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## Thinking outside the container: A machine learning approach to forecasting trade flows

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# KIEL WORKING PAPER

## Thinking Outside the Container: A Machine Learning Approach to Forecasting Trade Flows



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# ABSTRACT

## Thinking Outside the Container: A Machine Learning Approach to Forecasting Trade Flows

Vincent Stamer

Global container ship movements may reliably predict global trade flows. Aggregating both movements at sea and port call events produces a wealth of explanatory variables. The machine learning algorithm partial least squares can map these explanatory time series to unilateral imports and exports, as well as bilateral trade flows. Applying out-of-sample and time series methods on monthly trade data of 75 countries, this paper shows that the new shipping indicator outperforms benchmark models for the vast majority of countries. This holds true for predictions for the current and subsequent month even if one limits the analysis to data during the first half of the month. This makes the indicator available at least as early as other leading indicators.

**Keywords:** Trade, Forecasting, Machine Learning, Container Shipping

**JEL classification:** F17; C53

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# Thinking Outside the Container: A Machine Learning Approach to Forecasting Trade Flows

Vincent Stamer

## 1. Introduction

As the coronavirus spread across the globe, it disrupted the trade of goods in its wake. First hit by the pandemic China's exports fell by 17.2% in January and February of 2020 as compared to the previous year. European countries followed in April with year-over-year drops of 33.6 % in Germany and 44.5 % in France. One month later, the United States of America exported 36.3 % less than in May 2019. The violent swings in trade volume created uncertainty around the world as established methods failed to accurately quantify ongoing disruptions. For example, even in developed countries statistical offices publish unilateral trade data with a lag of several weeks and bilateral data often with a lag of months. Leading indicators typically measure industrial production or economic sentiment, but also merely provide a snapshot in time and are typically available towards the end of the current month. Governments and companies, however, require comprehensive and reliable data on an ongoing basis to make informed decisions. For instance, estimating trade disruptions in the spring 2020 was key to understand the extent of supply chain disruptions and vulnerability from import dependence. In the context of the US-China and Australia-China trade disputes, measuring changes of trade flows also assumes a geopolitical perspective.

This study introduces an indicator based on daily container ship movements and machine learning techniques to fill this gap. This indicator can in principle be produced at any point during a current month and would be specific to unilateral imports and exports, as well as bilateral trade flows of virtually any country or region at any desirable forecast horizon in the near future. In summary, the process follows the following steps: Container ship movements at sea are divided in geographic sectors and aggregated using a clustering algorithm. Together with monthly port arrival and departure events of these ships, the container ship movements yield over of 1,200 monthly time series potentially useful for forecasting. A partial least squares method, a supervised version of the principal component regression, filters, aggregates and maps this data onto official trade flow statistics. This study then performs rigorous procedures from the time series literature to establish the forecast quality of the produced indicator in out-of-sample tests. As a baseline, the algorithm is trained on import and export data of 75 countries that report monthly data to the WTO for unilateral trade and also trained on 40 bilateral trade flows reported to the IMF between China, the United States, the European Union and Germany with their largest trade partners, respectively. The baseline shows that including only the first 15 days of the month is sufficient to outperform autoregression models and ARX models

integrating popular leading indicators for almost all countries for the current and the subsequent month.

This work is related to a growing strand of the international economics literature that exploits the high frequency ship position data called AIS (Automatic Identification System). For instance, Brancaccio et al. (2017) determine if ships are carrying goods by probing positional AIS data of bulker ships at sea and develop a model of bulker shipping that explains transportation costs by implementing search frictions between ships and exporters. Heiland et al. (2017) and Wong and Ziv (2020) use port call data to construct their network of ports and causally estimate the effects of the Panama canal expansion and endogenous trade costs, respectively. This work, however, is most related to two proof-of-concept studies of the IMF: Arslanalp et al. (2019) derive a trade indicator from the activity of two Maltesian ports and compare it to Malta's official trade statistic. Cerdeiro et al. (2020) show that the net-draught change of freight ships entering and departing from ports tends to correlate positively with unilateral imports and exports of the same 3-month period of the countries in which the ports are located. The approach of this paper exceeds the ambition of the IMF studies in several ways: First, this paper offers a method to map any shipping activity in the world to unilateral imports and exports, as well as bilateral trade flows of any country in the world. Second, this mapping allows not only nowcasting, but also forecasting and takes into consideration only the first half of a month's observations. Third, this paper analyzes the forecasting properties and significance levels of the indicators using out-of-sample experiments as opposed to establishing correlation. In addition, out-of-sample forecasts are compared to benchmark ARX models that incorporate popular leading indicators. Lastly, container ship movements of this work encompass both port call activity and movements at high sea.

Using this more generalized approach forces thinking outside the box: Previous attempts match the exports of a specific country with the ships leaving ports of that particular country. While this is also important to this process, it does not exploit all sources of correlation. One obvious example is that central European countries besides the Netherlands and Belgium export through the mega ports Rotterdam and Antwerp. Similarly, the activity of transshipment hubs and other recurring patterns in the shipping network provide information for forecasting. Also, a country's exports likely correlate over time with other countries' exports and imports through input-output linkages, as well as through relationships involving compliments and substitutes. The machine learning algorithm used in this paper exploits all these sources of information.

The following chapter introduces the data used and the necessary steps to make AIS data interpretable to a machine learning model. The section on methodology describes the partial least squares model and the required time series tests. The results chapter performs these tests and presents the results. In the conclusion, further potential uses of the approach are discussed giving an outlook for the work ahead.

## 2. Data

### 2.1. AIS Data

The main data source of this study is derived from the maritime Automatic Identification System (AIS) - a radio system to monitor ship movements and avoid collisions at sea. Ships broadcast radio signals every few seconds containing ship identifiers, course, speed, draught and GPS position. The data provider Fleetmon.com collects this information from terrestrial receiver stations and satellites and interprets from the ship movements near ports whenever a ship stops at a port to load or unload cargo - a port call. One AIS position per day and the exhaustive set of all port calls of all container ships worldwide is purchased from Fleetmon.com for the years 2015 to 2020. This data is combined with ship information from MarineTraffic such as size, minimum draught ("ballast draught") and capacity measured in Twenty-Foot-Equivalent units (TEU).

For the AIS data to be truly useful for economic forecasting one must further organize the data into time series of independent variables. To organize the positions at sea, the first step partitions the world between 50°latitude South and 70°latitude North into sectors of 10°latitude and 10°longitude. The 100 sectors with the greatest number of container ship positions are kept while the rest is discarded to avoid overfitting the machine learning models in a later stage. Panel (a) of Figure 1 shows one such sector in the South China Sea and container ship positions recorded in the month of July 2020. Orange triangles represent ships moving on a Southern course and blue triangles represent ships on a Northern course. Determining two predominant directions follows the intuition that ships going in the opposite direction likely carry cargo destined for different countries. A simple k-means clustering algorithm assigns ships to their predominant course once the course in degrees is mapped into two-dimensional space using the sine and cosine functions.<sup>1</sup>

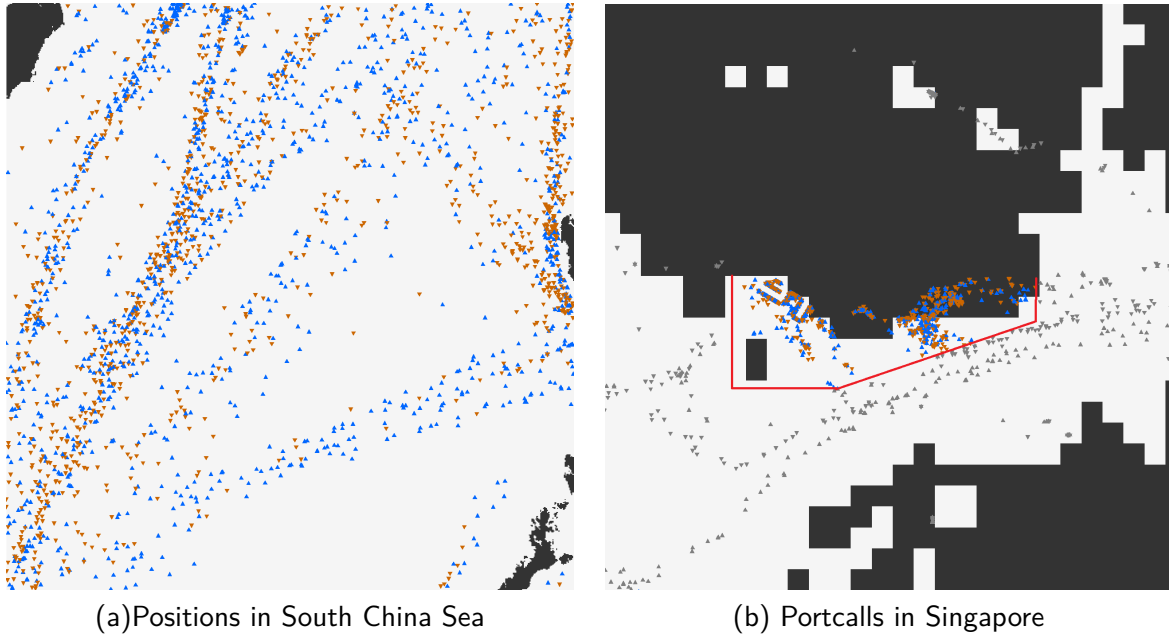
In addition to the positions, port calls provide the information when ships enter into and depart from a port such as the port of Singapore in panel (b) of Figure 1. In this largely oversimplified illustration orange triangles are ships departing from the port while blue triangles show ships that have just entered the port. The information such as the draught is recorded as the ships cross the imaginary red line - a step calculated by the dataprovider Fleetmon.

All ships, regardless of whether they enter or depart a port area or whether they cruise in one of the remaining sectors, are assigned their current TEU load. After all, a ship that approaches a port with a draught close to its minimum value likely carries less containers than a ship cruising with a draught near its maximum, *ceteris paribus*. Hence, the current draught is normalized by the potential range of possible draughts and multiplied by the total TEU capacity of the ship to approximate the

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<sup>1</sup>The course in the AIS message is given in degrees from zero to 360 and standard clustering algorithms fail to match the values zero and 360 to the same course without projection into two-dimensional space.

