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Nowcasting ASEAN+3 Goods Exports: Bridge and Machine Learning Models and Shipping "Big Data"

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Abstract

International merchandise trade statistics are closely monitored in the ASEAN+3 due to the importance of trade on the region's economies. However, statistics are typically released with a lag of at least one month, creating an information gap for real-time policy decisions. To address this challenge, we present two frameworks for nowcasting export growth across the 14 ASEAN+3 economies. Firstly, bridge models integrate two indicators derived from ship traffic with a few financial variables, estimated via linear regression and machine learning (ML) techniques. Secondly, large-scale ML models address the risk of overlooking critical predictors with the use of over 100 external and domestic variables. While large-scale ML models generally show greater predictive power, this difference is not significant across all economies. Indonesia, Japan, Lao PDR, Malaysia, and Singapore clearly benefit from the larger ML models, while the simpler bridge models suffice for others. The large-scale ML models exhibit reasonable accuracy up to three months ahead. Their wide range of predictors can also compensate for the absence of ship traffic data in most cases.

JEL classification: C43, E01, E61, O40, O53, P52

Keywords: nowcasting, forecasting, exports, trade, alternative indicators, AIS, machine learning, bridge equations

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[2] The authors would like to thank Jorge Chan-Lau, Li Lian Ong, and Rui (Aruhan) Shi for useful comments. All remaining mistakes are the responsibility of the authors.

[3] For brevity, Brunei Darussalam is referred to as "Brunei" and Hong Kong, China is referred to as "Hong Kong" in the text.

Abbreviations

AIS	automated identification system
ADB	Asian Development Bank
ADF	augmented Dickey–Fuller
ALASSO	adaptive LASSO
AMRO	ASEAN+3 Macroeconomic Research Office
ASEAN	Association of Southeast Asian Nations (Brunei, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam)
ASEAN+3	ASEAN plus China (including Hong Kong), Japan, Korea
COVID-19	Coronavirus disease 2019
DFM	dynamic factor model
DM	Diebold-Mariano
GDP	gross domestic product
IMF	International Monetary Fund
IMO	International Maritime Organization
LASSO	least absolute shrinkage and selection operator
LCY	local currency
ML	machine learning
OLS	ordinary least squares
RBF	radial basis function
RMSE	root mean squared error
SVM	support vector machine
UNCTAD	United Nations Conference on Trade and Development
UNGP	UN Global Platform
VAR	vector autoregression

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"The goal is to turn data into information, and information into insight."

~ Carly Fiorina, former Chairman and Chief Executive Officer
Hewlett-Packard Company

I. Introduction

Accurate, timely, and reliable economic statistics are crucial for effective policymaking. They enable decision-makers to make informed policy choices in response to prevailing economic conditions. The COVID-19 crisis, with its rapid and unprecedented developments, particularly underscored the value of accessible real-time, high-quality information. While the pandemic itself has subsided, the global economy remains fraught with multiple sources of volatility. Navigating the risks from geopolitical instability, tighter financial conditions, and climate change, among others, continues to highlight the need for more timely indicators than provided by official economic statistics.

International merchandise trade statistics are among the most widely monitored economic indicators globally, particularly in Asia given the region's prominent role in global value chains (GVC) and the significance of trade to its economies. The expansion of international trade since the 1990s has generally fostered economic prosperity through productivity growth and job creation especially in sectors and countries engaged in GVCs (World Bank 2023). The ASEAN+3 region accounts for nearly a quarter of global GVC activity (AMRO 2021).[4] The economic contribution of international merchandise exports varies across ASEAN+3 economies, ranging from 10 percent of GDP for the Philippines to as high as 157 percent in the case of Hong Kong, China (hereafter "Hong Kong").

Despite their importance, official trade statistics are often released with a lag. In the ASEAN+3, monthly trade statistics are mostly available between one to six weeks after the end of the reference month (del Rosario and Quách 2020). The lack of timely information on trade poses a challenge for policymakers, businesses, and analysts who rely on timely and accurate trade data for decision-making and analysis. As such, there is a need to develop nowcasting models that can provide real-time or near-real-time estimates of trade activity.

Nowcasting, which is a blend of "now" and "forecasting," refers to the prediction of the recent past, the present, and very near future of an indicator of interest. British meteorologist Keith Browning first defined nowcasting in 1981 as "the description of the current state of the weather in detail and the prediction of changes that can be expected on a timescale of a few hours" (WMO 2017). The practice was initially adopted by the economics profession to estimate current-quarter real gross domestic product (GDP) growth using simple small-scale models called "bridge equations" that are typically combined with qualitative judgement.[5]

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4 ASEAN+3 comprises China; Hong Kong, China (hereafter, Hong Kong); Japan; Korea; Indonesia; Malaysia; Philippines; Singapore; Thailand; Brunei Darussalam (hereafter, Brunei); Cambodia; Lao PDR; Myanmar; and Vietnam.

5 Bridge equations refer to simple linear models that "bridge" high-frequency data, such as monthly or daily economic and financial indicators, with lower-frequency target variables like GDP, which is available on a

Economic nowcasting was later formalized by the seminal paper of Giannone, Reichlin, and Small (2008) with the introduction of a single statistical framework for updating GDP nowcasts as monthly data are released throughout the quarter.

In the practice of trade nowcasting, two approaches have dominated literature in the recent decade. First is the exploration of an alternative data source—geospatial ship traffic data—as a viable indicator of trade activity in real time. Indeed, this area has grown in popularity since the leading works of Adland, Jia, and Strandener (2017), Arslanalp, Marini, and Tumbarello (2019), Cerdeiro and others (2020), and Arslanalp, Koepke, and Verschuur (2021). Second is the use of econometric techniques and machine learning (ML) approaches to systematically extract relevant information afforded by large sets of traditional economic and financial indicators, as in Hopp (2021) and Chinn, Meunier, and Stumpner (2023).

Our study adds to the trade nowcasting literature by exploring two frameworks—bridge and large-scale models—to nowcast merchandise export growth for each of the 14 ASEAN+3 economies. We introduce parsimonious bridge models, which rely on a small set of explanatory variables estimated through linear and nonlinear techniques. The bridge models are an extension of del Rosario and Quách (2020) in which near real-time indicators of ASEAN+3 exports are derived from ship traffic "big data." In particular, the bridge models incorporate an explicit model for export price to account for the lack of pricing information from the ship traffic data. Furthermore, to mitigate the risk of variable omission and cover a wider range of countries without ship traffic data, the bridge models are complemented with large-scale models estimated through various ML techniques.

Our findings indicate that the two frameworks offer reasonable nowcasting capabilities for exports of 10 of the 14 ASEAN+3 economies. Large-scale ML models generally yield greater predictive power, leveraging on their extensive array of predictors to compensate for the absence of ship traffic data in most economy cases. These models also exhibit reasonable accuracy in predicting export growth up to three months ahead. Specifically, Indonesia, Japan, Lao PDR, Malaysia, and Singapore benefit significantly from the enhanced predictive abilities of the large-scale ML models. However, the simpler bridge models prove equally effective as the larger ML models in nowcasting exports of Brunei, Hong Kong, Korea, Myanmar, and Thailand. It is worth noting that both models demonstrate limited power in explaining export growth for Cambodia, China, the Philippines, and Vietnam.

The remainder of this paper is structured as follows: Section II provides a review of the literature in trade nowcasting. Section III describes the data used in the study. Section IV presents the nowcasting models, and Section V discusses the modelling results. Section VI concludes with a summary and set of lessons from our exercise.

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quarterly basis. In statistical modelling, this mixed-frequency problem is addressed by temporally aggregating the predictors to the lower frequency. Cascaldi-Garcia, Luciani, and Madugno (2023) provides a description of the various approaches in economic nowcasting.

II. Literature Review

Economic nowcasting models have evolved from using a limited number of indicators to leveraging vast amounts of data. Traditionally, modelling techniques have likewise ranged from employing bridge equations to factor models and vector autoregressions (VAR) that can handle larger datasets.[6] Recently, ML algorithms have emerged as powerful alternatives to time-series regression methods. A similar trend can be observed with trade nowcasting, with the past decade dominated by the development of alternative indicators from ship traffic data and the use of factor-based and ML methods on extensive datasets.

Big data on ship traffic have become a prominent source for tracking trade activity in real time. Utilizing ship traffic data as an alternative indicator for trade is logical, given that the bulk of international merchandise trade is transported by sea (UNCTAD 2018). The data are collected from the Automatic Identification System (AIS)—a vessel signaling system that is meant to prevent ship collisions and facilitate efficient traffic management at sea (Arslanalp, Marini and Tumbarello 2019).[7] AIS signals contain ***dynamic information*** of a ship's course, speed, and position that are automatically transmitted every 2–12 seconds; and ***static information*** about the ship's characteristics that are manually provided by the ship's crew and transmitted every six minutes (Svanberg and others 2019).[8] Related vessel information on port arrival and departure are useful AIS signals for deriving alternative trade indicators.

The integration of AIS data into trade analysis started with a case study on crude oil exports. Adland, Jia, and Strandener (2017) derives crude oil export volume indicators from AIS, which are then compared with official customs data in the crude oil market. The authors filter the AIS dataset to extract crude oil tankers undertaking international voyages, which are then mapped with cargo information from port agent reports to derive export shipment volumes.

Subsequent studies focus on aggregate trade activity both globally and across economies. Arslanalp, Marini, and Tumbarello (2019) introduces a filtering process from port-specific AIS data to derive trade-related indicators. The two AIS-derived indicators are "cargo number"—a count of the number of ships visiting ports—and "cargo load"—a cargo volume measure of the visiting ships. Using Malta as a test case, the AIS-derived indicators are found to track official trade (sum of exports and imports) statistics reasonably well, and thus, can improve the latter's timeliness. Adopting a similar approach, del Rosario and Quách (2020) derives the two AIS-based indicators for tracking goods exports of ASEAN+3 economies.

Recent developments in the processing and availability of AIS data have introduced an alternative source to the proprietary AIS data used in earlier studies. Cerdeiro and others (2020) employs ML algorithms on raw AIS signals to identify port boundaries and generate their own port call dataset. They then derive global export and import volume measures, which exhibit a 40 percent correlation with the growth rate of official trade statistics. This study has contributed to greater usage of AIS data from the United Nations Global Platform

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[6] Various approaches to economic nowcasting have been reviewed in Bańbura and others (2013), Bok and others (2017), Dauphin and others (2022), and Cascaldi-Garcia, Luciani, and Madugno (2023).

[7] Commercial ships have been regulated by the International Maritime Organization to be equipped with an AIS transponder since 2004.

[8] Voyage-related information, such as a ship's draught, destination, and estimated time of arrival, are also provided by the crew and transmitted every six minutes.

(UNGP) by the global statistical community.[9] The Asian Development Bank (ADB), for example, has demonstrated the use of the same cluster-based ML algorithm as Cerdeiro and others (2020) on the AIS data provided by UNGP (ADB 2023).

Succeeding studies underscore the value of integrating AIS signals with other data sources to enhance the accuracy of estimates. For example:

- Arslanalp, Koepke, and Verschuur (2021) constructs daily measures of import volume for Pacific Island countries from AIS data that are overlaid with detailed information on shipping liner schedules to overcome challenges in the measurement of cargo volume. In addition, they use geospatial location data from the US National Geospatial-Intelligence Agency to define port boundaries from the raw AIS data.

- Furukawa and Hisano (2022) also combines AIS and information on port characteristics to construct export volume indicators for Japan. They show that estimations at the port level using ML techniques, such as kernel and deep learning, improve the accuracy of the AIS-derived indicators in making predictions.

- Nickelson, Nooraeni, and Efliza (2022) derives several export and import-related indicators for Indonesia from a combination of AIS and geospatial port data. The indicators are introduced as predictors in nowcasting Indonesia's export and import statistics using autoregressive integrated moving average (ARIMA) and artificial neural network (ANN). They conclude that ANN is superior at predicting export value, export volume, and import volume, while ARIMA works better at predicting Indonesia's import value statistics.

- Ueda, Hirose, and Izumi (2023) utilizes data from AIS and foot traffic at assembly plants to nowcast export volume of major Japanese automakers. They show that the combination of foot traffic data with AIS enhances the accuracy of timely export volume estimates.

Various national statistical offices are already using AIS data to improve the timeliness and sometimes, quality of current trade statistics. Among them, a number of offices primarily in Europe, along with Indonesia within the ASEAN+3, are part of the UN's AIS Task Team that is tasked to demonstrate the application of AIS data across various purposes (UN 2024). Aside from trade nowcasting, AIS data have proven valuable in tracking global supply chain disruptions (del Rosario and Quách 2021; del Rosario and others 2022) and the resumption of tourism flows post-pandemic (Choo, del Rosario, and Quách 2021). Additionally, AIS data can be used to monitor shifts in trade patterns due to geopolitical tensions and estimate carbon dioxide emissions within the context of global efforts to fight climate change.

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[9] The UNGP offers access to novel data sources and methodologies to help countries measure their Sustainable Development Goals (SDGs) and deliver on the 2030 Sustainable Development Agenda.

Another approach to trade nowcasting involves the use of an extensive set of indicators estimated through either traditional econometric methods or ML techniques. Among existing studies:

- Hopp (2021) shows that complex modeling approaches like deep learning can serve as competitive alternatives to traditional techniques. Utilizing 116 economic indicators of mixed monthly and quarterly frequency, he finds that long short-term memory networks (LSTM), a type of deep learning method, outperform dynamic factor models (DFMs) in nowcasting global trade indicators.

- Chinn, Meunier, and Stumpner (2023) demonstrates that prior data selection and factor extraction improve the accuracy of ML-based predictions of world trade volumes. Starting with 536 indicators, pre-selection techniques bring the number of regressors down to within 5–70, with accuracy gains of 10–15 percent relative to the no pre-selection benchmark. Boivin and Ng (2006) and Bai and Ng (2008) have likewise shown that fewer but informative predictors work better with factor models.

Two other references are relevant to our study. Kucharčuková and Brůha (2016) explores various regression-based models to predict export values and price indices of the Czech Republic across different time horizons. Mourougane and others (2023) demonstrates the use of ML methods to improve the timeliness of trade-in-value added indicators, which are often released with two-to-three-year delays.

III. Data Description

This study utilizes AIS-based indicators of export activity. First is ***ship count***—a daily measure of the total number of international ship voyages recorded across all ports in an economy. Second is ***cargo tonnage***—an estimate of overseas-bound cargo volume imputed from the ship's draught (the depth of a ship in water) and deadweight tonnage (the ship's maximum carrying capacity). These indicators are derived after processing port call data. Data processing primarily entails filtering out ships not involved in international trade, such as passenger ships and cargo vessels on domestic voyages. The derived indicators are validated against official export value and volume statistics for all ASEAN+3 economies, with the exception of Lao PDR, a landlocked country without seaports for AIS signal collection.

The two economy-specific AIS indicators are made available across commercial vessel types—containers, general cargo and bulk carriers, and oil/gas tankers. The indicators are originally available in daily frequency, but they have been aggregated to monthly in order to align with the target variables—export statistics—that are available in monthly frequency across most ASEAN+3 economies. The AIS indicators start in 2019 due to data quality issues in prior periods as noted in del Rosario and Quách (2020).

Another AIS-derived indicator—vessel turnaround time at ports—serves as an explanatory variable representing supply chain disruptions. This indicator measures the duration of vessels' stay at ports within national jurisdictions. Following the methodology of del Rosario and Quách (2021), it is derived from the average of the daily median stay of vessels at ports, by vessel type and size, from the ship count data discussed above. The derived global turnaround time series is aligned with movements in global shipping freight rates, which surged during the height of the global supply chain disruptions in 2021–22.

Conventional economic and financial variables are also employed in this study, in addition to the AIS-derived indicators. The target variables are the export statistics released by national authorities, or the IMF Direction of Trade Statistics if data from national authorities are not available or not as timely as the IMF's. The list of explanatory variables differs depending on the model and is summarized in Table 1. The variables are either available in daily, weekly, or monthly frequency, but aggregated to monthly frequency for estimation purposes. Variable series are collected starting from January 2000, depending on availability, mostly from national authorities and international organizations via Haver Analytics (see Appendix Tables 1 and 2 for a complete list of the variables).

The predictor set also comprises domestic or economy-specific indicators. These include bilateral exchange rates, consumer and producer prices, and lagged values of merchandise export and import statistics. Imports could be a leading indicator for exports, especially if the import intensity of the latter is high. Changes in the exchange rate and producer prices could have implications for domestic production, including on export-oriented industries. Consumer prices serve as proxy for producer prices as the latter is not available in all ASEAN+3 economies.

Table 1. Target and Explanatory Variables by Model Type

<table>
<tr><th>Target Variable</th><th colspan="2">Explanatory Variables</th></tr>
<tr><th rowspan="2">Model Type</th><th colspan="2">Bridge Models</th></tr>
<tr><th>Export Volume Model</th><th>Export Unit Price Model</th></tr>
<tr><td>Export volume
(Percent year-on-year)</td><td>*OLS-based models:*
• AIS-derived indicator: **Ship count** or **cargo tonnage** (aggregated across vessel types)

OLS-ML-based models:
• Ship count for each vessel type (container, general cargo, bulk carrier, tanker)
• Cargo tonnage for each vessel type
• Vessel turnaround time at ports
• Lagged values of export volume (target variable)</td><td></td></tr>
<tr><td>Export unit price
(Percent year-on-year)</td><td></td><td>• Crude oil price (global)
• Shipping freight rate (global)
• Local currency against the US dollar</td></tr>
<tr><td colspan="3">*The above explanatory variables are also used in the ML-based models below; more information is available in Appendix Tables 1 and 2.*</td></tr>
<tr><th>Model Type</th><th colspan="2">Machine Learning Models</th></tr>
<tr><td>Export value
(Percent year-on-year)</td><td colspan="2">• 111 leading and coincident indicators of external demand, including economic and financial indicators of the world, US, Europe, Asia, China, and Japan, as well as exports of Korea and Taiwan Province of China—known bellwethers of global trade.
• Domestic or economy-specific variables, including AIS-derived indicators.</td></tr>
<tr><td colspan="3">*All variables are transformed in percent year-on-year, unless otherwise stated in Appendix Tables 1 to 3.*</td></tr>
</table>

Source: AMRO staff illustration.
Note: OLS = ordinary least squares.

All variables are transformed to ensure stationarity as much as possible. Most variables are transformed in year-on-year growth rates, unless stated otherwise in Appendix Tables 1 to 3. Stationarity assessments conducted via the augmented Dickey–Fuller (ADF) test indicate that the transformed variables with a long time series tend to be stationary, while some variables with shorter time series do not exhibit stationarity.

IV. Methodology

This section is divided into two parts. The first part discusses the parsimonious bridge models, which rely on a handful of explanatory variables that have been selected based on economic intuition and data timeliness. The bridge models are estimated in two ways: ordinary least squares (OLS) regression and a blend of OLS and ML techniques. The second part of this section presents an alternative large-scale nowcasting model that is estimated using ML techniques.

A. Bridge Models

OLS Estimations

The OLS-based bridge models present a simple and interpretable approach to export nowcasting. While the primary goal is to nowcast the growth rate of merchandise exports, the framework also enables the timely prediction of the components—unit price and volume decompositions—where data availability allows. Thus, the framework not only provides headline findings but also granular insights. The OLS-based bridge models are estimated for nine of the 14 ASEAN+3 economies, namely: China, Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, and Thailand. Estimates of the unit price and volume are then combined for each economy to derive an estimate for export value. As for the remaining ASEAN+3 economies without price-volume decompositions, export value is directly estimated using a similar approach presented below.

The ***export unit price*** model relies on a select few explanatory variables chosen by the authors based on their ability to provide timely indications of changes in the export price. As the target variable (unit price) is often in monthly frequency released with a delay of one to two months, the choice of explanatory variables is confined to higher-frequency variables—those in daily or weekly frequencies—that are released on a timely basis. An explicit model for the unit price of exports presents a thorough approach to export nowcasting, especially when changes in export growth are driven by swings in the unit price rather than volume.

The model for the unit price of exports P_{it} for a given economy i and time t is represented by the following equation:

$$\Delta \ln P_{it} = f(\Delta \ln Crude_t, \Delta \ln Shipping_t, \Delta \ln FX_{it}), \qquad (1)$$

where,

- $Crude_t$ and $Shipping_t$ refer to the global crude oil price and shipping freight rate, in US dollars, respectively, at time t.

- FX_{it} is the bilateral exchange rate of the local currency against the US dollar.

- Δ refers to the difference of a variable between two periods, such that $\Delta \ln P_{it} = \ln P_{it} - \ln P_{it-12}$, where $\ln$ refers to the natural logarithm.

Equation (1) bridges the target variable of monthly frequency to the explanatory variables that are available in weekly ($Shipping_t$) or daily ($Crude_t$ and FX_{it}) frequencies.

Each of the three explanatory variables can reasonably influence export prices. $Crude_t$ serves as a proxy for global demand—export prices typically rise as global demand strengthens. FX_{it} changes affect export prices via changes in the cost of imports. For instance, a local currency depreciation increases the cost of imported goods, potentially raising export prices especially for sectors that are import-intensive. $Shipping_t$ represents logistics costs—an increase in freight rates could contribute to higher export prices.

The ***export volume*** model is solely based on the AIS-derived indicators. These indicators have been shown by del Rosario and Quách (2020) to align with the export growth rates of ASEAN+3 economies. Specifically, the annual growth rate of export volume, $\Delta \ln Q_{it}$, for a given economy i and time t is modelled as follows:

$$\Delta \ln Q_{it} = f(\Delta \ln AIS_{it}), \tag{2}$$

where AIS represents the AIS-based indicator—cargo tonnage or ship count. Cargo tonnage, a measure of volume, generally serves as a good proxy for official export volume, except in cases where the bulk of exports are transported by land or air rather than sea. To address potential measurement errors, an alternative AIS-based indicator, ship count, is considered. While ship count is a simplistic measure, an increase in ship traffic or the number of international voyages over a certain period can also be indicative of a rise in international cargo shipments. The AIS indicators are available on a daily basis and can thus provide timely estimates of the export volume.

The export unit price and volume models in Equations (1) and (2), respectively are estimated using OLS regression. The export price model utilizes data from January 2019–December 2023.[10] The volume model covers a shorter sample period, January 2020–December 2023, due to the shorter range of the AIS indicators. As mentioned above, the exercise is limited to ASEAN+3 economies with unit price-volume decompositions of goods exports that are available in monthly frequency, particularly referring to China, Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, and Thailand.

