97
Services	0.87	0.91	0.90	0.97
Wholesale and retail trade; Transport activities; Accommodation and food and service activities	0.78	0.79	0.87	0.80
Financial and insurance	0.92	0.94	0.93	0.83
Telecommunications; IT and other information services	0.86	0.89	0.87	0.81
Professional, scientific and technical activities; Administrative and support services	0.82	0.88	0.83	0.82
Other service activities	0.80	0.90	0.84	0.83
All indicator-country-sector instances	0.82	0.88	0.86	0.86

Note: Relative RMSEs for two-years ahead predictions with respect to the benchmark AR1, average across the countries. Since more aggregated sectors like Manufacturing (D10T33) and Services (D45T98) were estimated independently of their corresponding disaggregated sectors, the relative RMSEs of former do not represent the average of the latter.

Table A.2. 2: United States. Relative RMSEs, one-year ahead, by sector and indicator

Best model RMSE relative to benchmark AR1

	Domestic value- added share of exports	Domestic services value-added share of exports	Foreign services value-added share of exports	Share of domestic value added embodied in foreign final demand
Economy Wide	0.44***	0.54***	0.58***	0.85***
Mining and quarrying	1.00	0.95***	1.00	0.97***
Agriculture	0.69***	0.8***	0.76***	0.67***
Manufacturing	0.45***	0.88*	0.49***	0.95***
Food products, beverages and tobacco	0.51***	0.96**	0.51***	0.55***
Textiles, leather and footwear	0.53***	0.98	0.59***	0.94***
Wood and products of wood and cork; Paper	0.49***	0.96**	0.51***	0.92***
Basic metals; Fabricated metal products	0.75***	0.84**	0.89**	0.99
Coke and refined petroleum; Chemical; Pharmaceuticals; Rubber and plastics; Other non-metallic minerals	0.52***	0.73***	0.78***	1.00
Computer, electronic and optical equipment; Electrical equipment	0.65***	1.00	0.47***	1.00
Motor vehicles; Other transport equipment	0.51***	0.97	0.72***	0.97
Machinery and equipment, nec	0.57***	0.92*	0.8***	1.00
Services	0.49***	0.41***	0.75***	0.63***
Wholesale and retail trade; Transport activities; Accommodation and food and service activities	0.53***	0.43***	0.84***	0.57***
Financial and insurance	0.74***	0.68***	0.73***	0.82***
Telecommunications; IT and other information services	0.58***	0.71***	0.46***	0.71***
Professional, scientific and technical activities; Administrative and support services	0.95***	0.72***	0.76***	0.75***
Other service activities	0.55***	0.89***	0.79***	0.89***
All indicator-country-sector instances	0.61	0.80	0.69	0.84

Table A.2. 3: China. Relative RMSEs, one-year ahead, by sector and indicator

Best model RMSE relative to benchmark AR1

	Domestic value- added share of exports	Domestic services value-added share of exports	Foreign services value-added share of exports	Share of domestic value added embodied in foreign final demand
Economy Wide	0.45***	0.67***	0.64***	0.43***
Mining and quarrying	0.96	0.74***	0.9*	0.64***
Agriculture	0.65***	0.77***	0.91***	0.83***
Manufacturing	0.51***	0.52***	0.72***	0.6***
Food products, beverages and tobacco	0.61***	0.63***	0.76***	0.78***
Textiles, leather and footwear	0.58***	0.66***	0.48***	0.66***
Wood and products of wood and cork; Paper	0.41***	0.71***	0.51***	0.57***
Basic metals; Fabricated metal products	0.63***	0.66***	0.76***	0.85***
Coke and refined petroleum; Chemical; Pharmaceuticals; Rubber and plastics; Other non-metallic minerals	0.48***	0.69***	0.62***	0.7***
Computer, electronic and optical equipment; Electrical equipment	0.74***	0.72**	0.7***	0.71**
Motor vehicles; Other transport equipment	0.61***	0.73***	0.48***	0.65**
Machinery and equipment, nec	0.58***	0.69***	0.67***	0.76
Services	0.58***	0.67***	0.8***	0.67***
Wholesale and retail trade; Transport activities; Accommodation and food and service activities	0.52***	0.72***	0.79**	0.65***
Financial and insurance	0.96	0.97	0.97	0.65***
Telecommunications; IT and other information services	0.79***	0.79***	0.74***	0.71**
Professional, scientific and technical activities; Administrative and support services	0.72***	0.86***	0.89***	0.68***
Other service activities	0.83***	0.97***	0.87***	0.95*
All indicator-country-sector instances	0.64	0.73	0.73	0.69