Figure 1: Illustration of ship data aggregation



number of of containers the ship currently carries.

$$TEUload_{it} = TEU_{i,max} \times \frac{draught_{it} - draught_{i,min}}{draught_{i,max} - draught_{i,min}} \quad (1)$$

The formula (1) translates this into an equation for the TEU load of the ship. It also highlights a subtle difference between this approach and the study by the IMF: While the IMF subtracts the departure load from the arrival load to calculate a net gain of the ship's cargo during a port call, both the gross load of the ship while entering and while departing are kept as two separate time series. In theory, both approaches have merit: Calculating the net gain may avoid overstating the economic importance of transshipment hubs. In contrast, keeping the gross arrival and departure loads is an accurate depiction of ports where imports and exports offset each other and ships enter and depart with the same draught. In practice, however, the machine learning algorithm automatically accounts for transshipment effects and the positions at sea which do not feature in the IMF study only have a gross TEU load value. Lastly, the monthly observations per sector sum the TEU loads of all ships by predominant course during the first 15 days of the month and the last 15 days of the previous month. This yields two observational series per sector. Monthly observations per port sum the TEU load of ships entering the port and ships departing the port during the first 15 days of the month and the last 15 days of the previous month. Again, this yields two series per port. In total, the 100 sectors and 500 ports generate 1200 time series serving as independent variables.

## 2.2. Other Data

Data sources for dependent time series include the WTO (2020) for monthly unilateral trade data, IMF (2020) for monthly bilateral trade flows and DESTATIS (2020a) for a second source of seasonally adjusted trade data of Germany. European economic sentiment indicators (ESI) and industrial confidence indicators (COF) originate from the European Commission (2020), US industrial production (US IP) from the Federal Reserve Bank of St. Louis (2020), both German export expectations (Grimme and Wohlrabe, 2014) and import and export climate (Grimme et al., 2018) from the ifo institute (Ifo institute, 2020), German truck toll index, order entry and order stock from abroad originate from DESTATIS (2020b) and a port throughput index (Döhrn and Maatsch, 2012) comes from RWI/ISL (2020). The benchmark models described below exclusively use the seasonally adjusted versions of the indicators and utilize a time series as long as possible.

## 3. Methodology

This study brings together a machine learning (ML) method to make predictions from the explanatory variables and time series econometrics to test the quality of the prediction. In essence, the entire training procedure described in subsection 3.1 is repeated for every single out-of-sample prediction of every dependent time series. Various tests explained in subsection 3.2 compare the quality of the collective out-of-sample predictions against the actual dependent time series and benchmark models.

### 3.1. Partial Least Squares

This study establishes the forecast properties of the container ship movements for monthly trade flows using data from 2015 to 2020. This yields 65 to 70 monthly observations for the dependent time series depending on the reporting lag. At the same time, the shipping network generates over 1200 explanatory time series making filtering and dimensionality reduction the crucial features of this study. The well established machine learning algorithm partial least squares (PLS) does precisely that for every specific dependent time series.

Wold (1975) introduced the concept as early as 1975 and handbooks such as Haenlein and Kaplan (2004) and Vinzi V et al. (2010) document the procedure. Using notation and nomenclature more familiar to the econometrician Lohmöller (2013) and in particular Garthwaite (1994) serve as excellent introductions to the modeling approach. Borrowing from the later, the following briefly outlines the PLS system. The dependent time series  $Y$  is estimated using ordinary least squares in



the form

$$Y = \alpha + \sum_{j=1}^J \beta_j T_j + \varepsilon \quad (2)$$

where  $T_j$ , for  $j = 1, \dots, J$ , are components aggregated from the centered explanatory variables  $V_{jk}$ , for  $k = 1, \dots, K$ , using

$$T_j = \sum_{k=1}^K w_{jk} \phi_{jk} V_{jk} \quad (3)$$

$$V_{jk} = X_{jk} - \bar{x}_j \quad (4)$$

One derives the component and explanatory variable specific correlation coefficients  $\phi_{jk}$  from individually regressing the centered dependent variable  $U_j$  sequentially on each of the explanatory variables directly:

$$U_j = Y_j - \bar{y}_j \quad (5)$$

$$U_j = \phi_{jk} V_{jk} \quad (6)$$

The choice of weights  $w_{jk}$  depends on the specific PLS algorithm. The weights are commonly set proportional to the variance of the centered explanatory variables implying that the magnitude of the component is proportional to the covariance of the dependent variable and the underlying independent variables. Furthermore, the algorithm calculates the components iteratively, so that the first component is constructed from the original dependent and independent time series. The second component uses, however, only the residuals of the regression of  $U_1$  on  $T_1$  as the new dependent variable  $U_2$  and uses the residuals of the regression of  $V_1$  on  $T_1$  as the new explanatory variables  $V_2$ .

Note that this procedure not only is robust to multicollinearity between explanatory variables, but exploits this to group the variables into a component and reduce dimensionality. In contrast to other machine learning algorithms such as random forests and neural nets, PLS can also be understood intuitively in the context of the task at hand: Let the dependent variable  $Y$  be the unilateral imports of the United States of America in time  $t = 1$  and the explanatory variables be the shipping activity measured at geographic sectors and ports in time  $t = 0$ . It is conceivable that the first component weights heavily the departure activity of Chinese ports and eastbound positions in sectors of the Pacific Ocean. The following component may then group shipping activity of Latin American ports and ships moving North and so on. In contrast to the closely related principal component regression,

PLS chooses these components based on correlations with the dependent variable allowing for an even smaller number of components. This example also illustrates that any forecasts and indicators derived for the time series "Imports of the United States" are specific to the forecast horizon: The algorithm can measure what current ship movements imply for imports in the current month, for one month from now and so on.

In practise, this study performs PLS many times for a single out-of-sample prediction for every single dependent time series: A first iteration of the PLS is run on the entire universe of shipping measures. Using the results, the 30 shipping variables are filtered that carry the highest variable importance score - a measure of the dependent variable's variation explained by every single explanatory variable. This first step dramatically reduces noise and erroneous estimation in the following steps. Next, cross-validation determines the optimal number of components  $J$ . The maximum number of components is constrained to 10 to avoid overfitting, although rarely more than three components are optimal. The last PLS iteration serves as the actual model in which the remaining 30 variables are fit into the optimal number of components. This final model then predicts the dependent variable observation for the time period that was not used in the training process.

To illustrate the power of this process Table 1 shows the 30 shipping measures selected for the final estimation of the imports of the United States from China in the current period, i.e.  $h = 0$ .

Table 1: Variables for estimation of US-American imports from China in current month

Course/Orientation	Description
Southern course	(20 to 30) <sup>o</sup> lat × (-110 to -120) <sup>o</sup> long
Southern course	(30 to 40) <sup>o</sup> lat × (-120 to -130) <sup>o</sup> long
Southern course	(30 to 40) <sup>o</sup> lat × (-130 to -140) <sup>o</sup> long
Eastern course	(40 to 50) <sup>o</sup> lat × (150 to 160) <sup>o</sup> long
Northern course	(-30 to -40) <sup>o</sup> lat × (170 to 180) <sup>o</sup> long
Arrival	Los Angeles, USA
Arrival	Long Beach, USA
Arrival	Oakland, USA
Arrival	Tacoma, USA
Departure	Los Angeles, USA
Arrival	Zarate, Argentina
Departure	Iquique, Chile
Arrival	Iquique, Chile
Departure	Cartagena, Columbia
Arrival	Cartagena, Columbia
Departure	Castellon, Spain
Arrival	Ilulissat, Greenland
Arrival	Merauke, Indonesia
Departure	Kattupalli, India
Arrival	Ravenna, Italy
Arrival	Beirut, Lebanon
Departure	Castries, St Lucia
Arrival	Port Klang, Malaysia
Departure	Luderitz, Namibia
Departure	Marsden Point, New Zealand
Arrival	Vlissingen, Netherlands
Arrival	Szczecin, Poland
Departure	Acajutla, El Salvador
Arrival	Acajutla, El Salvador
Arrival	Charlotte Amalie, St. Thomas

The order of variables does not reflect the variable importance in the final estimation of the PLS.

The largest volume of Chinese goods likely reaches the United States first through the major container ports on America's West Coast. And indeed, among 1200 variables the four largest container ports of the American West Coast are selected: Los Angeles, Long Beach, Oakland and Tacoma. Additionally, only positions in the Pacific Ocean are considered. At first glance, however, the final model still takes into account a large number of shipping measures seemingly unrelated to the dependent time series at hand. It is important to understand that the PLS only exploits correlation and does not trace the actual flow of goods. Even though ships arriving in Argentina, Chile and Colombia do not carry goods destined to America, Latin American imports from China are likely correlated with the dependent time series. Similarly, exports of Latin America to the United States may very well be correlated to the dependent variable, too.

### 3.2. Forecast evaluation

To evaluate the forecast quality of the algorithm above, the dependent and explanatory shipping time series are first seasonally adjusted using the X13-ARIMA-SEATS procedure of the US Census Bureau and Methodology (2017) and converted to month-over-month growth rates. PLS then calculates leave-one-out out-of-sample (LOO) forecasts for the entire time span. Let the forecast horizon,  $h$ , - specific LOO prediction from the PLS procedure for the seasonally adjusted growth rate of the dependent variable be  $\widehat{y_{t+h}^{PLS}}$ .

To mimic the use of the shipping indicator in an actual forecasting setting, an ARX-model with distributed lags up until  $p = 3$  embeds the shipping indicator as follows:

$$y_{t+h} = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \sum_{i=1}^p \gamma_i \widehat{y_{t-i,h+i}^{PLS}} + \varepsilon_{t+h} \quad (7)$$

where  $y_{t+h}$  denotes the month-over-month growth rate of the adjusted time series from time period  $t+h-1$  to  $t+h$ . The intercept  $\alpha$  and coefficients  $\beta_i$  and  $\gamma_i$  are estimated in a LOO method in the same fashion as the actual shipping indicator. The Akaike information criterion determines the number of lags. As the PLS inherently forecasts in a direct-step fashion, the ARX fitting follows accordingly. This forms the main specification of the ARX shipping indicator (ARX-PLS).