Estimates for export value are derived from bridging the export price and volume models. That is, the growth rate of export value $\Delta \ln V_{it}^{OLS}$ is estimated by the following equation:

$$\Delta \ln V_{it}^{OLS} = \Delta \ln P_{it}^{OLS} + \Delta \ln Q_{it}^{OLS}, \tag{3}$$

where, $\Delta \ln P_{it}^{OLS}$ and $\Delta \ln Q_{it}^{OLS}$ refer to the estimates of unit price and volume, respectively, in year-on-year growth rates. Equation (3) can be derived from the first difference of the logarithmic transformation of $P_{it} \times Q_{it} = V_{it}$, where V_{it} is the (US dollar) value of exports at

[10] Expanding the sample size to January 2012–December 2023 generates broadly similar regression results. A shorter sample size is selected to align with estimations of the volume model.

time t for a given economy i. Equation (3) indicates equal importance for the two terms, but in practice, it is estimated using OLS to minimize estimation errors.

For economies without price-volume decompositions, export value growth is directly estimated using OLS after combining the predictors in Equations (1) and (2) into a single equation. This approach applies to Brunei, Cambodia, Myanmar, and Vietnam, where the export value model is estimated using January 2020–December 2023 data. An exception is Myanmar where estimation ends in November 2023.

OLS-ML Estimations

The ***export volume*** model is estimated alternatively via ML techniques to explore nonlinearities in the data. As ML models can handle a greater number of explanatory variables compared to OLS models, Equation (2) above is modified to include more AIS-based indicators, as follows:

$$\Delta \ln Q_{it} = f\left(\Delta \ln CT_{it}^{x}, \Delta \ln SC_{it}^{x}, \Delta \ln VT_{it}, \Delta \ln Q_{it-\{1,2,\ldots,6\}}\right). \quad (4)$$

where,

- CT_{it}^{x} and SC_{it}^{x} refer to the two AIS indicators—cargo tonnage and ship count, respectively—for each vessel type x (containerships, general cargo/bulk carriers, and tankers), for a given economy i and time t.

- VT_{it} refers to the vessel turnaround time at ports, an AIS-based indicator for supply chain disruptions. Heightened global supply chain disruptions can restrict trade flows and weaken export activity.

- The annual growth rate of export volume, given by $\Delta \ln Q_{it}$, is defined as $\Delta \ln Q_{it} = \ln Q_{it} - \ln Q_{it-12}$, where $\ln$ refers to the natural logarithm. Lagged values of the dependent variable $\Delta \ln Q_{it}$ up to order six are added to the predictor set in an attempt to enhance the model's fit.

The explanatory variables undergo distinct transformations compared to the dependent variable. In particular, they are transformed to their monthly growth rates such that $\Delta \ln Z_{it} = \ln Z_{it} - \ln Z_{it-1}$, for $Z = CT^{x}$, SC^{x}, and VT. The choice of monthly over yearly transformation is done to minimize the loss in data points from the transformations. As such, the estimation of Equation (4) using ML techniques commences earlier than with OLS, from February 2019 to December 2023.

Similar to the previous section, an alternative estimate for export value is derived from combining the ML-estimated export volume and OLS-estimated export price models. This OLS-ML hybrid estimate of the annual growth rate of export value, signified by $\Delta \ln V_{it}^{OLS-ML}$, is summarized by the following equation:

$$\Delta \ln V_{it}^{OLS-ML} = \Delta \ln P_{it}^{OLS} + \Delta \ln Q_{it}^{ML}. \quad (5)$$

where $\Delta \ln P_{it}^{OLS}$ and $\Delta \ln Q_{it}^{ML}$ refer to the price and volume estimates, respectively. $\Delta \ln P_{it}^{OLS}$ is estimated via OLS from Equation (1) and $\Delta \ln Q_{it}^{ML}$ via ML techniques from Equation (4). As discussed previously, while Equation (5) above presents equal weights for the two terms, it is actually estimated via OLS to minimize errors in estimation.

As for economies without price-volume export decompositions, export value is estimated solely using ML techniques from the explanatory variables in Equations (1) and (4). The approach is presented as follows:

$$\Delta \ln V_{it} = f\begin{pmatrix} \Delta \ln Crude_{it}, \Delta \ln Shipping_{it}, \Delta \ln FX_{it}, \\ \Delta \ln CT_{it}^{x}, \Delta \ln SC_{it}^{x}, \Delta \ln VT_{it}, \ \Delta \ln Q_{it-\{1,2,\ldots,6\}} \end{pmatrix}. \tag{6}$$

Seven ML techniques are employed in the estimations and the models' predictive performance is assessed based on the root mean square error (RMSE). The seven techniques are regularized regressions—ridge, least absolute shrinkage and selection operator (LASSO), and elastic net; two kernel-based support vector machine (SVM) approaches; and tree-based techniques—random forest and extreme gradient boosting (XGBoost). Regularized regression techniques enhance the predictive power of linear regressions while mitigating overfitting. The rest are nonlinear methods of estimation. SVMs capture nonlinear relationships by transforming variables through the use of kernel functions.[11] Random forest and XGBoost are tree-based techniques that construct decision trees by splitting input variables into subsets corresponding to outcomes. Appendix II discusses these ML techniques in greater detail.

B. Large-Scale ML Models

Large-scale ML models provide several advantages over parsimonious bridge models. Drawing from a more comprehensive dataset, they mitigate the risk of overlooking critical predictors, an issue that may arise with the bridge models in the previous section. Moreover, ML techniques can handle nonlinearities in the data and thus, hold the potential to provide more accurate estimates compared to bridge models. Additionally, the large-scale ML models enable the nowcasting of a wider range of economies, including Lao PDR within the ASEAN+3, which lacks AIS-based ship traffic data due to its landlocked nature.

The large-scale ML models in this study express export value growth as a function of domestic and external variables and its past values. The general form of the model is presented as follows:

$$\Delta \ln V_{it} = f\left(Y_{it-\{0,1,\ldots,6\}}, Z_{t-\{0,1,\ldots,6\}}, \Delta \ln V_{it-\{1,2,\ldots,6\}}\right). \tag{7}$$

where $\Delta \ln V_{it}$ refers to the annual growth rate of export value for a given economy i at time t. Y_{it} represents the set of variables specific to economy i and Z_t refers to the set of external variables common across economies. In addition to their contemporaneous effect on $\Delta \ln V_{it}$, the economy-specific and external variables (enumerated in Appendix Tables 1 and 2) enter the models with a lag order of six to exploit the potential forward-looking characteristics of the variables. The presence of the contemporaneous terms (predictors with lag order of zero) depends on the availability of predictor data at time t.

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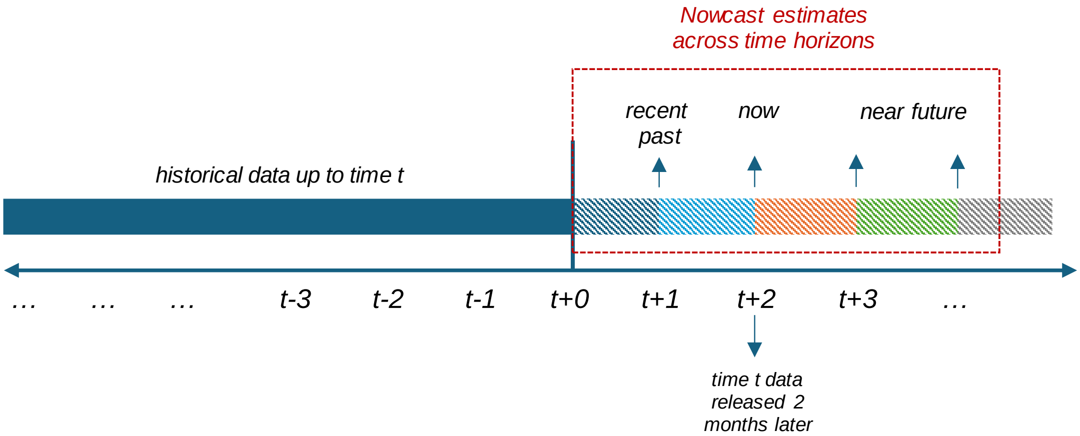
[11] Kernel functions are functions that map data into a higher-dimensional space, enabling the modelling of complex relationships.

The ML estimation of Equation (7) using data at time t provides a one month-ahead estimate of export value growth, which is effectively a "backcast." This one-month ahead estimate of export value growth, $\Delta \ln V_{it+1}$, is considered an advance estimate of the official export statistic at time t which, in most cases across economies in the study, will be released only at $t+2$. Likewise, in most cases, predictor data for $t+1$ are also released with a lag—that is, only at $t+2$. So if $t+2$ is the current month, nowcast $\Delta \ln V_{it+1}$ is actually an estimate for the preceding month—in other words, a "backcast" (Figure 1).

Figure 1. Periodic Illustration of Nowcasting Exercise



Source: AMRO staff visualization

To provide more timely estimates, we extend our analysis by estimating alternative versions of Equation (7) to predict the near future. Following Hopp (2021) and Chinn, Meunier, and Stumpner (2023), we map the same explanatory variables in Equation (7) with future values of $\Delta \ln V_i$ to assess the model's forecasting ability. We explore various time horizons, as shown below:

$$\Delta \ln V_{it+x} = f\left(Y_{it-\{0,1,\dots,6\}}, Z_{t-\{0,1,\dots,6\}}, \Delta \ln V_{it-\{1,2,\dots,6\}}\right), \text{ for } x = 2 \dots 7 \text{ months.} \qquad (8)$$

In summary, estimation of Equations (7) and (8) offers estimates of export value growth $\Delta \ln V_i$ across time horizons. That is, our nowcasting exercise enables the generation of estimates of the recent past $(t+1)$, the now $(t+2)$ and the near future $(t+3 \dots 7)$ (Figure 1). Equations (7) and (8) are estimated using the same seven ML approaches presented in the previous section: regularized regressions—ridge, LASSO, and elastic net; two kernel-based SVM approaches; random forest; and XGBoost. Appendix II discusses these ML techniques in greater detail. In addition, each of the ML models is subject to hyperparameter tuning as discussed in Appendix III.

Noise becomes a concern with a large number of predictors. To address this issue, we employ two variable selection techniques—LASSO and adaptive LASSO (ALASSO). Both techniques serve as a systematic, automated, and replicable variable filter compared to the discretionary selection of variables in the parsimonious bridge models (Appendix II). The predictive performance of the ML models, after being subject to LASSO and ALASSO selection techniques, is compared to the same models that utilize the full list of explanatory variables.

The ML estimations cover three data compositions to account for asynchronous publication dates and to evaluate the significance of the AIS indicators in the predictor set. Set 1 covers indicators with available data starting from January 2000 to December 2023. Sets 2 and 3 have a shorter sample size, starting from February 2019 in order to evaluate the presence of the AIS-derived indicators in the predictor set. As a control set, Set 2 is a shorter-period version of Set 1 which does not include the AIS indicators. Set 3 contains the AIS-derived indicators that are enumerated in Appendix Table 3.

In total, 63 ML iterations are conducted for each of the 14 ASEAN+3 economies. These permutations arise from seven ML techniques, two variable selection techniques in addition to the full-sample coverage, and three data compositions. The ML models are evaluated based on their out-of-sample RMSEs, with the lowest score identified as the best-performing. ML training starts from the first data point of Sets 1, 2, or 3 up to December 2021. The out-of-sample evaluation covers the January 2022-to-December 2023 period, except for Lao PDR and Myanmar where data end in November 2023.

V. Discussion of Results

This section is divided into two parts, consistent with the flow of Section IV. First, we discuss results from the parsimonious bridge models. These include OLS estimations for three models: export price, export volume, and export value. To enhance model fit, ML techniques are alternatively applied to export volume and value models. Second, we delve into the results from the ML estimation of large-scale models aimed at nowcasting export value.

A. Bridge Models

OLS Estimations

The parsimonious ***export price*** models yield a very good fit for most of the ASEAN+3 economies in the sample. In particular, the models for Indonesia, Japan, Korea, Malaysia, Singapore, and Thailand—six of the nine economies with export price-volume series—report an adjusted R-squared of over 85 percent (Table 2). These findings indicate that while limited in number, the explanatory variables—changes in crude oil prices, FX rates, and shipping freight rates—are sufficient to explain the export price dynamics of these six economies. Moreover, Hong Kong yields a decent adjusted R-squared of 72 percent, while the model for China is also acceptable with an adjusted R-squared of 37 percent. The signs of the coefficients are likewise intuitive—increases in the oil price and freight rate as well as depreciations in the local currency push up export prices in most cases.

The ***export volume*** models exhibit moderate explanatory power compared to the strong performance of the price models. Among the sampled economies, Hong Kong and Thailand have adjusted R-squared estimates of about 30 percent for the two models (Model 1 for cargo tonnage, Model 2 for ship count) (Table 2). China and Indonesia yield a slightly better fit for the cargo tonnage-based volume models, while the ship count-based model has some explanatory power for Japan’s export volume statistics. For these aforementioned economies, the AIS indicators have a positive and statistically significant impact on official volume statistics. However, for Korea, Malaysia, Philippines, and Singapore, the models are not sufficient to explain their respective export price dynamics.

One factor behind the weak outcome for the volume models is the high variability in the correlations of the AIS indicators with official export volume statistics. In most economies, the correlations dropped substantially in 2022 or 2023, a trend likely associated with the global supply chain disruptions from the COVID-19 pandemic and escalation of geopolitical tensions (Appendix Figure 3). As maritime ports got heavily congested in 2021–22, trade was diverted to other modes of transport such as by land and air, as in the case with Hong Kong and Malaysia, thereby weakening the predictive ability of the AIS indicators for aggregate exports (Appendix Figure 5). The correlations only showed modest improvements in 2023, likely as disruptions to maritime traffic had persisted owing to conflicts in Ukraine and the Middle East.

China, Indonesia, and Thailand stand out for having sustained relatively high correlations between export volume and cargo tonnage throughout 2020–23. China and Indonesia maintained correlations of at least 60 percent within the same period, while Thailand sustained correlations of within 40–60 percent (Appendix Figure 3). These observations are consistent with the better performance of the three countries' cargo tonnage-based regression models as discussed above (Table 2). Meanwhile, aside from data issues, the weak performance of the OLS-based export volume models could imply a nonlinear relationship—as noted in Furukawa and Hisano (2022)—or irrelevance, between the AIS indicators and volume index. We investigate such possibilities in the next section.

The OLS-based bridge models exhibit considerable potential in nowcasting ***export values*** for several ASEAN+3 economies. Indonesia, Korea, and Singapore indicate the best fit, with their models recording adjusted R-squared values of 67–82 percent (Table 3 and Appendix Figure 7). Likewise, Indonesia and Thailand have decent alignments with their official export value statistics. However, the models suggest weak predictive power for China, Hong Kong, Malaysia, and the Philippines. Interestingly, the AIS-based volume estimates tend to have larger coefficients than the price estimates, even as the volume models indicated inferior alignments compared to the price models. These findings suggest that the AIS indicators are still valuable in explaining export value dynamics, despite their lack of explicit price information. After all, an increase in outbound cargo shipment (and traffic) can also be motivated by an increase in export price, which in turn is driven by demand-supply forces.

As for the four economies without price-volume export decomposition, the OLS-based bridge models only generate a strong alignment with Brunei's official statistics. The models for Brunei have adjusted R-squared values of over 82 percent, with all explanatory variables—except for ship count—being statistically significant and displaying the expected positive signs. On the other hand, Cambodia, Myanmar, and Vietnam demonstrate weak alignments with official export statistics. The weakness may stem from the inability of OLS to capture nonlinearities in the data or the likelihood of missing variables in the models, both of which are explored in the exercises discussed in the next sections.

Table 2. Selected ASEAN+3: OLS Estimates of Bridge Models—Export Unit Price and Export Volume

	China	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Thailand
Export Unit Price Model									
Constant	0.04	3.38***	0.00	1.85***	-3.24***	-1.56*	-5.16	-0.55	1.25***
Oil price	0.03	0.01	0.21***	0.01	0.14***	0.12***	0.05	0.21***	0.04***
LCY/USD	0.94***	3.80***	0.23*	0.77***	-0.25**	1.49***	1.33	1.84***	0.11***
Freight rate	0.03**	0.00	0.01*	0.01***	0.03***	0.02***	0.04	0.01	0.00**
Adj. R-squared	0.37	0.72	0.93	0.93	0.93	0.87	0.05	0.91	0.86
Export Volume Model 1 *(Cargo tonnage as explanatory variable)*									
Constant	-4.48	-2.53	-8.77***	-2.25	1.69	4.28	11.24	4.11**	-4.20*
Cargo tonnage	1.80**	-0.80***	0.66***	0.55**	0.29**	0.07	1.33	-0.27	0.78***
Adj. R-squared	0.47	0.25	0.40	0.19	0.15	-0.02	0.02	0.07	0.32
Export Volume Model 2 *(Ship count as explanatory variable)*									
Constant	1.67	-1.16	-3.43	-1.66	2.44	1.85	17.55	2.68	-1.91
Ship count	1.39	-0.88***	0.58***	0.75***	0.20*	0.45	0.32	-0.02	0.71***
Adj. R-squared	0.12	0.31	0.16	0.29	0.10	0.05	-0.02	-0.02	0.35

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff estimates.
Note: LCY = local currency. The country list covers ASEAN+3 economies with official unit price-volume decompositions of goods exports. Higher LCY/USD rate means weaker LCY relative to the US dollar. All variables are in year-on-year terms. OLS regression for the price model covers the January 2019–December 2023 period, while the export volume model covers the January 2020–December 2023 period. The significance of the coefficients is determined based on the Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors. ***, **, * refer to 1, 5, and 10 percent significance levels, respectively.

Table 3. Selected ASEAN+3: OLS Estimates of Bridge Models—Export Value

	China	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Thailand
Export Value Model 1 ***(based on Export Volume Model 1 in Table 2)***									
Constant	13.73***	10.01*	6.22*	3.55	6.82***	0.23	-1.63	6.44***	-3.34**
Estimated Price	0.45	0.85***	0.39**	0.55***	-0.23	-0.12	0.15**	-0.30**	0.50***
Estimated Volume	-2.18***	-1.65	1.77***	0.76**	1.63***	1.60***	0.26**	1.15***	3.17***
Adj. R-squared	0.29	0.25	0.74	0.49	0.81	0.30	0.15	0.67	0.53
Export Value Model 2 ***(based on Export Volume Model 2 in Table 2)***									
Constant	19.39***	3.62	7.11*	3.47	7.45***	-0.02	-3.74	6.56**	-1.63
Estimated Price	0.05	0.22	0.42	0.61***	-0.30	0.00	0.18**	-0.30**	0.49***
Estimated Volume	-2.75**	-0.42	1.83***	0.76**	1.63***	1.55***	0.21	1.17***	2.21**
Adj. R-squared	0.21	0.03	0.74	0.56	0.81	0.30	0.23	0.67	0.56

	Brunei	Cambodia	Myanmar	Vietnam
Export Value Model 1 ***(Cargo tonnage as one of the explanatory variables)***				
Constant	-2.71	14.15***	0.60	9.58***
Oil price	0.36**	0.14	0.21	0.19**
LCY/USD	3.59***	6.54	0.99***	-3.11***
Freight rate	0.22***	-0.03	-0.12**	-0.04*
Cargo tonnage	0.15**	-0.14***	0.08*	0.08
Adj. R-squared	0.82	0.08	0.41	0.26
Export Value Model 2 ***(Ship count as one of the explanatory variables)***				
Constant	-1.50	18.00***	2.10	9.39***
Oil price	0.38**	0.14	0.20	0.20**
LCY/USD	3.67***	3.62	0.92**	-3.03***
Freight rate	0.21***	-0.04	-0.12**	-0.04*
Ship count	0.05	-0.16***	0.02**	0.05
Adj. R-squared	0.81	0.21	0.37	0.26

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff estimates.
Note: LCY = local currency. The country list in the first panel covers ASEAN+3 economies with official price-volume decompositions of goods exports. Export values are in US dollars. Higher LCY/USD rate means weaker LCY relative to the US dollar. All variables are in year-on-year terms. OLS regression for the export value model covers the January 2020–December 2023 period. The significance of the coefficients is determined based on the Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors. ***, **, * refer to 1, 5, and 10 percent significance levels, respectively.

OLS-ML Estimations

ML approaches are employed in an attempt to improve the fit of the ***export volume*** models by capturing nonlinearities that are missed by the OLS estimations. The out-of-sample RMSEs of the models estimated using various ML techniques are then compared against those of the OLS-estimated models. We employ the Diebold-Mariano (DM) test (Diebold and Mariano 1995; Harvey, Leybourne, and Newbold 1997) to determine the statistical difference of the forecasts obtained from the various estimation techniques. Note that this exercise only applies to the nine ASEAN+3 economies with export volume statistics.

Our findings reveal that ML techniques can improve the predictive accuracy of the export volume models for five out of the nine ASEAN+3 economies. ML models outperform OLS for China, Hong Kong, Malaysia, Singapore, and Thailand, indicating the presence of nonlinearities between the AIS indicators and the export volume statistics (Table 4). Among the seven ML techniques considered in this study, support vector machines–linear epsilon-insensitive (svmLinear) have the lowest RMSE for four out of the five economies (Appendix Table 4). SvmLinear tends to outperform other ML techniques due to their robustness against outliers and their ability to find a simple yet optimal trend.

Meanwhile, the ML models are not necessarily better in their predictive accuracies than OLS for the other four economies in the sample. This finding is true for Indonesia, Japan, Korea, and the Philippines, suggesting that the ML techniques are unable to model potential nonlinearities in the data. Particularly for Indonesia and the Philippines, the export volume series exhibit high volatility within the out-of-sample period (from January 2022–December 2023), which limits the predictive abilities of any modelling technique (Appendix Figure 6). Additionally, weak performance can be attributed to the absence of potentially important variables in the volume models, such as price indicators. For comparison, the normalized out-of-sample RMSEs of the ***export value*** models are generally lower than those of the export volume models (Table 5). These findings suggest that the models' predictive power could be improved by integrating the AIS indicators with price indicators in export models.