Table A.2. 4: Portugal. Relative RMSEs, one-year ahead, by sector and indicator

Best model RMSE relative to benchmark AR1

	Domestic value- added share of exports	Domestic services value-added share of exports	Foreign services value-added share of exports	Share of domestic value added embodied in foreign final demand
Economy Wide	0.67***	0.93	0.81***	0.87***
Mining and quarrying	1.00	1.00	1.00	1.00
Agriculture	0.63***	0.86***	0.74***	0.98
Manufacturing	0.73***	0.6***	0.78***	0.99*
Food products, beverages and tobacco	0.76***	0.88***	0.83**	0.98
Textiles, leather and footwear	0.81**	0.97***	0.78**	1.00
Wood and products of wood and cork; Paper	0.8***	0.87***	0.88***	1.00
Basic metals; Fabricated metal products	0.92*	0.81***	0.85***	0.73**
Coke and refined petroleum; Chemical; Pharmaceuticals; Rubber and plastics; Other non-metallic minerals	0.69***	0.93***	0.97	0.96
Computer, electronic and optical equipment; Electrical equipment	1.00	0.92*	1.00	1.00
Motor vehicles; Other transport equipment	0.81***	0.86***	0.96	0.94***
Machinery and equipment, nec	0.78***	0.95***	0.9***	0.99*
Services	0.69***	0.65***	0.99*	0.68***
Wholesale and retail trade; Transport activities; Accommodation and food and service activities	0.67***	0.64***	0.95*	0.89***
Financial and insurance	0.96	0.93	0.94	1.00
Telecommunications; IT and other information services	0.97	0.99	1.00	0.91***
Professional, scientific and technical activities; Administrative and support services	0.78**	0.77***	0.84**	0.83***
Other service activities	0.66***	0.91**	0.95*	0.89***
All indicator-country-sector instances	0.8	0.86	0.9	0.92

Table A.2. 5: Slovakia. Relative RMSEs, one-year ahead, by sector and indicator

Best model RMSE relative to benchmark AR1

	Domestic value- added share of exports	Domestic services value-added share of exports	Foreign services value-added share of exports	Share of domestic value added embodied in foreign final demand
Economy Wide	0.7***	0.91**	0.86**	0.61***
Mining and quarrying	0.98	1.00	0.88***	0.97
Agriculture	1.00	1.00	0.99	0.92***
Manufacturing	0.89**	0.91***	0.99	1.00
Food products, beverages and tobacco	0.88**	0.85***	0.96*	0.82***
Textiles, leather and footwear	1.00	1.00	1.00	1.00
Wood and products of wood and cork; Paper	0.83***	0.93**	0.97	1.00
Basic metals; Fabricated metal products	0.98	0.9**	1.00	1.00
Coke and refined petroleum; Chemical; Pharmaceuticals; Rubber and plastics; Other non-metallic minerals	0.78***	0.96	0.86***	1.00
Computer, electronic and optical equipment; Electrical equipment	1.00	0.97	0.99	1.00
Motor vehicles; Other transport equipment	0.85***	0.97*	0.99	1.00
Machinery and equipment, nec	1.00	0.92***	1.00	1.00
Services	0.88*	0.96	0.79***	0.7***
Wholesale and retail trade; Transport activities; Accommodation and food and service activities	0.87***	0.91*	0.82***	0.83***
Financial and insurance	0.88***	0.83***	0.92**	0.94
Telecommunications; IT and other information services	1.00	0.94***	0.92***	0.8***
Professional, scientific and technical activities; Administrative and support services	1.00	1.00	0.92	0.92**
Other service activities	0.81	0.91	0.94	0.9*
All indicator-country-sector instances	0.91	0.94	0.93	0.91

Annex 3. Additional information on one-step ahead nowcasting performance by indicator, sector and countries