A standard root mean squared forecast error (RMSFE) calculation evaluates the difference between the out-of-sample forecast and the actual value as such:

$$RMSFE_h = \sqrt{\frac{1}{T} \sum_{t=1}^T (FE_{t+h})^2} \quad (8)$$

This quantifies the accuracy of the model. In a second step, a comparison between the forecasting accuracy of the shipping model and a competing model assesses whether the new model makes more accurate forecasts than existing models. A standard direct step autoregression (AR) model and direct step ARX models with other leading indicators serve as benchmarks:

$$y_{t+h} = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \varepsilon_{t+h} \quad (9)$$

$$y_{t+h} = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \sum_{i=1}^p \gamma_i Indicator_{t-i} + \varepsilon_{t+h} \quad (10)$$

Again, the Akaike criterion guides the selection of the lags structure for both the AR and the

ARX models. Note a very subtle, but important difference between the shipping ARX model and the benchmark ARX indicator model. Common leading indicators such as business surveys are not specific to the forecast horizon. Hence, the lags of standard indicators are truly past nowcasts, whereas the lags of the shipping indicators are forecasts further into the future several lagged months back. Also, the fitting period for benchmark ARX indicator models dates back as long as possible limited only by the availability of the indicator or the dependent time series.

A relative RMSFE (rRMSFE) divides the forecast error of the shipping indicator by the benchmark error.

$$rRMSFE_h = \frac{RMSFE_h^{ARX-PLS}}{RMSFE_h^{ARX-Other}} \quad (11)$$

Hence, a value below 1 for the rRMSFE indicates lower forecast errors for the new shipping model. To sharpen the intuition for the rRMSFE-values Figure 2 previews results on forecasting European imports. In particular, the figure compares the RMSFE of the ARX-PLS forecast on the y-axis against the RMSFE of the ARX-COF forecast on the x-axis. The ARX-COF model in this case refers to model of equation (10) using the European Commission's industrial confidence indicator specific to every country (and the EU27 and EURO area) as the leading indicator. A point below the 45°line shows that the ARX-PLS model produces lower forecast errors than the benchmark model, i.e. the rRMSFE is below 1. The figure also illustrates that the lower the errors, the more difficult it is to ascertain which model performs better. For the large unilateral imports of Germany, the EU and the Eurozone, the autoregressive terms of the models capture a major portion of the import variation. Hence, the RMSFE for both models is around 0.025, i.e. a standard error of 2.5 percentage points around month-over-month growth rates. This also implies lower variation for the indicators to explain, a similar RMSFE and, therefore, an rRMSFE closer to 1.

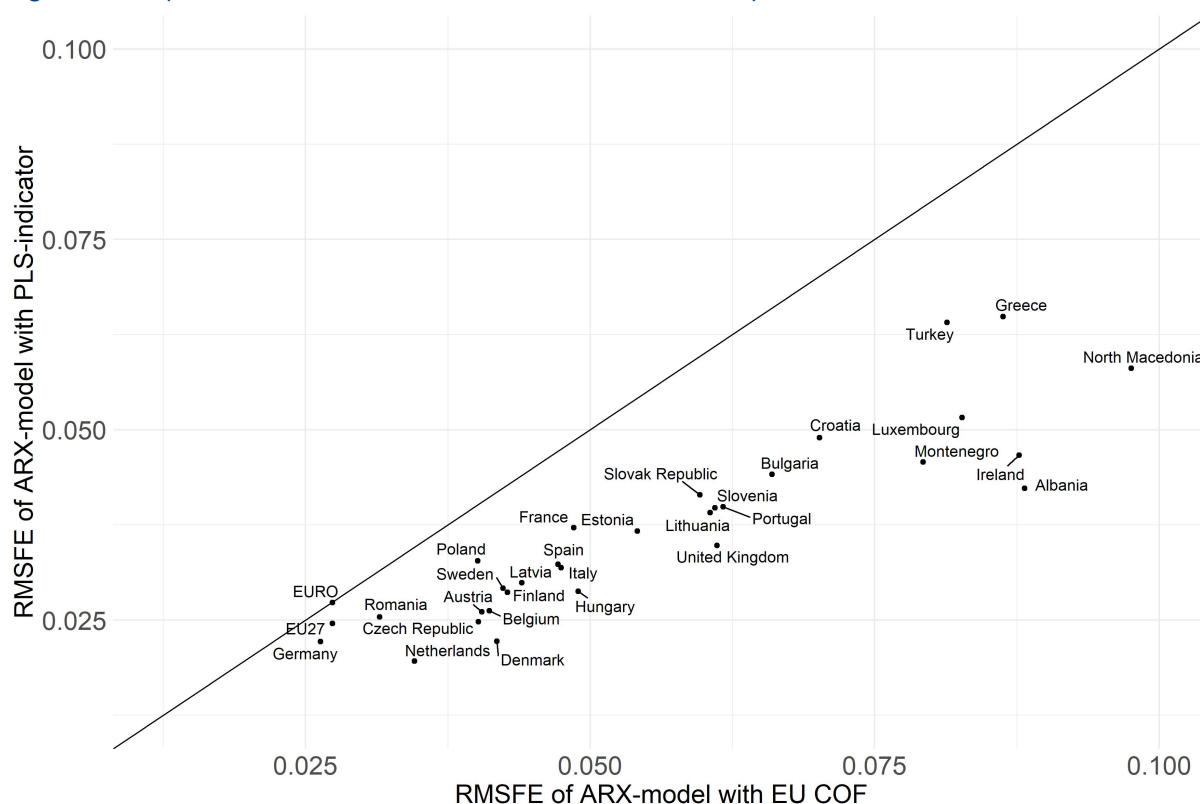
Lastly, the Diebold-Mariano (DM) test (Diebold and Mariano, 2002) establishes the significance of the difference between ARX-PLS and ARX leading indicator model errors. To correct for concerns related to nested models, the Clark and West (CW) statistic (Clark and West, 2007) calculates the significance of the differences of the ARX-PLS and the AR process.

## 4. Results

### 4.1. Imports

The results section begins with forecasts for European imports as foreshadowed by Figure 2. Table 2 quantifies the forecast errors for the current month ( $h=0$ ) and one month ahead ( $h=1$ ). The columns PLS RMSFE show the forecasting error of the LOO out-of-sample forecasts for the PLS system embedded in an ARX model and can be read as follows: Forecasts for German imports deviate by 2.2

Figure 2: Comparison of ARX-PLS and ARX-COF - forecasts of imports



percentage points from recorded month-over-month, seasonally adjusted import growth. The four columns marked as rRMSFE compare the ARX-PLS forecast errors to those of the ARX indicator models using the industrial confidence indicator (COF) or economic sentiment indicator (ESI) as benchmarks. Note that the benchmark indicators are also country specific. An rRMSFE value below one indicates that the PLS-ARX model produces lower forecast errors than the benchmark models. Due to the importance of this cutoff, rRMSFE values above one are shown in grey cells. The partial least squares system yields better import predictions for all European countries, with the one month ahead forecast of Luxembourg being the sole exception. The rRMSFE value around 0.8 for Germany for instance shows that the shipping model predictions can reduce the benchmark’s errors to approximately 80% of their value. Moreover, the Diebold Mariano test shows that these difference are statistically significant for the majority of countries. Table 3 repeats this exercise for all other countries of the world reporting monthly trade data to the WTO. As global leading indicators specific to single countries do not exist, the best benchmark may be the simple AR process with distributed lags and an ARX model with US industrial production. The results for non-EU countries show a greater heterogeneity as they include landlocked countries such as Belarus and Switzerland, countries with major transshipment hubs such as Egypt and South Korea, as well as countries like Russia and Chile that focus on exporting natural resources. Nevertheless, if the shipping model produces lower forecast errors than the AR model, results are always highly statistically significant.

Out of the 43 countries listed, for 28 of them the shipping model also performs better than the ARX US industrial production indicator and in the remaining cases results are never significant. A closer look at Germany is worthwhile as there is an ample number of leading indicators, of which some are specific to German exports and imports, respectively. Also, the German statistical office publishes its own X-13-ARIMA seasonally adjusted data values which serve as an additional dependent variable. The new shipping indicator significantly outperforms all existing indicators for the adjusted WTO time series. While errors are also smaller as compared to other leading indicators when forecasting the time series provided and seasonally adjusted by DESTATIS, p-values remain just above the 10% threshold. This may result from different X-13 specifications of the DESTATIS data or the longer fitting period dating back to 1991.