For the ***export value*** models, the OLS-ML hybrid approach outperforms the predictive performance of the OLS-based bridge models for four out of nine economies. These four economies are China, Hong Kong, Malaysia, and Thailand, where the models' out-of-sample estimates closely align with actual export value growth rates (Table 5 and Appendix Figure 7). Similarly, the ML models outperform OLS for Brunei and Myanmar among the four countries without export price-volume decompositions (Table 5 and Appendix Table 5). Interestingly, the results show that OLS is just as good as OLS-ML for the remaining seven economies in the sample—Indonesia, Japan, Korea, the Philippines, Singapore, Cambodia, and Vietnam, where both approaches do not yield statistically different forecasts. That said, visually weak alignments of the out-of-sample estimates with actual data, especially for Cambodia and the Philippines, indicate room for enhancing the models (Appendix Figure 7).

Table 4. Selected ASEAN+3: Normalized Out-of-Sample RMSE of OLS and ML Bridge Models—Export Volume

Economy	OLS		ML	Best Performing ML Technique
	Model 1	Model 2		
China	1.98	2.50	**0.95****	svmLinear
Hong Kong	1.45	1.45	**0.93****	svmLinear
Indonesia	**0.88**	1.03	0.88	xgb
Japan	1.45	1.65	**1.00**	LASSO
Korea	0.97	1.07	**0.91**	svmRBF
Malaysia	1.28	1.28	**0.79*****	svmLinear
Philippines	**1.00**	1.01	1.02	svmRBF
Singapore	1.24	1.31	**0.78*****	svmLinear
Thailand	1.48	1.45	**0.84*****	elnet

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: elnet = elastic net; LASSO = LASSO regression; xgb = XGBoost; svmLinear = linear epsilon-insensitive SVM; and svmRBF = radial basis function kernel SVM. Figures in bold refer to models with lower RMSE. Model 1 is based on export volume estimates from cargo tonnage and Model 2 on ship count. ***, **, * refer to 1, 5, and 10 percent levels of significance, respectively, based on the two-sided DM test between ML and OLS Model 1 with correction introduced by Harvey, Leybourne, and Newbold (1997). Table 4 focuses on evaluating ML against Model 1, as Model 1 consistently shows lower RMSEs compared to Model 2 for most economies. DM tests between ML and Model 2 show similar results. RMSEs are calculated from out-of-sample predictions covering the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy's export volume growth for the same period. Selected ML technique is based on the lowest RMSE.

Table 5. Selected ASEAN+3: Normalized Out-of-Sample RMSE of OLS and OLS-ML Bridge Models—Export Value

Economy	OLS		OLS-ML
	Model 1	Model 2	
China	1.99	1.25	**1.00*****
Hong Kong	1.53	1.72	**0.89*****
Indonesia	0.59	0.64	**0.53**
Japan	1.70	1.50	**1.40**
Korea	0.50	**0.49**	0.51
Malaysia	0.93	0.96	**0.68*****
Philippines	1.05	**0.92**	0.93
Singapore	**0.60**	0.61	0.64
Thailand	0.96	0.91	**0.75*****

Economies without unit price-volume export decompositions

Economy	OLS		ML	Best Performing ML Technique
	Model 1	Model 2		
Brunei	0.74	0.69	**0.46***	xgb
Cambodia	1.06	1.13	**0.94**	RF
Myanmar	0.93	0.89	**0.65*****	LASSO
Vietnam	0.94	0.94	**0.86**	RF

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: LASSO = LASSO regression; RF = random forest; and xgb = XGBoost. Figures in bold refer to models with lower RMSE. ***, **, * refer to 1, 5, and 10 percent levels of significance, respectively, based on the two-sided DM test between ML and OLS Model 1 with correction introduced by Harvey, Leybourne, and Newbold (1997). RMSEs are calculated from out-of-sample predictions for the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy's export value growth for the same period.

B. Large-Scale ML Models

Large-scale ML models use an extensive list of explanatory variables, which are estimated using various ML techniques. We explore such models as an alternative to the parsimonious bridge models for export nowcasting. As discussed in Section IV, we take this approach to mitigate the risk of overlooking critical predictors as the explanatory variables in the bridge models have been identified based on economist judgment. Also, as the large-scale ML models are not solely dependent on the AIS indicators, they enable the nowcasting of a wider range of economies, including Lao PDR within the ASEAN+3.

The large-scale ML models are found to improve the predictive power of the bridge models in nowcasting exports. The best-performing ML model for each economy refers to the model that generates the minimum out-of-sample RMSE across 63 model iterations, arising from seven ML techniques across three variable selection criteria and three dataset compositions. The best-performing ML models outperform the bridge models in 12 out of 14 economies, resulting in RMSE reductions ranging from 4–35 percent (Table 6). Regularized regression and SVM techniques prove superior to tree-based ML approaches due to their ability to capture complex relationships while mitigating the risk of overfitting (Box A). Interestingly, the inclusion of AIS indicators among the predictors is limited to the optimal ML models of Brunei, China, Thailand, and Vietnam (Box Table 1).

Table 6. ASEAN+3: Normalized Out-of-Sample RMSEs of Best-Performing Bridge and Large-Scale ML Models—Export Value

Economy	Bridge Model	Large ML Model
Brunei	**0.46**	0.54
Cambodia	0.94	**0.89**
China	1.00	**0.80**
Hong Kong	0.89	**0.75**
Indonesia	0.53	**0.40***
Japan	1.40	**0.75*****
Korea	0.49	**0.40**
Lao PDR	-	**0.78**
Malaysia	0.68	**0.51***
Myanmar	0.65	**0.60**
Philippines	0.92	**0.84**
Singapore	0.60	**0.40****
Thailand	0.75	**0.61**
Vietnam	**0.86**	0.86

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Figures in bold refer to models with a lower RMSE. Highlighted rows refer to economies with viable nowcasting models reporting normalized RMSEs of 78 percent or less. ***, **, * refer to 1, 5, and 10 percent levels of significance, respectively based on the two-sided DM test between bridge and large ML models. RMSEs are calculated from out-of-sample predictions for the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy's export growth for the same period. Bridge models refer to those economy-specific models with the lowest RMSE (or those in bold) in Table 5.

Comparison with Bridge Models

Nonetheless, the parsimonious bridge models exhibit comparable performance to the larger ML models across most ASEAN+3 economies. DM tests reveal that only for four economies—Indonesia, Japan, Malaysia, and Singapore—do the large-scale ML models demonstrate superior predictive power over the bridge models (Table 6). These findings suggest that large and complex models do not always guarantee better performance. In fact, among the large-scale ML models, the best-performing ones are associated with a reduced sample size, in terms of either estimation period or the number of predictors (Box A).

Our analysis across 63 ML iterations for each economy likewise indicates that most ML models are unable to beat the nowcasting power of the bridge models. We find that only 35 percent of the examined ML iterations yield lower RMSEs compared to the bridge models. While ML models exhibit relatively higher "success rates" for Hong Kong, Indonesia, Malaysia, Singapore, and Thailand, at around 40 percent, their RMSE reductions are modest, with the highest being only 0.09 percentage point (Table 7). Japan is the sole exception, with over three-quarters of its ML models surpassing the RMSEs of the bridge models and reporting a median RMSE reduction of 0.41 percentage point.

Table 7. ASEAN+3: Performance Summary of ML Models

Economy	Performing Models	Underperforming Models	Success Rate of ML over Bridge	RMSE Reduction	RMSE Increase
	(Number of models)		(Percent)	(Median of normalized out-of-sample RMSE)	
Brunei	0	63	0.0	-	0.31
Cambodia	8	55	12.7	0.03	0.09
China	20	43	31.7	0.13	0.32
Hong Kong	25	38	39.7	0.08	0.13
Indonesia	28	35	44.4	0.09	0.14
Japan	48	15	76.2	0.41	0.43
Korea	5	58	7.9	0.03	0.13
Lao PDR	-	-	-	-	-
Malaysia	30	33	47.6	0.08	0.11
Myanmar	1	62	1.6	0.05	0.29
Philippines	15	48	23.8	0.03	0.11
Singapore	30	33	47.6	0.07	0.10
Thailand	30	33	47.6	0.08	0.10
Vietnam	0	63	0.0	-	0.24

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Performing (underperforming) models refer to models with RMSEs that are lower (higher) than those from bridge models. Highlighted rows refer to economies with ML model success rates of 40 percent and higher. RMSEs are calculated from out-of-sample estimates for the January 2022–December 2023 period, and normalized by the standard deviation of respective economy's export growth for the same period.

Among the economy-specific large-scale ML models, we generate reasonable export nowcasting capabilities for 10 of the 14 ASEAN+3 economies. In particular, Brunei, Indonesia, Korea, Malaysia, Myanmar, Singapore, and Thailand have the lowest normalized RMSEs in the group with a maximum of 61 percent (Table 6).[12] However, evaluation based solely on RMSEs could overlook models capable of identifying turning points despite having

[12] Normalized RMSEs for Indonesia and Japan are higher than those generated by Furukawa and Hisano (2022) and Nickelson, Nooraeni, and Efliza (2022), respectively. That said, results from other studies are not necessarily comparable owing to differences in modelling techniques and the periods covered for model estimation and RMSE assessment.

relatively low predictive power, as in the case with Hong Kong, Japan, and Lao PDR (Appendix Figure 8). Another example is China, where the large ML model demonstrates a lower normalized RMSE compared to its bridge model counterpart. However, upon visual inspection, it is evident that the cargo tonnage-based bridge model does a decent job at capturing the sudden spikes and turning points in the growth rate of export value (Appendix Figure 7).

On the other hand, both bridge and ML models exhibit limited power in explaining export growth for Cambodia, China, the Philippines, and Vietnam. One reason behind the models' less favorable outcome in these four countries is the greater presence of outliers or fluctuations in the target variable (Appendix Figure 7). To address this issue, potential solutions include smoothing the target variable and incorporating additional indicators that could better explain the dynamics of the target variable. On the latter, data that capture the extent of the COVID-19 pandemic's impact on the export sector, such as the stringency and duration of social distancing measures during the pandemic, represent viable candidates.

Our nowcasting exercises also highlight the absence of a universal model for nowcasting ASEAN+3 exports. Large-scale ML models generally yield greater predictive power but not significantly so for all the economies. In particular, Indonesia, Japan, Lao PDR, Malaysia, and Singapore can count on the superior predictive power of the large-scale ML models for export nowcasting. As for Brunei, Hong Kong, Korea, Myanmar, and Thailand, the parsimonious bridge models can work as well as the larger ML models. As highlighted in the preceding paragraphs, a narrow focus on achieving the lowest RMSE may overlook alternative models adept at identifying critical turning points. Therefore, the identification of appropriate nowcasting models for each economy can be complemented by considering models with strong out-of-sample alignment with the actual data, even of they exhibit a relatively higher RMSE (Appendix Figure 8).

Drivers of ML-based Predictions

Shapley values derived from the large-scale ML models offer crucial insights into variable importance within the predictions.[13] We find that variable importance varies over time across economies, underscoring the flexibility of ML models in handling complex relationships (Appendix Figures 9 and 10). Overall, the Shapley values indicate key variable groups that typically correspond to each economy's export profile. We explore the results for the four economies with the lowest RMSEs among the ML models listed in Table 6 (Figure 2):

- In the case of ***Indonesia***, the largest Shapley values are attributed to global commodity prices and global economic activity (Figure 2). These results are to be expected, considering that commodities, such as crude oil, natural gas, and palm oil, comprise nearly 35 percent of Indonesia's exports, and commodity prices are often influenced by global economic conditions.

- ***Malaysia*** is also a major commodity exporter, but its Shapley values underscore nuanced differences in its export profile compared to Indonesia. In Malaysia's case,

[13] Shapley values offer a widely used method for quantifying the marginal impact of individual variables within a predictive model. They originate from cooperative game theory (Shapley 1953) and have been adapted for machine learning by Strumbelj and Kononenko (2010). The values are computed by evaluating the outcomes across multiple combinations of input variables.

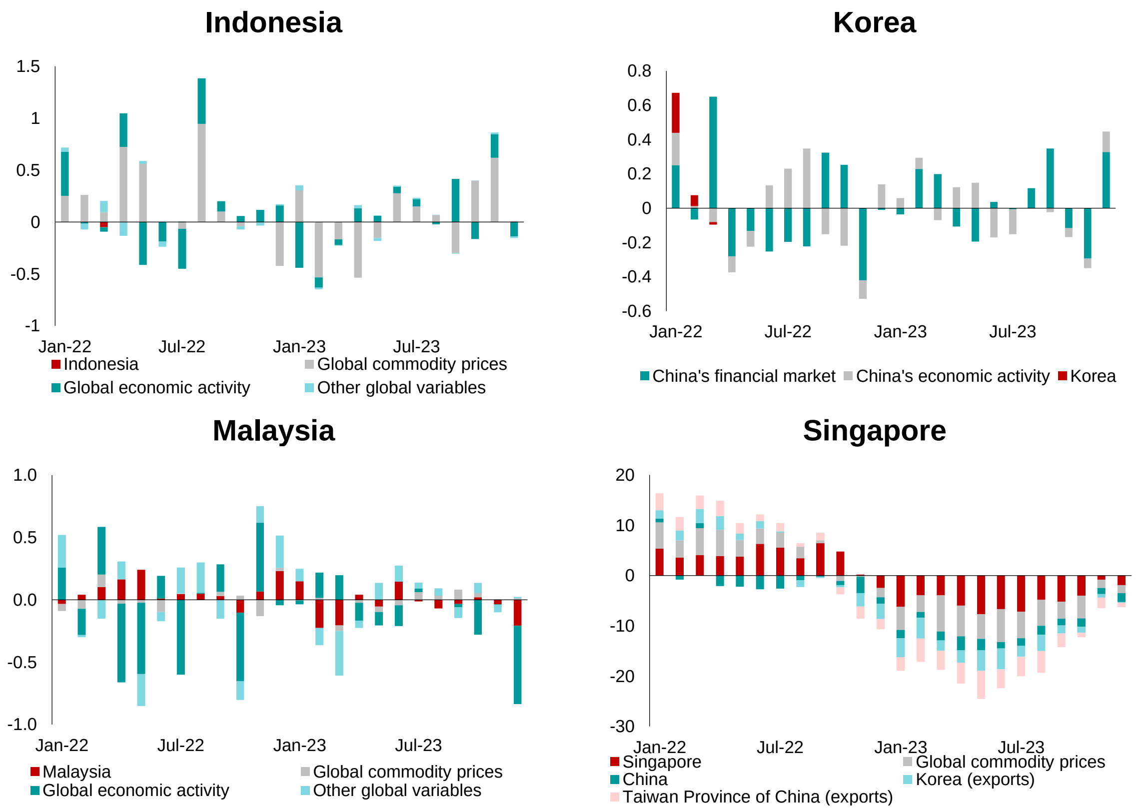
indicators for global economic conditions primarily influence predictions, with global commodity prices playing a less prominent role. These findings align with the diversification of Malaysia's export base. For instance, electrical machinery and electronics constitute over a third of Malaysia's exports while mineral fuels and palm oil-based exports account for another 22 percent. As a result, Malaysia boasts a more even range of export markets than Indonesia.

- ***Korea***'s export nowcasts are considerably influenced by China's economic conditions and financial markets. China is Korea's largest export market, accounting for 21 percent of total exports in 2022–23 compared to the less than 20 percent share accounted for by the US. About 20 percent of Korea's exports are in fact absorbed by China's domestic demand. Apart from the direct impact from China's economic conditions, fluctuations in China's financial market conditions can also affect the demand for and competitiveness of Korea's exports (Cheong 2011).

- Similarly, ***Singapore***'s export nowcasts are shaped by indicators reflecting the city-state's highly open economy and specific export patterns. Global commodity prices and China's economic indicators particularly play important roles, consistent with Singapore's position as a leading oil trading and refining hub and its substantial exposure to the Chinese market. Export trends of fellow Asian trade bellwethers Korea and Taiwan Province of China also contribute significantly to the nowcasts.

Figure 2. Selected ASEAN+3: Marginal Variable Contributions in Large-Scale ML Prediction Models

(Percentage point contribution to year-on-year growth)



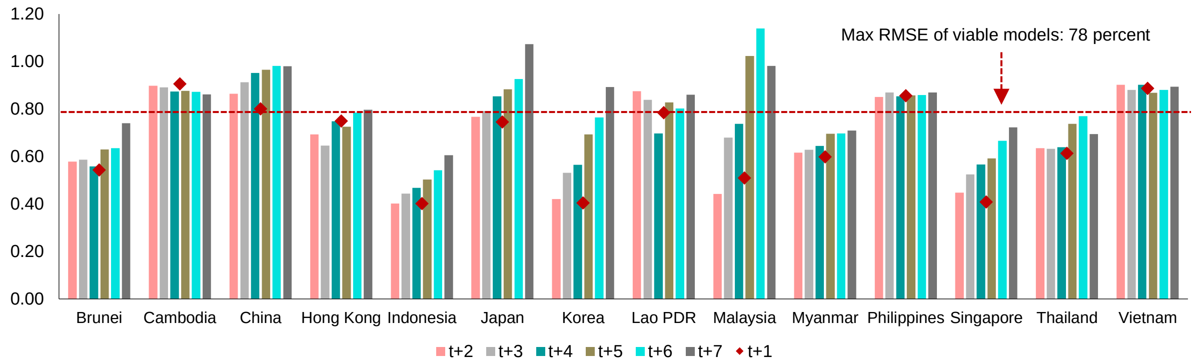
Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Marginal variable contributions are derived from Shapley values, which provide an estimate of a variable's contribution to the prediction for a given period relative to the average prediction (Strumbelj and Kononenko 2010). The values are additive. Variable groupings are based on the categories indicated in Appendix Tables 1 and 2.

Expanding the Forecast Horizon

The nowcasting models can also be used to estimate the near future. Thus far, model evaluation has focused on predicting exports at time $t+1$ while also utilizing new information at time $t+1$. As discussed in Section IV, such estimates are actually "backcasts," given that export statistics in the ASEAN+3 mostly come with a lag of at least one month. In this regard, the nowcasting exercise is expanded to explore the ability of the identified best-performing ML models in generating forecasts across time horizons—that is, in the present ($t+2$) and the next five months ($t+3 \ldots 7$). After all, nowcasting is the practice of predicting the recent past, the now, and the near future.

The best-performing ML models exhibit reasonable accuracy in predicting export growth up to three months ahead. As expected, RMSEs of the ML models rise with increasing distance from the data reference period at time t, reflecting deterioration in forecasting accuracy (Figure 3). This trend is not evident for Cambodia, Philippines, and Vietnam; however, these countries also display weaker model performance in the study. Among the countries with viable export nowcasting models, RMSEs tend to show a notable increase mostly at $t+4$ or $t+5$ forecasting windows, which correspond to two to three months ahead of the present.[14]

Figure 3. ASEAN+3: Normalized RMSEs across Forecast Horizons



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: The figure features the RMSEs of the best-performing ML model for each economy across forecast horizons. RMSEs are calculated based on out-of-sample predictions for the January 2022 to December 2023 period, normalized by standard deviations of export growth of each economy for the same period.

14 To simplify, we have assumed that the best-performing ML model for each economy remains consistent across time horizons. However, this assumption may not always hold true, as demonstrated in Figure 2.

Box A. Results from the Horserace of ML Techniques

Regularized regression and SVM techniques demonstrate superior performance over tree-based ML techniques across the 63 ML iterations evaluated for each ASEAN+3 economy. Ridge, LASSO, and elastic net, which are regularized regressions, and SVMs (specifically, radial basis function kernel and linear epsilon-insensitive) emerge as the optimal methods in 10 out of 14 economies (Box Table 1). The techniques' superior predictive performance can be attributed to their relatively straightforward approaches, which help them better balance between model complexity and predictive accuracy. In contrast, although tree-building and ensemble methods such as random forest and XGBoost are adept at capturing complex variable relationships, they are also susceptible to overfitting in-sample estimates, resulting in sub-optimal out-of-sample predictions.

The optimal ML models are associated with a smaller sample size, in terms of either estimation period or the number of predictors. The best-performing ML models in nine of the 14 economies make use of data starting in 2019, in contrast to the full sample that starts in January 2000. This suggests that there could be a structural break within the longer timeframe that renders the extended series less valuable to the model. In such cases, a shorter timeframe may be preferred if it contains the pertinent information necessary to generate accurate estimates.

Box Table 1. ASEAN+3: Best-Performing ML Model Characteristics—Export Value

Economy	RMSE	ML Technique	Variable Selection Method	Dataset Composition
Brunei	0.54	svmLinear	None (All variables)	From 2019, with AIS indicators
Cambodia	0.89	RF	None (All variables)	From 2019
China	0.80	svmRBF	None (All variables)	From 2019, with AIS indicators
Hong Kong	0.75	LASSO	ALASSO	From 2000
Indonesia	0.40	LASSO	None (All variables)	From 2019
Japan	0.75	ridge	None (All variables)	From 2019
Korea	0.40	LASSO	ALASSO	From 2019
Lao PDR	0.78	svmLinear	LASSO	From 2000
Malaysia	0.51	svmLinear	None (All variables)	From 2000
Myanmar	0.60	svmLinear	None (All variables)	From 2019
Philippines	0.84	RF	None (All variables)	From 2000
Singapore	0.40	RF	LASSO	From 2000
Thailand	0.61	elnet	ALASSO	From 2019, with AIS indicators
Vietnam	0.86	RF	None (All variables)	From 2019, with AIS indicators

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: ALASSO = adaptive LASSO; elnet = elastic net; LASSO = LASSO regression; RF = random forest; ridge = ridge regression; svmLinear = linear epsilon-insensitive SVM; and svmRBF = radial basis function kernel SVM. The best-performing models are those with minimum RMSEs within the 63 ML iterations (Appendix Table 6). RMSEs are calculated from out-of-sample predictions for the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy's export growth rate for the same period.

The automated variable selection methods—LASSO and ALASSO—exhibit superior performance in five economies. In these cases, LASSO reduces the number of input variables by more than 95 percent, while ALASSO achieves a reduction of 60–65 percent (Box Table 2). Utilizing LASSO as a variable selection method expectedly yields a notably higher proportion of discarded variables compared to ALASSO, as discussed in Appendix II. Although such aggressive reduction by LASSO effectively reduces noise in the training data and mitigates overfitting, it can also lead to the exclusion of important variables that are highly correlated with other predictors, ultimately diminishing the model's predictive power.

The variable selection techniques result to the inclusion of AIS indicators among the predictors in only four economies. Specifically, the AIS indicators are only utilized in the optimal ML models of Brunei, China, Thailand, and Vietnam (Box Table 1). It is plausible that the extensive array of predictors in the ML models has sufficiently compensated for the export-related information provided by the AIS indicators.