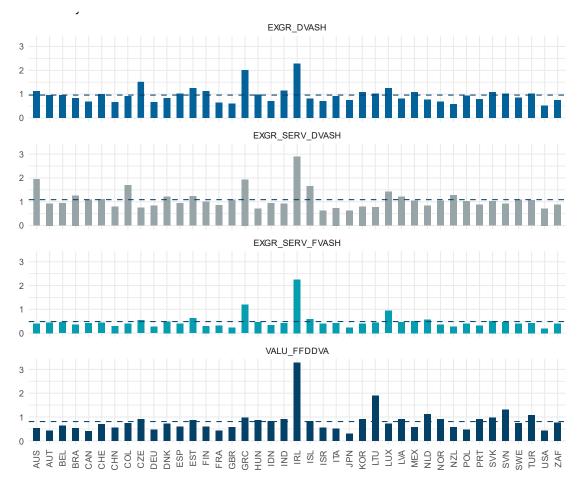
Keys to variables

EXGR_DVASH: domestic value-added share of exports EXGR_SERV_DVASH: domestic services value-added share of exports EXGR_SERV_FVASH: foreign services value-added share of exports VALU_FFDDVA: share of domestic value added embodied in foreign final demand

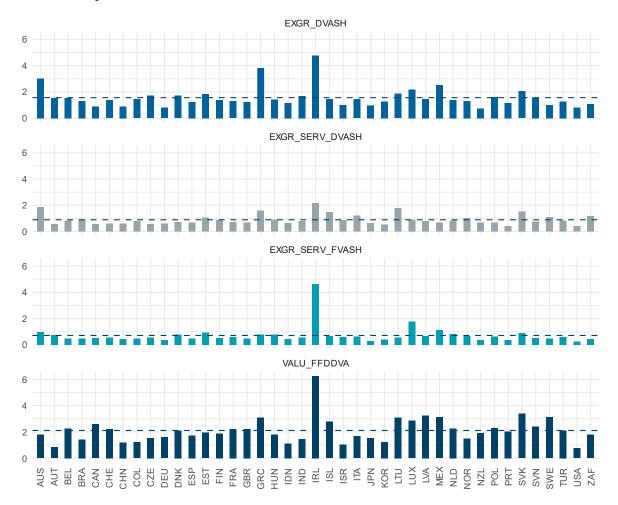
Figure A3.1. One-step ahead nowcasting errors

Per cent, average

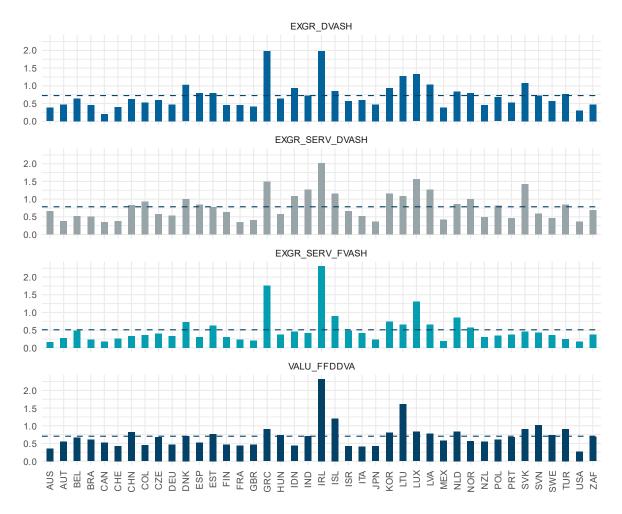
A - Economy wide



B – Manufacturing







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Annex 4. Additional information on nowcasts for 2021 and 2022

Keys to variables

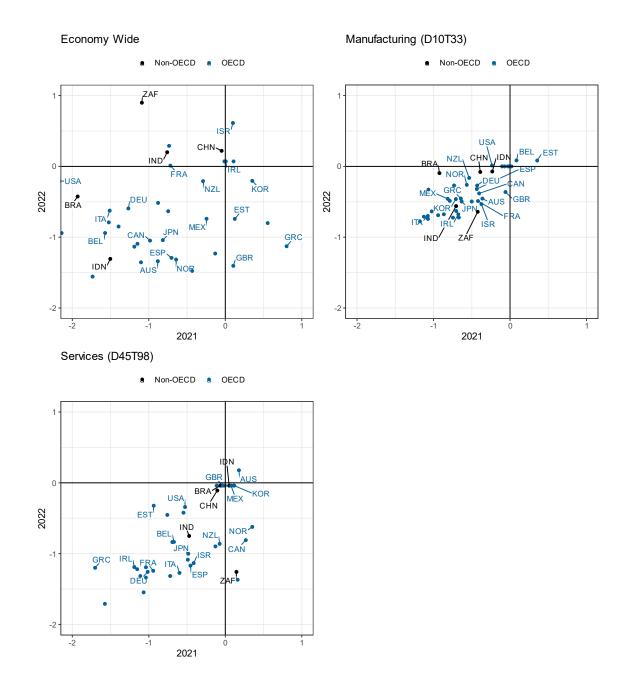
EXGR_DVASH: domestic value-added share of exports