Table 2: Comparing Forecast Models for European Unilateral Imports

	h=0			h=1		
	PLS RMSFE	COF rRMSFE	ESI rRMSFE	PLS RMSFE	COF rRMSFE	ESI rRMSFE
Albania	0.042	0.479**	0.451**	0.045	0.608*	0.608*
Austria	0.026	0.644***	0.604***	0.026	0.582***	0.565***
Belgium	0.026	0.637***	0.654***	0.031	0.716***	0.743**
Bulgaria	0.044	0.669**	0.661**	0.047	0.734**	0.738**
Croatia	0.048	0.697***	0.714***	0.048	0.654**	0.646**
Cyprus	0.181	0.705	0.710	0.212	0.759	0.763
Czech Rep.	0.024	0.616**	0.581**	0.030	0.720*	0.716*
Denmark	0.022	0.531***	0.518***	0.026	0.628***	0.623**
EU27	0.024	0.898	0.831	0.027	0.720	0.724
EURO	0.027	0.997	0.918	0.029	0.757	0.758
Estonia	0.036	0.678	0.671*	0.035	0.647	0.618*
Finland	0.028	0.669***	0.714***	0.029	0.626***	0.669***
France	0.037	0.764	0.675	0.045	0.807	0.836
Germany	0.022	0.842*	0.780***	0.022	0.652**	0.644*
Greece	0.064	0.751***	0.769***	0.070	0.842***	0.834***
Hungary	0.028	0.588*	0.593*	0.032	0.713*	0.711*
Ireland	0.046	0.531***	0.565***	0.053	0.568***	0.556***
Italy	0.031	0.671**	0.671**	0.037	0.789	0.785*
Latvia	0.029	0.679***	0.706***	0.032	0.642***	0.658***
Lithuania	0.039	0.646**	0.727***	0.042	0.688***	0.655***
Luxembourg	0.051	0.623***	0.608***	0.535	6.557	6.478
Malta	0.235	0.968	0.975	0.202	0.772**	0.771**
Montenegro	0.045	0.577**	0.604**	0.052	0.741***	0.737***
Netherlands	0.019	0.567***	0.600***	0.021	0.553***	0.541***
N. Macedonia	0.058	0.595	0.557	0.074	0.866	0.851
Poland	0.032	0.816*	0.692*	0.044	0.888	0.944
Portugal	0.039	0.646**	0.720**	0.047	0.716**	0.718**
Romania	0.025	0.806	0.752**	0.030	0.708**	0.726**
Slovak Republic	0.041	0.694	0.704*	0.051	0.825	0.828
Slovenia	0.039	0.651*	0.665*	0.047	0.758	0.757
Spain	0.032	0.684*	0.695*	0.039	0.772*	0.807**
Sweden	0.029	0.688***	0.716**	0.026	0.652***	0.653***
Turkey	0.064	0.787**	0.791**	0.058	0.538***	0.524***
UK	0.034	0.569***	0.568***	0.040	0.675***	0.679***

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against ARX-indicator models. COF refers to the industrial confidence indicator and ESI to the economic sentiment indicator. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01



Table 3: Comparing Forecast Models for Unilateral Imports

	h=0			h=1		
	PLS RMSFE	AR rRMSFE	US IP rRMSFE	PLS RMSFE	AR rRMSFE	US IP rRMSFE
Argentina	0.030	0.520***	0.479***	0.032	0.507***	0.516***
Australia	0.043	0.695***	0.710	0.039	0.604***	0.545*
Belarus	0.500	6.005	6.690	0.342	3.987	4.530
Bolivia	0.087	0.704***	0.696	0.083	0.648***	0.652**
Bosnia	0.043	0.662***	0.703*	0.044	0.689***	0.711**
Brazil	0.048	0.592***	0.527**	0.049	0.587***	0.529***
Canada	0.039	0.742***	0.947	0.047	0.882***	0.793
Chile	0.300	5.090	6.024	0.360	6.162	5.982
China	0.030	0.545***	0.555***	0.032	0.572***	0.559**
Chinese Taipei	0.035	0.573***	0.567***	0.036	0.497***	0.456**
Colombia	0.047	0.673***	0.808**	0.043	0.593***	0.587***
Costa Rica	0.875	11.28	10.23	0.052	0.583***	0.581**
Ecuador	0.059	0.875**	1.089	0.065	1.091	1.065
Egypt	0.347	0.945***	1.116	0.385	1.125	1.146
El Salvador	0.039	0.620***	0.845	0.037	0.590***	0.572**
Guatemala	0.035	0.622***	0.746	0.037	0.622***	0.639**
Hong Kong, China	0.028	0.625***	0.637***	0.028	0.541***	0.554***
Iceland	0.056	0.584***	0.611***	0.052	0.459***	0.465***
India	0.063	0.690***	0.673*	0.075	0.757***	0.725*
Indonesia	0.043	0.508***	0.494**	0.069	0.717***	0.674
Israel	0.638	8.973	9.651	0.049	0.601***	0.596***
Japan	0.090	2.091	2.050	0.023	0.543***	0.551***
Kazakhstan	0.051	0.715***	0.764**	0.161	2.265	2.416
Korea, Republic of	0.059	1.265	1.414	0.033	0.760***	0.761**
Malaysia	0.037	0.623***	0.557**	0.033	0.557***	0.444
Mexico	0.035	0.586***	0.663	0.041	0.681***	0.544
Morocco	0.053	0.705***	0.747*	0.051	0.658***	0.529**
New Zealand	0.022	0.754***	0.835	0.024	0.752***	0.747*
Norway	0.051	0.655***	0.642**	0.052	0.617***	0.597**
Paraguay	0.058	0.650***	0.596	0.062	0.711***	0.706
Peru	0.044	0.835***	1.030	0.040	0.785***	0.798***
Philippines	0.083	0.632***	0.553	0.080	0.615***	0.607
Russia	0.056	1.183	1.387	0.108	2.509	2.639
Singapore	0.025	0.652***	0.791**	0.027	0.648***	0.640**
South Africa	0.039	0.636***	0.561***	0.043	0.628***	0.631***
Switzerland	0.097	1.870	1.542	0.102	1.752	1.551
Thailand	0.037	0.594***	0.737**	0.039	0.601***	0.540***
Tunisia	0.110	1.035*	1.191	0.115	1.047*	0.999
Ukraine	0.037	0.683***	0.776**	0.142	2.678	2.705
USA	0.026	0.825***	1.218	0.027	0.843***	0.960
Uruguay	0.298	3.643	4.065	0.171	1.747	2.165
Viet Nam	0.043	0.577***	0.570**	0.051	0.588***	0.557*
WTO75	0.029	0.988***	1.062	0.029	0.937***	0.860

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against a distributed lags AR-model and an ARX-US IP model. Relativ RMSFE values above one marked in grey. Significance levels calculated using the Clark and West statistic for AR rRMSFE and Diebold-Mariano test for US IP rRMSFE.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 4: Comparing Forecast Models for German Unilateral Imports

WTO, X13 h=0				
PLS RMSFE	ifo Importklima rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.022	0.697**	0.661**	0.738***	0.704**
WTO, X13 h=1				
PLS RMSFE	ifo Importklima rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.022	0.652**	0.652***	0.616**	0.657***
Destatis, Spzl.H. h=0				
PLS RMSFE	ifo Importklima rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.022	0.766	0.760	0.731	0.717*
Destatis, Spzl.H. h=1				
PLS RMSFE	ifo Importklima rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.027	0.880	0.907	0.958	0.892**

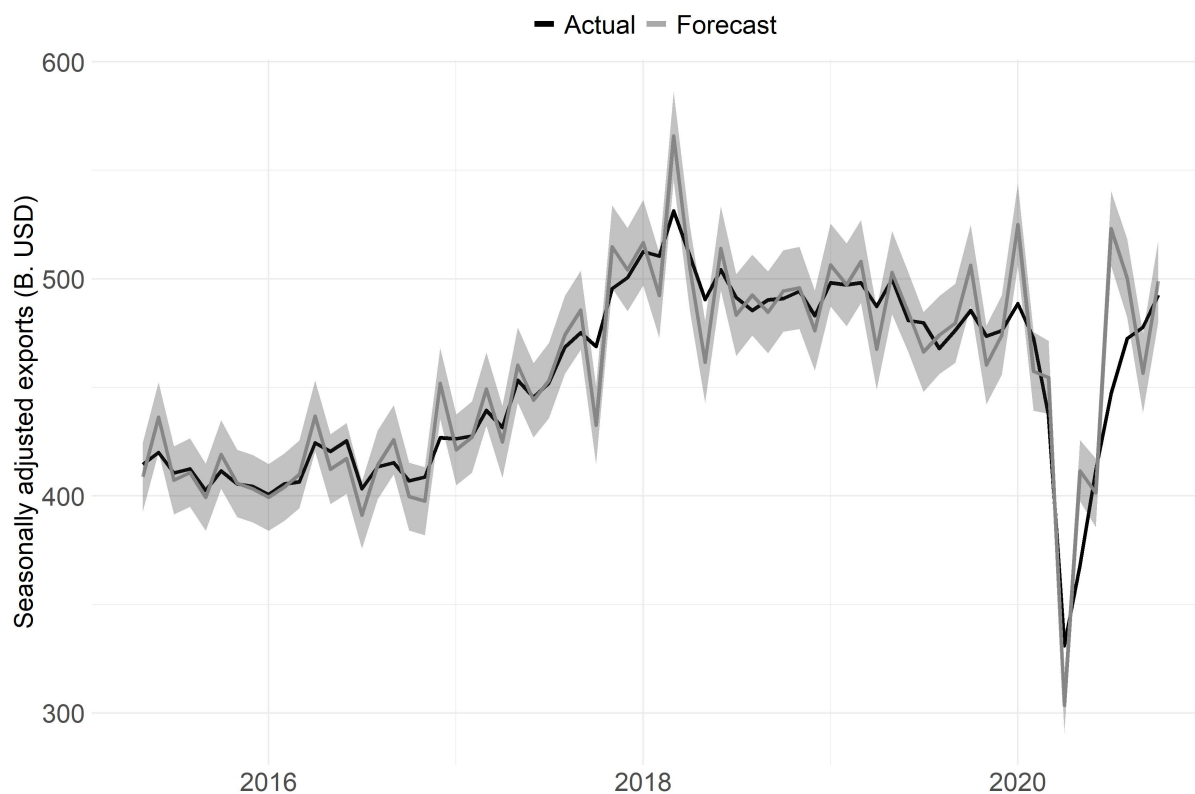
PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against ARX-indicator models. Seasonally adjusted versions of indicators are used. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 4.2. Exports

Results for exports generally track previous ones for imports, although forecast errors tend to be slightly higher. As a result, the ARX-PLS RMSFE narrowly exceeds the ARX industrial confidence indicator RMSFE for EU-27 and Eurozone exports. The reverse remains true for the one-month ahead forecast, although differences are not significant in either case. It is worth noting that an rRMSFE of 1.001 does not imply that forecasting the EU-27 exports in the current month is a fruitless exercise. In contrast, as Figure 3 illustrates, a root mean squared deviation of 3.8 % of adjusted growth rates is still an excellent forecast. Since the PLS-algorithm in this specification only takes into consideration the first 15 days of the month, the shipping derived indicator will be available earlier than the EU business and sentiment indicators. As is the case for European countries, forecast errors for export series in other major countries of the world tend to increase. In contrast to the results for imports, the shipping model performs much better than benchmark models for almost all countries. The model even outperforms the benchmark for resource exporting countries such as Chile and Russia, landlocked countries such as Belarus and Switzerland and countries serving as transshipment hubs like South Korea and Singapore. As for German exports in particular, relative RMSFEs lie well below one for both adjustment specifications of the dependent variable, for both forecast horizons and essentially all competing leading indicators except for the ifo export expectations. The ARX model using ifo export expectations as leading indicator edges out slightly lower forecast errors for the DESTATIS time series and the current month. As results for exports show lower forecasting accuracy than

Figure 3: PLS-ARX Out-of-Sample Forecasts with RMSFE as Confidence Bands Transformed to Absolute Values of EU-27 Exports,  $h=0$



those for imports, robustness checks test primarily export statistics. In particular, the first robustness check in section A.1 tests the forecast properties in an expanding window setting. Due to the scarcity of monthly observations, the analysis forfeits fitting an ARX-PLS model, but compares the single PLS forecast with fully fledged ARX indicator models. Results hold in general despite those changes. While significance further decreases for European exports, it increases for the various tests on German exports. Relative RMSFE values remain below one for the vast majority of countries. The section discusses multiple explanations for the results. A second robustness check in section A.2 shows that results hold independently of the addition of autoregressive terms. The tests repeat previous analyses for exports, but drop the autoregressive terms in the ARX models, so that distributed lags of the indicator alone remain. Results track the baseline models for almost all dependent time series. This shows that the indicators dominate the ARX models, not the autoregressive terms.