Box Table 2. Selected ASEAN+3: Summary Statistics from Variable Selection Methods

Economy	Selection Method	Variable Drop Rate (Percent)	Number of Selected Variables by Group					
			Total	Domestic	Asia	Europe	US	Global
Hong Kong	ALASSO	60	**302**	31	121	62	68	20
Korea	ALASSO	64	**269**	24	114	60	52	19
Lao PDR	LASSO	98	**19**	1	7	2	3	0
Singapore	LASSO	95	**38**	2	15	6	12	3
Thailand	ALASSO	65	**263**	16	113	45	67	22

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: ALASSO = adaptive LASSO; LASSO = LASSO regression. Variable drop rate is calculated as the number of discarded variables divided by the total number of input variables, including their lags of up to 6 months. Variable groups are detailed in Appendix I. Asia consists of variables belonging to the following categories in Appendix I Table: China, Japan, Korea, Singapore, and Taiwan Province of China.

VI. Summary and Conclusion

This study explores two main frameworks for nowcasting merchandise export growth for each of the 14 ASEAN+3 economies. First, we introduce parsimonious bridge models, incorporating AIS-derived indicators and three financial variables that are estimated via OLS and linear and nonlinear ML techniques. Aside from providing headline nowcasts, the bridge framework provides insights into the unit price-volume contributions of export value estimates. Second, we develop large-scale models estimated through ML techniques as an alternative to the simple bridge models. These large-scale ML models address the risk of omitting critical predictors in the bridge models, with the use of over 100 external and domestic variables. They also enable the nowcasting of a wider range of economies without AIS-based ship traffic data.

Overall, both frameworks—the bridge and large-scale ML models—offer reasonable export nowcasting capabilities for 10 of the 14 ASEAN+3 economies. While large-scale ML models generally yield greater predictive power, this advantage over the simpler bridge models does not necessarily hold true for all economies in the sample. Notably, Indonesia, Japan, Lao PDR, Malaysia, and Singapore record significant improvements in predictive power with the large-scale ML models. As for Brunei, Hong Kong, Korea, Myanmar, and Thailand, the simpler bridge models can be as effective as the larger ML models in export nowcasting. However, both frameworks exhibit weak explanatory power for export growth of Cambodia, China, the Philippines, and Vietnam, due in part to the higher volatility of their export growth data within the estimation period.

Our study also validates the effectiveness of AIS-derived indicators in real-time monitoring of export developments and introduces an alternative framework to overcome challenges posed by the use of AIS data. Despite lacking explicit price information, the AIS-derived indicators within bridge models show strong power in explaining export value growth in most ASEAN+3 economies. At the same time, potential issues surrounding the availability and quality of the AIS indicators can be overcome by using a large set of traditional economic and financial indicators estimated using ML techniques. We find that the optimal large-scale ML models across the ASEAN+3 economies do not include the AIS indicators in the predictor set, with the exception of Brunei, China, Thailand, and Vietnam.

The large-scale ML models used in this study are capable of producing interpretable predictions that extend into the near future. Utilizing Shapley values, we find that variable importance varies over time across economies, typically aligning with each economy's export profile. For example, indicators representing global commodity prices and global economic activity are influential in driving the nowcasts for Indonesia and Malaysia, both major commodity exporters. Additionally, the best-performing models exhibit reasonable accuracy in predicting export growth up to three months ahead, reflecting the essence of nowcasting, which encompasses the recent past, present, and near future.

Finally, our exercise underscores that large and complex models do not always guarantee considerable improvements in predictive performance. In fact, the bridge models, which comprise a few indicators selected based on economic judgment, demonstrate comparable performance to the larger ML models for several ASEAN+3 economies. Moreover, among the large-scale ML models, the best-performing ones are associated with a reduced sample size, either in terms of estimation period or the number of predictors.

Appendix I. Lists of Variables Used in the Machine Learning Models

Appendix Table 1. World: List of External Explanatory Variables

Economy	No.	Indicator	Haver Code	Transformation
Global	1	**[Commodity price]** Brent crude oil spot	PEOBR@WBPRICES	Year-on-year growth
	2	**[Commodity price]** Energy index	IE@WBPRICES	Year-on-year growth
	3	**[Commodity price]** Non-energy index	IN@WBPRICES	Year-on-year growth
	4	**[Commodity price]** Coal	PECAU@WBPRICES	Year-on-year growth
	5	**[Commodity price]** Natural gas	PEGDX@WBPRICES	Year-on-year growth
	6	**[Shipping cost]** Harper Petersen (container ship) charter rate index	W1NTWHI@TRANSPRT	Year-on-year growth
	7	**[Shipping cost]** Bunker/marine fuel oil price	G2MGO@TRANSPRT	Year-on-year growth
	8	**[Manufacturing activity]** Global PMI (seasonally adjusted)	S006T@MKTPMI	Month-on-month difference
	9	**[Manufacturing activity]** Composite PMI, new orders	SGBLTO@MKTPMI	None
	10	**[Transport cost, manufacturing activity]** Global supply chain pressure index	W1NGSCPI@TRANSPRT	None
	11	**[Semiconductor cycle]** Global semiconductor cycle	ARTEMIS (AMRO)	Year-on-year growth and year-on-year growth, 6-month moving average
	12	**[Semiconductor cycle]** Global memory semiconductor cycle	ARTEMIS (AMRO)	
	13	**[Semiconductor cycle]** Global non-memory semiconductor cycle	ARTEMIS (AMRO)	
	14	**[Semiconductor cycle]** Capital expenditure cycle (aggregated for Euro Area, Japan, and the US	ARTEMIS (AMRO)	
	15	**[Financial market]** Global economic policy uncertainty index	N001VIUC@G10	Month-on-month difference after seasonal adjustment
	16	**[Financial market]** CBOE market volatility index (VIX)	SPVIX@USECON	None
US	17	**[Manufacturing activity]** Composite PMI	NAPMC@USECON	None
	18	**[Manufacturing activity]** Manufacturers' new orders, all manufacturing industries	NMO@USECON	Year-on-year growth
	19	**[Manufacturing activity]** Supplier deliveries index	NAPMVDI@USECON	None
	20	**[Manufacturing activity]** Industrial production	IP@USECON	Year-on-year growth
	21	**[Manufacturing activity]** New orders, non-defence capital goods	NMONC@USECON	Year-on-year growth
	22	**[Services activity]** Supplier deliveries index	NMFVDI@USECON	Month-on-month difference after seasonal adjustment
	23	**[Services activity]** Services business activity index	CCIN@USECON	None
	24	**[Consumer conditions]** Consumer confidence index (seasonally adjusted)	NMFBAIA@USECON	Month-on-month difference
	25	**[Consumer conditions]** Conference Board consumer confidence	S111VCC@G10	Month-on-month difference
	26	**[Consumer conditions]** Unemployment rate (seasonally adjusted)	LR@USECON	Month-on-month difference
	27	**[Consumer conditions]** Labor participation rate (seasonally adjusted)	LP1X@USECON	Month-on-month difference
	28	**[Consumer conditions]** Total nonfarm payrolls	LANAGRA@USECON	Year-on-year growth
	29	**[Consumer conditions]** Average weekly hours worked, private sector	LRPRIVA@USECON	Year-on-year growth
	30	**[Consumer conditions]** Retail sales and food services volume	S111RSIC@G10	Year-on-year growth
	31	**[Consumer conditions]** Retail sales and food services	NRSTN@USECON	Year-on-year growth
	32	**[Consumer conditions]** PCE-based consumer price index	JCBM@USECON	Year-on-year growth
	33	**[Consumer conditions]** Harmonized index of consumer prices (HICP)	USH@CPIDATA	Year-on-year growth
	34	**[Consumer conditions]** HICP less food and energy	USHLFE@CPIDATA	Year-on-year growth

Economy	No.	Indicator	Haver Code	Transformation
	35	**[Consumer conditions]** Initial claims for unemployment insurance (seasonally adjusted)	LICM@USECON	Month-on-month growth
	36	**[Overall economic activity]** Total leading indicator (seasonally adjusted)	C111LIAT@OECDMEI	month-on-month difference
	37	**[Overall economic activity]** Housing units started	HSTN@USECON	Year-on-year growth
	38	**[Overall economic activity]** Housing units authorized	HPT@USECON	Year-on-year growth
	39	**[Overall economic activity]** Housing units under construction in permit areas	HCCPT@USECON	Year-on-year growth
	40	**[Overall economic activity]** Real money stock (M2)	FM2C@USECON	Year-on-year growth
	41	**[Overall economic activity]** Bank credit, all commercial banks	FAB@USECON	Year-on-year growth
	42	**[Overall economic activity]** Deposits, all commercial banks	FBD@USECON	Year-on-year growth
	43	**[Overall economic activity]** Nowcasting index of economic activity	N111GNCI@G10	
	44	**[Overall economic activity]** Merchandise exports	BPXMMN@USECON	Year-on-year growth
	45	**[Overall economic activity]** Merchandise imports	BPMMMN@USECON	Year-on-year growth
	46	**[Financial market]** US dollar index	FXWSJ@DAILY	Year-on-year growth
	47	**[Financial market]** Standard & Poor's 500 composite index	SP500@USECON	Year-on-year growth
	48	**[Financial market]** Interest rate spread: 10-Year Treasury Bond Less Fed Funds Rate	F10FED@USECON	None
Europe	49	**[Consumer conditions]** EU consumer confidence indicator	E997CF@EUDATA	Year-on-year growth
	50	**[Consumer conditions]** EA New loans to households	M023CAAH@EUDATA	Year-on-year growth
	51	**[Consumer conditions]** EU27 Unemployment rate (seasonally adjusted)	S997R@EUDATA	Month-on-month difference
	52	**[Consumer conditions]** EU27 Retail trade excluding autos and motorcycles (seasonally adjusted)	S997D47@EUDATA	Month-on-month difference
	53	**[Business conditions]** EA20 business climate indicator	E025BC@EUDATA	None
	54	**[Manufacturing activity]** EU27 industry volume of order books (seasonally adjusted)	E997IO@EUDATA	Month-on-month difference
	55	**[Overall economic activity]** EU27 economic sentiment indicator	E997ES@EUDATA	None
	56	**[Overall economic activity]** EU27 retail trade confidence indicator (seasonally adjusted)	E997R@EUSRVYS	Month-on-month difference
	57	**[Overall economic activity]** EA harmonized index of consumer prices	P023H@EUDATA	Year-on-year growth
	58	**[Overall economic activity]** EA Sentix overall economic index	N023VSGX@EUDATA	None
	59	**[Overall economic activity]** Nowcasting index of economic activity	N025GNCI@G10	None
	60	**[Overall economic activity]** EU27 industry output excluding construction	W997QBCD@EUDATA	Year-on-year growth
	61	**[Overall economic activity]** EU27 manufacturing	W997QBC@EUDATA	Year-on-year growth
	62	**[Overall economic activity]** EU27 merchandise exports	X997H010@EUINT	Year-on-year growth
	63	**[Overall economic activity]** EU27 merchandise imports	M997H010@EUINT	Year-on-year growth
	64	**[Financial market]** EA composite index of sovereign systemic stress	V023CSSG@EUDATA	Month-on-month difference
	65	**[Financial market]** EA STOXX 50 price index	S023T5U@EUDATA	Year-on-year growth
	66	**[Financial market]** EA 10-year AAA government bond yield	I023BAYE@EUDATA	Month-on-month difference
	67	**[Financial market]** European economic policy uncertainty index	N100IEPN@EUDATA	Month-on-month difference after seasonal adjustment

Economy	No.	Indicator	Haver Code	Transformation
	68	**[Financial market]** US dollar per Euro, average	X111EXR@EUDATA	Year-on-year growth
	69	**[Overall economic activity]** Composite PMI, new orders	S505TO@MKTPMI	None
	70	**[Overall economic activity]** Emerging markets PMI	S200T@MKTPMI	Month-on-month difference
China	71	**[Overall economic activity]** Composite PMI (seasonally adjusted)	S924VPMI@EMERGEPR	None
	72	**[Overall economic activity]** Emerging industries PMI (seasonally adjusted)	S924VEIP@EMERGEPR	None
	73	**[Overall economic activity]** Logistics prosperity index	N924VTLP@EMERGEPR	Month-on-month difference after seasonal adjustment
	74	**[Overall economic activity]** Yicai chief economists confidence index	N924VECI@EMERGEPR	Month-on-month difference after seasonal adjustment
	75	**[Overall economic activity]** Nowcasting index of economic activity	N924GNCI@EMERGE	None
	76	**[Overall economic activity]** Freight volume of exports (seasonally-adjusted)	H924IJ@EMERGEPR	Month-on-month growth
	77	**[Overall economic activity]** Freight volume of imports (seasonally-adjusted)	H924IK@EMERGEPR	Month-on-month growth
	78	**[Overall economic activity]** Real industrial value added	N924D@EMERGEPR	Year-on-year growth
	79	**[Overall economic activity]** Steel output	N924OMIQ@EMERGEPR	Year-on-year growth
	80	**[Overall economic activity]** Electricity production	H924OVU@EMERGEPR	Year-on-year growth
	81	**[Overall economic activity]** Volume of transported foreign trade goods	H924TTHG@EMERGEPR	Year-on-year growth
	82	**[Overall economic activity]** Freight cargo traffic	H924TTF@EMERGEPR	Year-on-year growth
	83	**[Overall economic activity]** Passenger traffic (seasonally adjusted)	H924TTP@EMERGEPR	Month-on-month growth
	84	**[Overall economic activity]** General government expenditure	N924FTE@EMERGEPR	Year-on-year growth
	85	**[Overall economic activity]** General government revenue	N924FTR@EMERGE	Year-on-year growth
	86	**[Overall economic activity]** Investment in fixed assets, month-on-month change	S924VP@EMERGEPR	None
	87	**[Overall economic activity]** Producer price index	N924PP@EMERGEPR	Year-on-year growth
	88	**[Overall economic activity]** Consumer price index	N924PC@EMERGEPR	Year-on-year growth
	89	**[Overall economic activity]** Money supply, M1	H924FM1@EMERGE	Year-on-year growth
	90	**[Overall economic activity]** Money supply, M2	H924FM2@EMERGE	Year-on-year growth
	91	**[Overall economic activity]** Merchandise imports	N924IM@EMERGEPR	Year-on-year growth
	92	**[Overall economic activity]** Merchandise exports	N924IX@EMERGEPR	Year-on-year growth
	93	**[Overall economic activity]** Import volume index	N924IQM@EMERGEPR	Year-on-year growth
	94	**[Overall economic activity]** Export volume index	N924IQX@EMERGEPR	Year-on-year growth
	95	**[Overall economic activity]** Import price index	N924PFMI@EMERGE	Year-on-year growth
	96	**[Overall economic activity]** Export price index	N924PFXI@EMERGE	Year-on-year growth
	97	**[Manufacturing activity]** PMI survey for Manufacturing	S924VM@EMERGEPR	None
	98	**[Services activity]** PMI survey for services	S924VNGS@EMERGEPR	None
	99	**[Consumer conditions]** Consumer price index	N924PC@EMERGEPR	Year-on-year growth
	100	**[Consumer conditions]** Retail sales	N924TRS@EMERGEPR	Year-on-year growth
	101	**[Consumer conditions]** Urban unemployment rate	N924EURU@EMERGEPR	Month-on-month difference after seasonal adjustment
	102	**[Consumer conditions]** Passenger car domestic sales	N924CVLT@EMERGEPR	Year-on-year growth

Economy	No.	Indicator	Haver Code	Transformation
	103	**[Consumer conditions]** Consumer confidence (seasonally adjusted)	H924VCC@EMERGEPR	Month-on-month difference
	104	**[Financial market]** Shanghai-Shenzhen-300 stock price index	N924FKAV@EMERGE	Year-on-year growth
	105	**[Financial market]** Economic policy uncertainty index	N924VIUC@EMERGEPR	Month-on-month after seasonal adjustment
	106	**[Financial market]** US dollar per renminbi, average	N924XUSV@EMERGEPR	Year-on-year growth
	107	**[Financial market]** News-based economic policy uncertainty index	N924VIUC@EMERGEPR	Month-on-month after seasonal adjustment
	108	**[Financial market]** Financial conditions index	N924VFCI@EMERGEPR	Month-on-month difference
Japan	109	**[Overall economic activity]** Nowcasting index of economic activity	N158GNCI@G10	None
	110	**[Financial market]** US dollar per Japanese yen, average	JPXRSDV@JAPAN	Year-on-year growth
Korea	111	**[Overall economic activity]** Merchandise exports	N542IXD@EMERGEPR	Year-on-year growth
Singapore	112	**[Overall economic activity]** Merchandise exports	N576IX@EMERGEPR	Year-on-year growth
Taiwan Province of China	113	**[Overall economic activity]** Merchandise exports	N528IXD@EMERGEPR	Year-on-year growth

Source: Authors.

Note: ARTEMIS (AMRO) is an online platform that contains a suite of macroeconomic surveillance tools developed by AMRO staff. The platform is accessible to anyone employed by government institutions in the ASEAN+3. Data used in this study is available upon request.

Appendix Table 2. ASEAN+3: Economy-specific Indicators

Economy	No.	Indicator	Haver Code	Transformation
Brunei	1	**[Trade]** Merchandise exports	N516IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N516IMD@EMERGEPR	Year-on-year growth
	3	**[Overall economic activity]** Consumer price index	N516PC@EMERGEPR	Year-on-year growth
	4	**[Financial market]** Brunei dollar per US dollar, average	N516XUSV@EMERGEPR	Year-on-year growth
Cambodia	1	**[Trade]** Merchandise exports	N522IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N522IMD@EMERGEPR	Year-on-year growth
	3	**[Overall economic activity]** Consumer price index, Phnom Penh	N522PC@EMERGEPR	Year-on-year growth
	4	**[Financial market]** Riel per US dollar, average	N522XUSV@EMERGEPR	Year-on-year growth
Hong Kong	1	**[Trade]** Merchandise exports	N532IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N532IMD@EMERGEPR	Year-on-year growth
	3	**[Trade]** Export unit value index	N532PFXI@EMERGE	Year-on-year growth
	4	**[Trade]** Import unit value index	N532PFMI@EMERGE	Year-on-year growth
	5	**[Overall economic activity]** Consumer price index	N532PC@EMERGEPR	Year-on-year growth
	6	**[Financial market]** Hong Kong dollar per US dollar, average	N532XUSV@EMERGEPR	Year-on-year growth
	7	**[Financial market]** News-based economic policy uncertainty index	N532VIUC@EMERGEPR	Month-on-month difference after seasonal adjustment
Indonesia	1	**[Trade]** Merchandise exports	N536IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N536IMD@EMERGEPR	Year-on-year growth
	3	**[Overall economic activity]** Consumer price index	N536PC@EMERGEPR	Year-on-year growth
	4	**[Financial market]** Indonesian rupiah per US dollar, average	N536XUSV@EMERGEPR	Year-on-year growth
Japan	1	**[Trade]** Merchandise exports	VEATTL@JAPAN	Year-on-year growth
	2	**[Trade]** Merchandise imports	VIATTL@JAPAN	Year-on-year growth
	3	**[Trade]** Export price index	JPEPCA@JAPAN	Year-on-year growth
	4	**[Trade]** Import price index	JPIPCA@JAPAN	Year-on-year growth
	5	**[Trade]** Export volume index	JPITWQX@JAPAN	Year-on-year growth
	6	**[Trade]** Import volume index	JPITWQM@JAPAN	Year-on-year growth
	7	**[Overall economic activity]** Consumer price index	JPCIJ@JAPAN	Year-on-year growth
	8	**[Overall economic activity]** Producer price index	JPDCGI@JAPAN	Year-on-year growth
	9	**[Financial market]** Japanese yen per US dollar, average	JPXRSDV@JAPAN	Year-on-year growth
Korea	1	**[Trade]** Merchandise exports	N542IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N542IMD@EMERGEPR	Year-on-year growth
	3	**[Trade]** Export price index	N542PFXI@EMERGE	Year-on-year growth
	4	**[Trade]** Import price index	N542PFMI@EMERGE	Year-on-year growth
	5	**[Overall economic activity]** Consumer price index	N542PC@EMERGEPR	Year-on-year growth
	6	**[Overall economic activity]** Producer price index	N542PPF@EMERGEPR	Year-on-year growth
	7	**[Financial market]** Korean won per US dollar, average	N542XUSV@EMERGEPR	Year-on-year growth
	8	**[Financial market]** News-based economic policy uncertainty index	N542VIUC@EMERGEPR	Month-on-month difference after seasonal adjustment
Lao PDR	1	**[Trade]** Merchandise exports	X544T001@IMFDOTM	Year-on-year growth
	2	**[Trade]** Merchandise imports	M544F001@IMFDOTM	Year-on-year growth
	3	**[Overall economic activity]** Consumer price index	C544PC@IFS	Year-on-year growth
	4	**[Financial market]** Laotian Kip per US dollar, average	C544ECMA@IFS	Year-on-year growth
Malaysia	1	**[Trade]** Merchandise exports	N548IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N548IMD@EMERGEPR	Year-on-year growth
	3	**[Trade]** Export price index	N548PFXI@EMERGE	Year-on-year growth
	4	**[Trade]** Import price index	N548PFMI@EMERGE	Year-on-year growth
	5	**[Overall economic activity]** Consumer price index	N548PC@EMERGEPR	Year-on-year growth
	6	**[Overall economic activity]** Producer price index	N548PP@EMERGEPR	Year-on-year growth

Economy	No.	Indicator	Haver Code	Transformation
	7	**[Financial market]** Malaysian ringgit per US dollar, average	N548XUSV@EMERGEPR	Year-on-year growth
Myanmar	1	**[Trade]** Merchandise exports	X518T001@IMFDOTM	Year-on-year growth
	2	**[Trade]** Merchandise imports	M518F001@IMFDOTM	Year-on-year growth
	3	**[Financial market]** Myanmar kyat per US dollar, average	N518XUSV@EMERGEPR	Year-on-year growth
Philippines	1	**[Trade]** Merchandise exports	N566IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N566IMD@EMERGEPR	Year-on-year growth
	3	**[Overall economic activity]** Consumer price index	N566PC@EMERGEPR	Year-on-year growth
	4	**[Overall economic activity]** Producer price index	N566PPM@EMERGEPR	Year-on-year growth
	5	**[Financial market]** Philippine peso per US dollar, average	N566XUSV@EMERGEPR	Year-on-year growth
Singapore	1	**[Trade]** Merchandise exports	N576IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N576IMD@EMERGEPR	Year-on-year growth
	3	**[Trade]** Export price index	N576PFXI@EMERGE	Year-on-year growth
	4	**[Trade]** Import price index	N576PFMI@EMERGE	Year-on-year growth
	5	**[Overall economic activity]** Consumer price index	N576PC@EMERGEPR	Year-on-year growth
	6	**[Overall economic activity]** Manufactured products price index	N576PPM@EMERGEPR	Year-on-year growth
	7	**[Financial market]** Singapore dollar per US dollar, average	N576XUSV@EMERGEPR	Year-on-year growth
	8	**[Financial market]** News-based economic policy uncertainty index	N576VIUC@EMERGEPR	Month-on-month difference after seasonal adjustment
Thailand	1	**[Trade]** Merchandise exports	N578IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N578IMD@EMERGEPR	Year-on-year growth
	3	**[Trade]** Export price index	N578PFXI@EMERGE	Year-on-year growth
	4	**[Trade]** Import price index	N578PFMI@EMERGE	Year-on-year growth
	5	**[Overall economic activity]** Consumer price index	N578PC@EMERGEPR	Year-on-year growth
	6	**[Overall economic activity]** Producer price index	N578PP@EMERGEPR	Year-on-year growth
	7	**[Financial market]** Thai baht per US dollar, average	N578XUSV@EMERGEPR	Year-on-year growth
Vietnam	1	**[Trade]** Merchandise exports	N582IXD@EMERGEPR	Year-on-year growth
	2	**[Trade]** Merchandise imports	N582IMD@EMERGEPR	Year-on-year growth
	3	**[Overall economic activity]** Consumer price index	N582PC@EMERGEPR	Year-on-year growth
	4	**[Financial market]** Vietnamese dong per US dollar, average	N582XUSV@EMERGEPR	Year-on-year growth

Source: Authors.