EXGR_SERV_DVASH: domestic services value-added share of exports

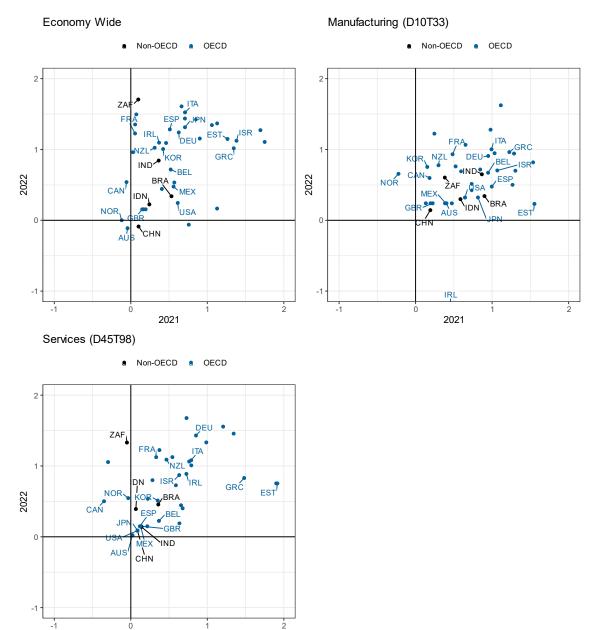
EXGR_SERV_FVASH: foreign services value-added share of exports

VALU_FFDDVA: share of domestic value added embodied in foreign final demand

EXGR_SERV_DVASH



EXGR_SERV_FVASH



VALU_FFDDVA

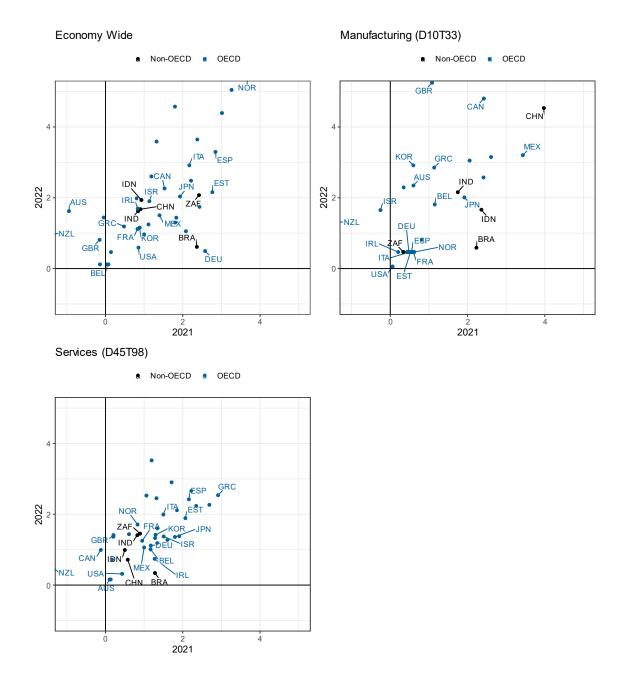


Table A 4.1 1 Nowcasts by country, economy wide, domestic value-added shares of exports

Country	Average 1995-2010	Average 2011-2019	2020	2021	2022
AUS	86.97	87.50	89.70	90.21 [89.14-91.28]	88.28 [87.21-89.35]
AUT	74.73	68.31	68.23	66.71 [65.89-67.53]	63.88 [63.06-64.71]
BEL	65.43	63.06	64.59	63.56 [62.71-64.41]	61.64 [60.79-62.49]
BRA	88.80	88.08	85.49	85.10 [84.31-85.89]	84.59 [83.80-85.38]
CAN	75.26	75.64	74.94	76.58 [75.83-77.32]	75.22 [74.48-75.96]