Table 5: Comparing Forecast Models for European Unilateral Exports

	h=0			h=1		
	PLS RMSFE	COF rRMSFE	ESI rRMSFE	PLS RMSFE	COF rRMSFE	ESI rRMSFE
Albania	0.063	0.647**	0.637**	0.062	0.694***	0.689***
Austria	0.031	0.691***	0.700***	0.033	0.662***	0.658***
Belgium	0.026	0.740***	0.806**	0.026	0.685***	0.655**
Bulgaria	0.022	0.613***	0.602***	0.022	0.521***	0.517***
Croatia	0.131	1.886	1.828	0.166	1.930	2.138
Cyprus	0.329	0.709	0.713	0.316	0.642	0.645
Czech Rep.	0.043	0.640	0.626*	0.055	0.873	0.871
Denmark	0.019	0.632***	0.626***	0.020	0.623***	0.623***
EU27	0.038	1.001	0.921	0.040	0.852	0.881
EURO	0.040	1.052	0.955	0.043	0.891	0.904
Estonia	0.029	0.695	0.712**	0.032	0.686**	0.636*
Finland	0.038	0.764**	0.780**	0.076	1.253	1.230
France	0.051	0.956	0.922	0.051	0.850*	0.873*
Germany	0.037	0.817*	0.778*	0.042	0.789	0.777
Greece	0.044	0.701***	0.678***	0.041	0.639***	0.640***
Hungary	0.047	0.733	0.718	0.053	0.880	0.879
Ireland	0.047	0.582***	0.538**	0.048	0.507*	0.507*
Italy	0.051	0.660	0.656	0.052	0.746	0.757
Latvia	0.022	0.644***	0.655***	0.025	0.647***	0.658***
Lithuania	0.032	0.653***	0.650***	0.032	0.639***	0.627***
Luxembourg	0.249	2.782	2.819	0.433	4.608	4.608
Malta	0.141	0.745	0.754	0.175	0.821*	0.822*
Montenegro	0.154	0.781*	0.771**	0.133	0.635***	0.633***
Netherlands	0.025	0.724***	0.646***	0.030	0.741***	0.735***
N. Macedonia	0.079	0.662	0.604	0.092	0.843	0.821
Poland	0.037	0.754	0.627	0.043	0.839	0.836
Portugal	0.058	0.886	0.913	0.055	0.831	0.830
Romania	0.049	0.811	0.719	0.058	0.809	0.817
Slovak Republic	0.056	0.671*	0.651*	0.067	0.806	0.829
Slovenia	0.039	0.777	0.788	0.041	0.825	0.845
Spain	0.044	0.711	0.745	0.049	0.819	0.825
Sweden	0.028	0.678***	0.730***	0.032	0.644***	0.608***
Turkey	0.091	0.949	0.886	0.100	0.951	0.944
UK	0.048	0.780***	0.771***	0.052	0.749***	0.773***

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against ARX-indicator models. COF refers to the industrial confidence indicator and ESI to the economic sentiment indicator. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 6: Comparing Forecast Models for Unilateral Exports

	h=0			h=1		
	PLS RMSFE	AR rRMSFE	US IP rRMSFE	PLS RMSFE	AR rRMSFE	US IP rRMSFE
Argentina	0.054	0.718***	0.683***	0.194	2.520	2.481
Australia	0.041	0.838***	0.798**	0.048	0.985***	0.951
Belarus	0.035	0.625***	0.626***	0.044	0.781***	0.774**
Bolivia	0.101	0.747***	0.719	0.106	0.753***	0.637
Bosnia	0.038	0.744***	0.790	0.037	0.753***	0.773*
Brazil	0.043	0.650***	0.683***	0.046	0.667***	0.724***
Canada	0.045	0.809***	1.028	0.050	0.847***	0.986
Chile	0.045	0.788***	0.788**	0.062	1.036	1.095
China	0.044	0.733***	0.725*	0.041	0.543***	0.566*
Chinese Taipei	0.024	0.631***	0.635***	0.023	0.550***	0.515***
Colombia	0.078	0.786***	0.858*	0.069	0.682***	0.683***
Costa Rica	0.029	0.667***	0.767***	0.027	0.638***	0.619***
Ecuador	0.051	0.681***	0.585**	0.061	0.751***	0.754**
Egypt	0.344	1.173**	1.089**	0.366	1.121*	1.077
El Salvador	0.093	0.876***	1.018	0.115	1.097**	1.042
Guatemala	0.023	0.558***	0.548***	0.026	0.577***	0.579***
Hong Kong, China	0.028	0.603***	0.531***	0.030	0.503***	0.468***
Iceland	0.083	0.866**	0.832***	0.065	0.607***	0.592**
India	0.104	0.731***	0.763	0.104	0.815***	0.793
Indonesia	0.021	0.758***	0.761	0.019	0.722***	0.619*
Israel	0.045	0.622***	0.543***	0.049	0.527***	0.541***
Japan	0.025	0.714***	0.928	0.025	0.699***	0.726**
Kazakhstan	0.089	0.670***	0.703***	0.076	0.586***	0.638**
Korea, Republic of	0.046	0.755***	0.820	0.043	0.667***	0.659**
Malaysia	0.058	0.845***	0.972	0.059	0.892***	0.822
Mexico	0.053	0.746**	0.979	0.066	0.826***	0.889
Morocco	0.069	0.758***	0.771	0.069	0.817***	0.764*
New Zealand	0.025	0.634***	0.665***	0.024	0.625***	0.568***
Norway	0.036	0.675***	0.615***	0.044	0.687***	0.704***
Paraguay	0.092	0.635***	0.615	0.083	0.544***	0.553
Peru	0.059	0.620***	0.700***	0.074	0.771***	0.733***
Philippines	0.086	0.816***	0.886	0.081	0.808***	0.846
Russia	0.039	0.821***	0.688***	0.040	0.713***	0.678***
Singapore	0.033	0.678***	0.837	0.027	0.556***	0.547***
South Africa	0.124	0.810***	0.733	0.124	0.936***	0.891
Switzerland	0.053	0.719***	0.719***	0.050	0.642***	0.604***
Thailand	0.028	0.678***	0.665***	0.031	0.660***	0.589**
Tunisia	0.035	0.711***	0.693*	0.031	0.603***	0.638***
Ukraine	0.045	0.798***	0.803**	0.078	1.337	1.241
USA	0.038	0.812***	1.316	0.038	0.821***	0.759
Uruguay	0.048	0.539***	0.525***	0.052	0.541***	0.550***
Viet Nam	0.071	0.840***	0.889	0.070	0.707***	0.716
WTO75	0.031	0.785***	1.035	0.033	0.715***	0.974

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against a distributed lags AR-model and an ARX-US IP model. Relativ RMSFE values above one marked in grey. Significance levels calculated using the Clark and West statistic for AR rRMSFE and Diebold-Mariano test for US IP rRMSFE.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 7: Comparing Forecast Models for German Unilateral Exports

WTO, X13 h=0							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.037	0.714*	0.967	0.669*	0.724	0.695**	0.722*	0.709*
WTO, X13 h=1							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.042	0.796	0.766	0.779	0.775	0.818	0.753	0.747
Destatis, Spzl.H. h=0							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.030	0.685	1.006	0.680	0.838	0.715	0.692	0.671*
Destatis, Spzl.H. h=1							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.037	0.822	0.739	0.827	0.874	0.835	0.902	0.840

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against ARX-indicator models. Seasonally adjusted versions of indicators are used. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

### 4.3. Bilateral

The flexible setup of the PLS algorithm also allows forecasting specific bilateral trade flows. To exemplify this, the PLS algorithm is trained on the trade flows of the EU-27 with its ten most important trade partners outside the EU. Benchmark models are the ARX model with the industrial confidence indicator (COF) for the EU-27 and ARX models using an indicator specific to the partner country. For instance, the PLS-ARX model for EU-27 exports to the USA must measure against an ARX EU27-COF model and an ARX US IP model. Note that the European confidence indicator also covers non-EU members such as Turkey and the United Kingdom (UK).

The specificity of the PLS model to the bilateral trade flow serves the forecasting exercise well: Relative RMSFEs of 0.470 (to China), 0.448 (to the UK) and 0.535 (to the USA) show that exports to Europe's major trade partners can be estimated with roughly half the forecast error as compared to the generic ARX EU27 COF model. Tables in the Appendix show results for the equivalent exercise of China's, the US' and Germany's major bilateral trade flows.