Appendix Table 3. ASEAN+3: AIS-based Indicators

Economies	No.	Indicator	Transformation
ASEAN+3 excluding Lao PDR	1	Ship count (Containers)	Month-on-month growth
	2	Ship count (Bulk Carrier/ General Cargo)	Month-on-month growth
	3	Ship count (Tankers)	Month-on-month growth
	4	Cargo tonnage (Containers)	Month-on-month growth
	5	Cargo tonnage (Bulk Carrier/ General Cargo)	Month-on-month growth
	6	Cargo tonnage (Tankers)	Month-on-month growth
	7	Port turnaround duration (All vessel types)	Month-on-month growth

Sources: MarineTraffic; and authors' calculations (see del Rosario and Quách 2020).

Appendix II. Overview of the Machine Learning Methods Employed

A. Regularized Regressions

Ridge, LASSO, and elastic net algorithms are common regularized regression approaches. They extend the capabilities of multiple linear regressions by incorporating regularization techniques to prevent overfitting (Hoerl and Kennard 1970; Tibshirani 1996; Zou and Hastie 2005). Overfitting happens when the model aims to perfectly match the training data but struggles to process unseen data accurately. Ridge, LASSO, and elastic net tackle overfitting by adding penalty terms to the loss function in a linear regression.[15] The penalty term keeps the model from becoming overly complex, especially as the number of variables increases.

LASSO regressions add a penalty term called L1 that is proportional to the absolute value of the regression coefficients, $\lambda \sum_{j=1}^{p} |\beta_j|$, as shown in the equation below. The hyperparameter λ controls the strength of the regularization effect.

$$\beta = argmin \left[\sum_{i=1}^{n} \left(y_i - constant - \sum_{j=1}^{p} x_{ij}\, \beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right] \qquad \text{(A1)}$$

Ridge regressions add a penalty term L2, $\lambda \sum_{j=1}^{p} \beta_j^2$, that is proportional to the square of the coefficients, as shown below:

$$\beta = argmin \left[\sum_{i=1}^{n} \left(y_i - constant - \sum_{j=1}^{p} x_{ij}\, \beta_j \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right] \qquad \text{(A2)}$$

Elastic net regressions combine both L1 and L2 penalty terms. In this case, the weight of the two penalties is indicated by the variable α:

$$\beta = argmin \left[\sum_{i=1}^{n} \left(y_i - constant - \sum_{j=1}^{p} x_{ij}\, \beta_j \right)^2 + \lambda \sum_{j=1}^{p} [\alpha |\beta_j| + (1-\alpha)\beta_j^2 \right] \qquad \text{(A3)}$$

The hyperparameter λ plays a crucial role in controlling the trade-off between model complexity and accuracy. Increasing the value of λ enhances the model's ability to generalize or increases its regularization effect but weakens its ability to recognize patterns within the training variables. Conversely, reducing λ prompts the model to overfit the training data. When λ is zero, the algorithm behaves like a regression model. LASSO regularization can drive the coefficients to zero and hence, can be used as a feature selection tool as discussed in Appendix III. Ridge, on the other hand, only drives the coefficients *near* zero. In machine learning, λ and other hyperparameters are determined through tuning, also known as cross-validation.

[15] The ridge, LASSO, and elastic net algorithms are implemented in R using the $glmnet$ package.

In addition to LASSO, the adaptive LASSO (ALASSO) approach is used as an additional variable selection method. When dealing with correlated variables, LASSO is documented to have two major drawbacks: inconsistent variable selection and a tendency to arbitrarily retain only one variable and disregard every other from a group of correlated variables (Zou 2006). These drawbacks can compromise the reliability of the model and risk losing valuable information due to excessive variable exclusion. ALASSO addresses these challenges by introducing an additional weight element to the L1 penalty term in Equation (A1), as shown below. In this study, we set the weights ω_j of the coefficients to be inversely proportional to the magnitude of the Ridge-estimated coefficients.

$$\beta = argmin\left[\sum_{i=1}^{n}\left(y_i - constant - \sum_{j=1}^{p} x_{ij}\,\beta_j\right)^2 + \lambda\sum_{j=1}^{p}\omega_j|\beta_j|\right] \tag{A5}$$

$$\omega_j = \frac{1}{\left|\beta_{Ridge,j}\right|} \tag{A4}$$

B. Support Vector Machines

Similar to linear regressions, support vector machine (SVM) algorithms aim to find the hyperplane that minimizes the distance between the predicted and actual values. This distance is measured by a loss function, and the SVM algorithm adjusts its parameters to minimize this function until convergence. SVMs handle nonlinearities in the data by using kernel functions, which map the input data into a higher-dimensional plane. This study employs two common kernel-based SVM approaches: radial basis function (RBF) kernel and linear epsilon-insensitive SVM. These two approaches are implemented in R via the $ksvm$ function from the $kernlab$ package.

The RBF approach first maps the input data to a higher-dimensional plane and subsequently identifies the hyperplane that optimally fits the data points for regression. RBF is defined as:

$$K(x_i, x_j) = \exp\left(-\gamma\left|\left|x_i - x_j\right|\right|^2\right) \tag{A6}$$

where x_i and x_j are the input data point, and γ is a hyperparameter that determines how much influence each training sample has on the model. Higher values of γ lead to tighter decision boundaries, potentially resulting in overfitting. After the transformation, the algorithm creates additional dimensions to find the optimal separate hyperplanes.

The linear epsilon-insensitive SVM approach applies a linear kernel transformation on the input variables then solves for the coefficient, or weight, vector w. This approach uses the epsilon-insensitive loss function, which ignores prediction errors that are smaller than the ε threshold. This approach is defined as:

$$argmin\left[0.5|w|^2 + C\sum_{i=1}^{n}\max\{|y_i - \hat{y}_i| - \varepsilon, 0\}\right] \tag{A7}$$

where C is the hyperparameter controlling the balance between minimizing errors and penalizing overfitting. In practice, we also used $polynomial\ kernel$ in the linear epsilon-insensitive SVM to allow it to capture potential non-linearity relationship in the data.

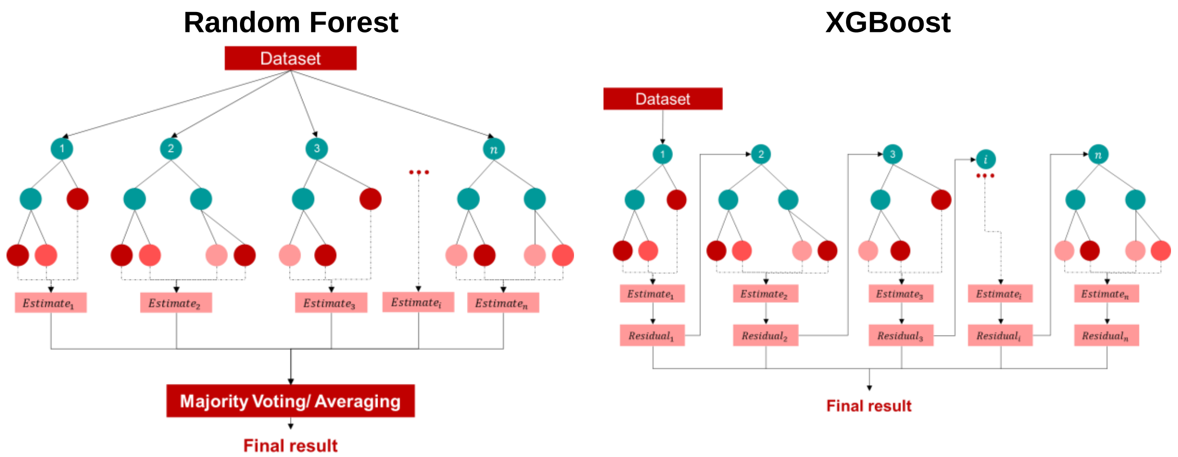
C. Random Forest and Extreme Gradient Boosting

Random forest and extreme gradient boosting (XGBoost) are two popular tree-based ML techniques. The two techniques work by splitting the input variables into subsets that correspond to a respective outcome, constructing decision trees that map the input with the output variables (Breiman 2001, Friedman 2001, Chen and Guestrin 2016). The algorithm first selects the input-output variable pairs that contain the best splits—splits that result in the greatest reduction of the sum of squared residuals. From these resulting splits, the algorithm further splits the variables to minimize the sum of squared residuals.

However, relying on a single tree can create overfitting, which arises when the algorithm splits the nodes excessively to fit the training data. Random forest and XGBoost tackle this issue by employing ensemble methods, that rely on a large number of small "trees," each capturing a subset of the data. In random forest, each "tree" creates a simple decision tree to map the input data with the outcome. This design allows different trees to capture different perspectives of the data and the algorithm will aggregate the total results from all of the trees to produce the final results. But where random forest builds trees independently, XGBoost creates trees sequentially with each tree attempting to correct the errors made by the previous ones (Appendix Figure 1).

A major drawback of random forest and XGBoost models is their limited out-of-sample predictive power. These models are trained and "pruned" to align with historical data, thereby restricting their adaptability to deal with extreme events where target values deviate significantly from historical ranges.

Appendix Figure 1. Illustrations of Random Forest and XGBoost



Source: AMRO staff visualization.

The models are implemented in R using the $randomForest$ and $xgboost$ packages. The key hyperparameter of the random forest algorithm is $mtry$, which controls the number of features to be considered for each split in a decision tree within the ensemble. The key hyperparameters of tree-based XGBoost algorithm that we have tuned are $nround$, which indicates the number of boosting trees to be constructed in the ensemble, max_depth, which sets the maximum depth allowed for each decision tree, and min_child_weight, which defines the minimum amount of data needed in a child node of each decision tree. To prevent overfitting, we also set the values of $alpha$ and $lambda$ to one to regularize the contribution of each variable toward the target to reduce the overfitting tendency of XGBoost.

It is also important to note that random forest and XGBoost contain a large degree of randomness in their algorithms, thus affecting their reproducibility. This is because both techniques employ random subsampling of the data to generate large amounts of decision trees. We have attempted to ensure reproducibility by fixing the random seed in R. However, our own experiments suggest that practitioners can also achieve a consistent range of results if the models are trained and tested repeatedly under different seeds.

Appendix III. Feature Selection and Model Configuration

Variable screening techniques to weed out noisy predictors in large-scale models improve forecasting accuracy. This has been shown in various studies, such as Bai and Ng (2008) and Chinn, Meunier, and Stumpner (2023). One variable selection technique is leveraging expert opinion; however, this approach suffers from limited replicability and thus, presents challenges in automation. To this end, LASSO and adaptive LASSO (ALASSO) are used to automate variable selection.

The shrinkage factor of LASSO, $\lambda \sum_{j=1}^{p} |\beta_j|$, reduces the coefficients to zero while balancing between the bias and variance of the model, and thus can act as a variable filter. ALASSO uses adaptive weights to penalize different coefficients in the LASSO penalty, allowing it to avoid overfitting by penalizing large coefficients. This adaptability makes it more flexible and accurate in model estimation and variable selection. LASSO and ALASSO variable selection techniques are evaluated by comparing their predictive performance against the same model employing a complete list of variables.

The estimation dataset is partitioned into in-sample and out-of-sample datasets. The in-sample dataset is used for hyperparameter tuning and ML estimation; the out-of-sample, for evaluating ML and variable selection techniques for their predictive performance (Appendix Figure 2). To do this, we create different combinations of the seven ML models and three variable groups—the complete set of variables as well as the variable set filtered by LASSO and ALASSO. These models are tuned and fitted using the in-sample dataset for each economy, and then evaluated for their the out-of-sample predictive performance.

The tuning process, also known as cross-validation, involves the selection of hyperparameters that minimizes the model's out-of-sample RMSE. The hyperparameters are selected within an expanding subset of the in-sample dataset following the approach described in Hyndman and Athanasopoulos (2018) and Cerqueira, Torgo and Mozetič (2020).[16] The tuning process involves sequentially training the model with the selected hyperparameters, starting with an initial subset of the data and then gradually expanding to include more data in temporal order, while measuring the RMSE at each iteration. Tuning starts from January 2020 and the validation range is the next three observations (Appendix Figure 2). This process continues until the entire in-sample dataset is used.[17,18]

This paper also evaluates the performance of three dataset compositions, all of which use the period from January 2022 to December 2023 as the out-of-sample dataset. Set 1 utilizes data from as early as January 2000 to December 2021 to train the models.[19] Sets 2 and 3 have a shorter sample size, starting from February 2019 in order to evaluate the AIS-derived

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[16] Hyndman and Athanasopoulos (2018) describe the method as "evaluation on a rolling forecasting origin" and Cerqueira, Torgo and Mozetič (2020) as "prequential method". We refer to the more common terminology of "expanding window validation" as it fits the nowcasting and cross-validation nature of the exercise.

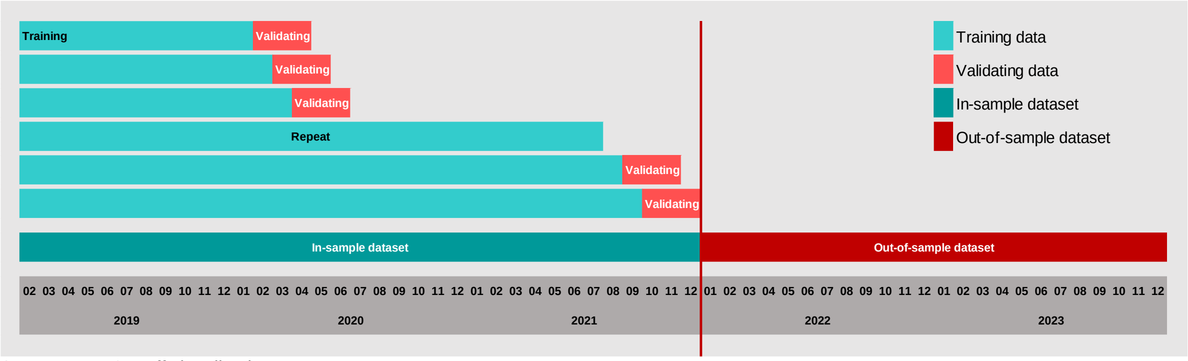
[17] It is important to note that the testing process in this step is to select the best hyperparameters of each algorithm and this process is applied on the in-sample dataset.

[18] We have simplified the process of evaluating ML models by using tuned hyperparameters based on the in-sample datasets. However, as models get exposed to new data, there's potential to retune these hyperparameters for improved performance.

[19] In this exercise, official export statistics for most of the economies in the study start from January 2000, except for Brunei, Cambodia, Myanmar, and Vietnam, of which the training data start from 2013, 2010, 2006, and 2005, respectively.

indicators in the predictor set. As the control set, Set 2 is a shorter-sample version of Set 1 without the AIS indicators. Set 3 contains the AIS-derived indicators in Appendix Table 3, with the AIS indicators transformed in month-on-month growth rates to save a few more observations.[20] As discussed earlier, the training-validation process expands to the next observation per iteration until the end of the in-sample dataset.

Appendix Figure 2. Expanding Window Cross-Validation



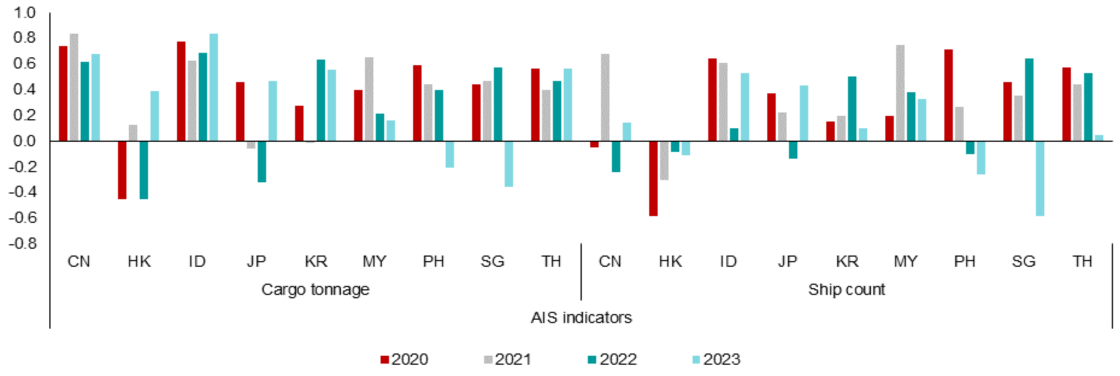
Source: AMRO staff visualization.
Note: The figure illustrates the training/testing data preparation, with the tuning period from February 2019 to December 2021 as a subset of the in-sample dataset. The tuning sample helps select the optimal hyperparameters that minimizes out-of-sample RMSE. The out-of-sample dataset evaluates performance across different models for each economy.

[20] ML estimations with year-on-year transformations of the AIS-derived indicators (cargo tonnage and ship count) resulted in worse performances across the models and the available training data are greatly limited to the January 2020–December 2021 period only.

Appendix IV. Figures Related to the 2021–22 Global Supply Chain Disruptions

Appendix Figure 3. Selected ASEAN+3: Correlation Coefficients for AIS Indicators versus Official Statistics—Export Volume

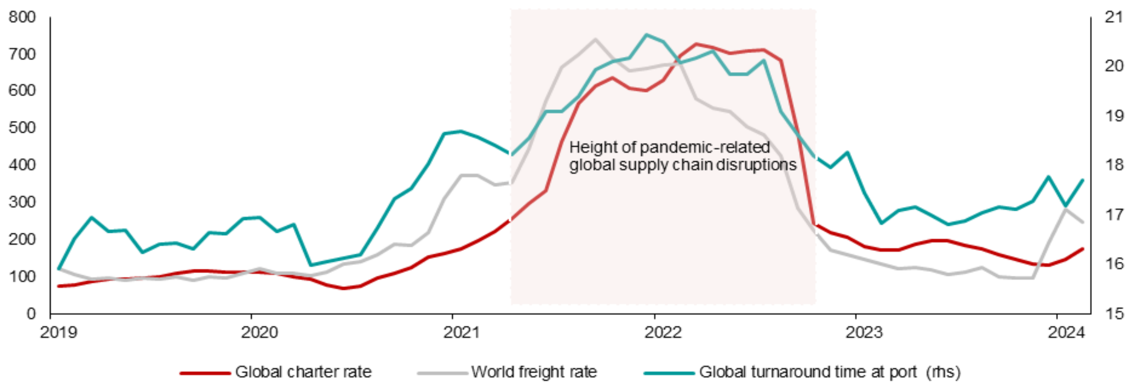
(Unit)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: CN = China; HK = Hong Kong; ID = Indonesia; JP = Japan; KR = Korea; MY = Malaysia; PH = Philippines; SG = Singapore; TH = Thailand. Coefficients are based on a 12-month correlation.

Appendix Figure 4. World: Shipping Freight Rates and Port Turnaround Time—Containerships

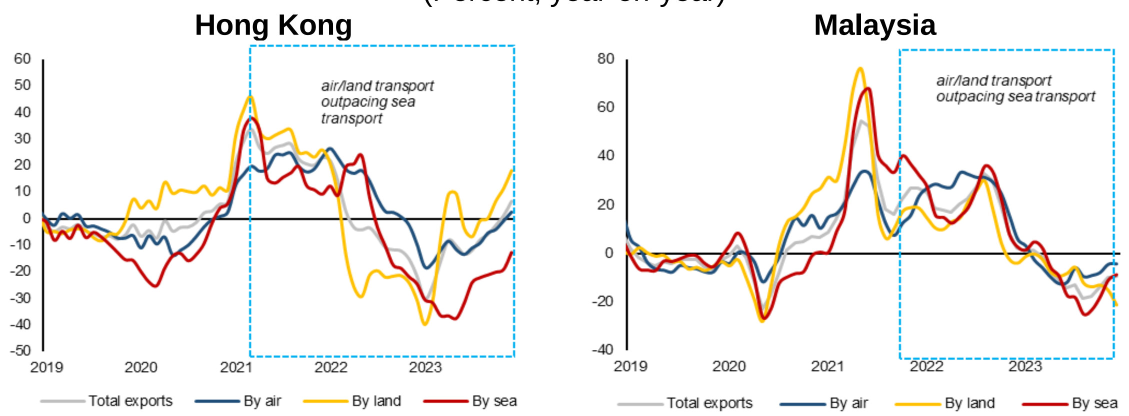
(2019=100)



Sources: Haver Analytics; MarineTraffic; and AMRO staff calculations.
Note: Freight rates and port turnaround time are indicators of supply chain disruptions. Global turnaround time at port refers to the median duration of time that containerships spend at ports.

Appendix Figure 5. Hong Kong and Malaysia: Merchandise Export Value by Modes of Transport

(Percent, year-on-year)



Sources: National authorities via CEIC; and AMRO staff calculations.