CHE	78.55	76.68	76.79	77.83 [76.98-78.68]	76.30 [75.45-77.15]
CHN	79.71	81.97	83.89	83.34 [82.64-84.05]	82.94 [82.24-83.65]
COL	88.37	88.58	88.63	86.97 [86.22-87.72]	85.72 [84.97-86.47]
CZE	64.42	55.78	60.59	58.31 [57.11-59.51]	56.37 [55.17-57.57]
DEU	81.11	76.32	77.51	76.33 [75.85-76.80]	74.32 [73.84-74.79]
DNK	72.06	66.94	68.13	66.31 [65.72-66.91]	64.55 [63.95-65.14]
ESP	76.70	75.21	75.33	75.33 [74.41-76.25]	73.21 [72.30-74.13]
EST	65.58	61.36	63.49	62.51 [61.21-63.80]	60.23 [58.93-61.53]
FIN	73.21	69.05	70.25	70.28 [69.23-71.32]	68.97 [67.93-70.01]
FRA	79.80	75.93	76.98	76.10 [75.58-76.62]	73.86 [73.34-74.38]
GBR	84.28	82.22	83.31	83.70 [83.28-84.12]	81.63 [81.20-82.05]
GRC	78.89	70.46	61.25	62.34 [60.13-64.55]	59.47 [57.26-61.68]
HUN	56.13	51.89	52.13	51.39 [50.50-52.28]	48.99 [48.10-49.88]
IDN	85.38	86.94	88.57	88.04 [87.32-88.77]	86.92 [86.20-87.65]
IND	82.79	79.22	83.71	82.77 [81.47-84.06]	80.37 [79.07-81.66]
IRL	59.49	55.08	56.93	54.83 [52.62-57.04]	52.29 [50.07-54.50]
ISL	73.87	69.79	71.13	70.44 [69.79-71.08]	66.82 [66.17-67.46]
ISR	76.63	80.53	84.75	83.05 [82.44-83.66]	81.02 [80.41-81.62]
ITA	80.55	75.83	77.89	76.48 [75.68-77.28]	74.31 [73.51-75.11]
JPN	91.24	85.90	86.83	85.79 [85.04-86.55]	82.55 [81.79-83.30]
KOR	67.66	64.27	69.79	66.96 [65.66-68.26]	63.62 [62.32-64.92]
LTU	72.05	70.26	70.62	67.35 [66.34-68.36]	67.17 [66.16-68.18]
LUX	45.77	37.63	35.06	34.14 [33.02-35.27]	33.96 [32.83-35.08]
LVA	75.90	74.88	75.72	74.98 [74.44-75.51]	72.98 [72.44-73.51]
MEX	66.97	65.03	65.34	64.74 [63.76-65.72]	64.55 [63.57-65.53]
NLD	75.30	68.36	68.97	67.86 [67.33-68.39]	65.53 [65.00-66.07]
NOR	84.47	84.72	83.38	83.48 [82.70-84.27]	83.30 [82.51-84.08]
NZL	83.79	85.25	87.58	86.40 [85.94-86.85]	84.44 [83.99-84.89]
POL	74.02	70.13	69.88	69.56 [68.85-70.28]	67.83 [67.12-68.55]
PRT	73.17	69.30	68.78	68.27 [67.54-69.00]	66.26 [65.53-66.98]
SVK	58.11	50.36	51.62	50.88 [49.84-51.93]	48.87 [47.83-49.91]
SVN	66.62	64.17	65.51	64.05 [63.13-64.97]	62.27 [61.36-63.19]
SWE	74.08	74.30	74.70	74.82 [74.08-75.57]	70.71 [69.96-71.45]
TUR	84.01	78.33	77.06	77.84 [76.95-78.72]	77.19 [76.31-78.08]
USA	89.69	89.41	91.79	91.16 [90.66-91.66]	90.47 [89.97-90.97]
ZAF	82.27	77.95	78.63	79.02 [78.25-79.79]	76.98 [76.21-77.74]

Table A 4.1 2: Nowcasts by country, economy wide, domestic services value-added shares of exports

Country	Average 1995-2010	Average 2011-2019	2020	2021	2022
AUS	41.65	42.72	38.65	41.03 [39.16-42.89]	39.69 [37.83-41.55]
AUT	40.65	39.54	38.30	38.85 [38.22-39.48]	37.69 [37.06-38.32]
BEL	40.17	43.85	44.45	44.31 [43.43-45.18]	43.37 [42.49-44.24]
BRA	38.62	40.51	39.27	38.70 [37.22-40.18]	38.27 [36.79-39.75]
CAN	33.04	39.05	41.14	40.19 [39.11-41.26]	39.14 [38.07-40.21]
CHE	47.81	47.77	46.11	46.36 [45.23-47.49]	45.84 [44.71-46.97]
CHN	26.18	29.83	32.67	32.12 [31.37-32.86]	32.34 [31.59-33.08]
COL	28.68	28.43	34.79	34.19 [32.29-36.09]	32.71 [30.81-34.61]
CZE	33.42	26.86	27.96	27.35 [26.74-27.96]	26.72 [26.11-27.33]