Table 8: Comparing Forecast Models for Bilateral Trade Flows of EU-27

Flow	Partner	h=0			h=1		
		PLS RMSFE	EU COF rRMSFE	Partner rRMSFE	PLS RMSFE	EU COF rRMSFE	Partner rRMSFE
Export	China, P.R.	0.013	0.470***	NA	0.015	0.545***	NA
Export	India	0.070	0.826*	NA	0.074	0.671**	NA
Export	Japan	0.024	0.585***	NA	0.040	0.869	NA
Export	S. Korea	0.036	0.640*	NA	0.032	0.554**	NA
Export	Norway	0.033	1.008	NA	0.030	0.749**	NA
Export	Russia	0.046	0.990	NA	0.040	0.672**	NA
Export	Switzerland	0.031	0.541**	NA	0.034	0.546***	NA
Export	Turkey	0.051	0.725	0.780	0.058	0.770**	0.814**
Export	UK	0.007	0.448***	0.515***	0.007	0.488***	0.527***
Export	USA	0.031	0.535**	0.511**	0.034	0.572*	0.580**
Import	China, P.R.	0.033	0.584	NA	0.030	0.609**	NA
Import	India	0.043	0.658***	NA	0.048	0.659***	NA
Import	Japan	0.025	0.586**	NA	0.027	0.560**	NA
Import	S. Korea	0.035	0.556***	NA	0.039	0.603***	NA
Import	Norway	0.074	1.216	NA	0.077	1.317	NA
Import	Russia	0.048	0.625***	NA	0.074	0.874	NA
Import	Switzerland	0.026	0.539***	NA	0.029	0.475***	NA
Import	Turkey	0.053	1.392	0.938	0.051	0.967	0.995
Import	UK	0.032	0.657	0.956	0.029	0.986	0.959
Import	USA	0.027	0.630***	0.684***	0.025	0.533***	0.536***

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against ARX-industrial confidence indicator of the EU-27 (EU COF) and ARX-Partner indicators. EU COF refers to the industrial confidence indicator. Partner indicators are the industrial confidence indicator (Turkey and UK) and the US industrial production index for the US. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 5. Conclusion

This paper introduces a partial least squares algorithm that estimates month-over-month growth of trade flows from high-frequency container ship movements. The method can forecast unilateral imports and exports, as well as bilateral trade flows of any country in the world. Although the time span to train the algorithm and to fit ARX models is relatively short in comparison to long time series of other leading indicators, results indicate lower forecast errors of the new shipping indicator. Additionally, one can calculate the indicators at any point in the month. In examples of this paper, setting the cutoff date at the 15th of every month implies that estimates of this approach could precede the publication of benchmark leading indicators in some cases by several weeks. The forecasting power ultimately derives from taking into account all sources of correlation in the shipping network with a given trade flow. While the partial least squares system does trace the physical movement of the goods represented by the trade flow, other sources of correlation such as input-output linkages, the movement of complement and substitutes, as well as repeating patterns in the shipping industry all may contribute to the forecasts. Future extensions of this work may apply these procedures to time series beyond headline trade figures. Estimating trade flows by trade mode or in real values such as weight are natural applications. Also, forecasting trade flows of regions and industrial sectors may be possible.



## References

- Arslanalp, S., Marini, M., and Tumbarello, P. (2019). Big data on vessel traffic: Nowcasting trade flows in real time.
- Brancaccio, G., Kalouptsi, M., and Papageorgiou, T. (2017). Geography, search frictions and endogenous trade costs. Technical report, National Bureau of Economic Research.
- Cerdeiro, D. A., Komaromi, A., Liu, Y., Saeed, M., et al. (2020). World seaborne trade in real time: A proof of concept for building ais-based nowcasts from scratch. Technical report.
- Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics*, 138(1):291–311.
- DESTATIS (2020a). Statistisches bundesamt. data. Seasonally adjusted Spezialhandel retrieved in December 2020, <https://www-genesis.destatis.de/genesis/online>.
- DESTATIS (2020b). Statistisches bundesamt. various leading indicators. Auftragseingänge, Auftragsbestand and LKW-Maut-Fahrleistungsindex, <https://www-genesis.destatis.de/genesis/online>.
- Diebold, F. X. and Mariano, R. S. (2002). Comparing predictive accuracy. *Journal of Business & economic statistics*, 20(1):134–144.
- Döhrn, R. and Maatsch, S. (2012). Der rwi/isl-containerumschlag-index. *Wirtschaftsdienst*, 92(5):352–354.
- European Commission (2020). Business and consumer surveys. Main Indicators, [https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series\\_en](https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en).
- Federal Reserve Bank of St. Louis (2020). Board of governors of the federal reserve system (us), industrial production. retrieved from FRED in December 2020, <https://fred.stlouisfed.org/series/INDPRO>.
- Garthwaite, P. H. (1994). An interpretation of partial least squares. *Journal of the American Statistical Association*, 89(425):122–127.
- Grimme, C., Lehmann, R., and Noeller, M. (2018). Forecasting imports with information from abroad.
- Grimme, C. and Wohlrabe, K. (2014). Die ifo exporterwartungen—ein neuer indikator zur lage der exportindustrie in deutschland. *ifo Schnelldienst*, 67(23):64–65.
- Haenlein, M. and Kaplan, A. M. (2004). A beginner's guide to partial least squares analysis. *Understanding statistics*, 3(4):283–297.
- Heiland, I., Moxnes, A., Ulltveit-Moe, K. H., and Zi, Y. (2017). Trade from space: Shipping networks and the global implications of local shocks. *Working Paper*.
- Ifo institute (2020). Various leading indicators. Ifo Zeitreihen - Exporterwartungen, Import- und Exportklima, <https://www.ifo.de/umfragen/zeitreihen>.
- IMF (2020). International monetary fund. dots. data retrieved from the Direction of Trade Statistics in December 2020, <https://data.imf.org/regular.aspx?key=61726508>.

- Lohmöller, J.-B. (2013). *Latent variable path modeling with partial least squares*. Springer Science & Business Media.
- RWI/ISL (2020). Containerumschlag-index. retrieved from RWI Essen in December 2020, <https://www.rwi-essen.de/containerindex>.
- US Census Bureau, Time Series Research Staff, C. f. S. R. and Methodology (2017). X-13arima-seats reference manual.
- Vinzi V, E., Chin, W. W., Henseler, J., Wang, H., et al. (2010). *Handbook of partial least squares*, volume 201. Springer.
- Wold, H. (1975). Path models with latent variables: The nipals approach. In *Quantitative sociology*, pages 307–357. Elsevier.
- Wong, W. F. and Ziv, O. (2020). Entrepã´ t: Hubs, scale, and trade costs.
- WTO (2020). World trade organization. wto data. data retrieved from data portal in December 2020, <https://data.wto.org/>.

## A. Appendix

### A.1. Robustness 1

A criticism of the leave-one-out out-of-sample (LOO) forecast approach is that estimations may factor in future relationships that would not be ex-ante known in an actual forecasting application. While this may artificially reduce the forecast errors, this criticism applies to both the ARX-PLS estimation, as well as the ARX benchmark indicator models. Hence, a relative evaluation such as an rRMSFE analysis or the Diebold-Mariano test are intrinsically more robust in this regard. Nevertheless, an expanding window approach to calculating out-of-sample forecasts is run here, as it removes precisely the information on future trends.

As many leading indicators date back several years, limiting the training period is not a problem: For instance, both the ifo indicators and the DESTATIS time series begin in 1991. Hence, the entire time period until the testing period serves as training data for fitting the ARX model. This is not the case for the shipping indicator. The 65 to 70 monthly observations beginning in 2015 must fulfill three purposes: Training of the partial least squares model, embedding the estimates into an ARX model and performing the Diebold-Mariano test. In the context of an expanding window analysis, the number of monthly observations simply does not suffice for the three tasks.

For that reason, the PLS estimates are not embedded into an ARX model, but used directly in comparisons with ARX models incorporating other leading indicators.

$$y_{t+h} \approx \widehat{y_{t,h}^{PLS}} \quad (12)$$

$$y_{t+h} = \alpha + \sum_{i=1}^p \beta_i y_{t-i} + \sum_{i=1}^p \gamma_i Indicator_{t-i} + \varepsilon_{t+h} \quad (13)$$

Note that the identification of significant forecasting improvements now faces several challenges: Simple PLS estimates must measure up to fully fledged ARX models, the first out-of-sample forecasts of the PLS are derived from 34 observations only and the Diebold-Mariano test ascertains significance based on 31 to 36 observations instead of 65 to 70. It is remarkable that results generally hold for European and other countries, although significance for some of the differences falls.

Table 9: Comparing Forecast Models for European Unilateral Exports - Expanding Window

	h=0			h=1		
	PLS RMSFE	COF rRMSFE	ESI rRMSFE	PLS RMSFE	COF rRMSFE	ESI rRMSFE
Albania	0.105	0.655**	0.563*	0.108	0.792***	0.777***
Austria	0.492	0.838	0.841	0.059	0.846	0.851
Belgium	0.039	0.768	0.824	0.051	0.775	0.769
Bulgaria	0.048	0.715***	0.655**	0.045	0.620***	0.608***
Croatia	0.050	0.642	0.507	0.119	0.528***	0.551***
Cyprus	1.888	1.518	1.502	2.115	0.862	0.860
Czech Rep.	0.085	0.667	0.638	0.105	0.815	0.820
Denmark	0.027	0.755***	0.747**	0.041	0.624***	0.624***
EU27	0.194	1.226	1.181	5.397	0.691	0.640
EURO	0.149	1.190	1.160	0.074	0.696	0.641
Estonia	0.050	0.809	0.731	0.054	0.656	0.632
Finland	0.068	0.645***	0.671**	0.122	0.659**	0.650**
France	0.092	0.842	0.919	0.079	0.805**	0.879
Germany	0.071	0.991	1.064	0.072	0.768	0.705
Greece	0.138	0.816**	0.820***	0.077	0.761**	0.761**
Hungary	0.176	0.694	0.783	0.110	0.755	0.760
Ireland	0.212	0.791	0.825	0.088	0.574	0.573
Italy	0.118	0.645	0.671	0.106	0.738	0.752
Latvia	0.053	1.006	1.023	0.116	0.611**	0.632***
Lithuania	0.055	0.813**	0.992	0.055	0.702	0.762
Luxembourg	0.113	0.792*	0.812*	0.125	0.676*	0.676*
Malta	0.180	0.916	0.990	0.369	0.735**	0.735**
Montenegro	0.146	0.837	0.753*	0.114	0.734**	0.734**
Netherlands	0.059	0.918	0.866	0.044	0.841	0.848
N. Macedonia	0.154	0.806	0.691*	0.146	0.747	0.739
Poland	0.298	0.699	0.627	0.073	0.763	0.828
Portugal	0.095	0.783	0.919	0.125	0.806	0.802
Romania	0.120	0.876	0.695	0.090	0.767	0.770
Slovak Republic	0.129	0.621	0.674	0.112	0.852	0.885
Slovenia	0.087	0.793	0.858	0.079	0.815	0.818
Spain	0.081	0.781	0.799	0.100	0.787	0.863
Sweden	0.041	0.828	0.860	0.053	0.646***	0.603***
Turkey	0.196	0.690	0.680*	0.170	0.681	0.682
UK	0.107	0.809*	0.804**	0.062	0.823**	0.874