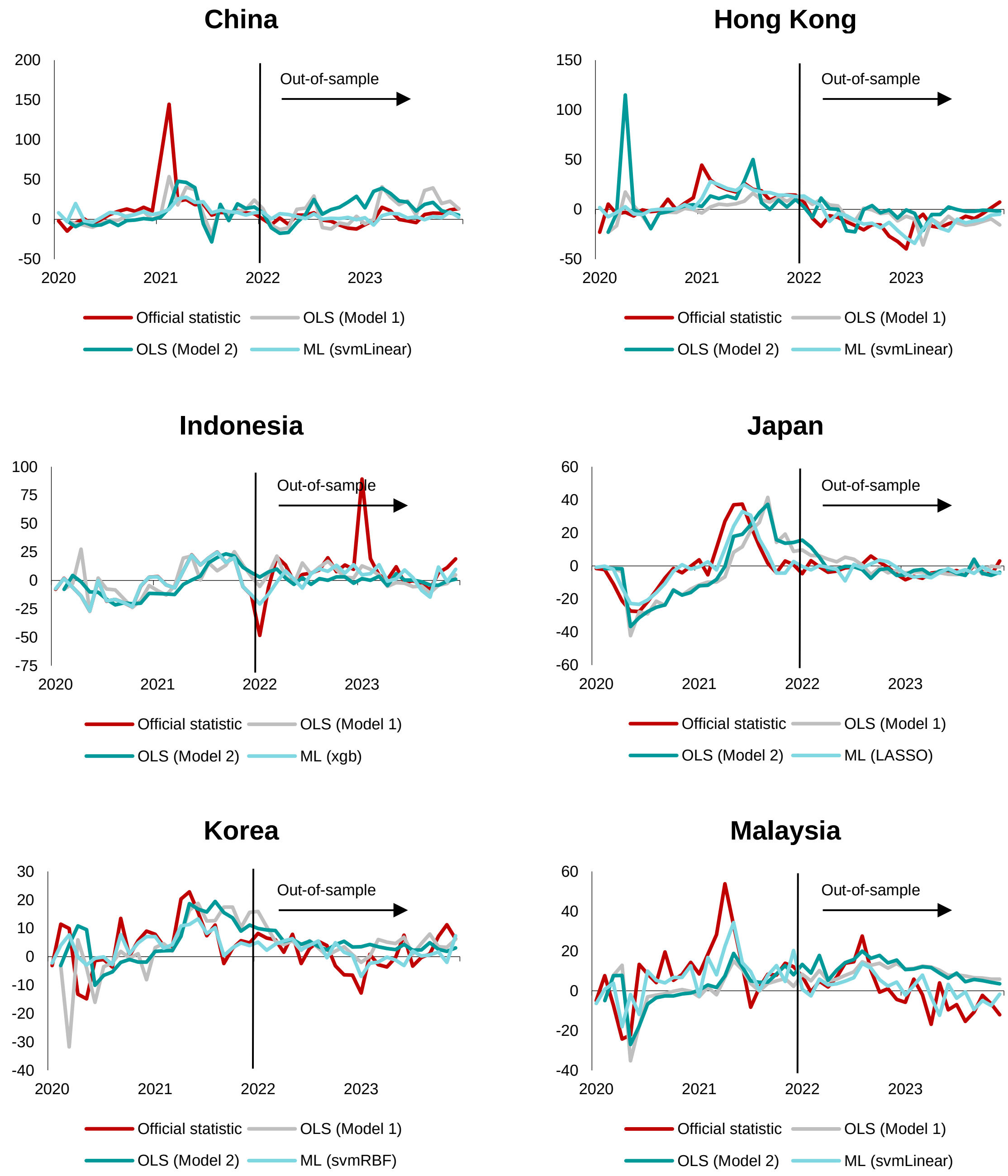
Appendix V. Bridge Model Estimates

Appendix Table 4. Selected ASEAN+3: Normalized Out-of-Sample RMSE of OLS and ML Bridge Models—Export Volume

Economy	OLS		ML Techniques						
	Model 1	Model 2	ridge	LASSO	elnet	RF	xgb	svmLinear	svmRBF
China	1.98	2.50	1.41	1.43	1.43	1.69	3.97	0.95	1.05
Hong Kong	1.45	1.45	1.08	0.98	1.07	1.12	1.25	0.93	1.16
Indonesia	0.88	1.03	1.05	1.02	1.03	0.92	0.90	1.07	0.94
Japan	1.45	1.65	1.48	1.00	1.01	1.21	1.12	1.48	1.22
Korea	0.97	1.07	0.95	0.96	0.94	0.95	1.12	1.02	0.91
Malaysia	1.28	1.28	0.86	0.82	0.84	0.91	0.90	0.79	0.81
Philippines	1.00	1.01	0.99	0.99	0.99	1.04	1.07	1.03	1.02
Singapore	1.24	1.31	0.95	0.90	0.91	0.85	0.88	0.78	0.85
Thailand	1.48	1.45	0.87	0.84	0.84	0.90	1.35	1.02	0.91

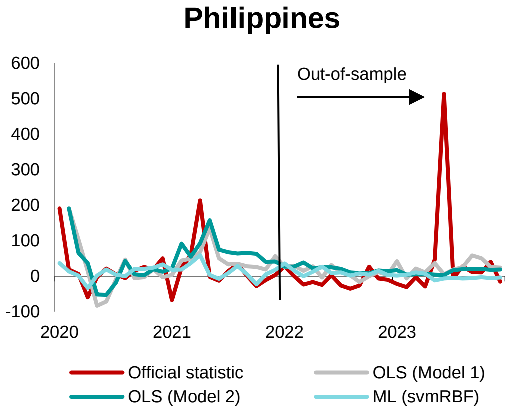
Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: elnet = elastic net; LASSO = LASSO regression; RF = random forest; xgb = XGBoost; Ridge = ridge regression; svmLinear = linear epsilon-insensitive SVM; and svmRBF = radial basis function kernel SVM. RMSEs are calculated from out-of-sample predictions for the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy's export volume growth for the same period. Models 1 and 2 refer to the OLS estimation of the cargo tonnage- and ship count-based volume models, respectively.

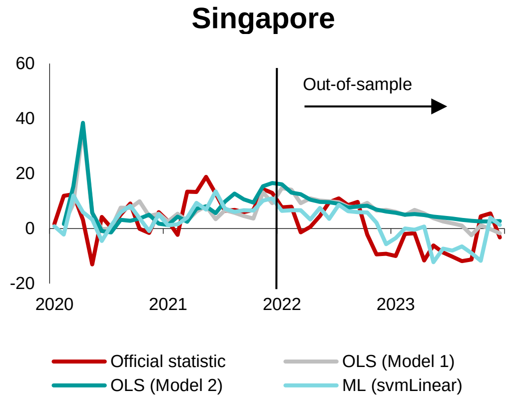
Appendix Figure 6. Selected ASEAN+3: Actual versus Estimates from OLS and Best ML Bridge Models—Export Volume
(Percent, year-on-year)

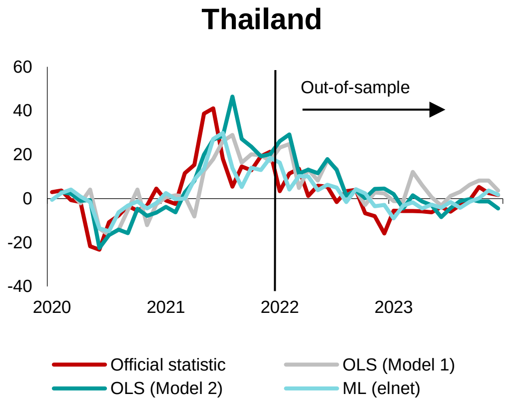


Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: elnet = elastic net; LASSO = LASSO regression; RF = random forest; xgb = XGBoost; svmLinear = linear epsilon-insensitive SVM; and svmRBF = radial basis function kernel SVM. Economy-level RMSEs are calculated from out-of-sample predictions for the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy's export volume growth for the same period. Models 1 and 2 refer to the OLS estimation of the cargo tonnage- and ship count-based volume models, respectively. Selected ML technique is based on the lowest RMSE.

Appendix Figure 6 (Cont'd). Actual versus Estimates from OLS and Best ML Bridge Models—Export Volume
(Percent, year-on-year)







Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: elnet = elastic net; LASSO = LASSO regression; RF = random forest; xgb = XGBoost; svmLinear = linear epsilon-insensitive SVM; and svmRBF = radial basis function kernel SVM. Economy-level RMSEs are calculated from out-of-sample predictions for the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy's export volume growth for the same period. Models 1 and 2 refer to the OLS estimation of the cargo tonnage- and ship count-based volume models, respectively. Selected ML technique is based on the lowest RMSE.

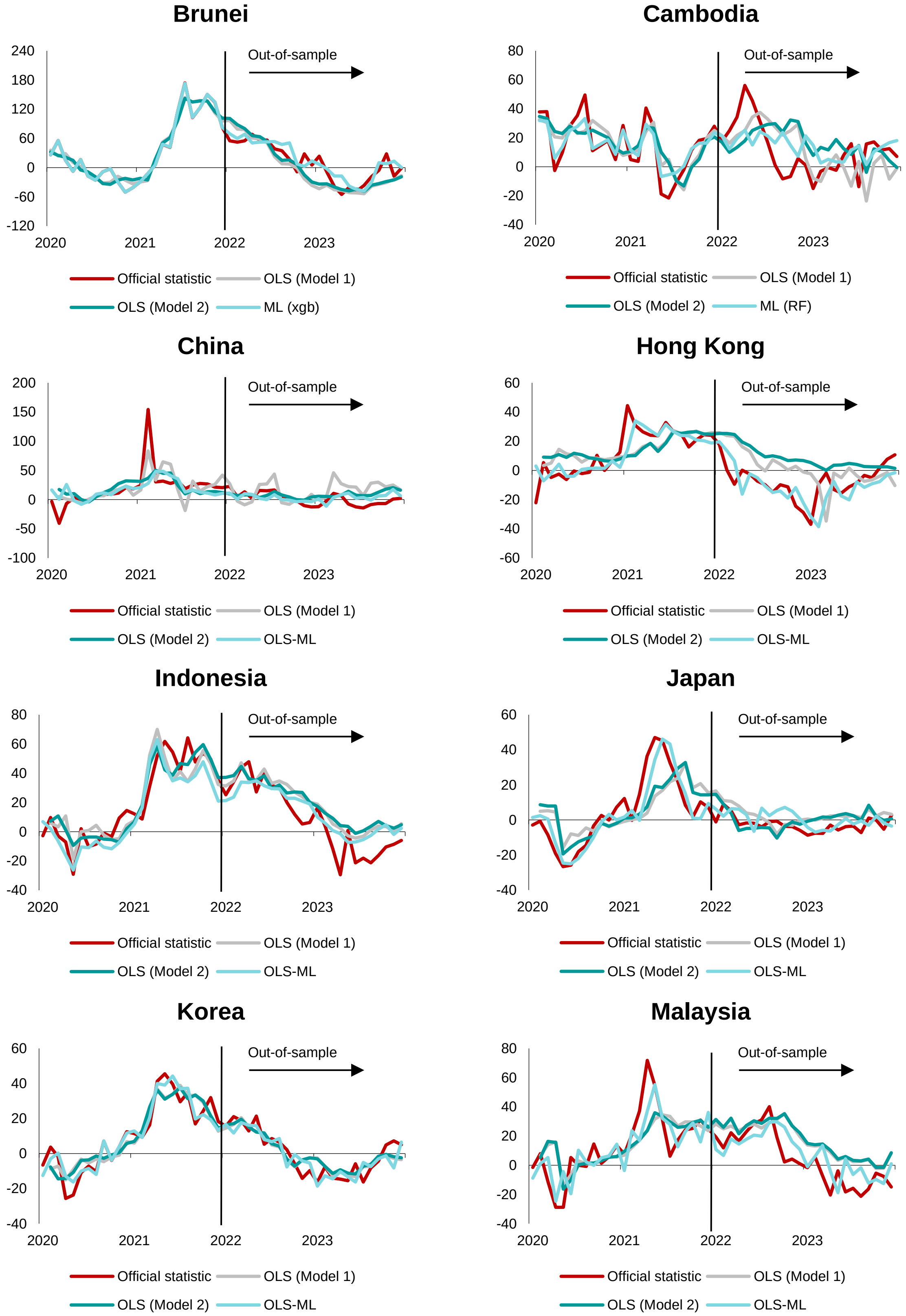
Appendix V. Estimates from Bridge Models—Export Value

Appendix Table 5. Selected ASEAN+3: Normalized Out-of-Sample RMSE of ML-based Bridge Models—Export Value

Economy	ridge	LASSO	elnet	RF	xgb	svmLinear	svmRBF
Brunei	0.51	0.50	0.51	0.51	0.46	0.60	0.60
Cambodia	1.05	0.99	0.97	0.94	0.99	1.92	0.95
Myanmar	0.89	0.65	0.75	0.77	0.70	0.75	0.86
Vietnam	1.04	1.10	1.09	0.86	0.96	0.90	0.88

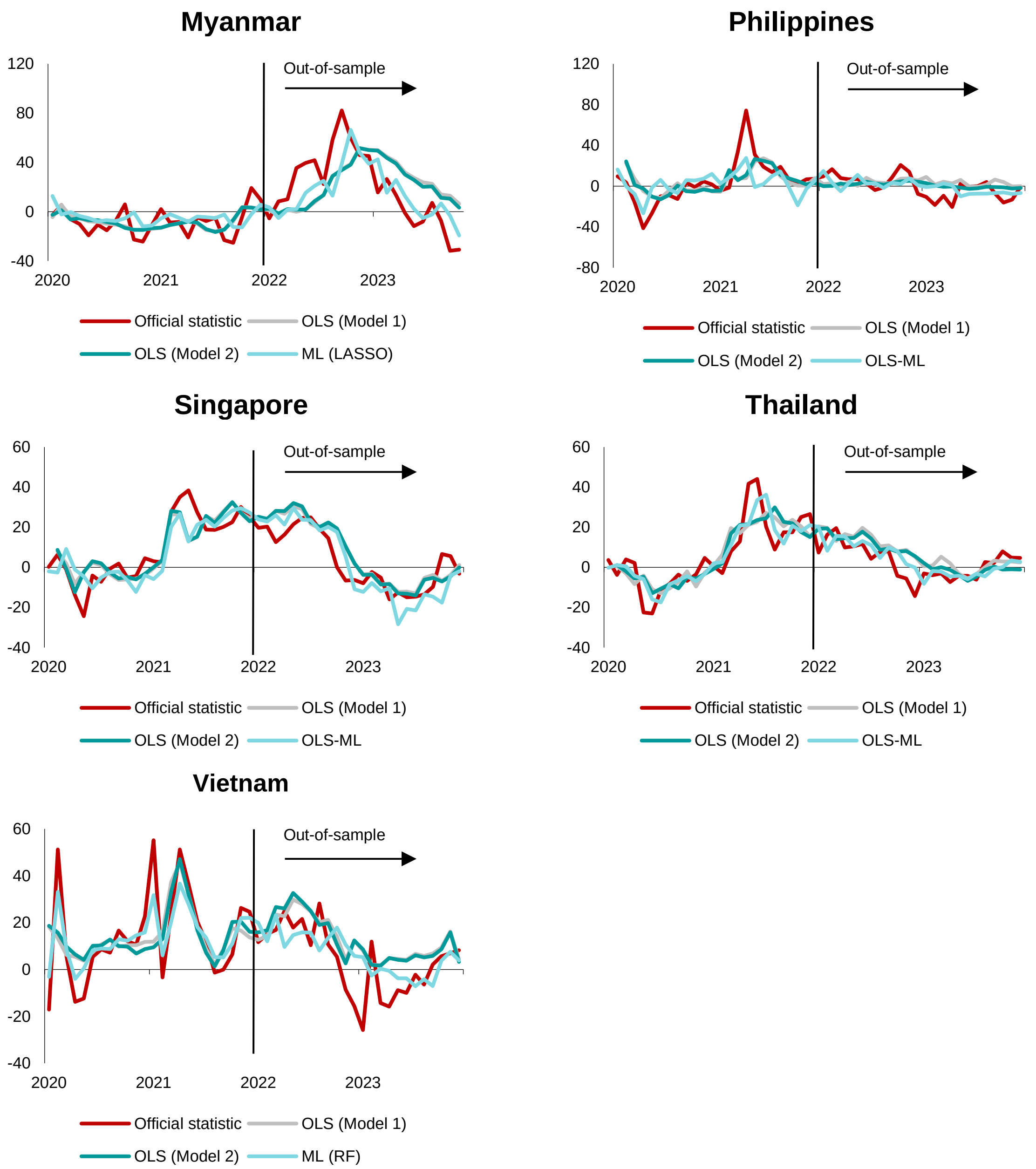
Sources: MarineTraffic; National authorities via Haver Analytics; and AMRO staff calculations.
Note: elnet = elastic net; LASSO = LASSO regression; RF = random forest; xgb = XGBoost; Ridge = ridge regression; svmLinear = linear epsilon-insensitive SVM; and svmRBF = radial basis function kernel SVM. Economy-level RMSEs are calculated from out-of-sample predictions for the January 2022–December 2023 period, and normalized by the standard deviation of the respective economy’s export volume growth for the same period.

Appendix Figure 7. ASEAN+3 excluding Lao PDR: Actual versus Estimates from OLS and OLS-ML Bridge Models—Export Value
(Percent year-on-year growth)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: LASSO = LASSO regression; xgb = XGBoost; and RF = random forest. Models 1 and 2 refer to the OLS estimation of the cargo tonnage- and ship count-based volume models, respectively. Export values are in US dollars.

Appendix Figure 7 (Cont'd). ASEAN+3 excluding Lao PDR: Actual versus Estimates from OLS- and ML-based Bridge Models—Export Value
(Percent year-on-year growth)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: LASSO = LASSO regression; xgb = XGBoost; and RF = random forest. Models 1 and 2 refer to the OLS estimation of the cargo tonnage- and ship count-based volume models, respectively. Export value are in US dollars.

Appendix VI. RMSEs Across ML-based Export Nowcasting Models

Appendix Table 6. ASEAN+3: Out-of-Sample RMSEs across ML Models—Export Value

Economy	Variable Selection Methods	Dataset Composition	svmRBF	svmLinear	elnet	LASSO	ridge	RF	xgb
Brunei	ALASSO	From 2000	66.76	188.71	42.76	44.20	42.52	34.13	38.73
	ALASSO	From 2019	25.35	31.18	28.65	29.26	25.61	29.51	45.16
	ALASSO	From 2019, with AIS indicators	25.28	31.08	28.65	29.26	25.84	30.67	38.25
	All variables	From 2000	40.27	264.19	39.39	38.90	68.27	32.33	32.84
	All variables	From 2019	23.62	20.71	24.16	23.78	21.36	28.91	32.93
	All variables	From 2019, with AIS indicators	23.64	20.62	24.16	23.78	21.37	27.99	32.61
	LASSO	From 2000	63.55	126.83	40.70	40.60	40.48	36.24	39.38
	LASSO	From 2019	22.92	22.32	24.72	23.44	33.65	28.04	28.24
	LASSO	From 2019, with AIS indicators	21.96	22.26	24.62	23.44	33.29	26.34	33.31
Cambodia	ALASSO	From 2000	18.09	57.75	18.67	18.43	19.24	18.52	25.07
	ALASSO	From 2019	17.87	16.07	18.17	18.25	17.99	16.39	20.64
	ALASSO	From 2019, with AIS indicators	17.87	16.33	18.17	18.25	18.00	16.18	21.02
	All variables	From 2000	18.09	42.12	18.69	18.43	19.63	18.84	22.79
	All variables	From 2019	17.87	16.41	18.17	18.25	17.60	15.84	18.39
	All variables	From 2019, with AIS indicators	17.87	16.75	18.17	18.25	17.65	16.07	22.24
	LASSO	From 2000	18.27	28.27	18.43	18.43	18.61	19.79	22.61
	LASSO	From 2019	17.79	19.27	18.17	18.29	18.03	16.50	18.83
	LASSO	From 2019, with AIS indicators	17.79	19.27	18.17	18.29	18.03	16.80	17.48
China	ALASSO	From 2000	8.74	32.12	17.18	16.49	15.17	11.78	17.41
	ALASSO	From 2019	9.51	19.30	13.71	14.19	11.06	10.96	19.27
	ALASSO	From 2019, with AIS indicators	9.18	20.99	13.71	14.19	11.01	10.92	19.70
	All variables	From 2000	8.89	18.87	11.33	9.91	11.34	10.91	10.37
	All variables	From 2019	8.83	14.29	12.66	14.19	8.78	10.36	14.93
	All variables	From 2019, with AIS indicators	8.65	14.00	12.66	14.19	8.83	10.46	29.80
	LASSO	From 2000	10.58	9.27	11.64	9.91	16.65	10.85	10.02
	LASSO	From 2019	12.09	11.94	12.66	14.19	8.78	10.36	18.09
	LASSO	From 2019, with AIS indicators	12.09	11.94	12.66	14.19	8.83	10.46	18.88
Hong Kong	ALASSO	From 2000	9.93	14.33	9.04	8.99	13.84	12.61	9.93
	ALASSO	From 2019	9.18	11.25	9.63	9.73	11.61	12.60	11.83
	ALASSO	From 2019, with AIS indicators	9.21	11.30	9.63	9.73	11.61	12.71	12.11
	All variables	From 2000	9.26	13.03	11.26	11.29	11.53	12.84	10.64
	All variables	From 2019	9.64	10.13	9.58	9.52	10.22	12.48	11.16
	All variables	From 2019, with AIS indicators	9.64	10.09	9.58	9.52	10.23	12.38	12.42
	LASSO	From 2000	12.22	11.44	13.39	12.87	16.35	13.14	10.81
	LASSO	From 2019	11.09	10.11	13.33	9.56	16.10	11.74	10.74
	LASSO	From 2019, with AIS indicators	11.09	10.11	13.33	9.56	16.10	11.78	10.94
Indonesia	ALASSO	From 2000	10.61	15.11	20.30	20.44	20.76	16.65	15.71
	ALASSO	From 2019	13.59	15.72	14.16	13.90	14.59	16.63	18.62
	ALASSO	From 2019, with AIS indicators	13.54	15.47	14.16	13.90	14.62	16.86	20.82
	All variables	From 2000	10.19	15.81	10.13	10.48	10.43	11.79	11.66
	All variables	From 2019	11.62	10.06	9.28	9.27	9.93	13.72	16.21