DEU	40.48	39.09	41.98	40.63 [39.92-41.33]	40.03 [39.33-40.74]
DNK	41.55	42.48	41.84	42.40 [41.37-43.43]	42.69 [41.66-43.72]
ESP	44.36	48.08	46.87	50.65 [49.88-51.42]	49.36 [48.59-50.13]
EST	40.80	38.81	39.49	43.54 [42.39-44.69]	42.80 [41.65-43.95]
FIN	29.31	36.00	36.55	36.78 [35.93-37.64]	35.84 [34.99-36.69]
FRA	47.40	51.45	51.39	51.17 [50.50-51.83]	51.18 [50.51-51.84]
GBR	54.09	60.40	62.18	63.96 [62.83-65.08]	62.55 [61.43-63.68]
GRC	54.93	51.19	43.29	48.52 [46.53-50.51]	47.39 [45.40-49.38]
HUN	28.17	26.34	25.82	27.43 [26.84-28.02]	27.50 [26.91-28.09]
IDN	26.65	26.78	29.83	31.27 [30.08-32.46]	29.96 [28.77-31.16]
IND	38.53	42.32	47.81	47.23 [46.35-48.11]	47.43 [46.56-48.31]
IRL	35.42	31.85	32.31	33.59 [30.92-36.27]	33.66 [30.99-36.34]
ISL	37.22	42.16	41.33	48.64 [46.86-50.42]	47.41 [45.63-49.19]
ISR	44.81	52.84	59.33	59.53 [58.72-60.34]	60.14 [59.33-60.95]
ITA	44.83	43.94	43.35	44.47 [43.88-45.05]	43.84 [43.26-44.43]
JPN	41.99	43.69	43.92	44.12 [43.49-44.74]	43.08 [42.45-43.70]
KOR	26.92	24.27	28.66	26.76 [26.06-27.45]	26.55 [25.86-27.25]
LTU	41.37	44.51	44.51	44.33 [43.41-45.25]	43.20 [42.28-44.12]
LUX	38.05	33.85	31.61	31.09 [29.67-32.52]	31.16 [29.74-32.59]
LVA	51.74	50.65	49.23	50.65 [49.57-51.72]	49.86 [48.78-50.93]
MEX	30.16	30.25	30.36	30.78 [29.71-31.84]	30.04 [28.97-31.10]
NLD	46.02	46.62	48.43	46.98 [46.20-47.75]	45.43 [44.66-46.21]
NOR	27.59	27.38	28.75	32.85 [31.47-34.24]	31.54 [30.15-32.92]
NZL	45.82	49.70	47.92	52.57 [51.45-53.68]	52.36 [51.24-53.48]
POL	40.10	39.74	39.88	40.30 [39.35-41.25]	39.45 [38.50-40.40]
PRT	41.17	43.50	40.41	44.02 [43.28-44.75]	41.56 [40.83-42.30]
SVK	29.83	26.35	27.45	26.56 [25.88-27.24]	25.47 [24.79-26.15]
SVN	32.12	33.98	33.57	34.74 [34.01-35.47]	33.38 [32.66-34.11]
SWE	36.86	44.73	46.16	45.91 [44.98-46.84]	44.35 [43.42-45.28]
TUR	44.13	41.89	38.84	43.60 [42.53-44.66]	42.80 [41.73-43.86]
USA	55.46	60.09	60.31	61.38 [60.80-61.96]	61.18 [60.60-61.75]
ZAF	37.27	37.07	35.25	35.12 [34.38-35.87]	36.02 [35.28-36.76]

Table A 4.1 3 Nowcasts by country, economy wide, foreign services value-added share of exports