PLS RMSFE refers to the root means squared forecast error of the PLS estimates derived from an expanding window analysis. rRMSFE refers to the relative RMSFE of PLS against ARX-indicator models. COF refers to the industrial confidence indicator and ESI to the economic sentiment indicator. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 10: Comparing Forecast Models for Unilateral Exports - Expanding Window

	h=0			h=1		
	PLS RMSFE	AR rRMSFE	US IP rRMSFE	PLS RMSFE	AR rRMSFE	US IP rRMSFE
Argentina	0.105	0.834	0.922	0.110	0.730	0.806
Australia	0.041	0.744***	0.506	0.090	1.008	0.982*
Belarus	0.059	0.864***	0.793	0.052	0.750***	0.680**
Bolivia	0.205	0.789**	1.023	0.190	0.792***	0.582
Bosnia	0.051	0.889***	0.933	0.060	0.847***	0.764
Brazil	0.247	0.842	0.849	0.056	0.826**	0.794**
Canada	0.198	0.698	0.991	0.210	0.762	0.829
Chile	0.043	0.882***	0.519*	0.055	0.778***	0.749***
China	0.097	0.865	0.694*	0.119	0.917	0.937**
Chinese Taipei	0.030	0.823***	0.742***	0.024	0.769***	0.683**
Colombia	0.104	0.640***	0.644*	0.112	0.862**	0.851***
Costa Rica	0.045	0.731***	0.712*	0.037	0.649***	0.630**
Ecuador	0.085	0.708***	0.895*	0.076	0.775***	0.711
Egypt	0.210	1.210	1.177	0.135	1.137	0.598
El Salvador	0.166	0.745***	0.865	0.201	0.975	0.974
Guatemala	0.042	0.747***	0.749**	0.034	0.707***	0.617*
Hong Kong, China	0.047	0.744***	0.505**	0.053	0.584***	0.557**
Iceland	0.224	1.186	1.118	5.424	0.781	0.735**
India	0.182	0.636**	0.897	0.179	0.762**	0.689
Indonesia	0.023	0.877***	0.894	0.047	0.744	0.576*
Israel	0.085	0.800***	0.577*	0.075	0.678***	0.633**
Japan	0.135	0.939	0.974	0.071	0.872	0.847
Kazakhstan	0.314	0.792	0.680*	0.112	0.673***	0.713***
Korea, Republic of	0.048	0.789***	1.073	0.055	0.761***	0.698*
Malaysia	0.114	0.725	0.719	0.117	0.754	0.574
Mexico	0.295	0.700	1.168	0.295	0.725	0.802
Morocco	0.126	0.875*	0.746	0.104	0.807**	0.783**
New Zealand	0.052	1.531	0.969	0.137	1.114	0.893
Norway	0.066	0.827**	0.775*	0.127	0.777	0.719***
Paraguay	0.100	0.947**	0.712	0.146	1.004	0.890
Peru	0.078	0.625***	0.751*	0.099	0.897***	0.879
Philippines	0.119	0.743***	1.006	0.125	0.826**	0.726
Russia	0.039	0.788***	0.745**	0.092	0.948	0.872**
Singapore	0.131	0.924	1.233	0.060	0.860*	0.779
South Africa	0.300	0.618	0.750	1.936	0.845	0.684
Switzerland	0.052	0.761***	0.734	0.130	0.679*	0.615***
Thailand	0.053	0.815***	0.880	0.048	0.739***	0.526
Tunisia	0.049	0.733***	0.522	0.069	0.666	0.705***
Ukraine	0.043	0.889***	0.572	0.040	0.674***	0.466***
USA	0.105	0.908	2.116	0.071	0.673**	0.646
Uruguay	0.069	0.749***	0.665**	0.140	0.774	0.766**
Viet Nam	0.112	0.881	0.818	0.110	0.751**	0.687
WTO75	0.090	0.778	0.861	0.090	0.750	0.911

PLS RMSFE refers to the root means squared forecast error of the PLS estimate derived from an expanding window analysis. rRMSFE refers to the relative RMSFE of PLS against a distributed lags AR-model and an ARX-US IP model. Relative RMSFE values above one marked in grey. Significance levels calculated using the Clark and West statistic for AR rRMSFE and Diebold-Mariano test for US IP rRMSFE.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 11: Comparing Forecast Models for German Unilateral Exports - Expanding Window

WTO, X13 h=0							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.071	0.877	1.320	0.646**	0.894	0.723**	0.776*	0.724**
WTO, X13 h=1							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.072	0.781	0.691	0.810	0.782	0.810	0.769	0.782
Destatis, Spzl.H. h=0							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.094	0.589*	0.861	0.487	0.870	0.555*	0.571	0.530*
Destatis, Spzl.H. h=1							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
1.105	0.725	0.624	0.788	0.710	0.787	0.851	0.800

PLS RMSFE refers to the root means squared forecast error of the PLS estimate derived from an expanding window analysis. rRMSFE refers to the relative RMSFE of PLS against ARX-indicator models. Seasonally adjusted versions of indicators are used. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## A.2. Robustness 2

This robustness check evaluates the forecasting quality of the indicators without additional autoregressive terms as follows:

$$y_{t+h} = \alpha + \sum_{i=1}^p \gamma_i \widehat{y_{t-i,h+i}^{PLS}} + \varepsilon_{t+h} \quad (14)$$

$$y_{t+h} = \alpha + \sum_{i=1}^p \gamma_i \text{Indicator}_{t-i} + \varepsilon_{t+h} \quad (15)$$

While forecast errors tend to increase, differences between forecast models remain robust and significant.

Table 12: Comparing Forecast Models for European Unilateral Exports

	h=0			h=1		
	PLS RMSFE	COF rRMSFE	ESI rRMSFE	PLS RMSFE	COF rRMSFE	ESI rRMSFE
Albania	0.063	0.658*	0.641**	0.064	0.711***	0.718***
Austria	0.032	0.683***	0.711***	0.033	0.656***	0.641***
Belgium	0.026	0.723***	0.765**	0.027	0.687***	0.692***
Bulgaria	0.023	0.604***	0.578***	0.022	0.520***	0.521***
Croatia	0.118	1.421	1.433	0.154	1.828	1.893
Cyprus	0.323	0.661	0.667	0.316	0.656	0.656
Czech Rep.	0.045	0.728*	0.709**	0.051	0.813	0.816
Denmark	0.018	0.587***	0.589***	0.020	0.638***	0.627***
EU27	0.036	1.004	0.931	0.038	0.810	0.822
EURO	0.036	1.013	0.940	0.040	0.829	0.837
Estonia	0.031	0.737*	0.740**	0.031	0.678**	0.630*
Finland	0.035	0.632***	0.653***	0.075	1.254	1.228
France	0.047	0.868	0.869	0.049	0.804**	0.835*
Germany	0.039	0.869	0.871	0.039	0.731	0.718
Greece	0.042	0.649***	0.624***	0.039	0.626***	0.632***
Hungary	0.045	0.735	0.742	0.051	0.851	0.849
Ireland	0.044	0.465**	0.463**	0.046	0.490*	0.488
Italy	0.052	0.683	0.672	0.050	0.712	0.721
Latvia	0.025	0.741***	0.754**	0.026	0.663***	0.676***
Lithuania	0.032	0.673***	0.697***	0.032	0.626***	0.615***
Luxembourg	0.250	2.900	2.826	0.432	4.709	4.704
Malta	0.141	0.663**	0.669**	0.174	0.828*	0.817*
Montenegro	0.147	0.693***	0.687***	0.125	0.596***	0.581***
Netherlands	0.026	0.804*	0.770**	0.030	0.770***	0.735***
N. Macedonia	0.087	0.734	0.662	0.093	0.844	0.820
Poland	0.038	0.785	0.697	0.042	0.828	0.828
Portugal	0.057	0.872	1.003	0.056	0.846*	0.839**
Romania	0.049	0.856	0.788	0.059	0.827	0.839
Slovak Republic	0.068	0.846	0.865	0.071	0.861	0.906
Slovenia	0.037	0.805	0.767	0.042	0.844	0.853
Spain	0.051	0.910	0.875	0.049	0.821	0.830
Sweden	0.026	0.615***	0.677***	0.031	0.661***	0.612***
Turkey	0.090	0.947	0.914	0.089	0.877	0.861
UK	0.046	0.732***	0.720***	0.052	0.763***	0.778***

PLS RMSFE refers to the root means squared forecast error of the distributed lags PLS model. rRMSFE refers to the relative RMSFE of PLS against distributed lags indicator models. COF refers to the industrial confidence indicator and ESI to the economic sentiment indicator. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01