Economy	Variable Selection Methods	Dataset Composition	svmRBF	svmLinear	elnet	LASSO	ridge	RF	xgb
	All variables	From 2019, with AIS indicators	11.65	9.98	9.29	9.27	9.89	13.43	12.53
	LASSO	From 2000	9.29	9.51	10.99	10.91	15.84	10.81	13.34
	LASSO	From 2019	12.70	12.44	9.83	9.43	16.99	14.79	15.73
	LASSO	From 2019, with AIS indicators	12.03	11.25	9.86	9.44	17.75	16.14	12.64
Japan	ALASSO	From 2000	4.81	10.07	9.21	9.43	3.46	3.94	5.74
	ALASSO	From 2019	4.93	7.99	6.59	7.12	3.42	4.21	7.22
	ALASSO	From 2019, with AIS indicators	4.95	8.19	6.58	7.11	3.42	4.14	5.54
	All variables	From 2000	3.30	7.33	4.45	4.50	4.12	4.64	5.69
	All variables	From 2019	3.33	3.47	3.48	3.52	3.10	4.53	8.87
	All variables	From 2019, with AIS indicators	3.34	3.60	3.48	3.52	3.11	4.27	6.99
	LASSO	From 2000	5.64	7.64	4.53	4.58	4.41	3.39	5.45
	LASSO	From 2019	4.45	4.79	3.95	4.07	4.76	3.82	7.88
	LASSO	From 2019, with AIS indicators	4.14	4.37	3.95	4.11	4.78	3.81	5.20
Korea	ALASSO	From 2000	6.73	10.51	8.22	8.25	10.98	9.51	6.57
	ALASSO	From 2019	6.68	7.81	6.28	5.06	8.04	9.36	11.38
	ALASSO	From 2019, with AIS indicators	6.71	7.75	6.28	5.06	8.07	9.56	9.36
	All variables	From 2000	5.75	9.78	6.25	6.12	7.29	8.59	7.61
	All variables	From 2019	6.77	6.28	6.01	6.71	6.63	8.43	9.19
	All variables	From 2019, with AIS indicators	6.80	6.30	6.01	6.71	6.63	8.69	7.74
	LASSO	From 2000	8.46	8.15	6.68	6.51	11.33	7.94	7.72
	LASSO	From 2019	7.65	7.40	7.43	7.26	10.24	8.09	9.96
	LASSO	From 2019, with AIS indicators	7.65	7.40	7.43	7.26	10.24	8.10	10.60
Lao PDR	ALASSO	From 2000	13.42	49.88	15.80	15.80	12.24	12.68	39.47
	ALASSO	From 2019	14.54	17.62	15.14	14.48	15.23	13.79	21.69
	All variables	From 2000	12.80	44.71	13.86	13.20	11.76	12.40	22.71
	All variables	From 2019	13.06	14.17	14.66	14.55	13.71	13.04	15.76
	LASSO	From 2000	13.08	11.69	13.89	13.20	15.27	12.46	20.15
	LASSO	From 2019	17.08	17.54	15.69	15.69	15.04	14.01	13.27
Malaysia	ALASSO	From 2000	10.49	12.07	15.64	15.67	16.58	13.64	13.14
	ALASSO	From 2019	11.59	12.45	14.36	14.25	15.42	13.87	15.62
	ALASSO	From 2019, with AIS indicators	11.62	12.47	14.36	14.25	15.43	13.60	14.13
	All variables	From 2000	9.32	9.13	11.04	11.12	12.29	10.71	10.64
	All variables	From 2019	10.49	9.32	10.25	10.09	11.49	11.97	15.97
	All variables	From 2019, with AIS indicators	10.52	9.41	10.25	10.09	11.48	12.17	12.56
	LASSO	From 2000	12.97	12.94	11.30	11.29	16.95	10.18	10.06
	LASSO	From 2019	15.27	11.56	12.23	12.04	17.58	14.35	11.41
	LASSO	From 2019, with AIS indicators	16.39	13.91	12.96	12.83	17.81	15.54	13.60
Myanmar	ALASSO	From 2000	29.42	96.78	30.32	30.61	31.55	24.28	32.22
	ALASSO	From 2019	33.58	22.12	28.93	28.52	26.09	24.98	28.05
	ALASSO	From 2019, with AIS indicators	33.38	21.37	28.80	28.43	23.43	24.07	27.49
	All variables	From 2000	29.31	91.15	26.95	27.81	29.88	23.91	34.63
	All variables	From 2019	33.37	18.63	27.53	26.78	23.60	24.39	25.10
	All variables	From 2019, with AIS indicators	33.38	19.18	26.89	26.06	23.45	24.54	25.01
	LASSO	From 2000	30.81	23.90	26.95	27.81	29.88	23.91	40.60
	LASSO	From 2019	36.16	26.88	31.86	31.45	33.74	26.98	29.28
	LASSO	From 2019, with AIS indicators	36.05	28.10	26.89	26.06	23.45	24.54	25.01

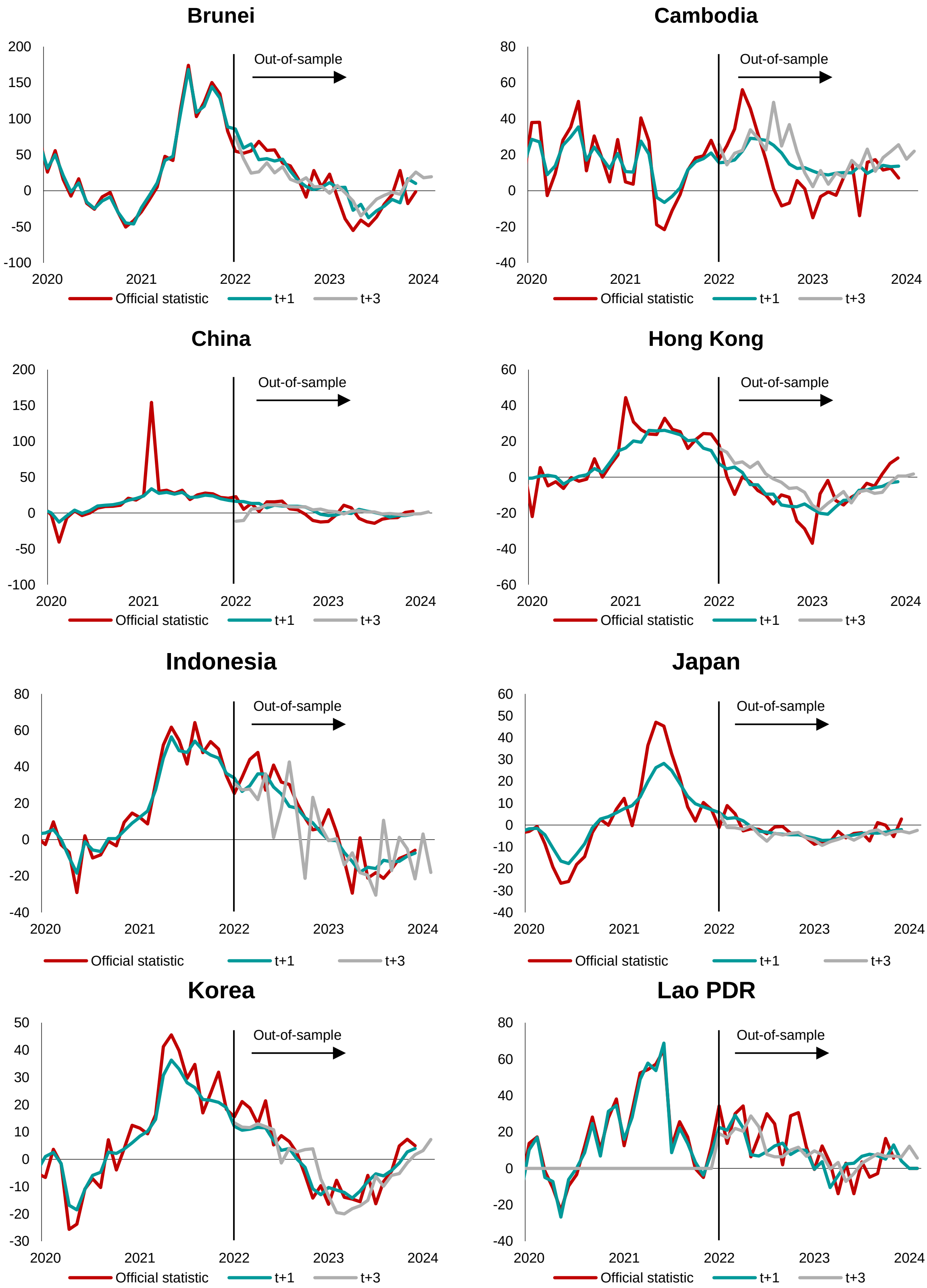
Economy	Variable Selection Methods	Dataset Composition	svmRBF	svmLinear	elnet	LASSO	ridge	RF	xgb
Philippines	ALASSO	From 2000	10.41	17.41	11.07	10.30	10.93	9.93	12.25
	ALASSO	From 2019	11.21	12.21	12.51	12.62	10.42	9.97	10.13
	ALASSO	From 2019, with AIS indicators	11.21	12.60	12.51	12.62	10.40	9.95	12.06
	All variables	From 2000	9.56	17.13	9.72	10.38	9.55	9.18	12.93
	All variables	From 2019	11.21	9.30	10.47	10.60	9.85	9.78	17.07
	All variables	From 2019, with AIS indicators	11.21	9.37	10.47	10.60	9.85	9.77	12.22
	LASSO	From 2000	10.67	11.85	9.82	10.31	11.18	9.32	13.94
	LASSO	From 2019	11.25	16.00	11.27	11.34	11.44	12.06	14.80
	LASSO	From 2019, with AIS indicators	11.20	15.92	11.07	11.20	11.40	11.23	16.69
Singapore	ALASSO	From 2000	7.59	15.86	14.86	14.59	13.05	10.46	11.58
	ALASSO	From 2019	9.03	9.72	8.69	8.31	12.32	11.20	12.01
	ALASSO	From 2019, with AIS indicators	9.06	9.72	8.69	8.31	12.32	10.95	11.74
	All variables	From 2000	6.71	10.30	7.36	6.93	8.76	7.76	7.72
	All variables	From 2019	7.78	6.94	7.55	7.75	8.59	9.00	9.51
	All variables	From 2019, with AIS indicators	7.78	6.99	7.55	7.75	8.60	9.28	9.18
	LASSO	From 2000	6.61	6.93	7.11	6.69	13.20	5.62	7.12
	LASSO	From 2019	7.56	7.91	7.65	7.41	13.13	9.94	8.55
	LASSO	From 2019, with AIS indicators	7.56	7.91	7.65	7.41	13.13	9.81	8.89
Thailand	ALASSO	From 2000	6.77	8.79	5.14	5.14	8.36	6.75	9.18
	ALASSO	From 2019	6.39	7.77	5.07	5.34	6.70	6.38	8.67
	ALASSO	From 2019, with AIS indicators	6.35	7.78	5.07	5.34	6.70	6.48	8.79
	All variables	From 2000	5.23	10.17	5.29	5.25	6.07	6.29	6.20
	All variables	From 2019	5.53	6.10	5.44	5.52	5.84	6.22	7.96
	All variables	From 2019, with AIS indicators	5.53	6.12	5.44	5.52	5.84	6.18	5.86
	LASSO	From 2000	5.29	5.26	5.42	5.40	8.86	5.76	7.00
	LASSO	From 2019	6.37	6.65	5.51	5.62	7.46	7.14	8.36
	LASSO	From 2019, with AIS indicators	6.37	6.65	5.51	5.62	7.46	7.02	8.86
Vietnam	ALASSO	From 2000	20.32	201.61	18.96	18.96	20.34	21.15	27.63
	ALASSO	From 2019	15.27	17.17	14.89	15.73	13.63	12.64	17.52
	ALASSO	From 2019, with AIS indicators	15.27	16.86	14.94	15.73	13.71	12.70	16.66
	All variables	From 2000	17.14	83.38	18.96	18.96	21.10	20.13	24.64
	All variables	From 2019	15.27	14.75	14.49	15.73	12.82	12.61	16.93
	All variables	From 2019, with AIS indicators	15.27	14.50	14.49	15.73	12.82	12.39	13.83
	LASSO	From 2000	18.10	18.42	18.96	18.96	18.95	18.18	18.78
	LASSO	From 2019	15.42	19.20	15.62	15.73	15.73	15.70	23.90
	LASSO	From 2019, with AIS indicators	15.42	19.20	15.62	15.73	15.73	15.68	19.49

Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: ALASSO = adaptive LASSO; elnet = elastic net; LASSO = LASSO regression; RF = random forest; xgb = XGBoost; svmLinear = linear epsilon-insensitive SVM; and svmRBF = radial basis function kernel SVM. RMSEs are calculated from out-of-sample predictions for the January 2022 to December 2023 period. The five models with the lowest RMSEs per economy are highlighted.

Appendix VII. Best-Performing Large-Scale ML Model Estimates—Export Value

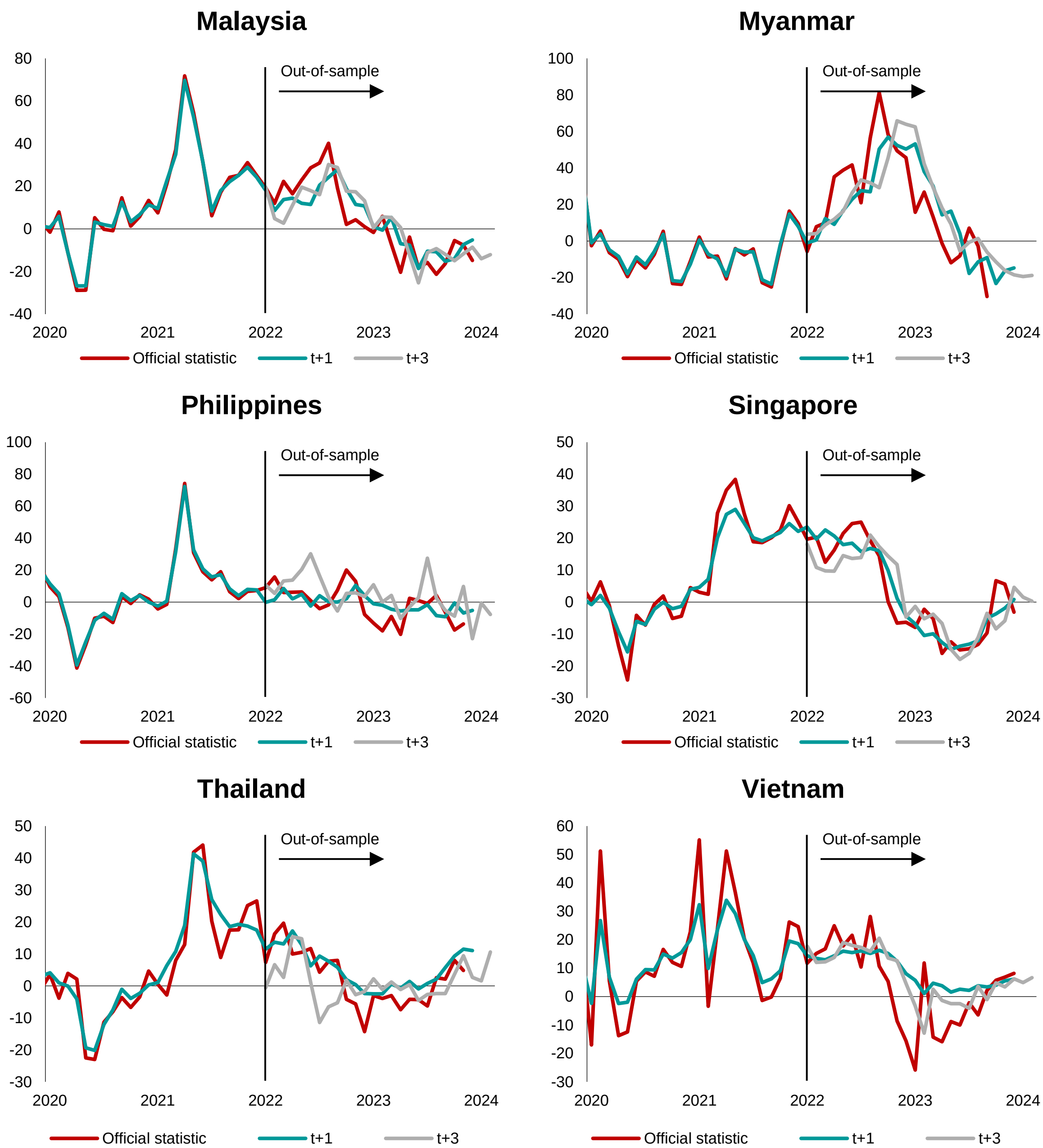
Appendix Figure 8. ASEAN+3: Actual versus ML Estimates—Export Value

(Percent year-on-year)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Figures illustrate t+1 and t+3 estimates of the best-performing ML models in comparison with official statistics.

Appendix Figure 8 (Cont'd). ASEAN+3: Actual versus ML Estimates—Export Value
(Percent year-on-year)

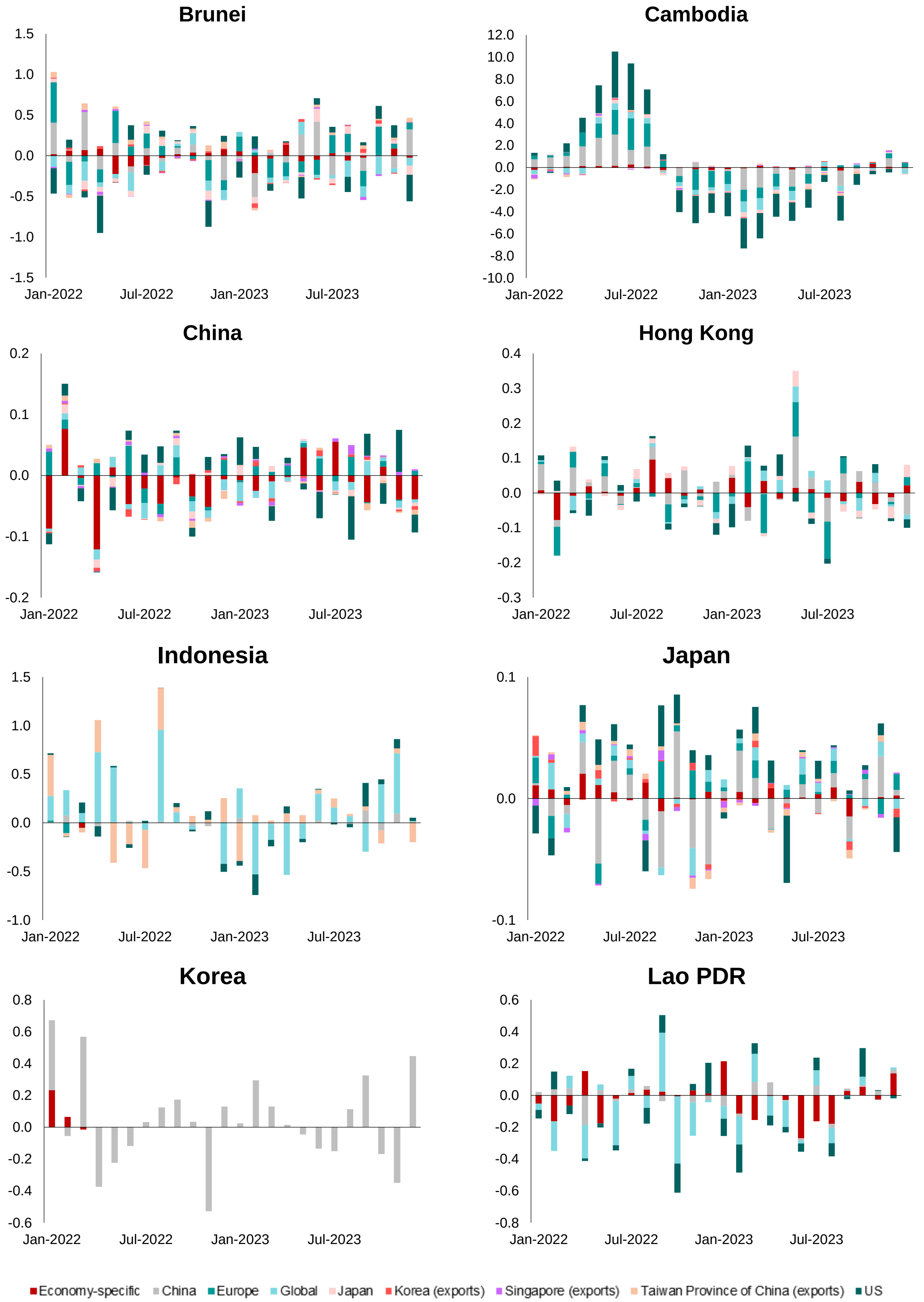


Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Figures illustrate t+1 and t+3 estimates of the best-performing ML models in comparison with official statistics.