Country	Average 1995-2010	Average 2011-2019	2020	2021	2022
AUS	5.60	5.44	4.63	4.96 [4.54- 5.38]	4.84 [4.43- 5.26]
AUT	12.22	16.19	16.80	17.76 [17.33-18.19]	18.86 [18.43-19.29]
BEL	17.82	21.25	21.91	21.98 [21.55-22.42]	22.70 [22.27-23.13]
BRA	4.86	5.80	7.12	6.94 [6.53- 7.35]	7.28 [6.87- 7.69]
CAN	11.00	11.77	12.61	12.15 [11.74-12.57]	12.69 [12.28-13.11]
CHE	11.85	13.66	13.83	14.30 [13.92-14.68]	14.23 [13.86-14.61]
CHN	8.09	6.75	6.08	5.82 [5.48- 6.15]	5.73 [5.39- 6.06]
COL	5.78	5.36	6.00	6.18 [5.81- 6.55]	6.63 [6.26- 7.00]
CZE	16.33	20.21	18.31	18.83 [18.31-19.35]	19.92 [19.40-20.44]
DEU	9.09	11.97	11.73	12.12 [11.89-12.34]	13.36 [13.13-13.58]
DNK	17.54	22.03	22.38	22.86 [22.35-23.37]	23.39 [22.88-23.90]
ESP	10.02	10.50	10.66	9.92 [9.60-10.25]	11.21 [10.88-11.53]
EST	18.31	20.93	21.16	20.81 [20.19-21.42]	21.95 [21.34-22.57]
FIN	12.63	15.99	16.43	16.62 [16.29-16.94]	17.58 [17.25-17.90]

504	0.05	40.00	10.00	44.00.144.00.44.001	40.04.740.00.40.001
FRA	9.25	12.08	12.38	11.68 [11.39-11.98]	12.91 [12.62-13.20]
GBR	7.67	9.12	9.65	10.06 [9.82-10.31]	10.22 [9.98-10.46]
GRC	9.42	13.94	18.10	18.01 [16.94-19.09]	19.03 [17.96-20.10]
HUN	19.98	22.80	22.72	22.00 [21.54-22.45]	23.35 [22.90-23.81]
IDN	6.66	5.57	5.02	4.92 [4.57- 5.27]	5.14 [4.79- 5.49]
IND	5.85	6.73	6.63	6.15 [5.75- 6.55]	7.00 [6.60- 7.39]
IRL	28.37	36.43	36.62	40.72 [38.47-42.97]	41.82 [39.57-44.07]
ISL	13.44	16.99	15.58	17.11 [16.64-17.58]	18.55 [18.08-19.02]
ISR	11.08	10.16	8.13	9.39 [8.96- 9.82]	10.51 [10.09-10.94]
ITA	8.72	11.09	10.61	10.37 [10.00-10.74]	11.89 [11.53-12.26]
JPN	3.38	5.25	5.63	5.48 [5.29- 5.66]	6.79 [6.61- 6.97]
KOR	11.69	12.83	12.02	12.46 [12.14-12.77]	13.46 [13.15-13.78]
LTU	12.50	14.55	14.55	15.90 [15.48-16.32]	17.27 [16.85-17.69]
LUX	45.73	55.50	59.19	60.77 [59.83-61.70]	60.93 [59.99-61.87]
LVA	12.16	13.33	12.96	14.08 [13.73-14.42]	15.35 [15.00-15.69]
MEX	14.68	15.47	15.31	15.86 [15.40-16.33]	16.34 [15.87-16.81]
NLD	13.22	18.43	18.30	18.86 [18.27-19.44]	20.35 [19.76-20.94]
NOR	8.51	8.59	9.29	10.02 [9.63-10.41]	10.02 [9.63-10.41]
NZL	8.08	7.07	6.09	6.83 [6.51- 7.15]	7.86 [7.54- 8.18]
POL	11.51	14.06	14.55	14.66 [14.35-14.97]	14.82 [14.51-15.13]
PRT	11.95	14.32	14.85	15.26 [14.99-15.53]	16.60 [16.33-16.87]
SVK	17.53	20.74	20.90	20.89 [20.53-21.25]	22.04 [21.68-22.40]
SVN	15.18	17.47	17.10	17.55 [17.13-17.97]	18.98 [18.56-19.40]
SWE	12.83	13.45	13.89	14.48 [14.10-14.87]	16.09 [15.71-16.47]
TUR	6.56	8.53	9.42	9.06 [8.66- 9.46]	9.22 [8.82- 9.62]
USA	3.95	4.25	3.61	3.64 [3.47- 3.81]	3.88 [3.72- 4.05]
ZAF	7.34	8.68	8.42	8.05 [7.71- 8.39]	9.76 [9.42-10.09]

Table A 4.1 4 Nowcasts by country, economy wide, share of domestic value added embodied in foreign final demand