Appendix VIII. Marginal Contribution of Variables to Large-Scale ML-based Nowcasts

Appendix Figure 9. ASEAN+3: Marginal Variable Contributions by Geographical Group

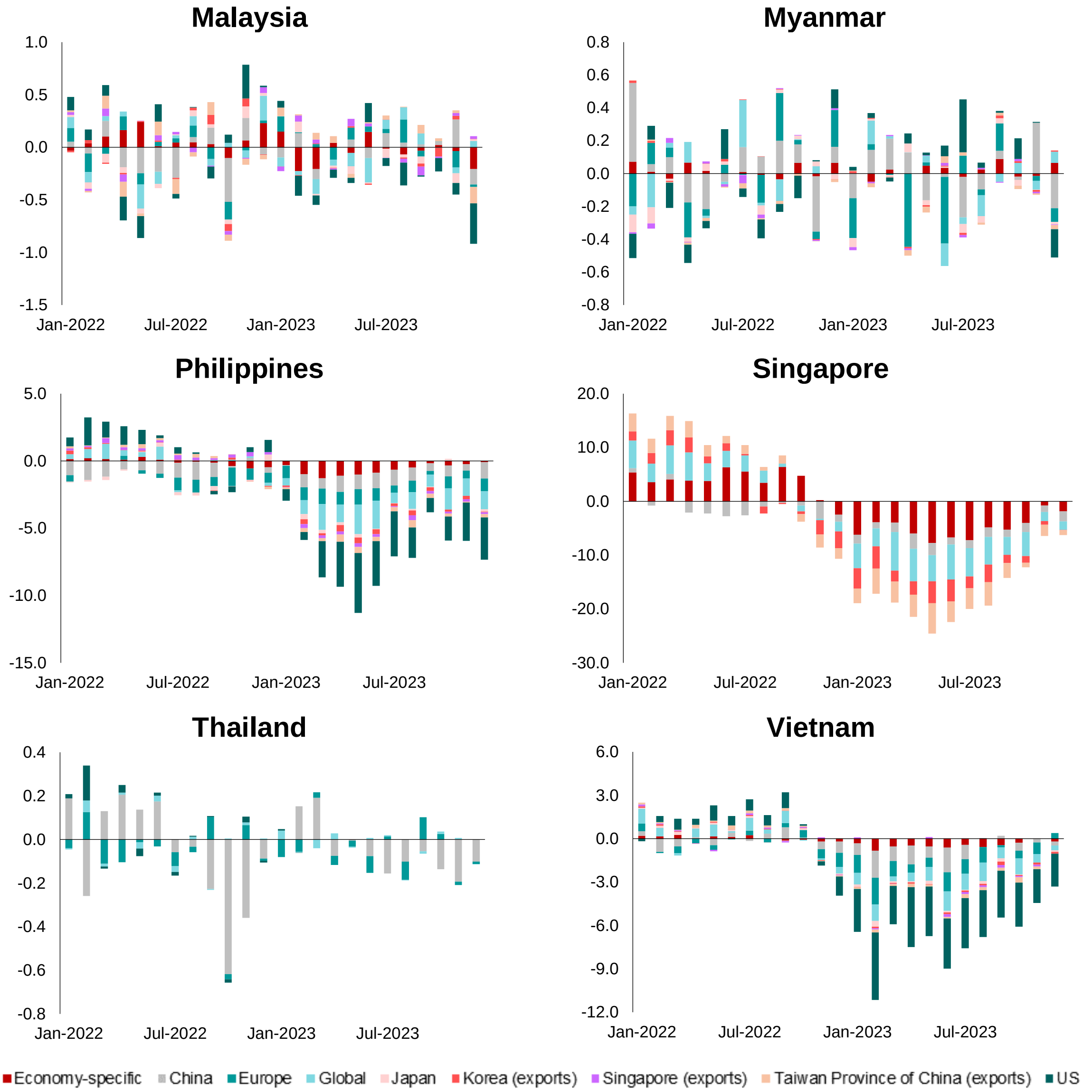
(Percentage point contribution to year-on-year growth)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Marginal variable contributions are derived from Shapley values, which provide an estimate of a variable's contribution to the prediction for a given period relative to the average prediction (Strumbelj and Kononenko 2010). The values are additive.

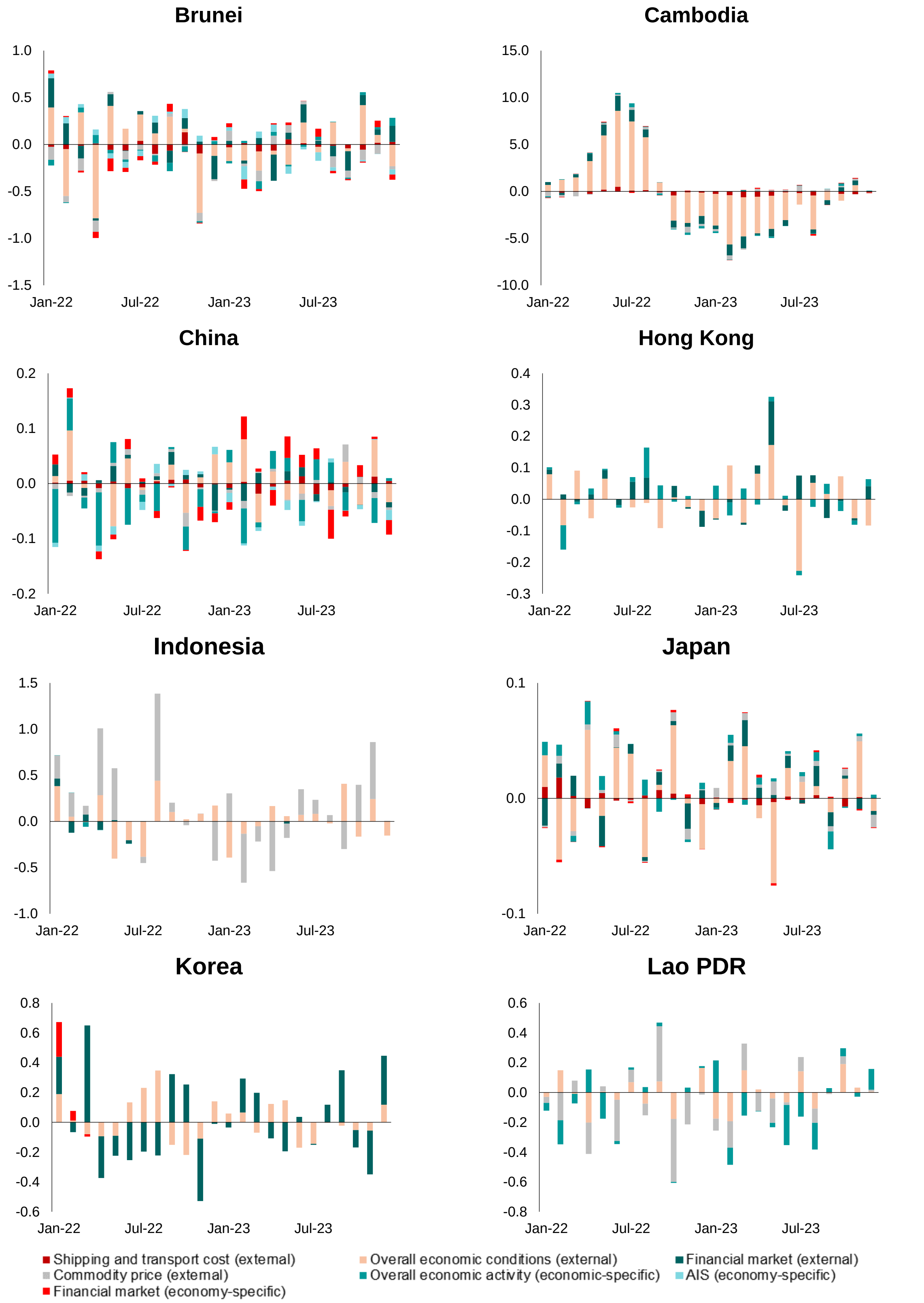
Appendix Figure 9 (Cont'd). ASEAN+3: Marginal Variable Contributions by Geographical Group

(Percentage point contribution to year-on-year growth)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Marginal variable contributions are derived from Shapley values, which provide an estimate of a variable's contribution to the prediction for a given period relative to the average prediction (Strumbelj and Kononenko 2010). The values are additive.

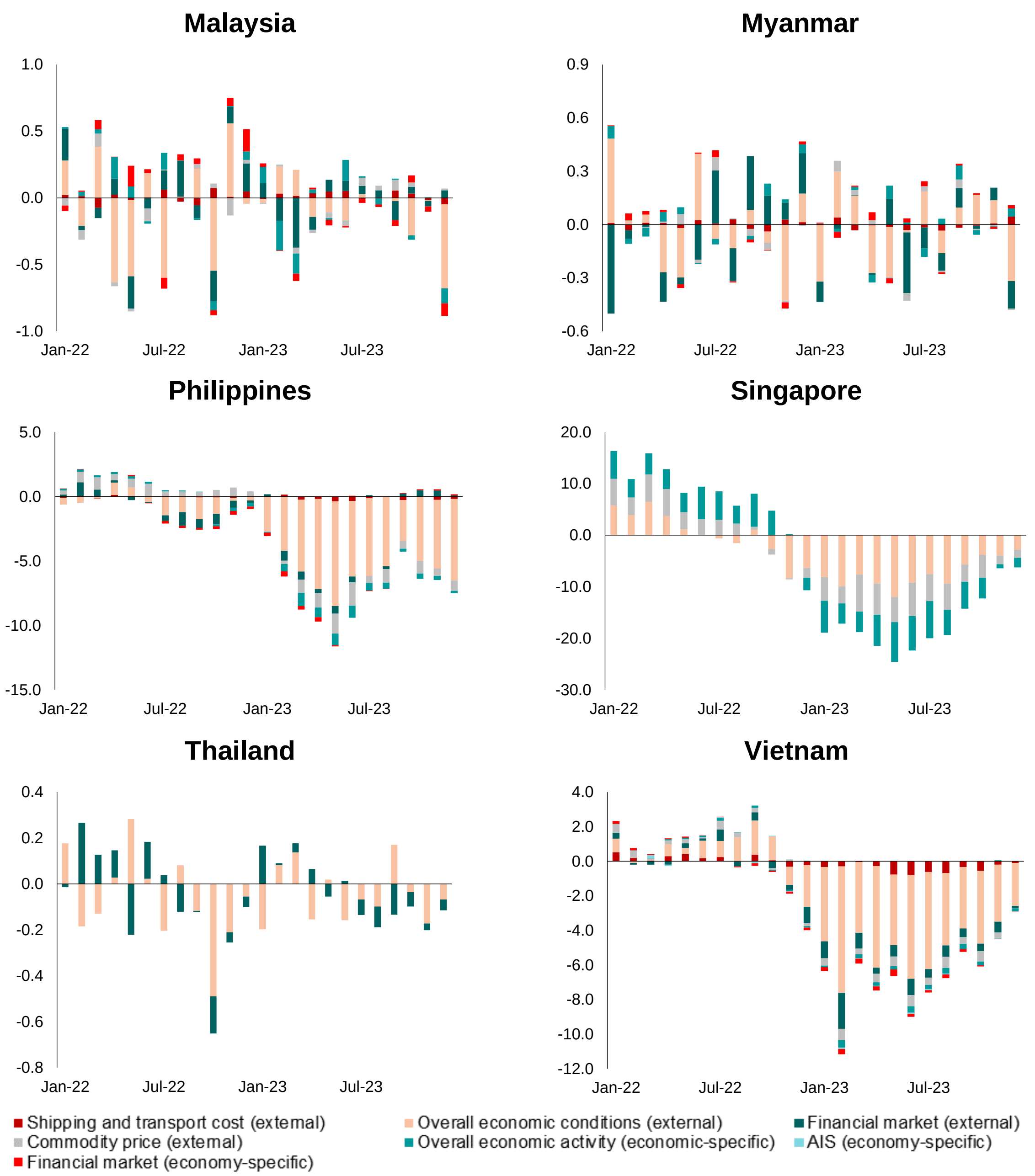
Appendix Figure 10. ASEAN+3: Marginal Variable Contributions by Variable Category
(Percentage point contribution to year-on-year growth)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Marginal variable contributions are derived from Shapley values, which provide an estimate of a variable's contribution to the prediction for a given period relative to the average prediction (Strumbelj and Kononenko 2010). The values are additive.

Appendix Figure 10 (Cont'd). ASEAN+3: Marginal Variable Contributions by Variable Category

(Percentage point contribution to year-on-year growth)



Sources: MarineTraffic; national authorities via Haver Analytics; and AMRO staff calculations.
Note: Marginal variable contributions are derived from Shapley values, which provide an estimate of a variable's contribution to the prediction for a given period relative to the average prediction (Strumbelj and Kononenko 2010). The values are additive.

References

Adland, Roar, Haiyang Jia, and Siri. P. Strandenes. 2017. “Are AIS-based Trade Volume Estimates Reliable? The Case of Crude Oil Exports.” *Maritime Policy & Management*, March, 1–9.

Arslanalp, Serkan, Marco Marini, and Patrizia Tumbarello. 2019. “Big Data on Vessel Traffic: Nowcasting Trade Flows in Real Time.” IMF Working Paper No. 2019/275, International Monetary Fund, Washington, DC, December 13. https://www.imf.org/en/Publications/WP/Issues/2019/12/13/Big-Data-on-Vessel-Traffic-Nowcasting-Trade-Flows-in-Real-Time-48837.

Arslanalp, Serkan, Robin Koepke, and Jasper Verschuur. 2021. “Tracking Trade from Space: An Application to Pacific Island Countries.” IMF Working Paper No. 2021/225, International Monetary Fund, Washington, DC, August 20. https://www.imf.org/en/Publications/WP/Issues/2021/08/20/Tracking-Trade-from-Space-An-Application-to-Pacific-Island-Countries-464345.

ASEAN+3 Macroeconomic Research Office (AMRO). 2021. “ASEAN+3 Regional Economic Outlook 2021.” Singapore, March 31. https://amro-asia.org/asean3-regional-economic-outlook-areo-2021/.

Asian Development Bank (ADB). 2023. “Methodological Framework for Unlocking Maritime Insights Using Automatic Identification System Data. A Special Supplement of Key Indicators for Asia and the Pacific 2023.” Mandaluyong, Philippines, October. https://www.adb.org/publications/maritime-insights-automatic-identification-system-data.

Bai, Jushan, and Serena Ng. 2008. “Forecasting Economic Time Series Using Targeted Predictors?” *Journal of Econometrics* 146 (2): 304–317.

Bańbura, Marta, Domenico Giannone, Michele Modugno, and Lucrezia Reichlin. 2013. “Now-Casting and the Real-Time Data Flow.” ECB Working Paper No. 1564, European Central Bank, Frankfurt, Germany, July. https://ideas.repec.org/p/ecb/ecbwps/20131564.html.

Boivin, Jean, and Serena Ng. 2006. “Are More Data Always Better for Factor Analysis?” *Journal of Econometrics* 132 (1): 169–194.

Bok, Brandyn, Daniele Caratelli, Domenico Giannone, Argia Sbordone, and Andrea Tambalotti. 2017. “Macroeconomic Nowcasting and Forecasting with Big Data.” FRB of New York Staff Report No. 830, Federal Reserve Bank of New York, New York, November. https://www.newyorkfed.org/research/staff_reports/sr830.html.

Breiman, Leo. 2001. “Random Forests.” *Machine Learning* 45: 5–32. https://link.springer.com/article/10.1023/A:1010933404324.

Cerdeiro, Diego, Andras Komaromi, Yang Liu, and Mamoon Saeed. 2020. “World Seaborne Trade in Real Time: A Proof of Concept for Building AIS-based Nowcasts from

Scratch." IMF Working Paper No. 2020/057, International Monetary Fund, Washington, DC, May 14. https://www.imf.org/en/Publications/WP/Issues/2020/05/14/World-Seaborne-Trade-in-Real-Time-A-Proof-of-Concept-for-Building-AIS-based-Nowcasts-from-49393.

Cerqueira, Vitor, Luis Torgo, and Igor Mozetič. 2020. "Evaluating Time Series Forecasting Models: An Empirical Study on Performance Estimation Methods." *Machine Learning* 109: 1997–2028. https://link.springer.com/article/10.1007/s10994-020-05910-7.

Chen Tianqi and Guestrin Carlos. 2016. "XGBoost: A Scalable Tree Boosting System." Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794. https://dl.acm.org/doi/10.1145/2939672.2939785.

Cheong, Young-rok. 2011. "Impact of China on South Korea's Economy." Korea Economic Institute of America, Seoul, May 25. https://keia.org/publication/impact-of-china-on-south-koreas-economy/.

Chinn, Menzie David, Baptiste Meunier and Sebastian Stumpner. 2023. "Nowcasting World Trade with Machine Learning: A Three-Step Approach." ECB Working Paper No. 2836, European Central Bank, Frankfurt, Germany, August 2. https://ssrn.com/abstract=4528798.

Choo, Chiang Yong (Edmond), Diana del Rosario, and Toàn Long Quách. 2021. "The Restart of Tourism in the ASEAN+3: When Will the Love Boat Sail Again?" AMRO Analytical Note, ASEAN+3 Macroeconomic Research Office, Singapore, October 11. https://amro-asia.org/the-restart-of-tourism-in-the-asean3-when-will-the-love-boat-sail-again/.

Dauphin, Jean-François, Kamil Dybczak, Morgan Maneely, Marzie Taheri Sanjani, Nujin Suphaphiphat, Yifei Wang, and Hanqi Zhang. 2022. "A Scalable Approach Using DFM, Machine Learning and Novel Data, Applied to European Economies?" IMF Working Paper No. 2022/052, International Monetary Fund, Washington, DC, March 11. https://www.imf.org/en/Publications/WP/Issues/2022/03/11/Nowcasting-GDP-A-Scalable-Approach-Using-DFM-Machine-Learning-and-Novel-Data-Applied-to-513703.

del Rosario, Diana, and Toàn Long Quách. 2020. "What Does the Real-Time Shipping "Crystal Ball" Tell Us about the Recovery in ASEAN+3 Trade?" AMRO Analytical Note, ASEAN+3 Macroeconomic Research Office, Singapore, October 7. https://amro-asia.org/what-does-the-real-time-shipping-crystal-ball-tell-us-about-the-recovery-in-asean3-trade/.

______. 2021. "Covid Congestion and Trade Fever in the ASEAN+3: A Prognosis with the Shipping 'Crystal Ball'" AMRO Analytical Note, ASEAN+3 Macroeconomic Research Office, Singapore, July 2. https://www.amro-asia.org/covid-congestion-and-trade-fever-in-the-asean3-aprognosis-with-the-shipping-crystal-ball/.

_____. 2022. “The Great Supply Chain Disruption: What Does the Shipping Crystal Ball Foretell?” AMRO Analytical Note, ASEAN+3 Macroeconomic Research Office, Singapore, July 25. https://amro-asia.org/the-great-supply-chain-disruption-what-does-the-shipping-crystal-ball-foretell/.

Diebold, Francis, and Roberto Mariano. 1995. “Comparing Predictive Accuracy.” *Journal of Business and Economic Statistics* 13 (3): 253–263.

Friedman Jerome. 2001. ‘‘Greedy Function Approximation: A Gradient Boosting Machine.’’ *The Annals of Statistics* 29 (5): 1189–1232. https://projecteuclid.org/journals/annals-of-statistics/volume-29/issue-5/Greedy-function-approximation-A-gradient-boosting-machine/10.1214/aos/1013203451.full.

Furukawa, Kakuho, and Ryohei Hisano. 2022. “A Nowcasting Model of Exports Using Maritime Big Data.” Bank of Japan Working Paper Series 22-E-19, Bank of Japan, Tokyo, Japan, December 23. https://www.boj.or.jp/en/research/wps_rev/wps_2022/wp22e19.htm.

Giannone, Domenico, Lucrezia Reichlin and David Small. 2008. “Nowcasting: The Real-Time Informational Content of Macroeconomic Data.” *Journal of Monetary Economics* 55 (4): 665–676.

Harvey, David, Stephen Leybourne, and Paul Newbold. 1997. “Testing the Equality of Prediction Mean Squared Errors.” *International Journal of Forecasting* 13 (2): 281–291.

Hoerl, Arthur E., and Robert W. Kennard. 1970. “Ridge Regression: Biased Estimation for Nonorthogonal Problems.” *Technometrics* 12 (1): 55–67.

Hopp, Daniel. 2021. “Economic Nowcasting with Long Short-Term Memory Artificial Neural Networks (LSTM).” UNCTAD Research Paper No. 62, United Nations Conference on Trade and Development, New York: United Nations, March 23. https://unctad.org/publication/economic-nowcasting-long-short-term-memory-artificial-neural-networks-lstm.

Hyndman, Rob J, and George Athanasopoulos. 2018. “Forecasting: Principles and Practice.” OTexts. https://otexts.com/fpp2/accuracy.html.

Kucharčuková, Oxana Babecká, and Jan Brůha. 2016. “Nowcasting the Czech Trade Balance.” CNB Working Paper No. 11/2016, Czech National Bank, Prague, Czech Republic, November. https://www.cnb.cz/en/economic-research/research-publications/cnb-working-paper-series/Nowcasting-the-Czech-Trade-Balance-00001.

Mourougane, Annabelle, Polina Knutsson, Rodrigo Pazos, Julia Schmidt, and Francesco Palermo. 2023. “Nowcasting Trade in Value Added Indicators.” OECD Statistics Working Papers No. 2023/03, Organisation for Economic Cooperation and Development, Paris, France, September 1.

https://www.oecd-ilibrary.org/economics/nowcasting-trade-in-value-added-indicators_00f8aff7-en.

Nickelson, Jimmy, Rani Nooraeni, and Efliza. 2022. "Export-Import Value Nowcasting Procedure Using Big Data-AIS and Machine Learning Techniques." *Asian Journal of Business Environment* 12 (3): 1–12. https://www.researchgate.net/publication/364273604_Export-Import_Value_Nowcasting_Procedure_Using_Big_Data-AIS_and_Machine_Learning_Techniques.

Shapley, Lloyd. 1953. "A Value for n-Person Games." RAND Paper Series, March 18. https://doi.org/10.7249/P0295.

Strumbelj, Erik, and Kononenko Igor. 2010. "An Efficient Explanation of Individual Classifications using Game Theory." *The Journal of Machine Learning Research* 11: 1–18. https://dl.acm.org/doi/10.5555/1756006.1756007.

Svanberg, Martin, Vendela Santén, Axel Hörteborn, Henrik Holm, and Christian Finnsgård. 2019. "AIS in Maritime Research." *Marine Policy* 106.

The World Bank. 2023. "Trade Has Been a Powerful Driver of Economic Development and Poverty Reduction." Washington, DC, February 12. https://www.worldbank.org/en/topic/trade/brief/trade-has-been-a-powerful-driver-of-economic-development-and-poverty-reduction.

Tibshirani, Robert. 1996. "Regression Shrinkage and Selection via the LASSO." *Journal of the Royal Statistical Society Series B (Methodological)* 58 (1): 267–288.

Ueda, Tsubasa, Takehide Hirose, and Kiyoshi Izumi. 2023. "Export Nowcasting with AIS and Foot Traffic Data." 14th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI): 486-489. Koriyama, Japan, July.

United Nations Conference on Trade and Development (UNCTAD). 2018. *Review of Maritime Transport 2018.* New York: United Nations. https://unctad.org/en/pages/PublicationWebflyer.aspx?publicationid=2245.

United Nations. 2024. "AIS Data Task Team." UN Committee of Experts on Big Data and Data Science for Official Statistics (UNCEBD). New York, Accessed on March 28. https://unstats.un.org/bigdata/task-teams/ais/index.cshtml.

Zou, Hui and Trevor Hastie. 2005. "Regularization and Variable Selection via the Elastic Net." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 67 (2): 301–320.

Zou, Hui. 2006. "The Adaptive Lasso and Its Oracle Properties." *Journal of the American Statistical Association* 101(476): 1418—1429.

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