Country	Average 1995-2010	Average 2011-2019	2020	2021	2022
AUS	17.91	19.04	21.18	19.11 [18.66-19.56]	20.73 [20.28-21.18]
AUT	31.15	34.66	33.23	34.15 [33.91-34.39]	37.74 [37.50-37.97]
BEL	37.51	37.63	38.57	39.39 [38.76-40.03]	39.51 [38.87-40.15]
BRA	10.50	11.53	15.20	16.11 [15.46-16.77]	16.73 [16.07-17.38]
CAN	27.49	22.94	21.36	23.04 [22.55-23.53]	25.30 [24.81-25.80]
CHE	33.00	37.91	36.66	39.19 [38.50-39.87]	40.24 [39.56-40.92]
CHN	19.67	15.85	13.99	15.23 [14.60-15.87]	16.91 [16.28-17.54]
COL	14.61	15.43	12.26	12.50 [11.73-13.27]	13.94 [13.17-14.71]
CZE	33.31	39.52	39.13	37.24 [36.46-38.01]	37.70 [36.93-38.48]
DEU	23.28	30.03	27.87	30.39 [30.03-30.74]	30.88 [30.53-31.23]
DNK	29.74	32.54	32.79	35.47 [35.19-35.74]	40.51 [40.24-40.79]
ESP	19.56	24.54	22.31	25.96 [25.59-26.32]	29.25 [28.89-29.62]
EST	38.35	43.94	39.76	45.47 [44.63-46.30]	47.62 [46.78-48.46]
FIN	29.73	26.00	24.96	26.57 [26.04-27.10]	29.05 [28.52-29.58]
FRA	20.52	21.54	20.28	21.60 [21.31-21.88]	22.72 [22.43-23.00]
GBR	19.34	20.91	20.22	20.89 [20.56-21.21]	21.70 [21.37-22.03]
GRC	15.69	22.43	19.64	24.21 [23.60-24.81]	25.40 [24.79-26.00]
HUN	36.82	44.29	42.04	44.12 [43.49-44.76]	44.24 [43.61-44.88]

IDN	25.09	19.27	15.39	15.25 [14.54-15.96]	17.18 [16.47-17.90]
IND	14.20	17.03	15.87	16.76 [16.19-17.34]	18.38 [17.80-18.96]
IRL	45.78	59.07	61.65	59.91 [56.84-62.98]	61.60 [58.53-64.68]
ISL	27.08	34.41	23.96	29.67 [28.67-30.66]	34.24 [33.25-35.23]
ISR	24.49	25.47	23.82	25.24 [24.74-25.75]	27.14 [26.64-27.65]
ITA	20.41	22.49	23.28	25.29 [24.91-25.67]	28.21 [27.83-28.59]
JPN	10.65	14.17	13.73	15.52 [15.11-15.92]	17.55 [17.15-17.96]
KOR	24.23	29.52	25.72	26.15 [25.35-26.95]	27.31 [26.51-28.10]
LTU	30.37	42.75	43.36	44.25 [42.36-46.15]	46.00 [44.10-47.89]
LUX	61.35	63.43	63.06	63.71 [62.98-64.44]	63.83 [63.10-64.56]
LVA	27.09	34.77	33.96	35.34 [34.53-36.14]	36.58 [35.78-37.38]
MEX	17.39	22.94	26.71	28.69 [28.19-29.19]	30.20 [29.69-30.70]
NLD	33.76	36.78	36.95	37.76 [36.59-38.93]	38.73 [37.56-39.90]
NOR	35.76	32.86	26.71	31.06 [30.02-32.10]	36.93 [35.89-37.97]
NZL	25.24	23.71	19.11	19.33 [18.74-19.92]	20.29 [19.71-20.88]
POL	23.74	33.26	37.05	39.32 [38.86-39.78]	40.61 [40.16-41.07]
PRT	21.06	27.97	25.73	30.93 [30.38-31.48]	35.32 [34.77-35.87]
SVK	36.93	41.43	38.71	39.98 [38.97-41.00]	41.97 [40.95-42.98]
SVN	36.22	43.40	43.20	45.33 [44.18-46.49]	47.94 [46.78-49.09]
SWE	31.21	30.07	29.97	32.19 [31.65-32.74]	35.84 [35.30-36.38]
TUR	18.44	19.74	21.85	26.25 [25.23-27.28]	27.69 [26.67-28.71]
USA	8.24	9.72	7.84	8.50 [8.27- 8.74]	9.10 [8.86- 9.33]
ZAF	21.12	21.98	22.22	25.25 [24.65-25.84]	27.32 [26.72-27.92]