Table 13: Comparing Forecast Models for Unilateral Exports

	h=0			h=1		
	PLS RMSFE	AR rRMSFE	US IP rRMSFE	PLS RMSFE	AR rRMSFE	US IP rRMSFE
Argentina	0.054	0.718***	0.685***	0.194	2.520	2.491
Australia	0.040	0.838**	0.789**	0.047	0.985	0.942
Belarus	0.035	0.625***	0.629***	0.043	0.781***	0.769**
Bolivia	0.104	0.747	0.706	0.107	0.753	0.650
Bosnia	0.038	0.744*	0.811	0.038	0.753*	0.793
Brazil	0.042	0.650***	0.647***	0.044	0.667***	0.699***
Canada	0.047	0.809	1.263*	0.050	0.847	0.980
Chile	0.042	0.788**	0.718***	0.060	1.036	1.049
China	0.046	0.733	0.645**	0.041	0.543*	0.579*
Chinese Taipei	0.024	0.631***	0.570***	0.022	0.550***	0.538***
Colombia	0.078	0.786**	0.842*	0.067	0.682***	0.677***
Costa Rica	0.028	0.667***	0.646***	0.027	0.638***	0.642***
Ecuador	0.056	0.681**	0.694**	0.061	0.751**	0.752**
Egypt	0.364	1.173	1.137*	0.365	1.121	1.074
El Salvador	0.111	0.876*	1.319**	0.119	1.097	1.067
Guatemala	0.023	0.558***	0.506***	0.026	0.577***	0.562***
Hong Kong, China	0.031	0.603***	0.481***	0.032	0.503***	0.488***
Iceland	0.083	0.866***	0.756***	0.065	0.607**	0.594*
India	0.103	0.731*	0.749	0.104	0.815	0.790
Indonesia	0.021	0.758*	0.765	0.020	0.722	0.630*
Israel	0.046	0.622***	0.488***	0.048	0.527***	0.523***
Japan	0.025	0.714***	0.937	0.024	0.699***	0.700**
Kazakhstan	0.085	0.670***	0.719**	0.074	0.586***	0.630**
Korea, Republic of	0.044	0.755**	0.670**	0.041	0.667**	0.648**
Malaysia	0.054	0.845	0.957	0.056	0.892	0.783
Mexico	0.066	0.746	1.367*	0.067	0.826	0.933
Morocco	0.071	0.758*	0.820	0.071	0.817**	0.789*
New Zealand	0.024	0.634***	0.607***	0.025	0.625***	0.591***
Norway	0.042	0.675***	0.729***	0.042	0.687***	0.691***
Paraguay	0.092	0.635*	0.618	0.083	0.544	0.551
Peru	0.064	0.620***	0.702***	0.075	0.771***	0.766***
Philippines	0.084	0.816	0.827	0.078	0.808	0.811
Russia	0.046	0.821*	0.818	0.040	0.713***	0.667***
Singapore	0.032	0.678***	0.778**	0.027	0.556***	0.564***
South Africa	0.124	0.810	0.747	0.123	0.936	0.884
Switzerland	0.050	0.719***	0.629***	0.048	0.642***	0.601***
Thailand	0.030	0.678**	0.706***	0.030	0.660***	0.574**
Tunisia	0.035	0.711***	0.644**	0.031	0.603***	0.628***
Ukraine	0.045	0.798**	0.780*	0.078	1.337	1.300
USA	0.037	0.812	1.393	0.038	0.821	0.761
Uruguay	0.048	0.539***	0.501***	0.052	0.541***	0.524***
Viet Nam	0.066	0.840	0.700	0.068	0.707	0.694
WTO75	0.031	0.785	1.108	0.032	0.715	0.908
	0.028	0.652	0.781	0.038	0.900	0.893

PLS RMSFE refers to the root means squared forecast error of the distributed lags PLS model. rRMSFE refers to the relative RMSFE of PLS against a distributed lags AR-model and a distributed lags-US IP model. Relativ RMSFE values above one marked in grey. Significance levels calculated using the Clark and West statistic for AR rRMSFE and Diebold-Mariano test for US IP rRMSFE.

Table 14: Comparing Forecast Models for German Unilateral Exports

WTO, X13 h=0							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.039	0.783*	0.957	0.735*	0.811	0.749**	0.791**	0.802**
WTO, X13 h=1							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.039	0.749	0.720	0.735*	0.730	0.754*	0.723*	0.702*
Destatis, Spzl.H. h=0							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.028	0.668*	0.953	0.662*	0.815*	0.661*	0.701	0.668*
Destatis, Spzl.H. h=1							
PLS RMSFE	ifo Exportklima rRMSFE	ifo Exportexp. rRMSFE	Mfg. order stock rRMSFE	Mfg. order entry rRMSFE	RWI/ISL Northr. rRMSFE	RWI/ISL rRMSFE	LKW-Maut rRMSFE
0.038	0.841	0.756	0.856	0.890	0.859	0.911	0.861

PLS RMSFE refers to the root means squared forecast error of the distributed lags PLS model. rRMSFE refers to the relative RMSFE of PLS against indicator models. Seasonally adjusted versions of indicators are used. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

### A.3. Other Bilateral Results

Table 15: Comparing Forecast Models Bilateral Trade Flows of USA

Flow	Partner	h=0			h=1		
		PLS RMSFE	US IP rRMSFE	Partner rRMSFE	PLS RMSFE	US IP rRMSFE	Partner rRMSFE
Export	Brazil	0.065	0.659***	NA	0.063	0.543***	NA
Export	Canada	0.056	1.838	NA	0.053	0.989	NA
Export	Hong Kong	0.059	0.650***	NA	0.053	0.488***	NA
Export	China, P.R.	0.052	0.765**	NA	0.045	0.583***	NA
Export	Germany	0.074	1.647	1.647	0.078	1.531	1.503
Export	Japan	0.033	0.546***	NA	0.031	0.467***	NA
Export	Korea, Rep. of	0.038	0.545***	NA	0.048	0.678**	NA
Export	Mexico	0.061	1.300	NA	0.058	0.992	NA
Export	Netherlands	0.027	0.603***	0.646***	0.026	0.558***	0.554***
Export	UK	0.045	0.746**	0.764***	0.050	0.823**	0.857*
Import	Canada	0.057	1.248	NA	0.054	0.788***	NA
Import	China, P.R.	0.052	0.746	NA	0.039	0.621*	NA
Import	France	0.058	0.619***	0.654***	0.053	0.567***	0.594***
Import	Germany	0.014	0.519***	0.530***	0.013	0.358***	0.367***
Import	India	0.045	0.910	NA	0.045	0.669***	NA
Import	Ireland	0.064	0.396**	0.484***	0.069	0.447***	0.449***
Import	Japan	0.035	0.906	NA	0.026	0.699***	NA
Import	Korea, Rep. of	0.026	0.512***	NA	0.026	0.469***	NA
Import	Mexico	0.065	1.291	NA	0.064	0.932**	NA
Import	UK	0.509	6.798	7.047	0.038	0.501***	0.524***

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against an ARX-US IP model and an ARX-Partner indicator model. Partner indicators are EU industrial confidence indicator, ifo import climate for German imports and ifo export expectations for German exports. Relative RMSFE values above one marked in grey. Significance levels calculated using the Clark and West statistic for AR RMSFE and Diebold-Mariano test for US IP rRMSFE.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 16: Comparing Forecast Models for Bilateral Trade Flows of China

Flow	Partner	h=0			h=1		
		PLS RMSFE	AR rRMSFE	Partner rRMSFE	PLS RMSFE	AR rRMSFE	Partner rRMSFE
Export	Hong Kong	0.039	0.515***	NA	0.051	0.563***	NA
Export	Germany	0.052	0.702***	0.725*	0.046	0.594***	0.637***
Export	India	0.068	0.687***	NA	0.059	0.519***	NA
Export	Japan	0.063	0.602***	NA	0.068	0.587***	NA
Export	S. Korea	0.050	0.579***	NA	0.061	0.614***	NA
Export	Netherlands	0.030	0.740***	0.653***	0.040	0.769*	0.903
Export	Singapore	0.054	0.623***	NA	0.064	0.619***	NA
Export	UK	0.073	0.702***	0.657*	0.075	0.555***	0.579*
Export	USA	0.044	0.682***	0.686***	0.037	0.520***	0.584***
Export	Vietnam	0.064	0.517***	NA	0.070	0.517***	NA
Import	Australia	0.062	0.574***	NA	0.061	0.582***	NA
Import	Brazil	0.045	0.648***	NA	0.042	0.620***	NA
Import	Germany	0.041	0.577***	0.545***	0.470	5.947	5.253
Import	Japan	0.027	0.705***	NA	0.025	0.615***	NA
Import	S. Korea	0.042	0.620***	NA	0.039	0.588***	NA
Import	Malaysia	0.043	0.590***	NA	0.042	0.512***	NA
Import	Russia	0.058	0.606***	NA	0.050	0.503***	NA
Import	Taiwan	0.074	0.928**	NA	0.081	0.887**	NA
Import	USA	0.035	0.498***	0.439***	0.170	2.432	2.319
Import	Vietnam	0.079	0.634***	NA	0.078	0.609***	NA

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against the autoregression model. (AR) and ARX-Partner indicator. Partner indicator is US-IP for the USA, EU industrial confidence indicator for EU-countries and ifo export expectations for German exports and ifo import climate for German imports. Relativ RMSFE values above one marked in grey. Significance levels calculated using the Clark and West statistic for AR rRMSFE and Diebold-Mariano test for Partner rRMSFE.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 17: Comparing Forecast Models for Bilateral Trade Flows of Germany

Flow	Partner	h=0			h=1		
		PLS RMSFE	ifo ind. rRMSFE	Partner rRMSFE	PLS RMSFE	ifo ind. rRMSFE	Partner rRMSFE
Export	Austria	0.040	1.050	0.758*	0.037	0.835***	0.808**
Export	Belgium	0.057	1.324	1.260	0.039	0.757***	0.808***
Export	China, P.R.	0.021	0.382***	NA	0.025	0.408***	NA
Export	France	0.066	1.003	1.084	0.060	0.710***	0.709***
Export	Italy	1.139	22.38	22.67	0.093	1.511	1.537
Export	Netherlands	0.022	0.666***	0.616***	0.018	0.523***	0.491***
Export	Poland	0.035	0.747	0.952	0.033	0.683**	0.696**
Export	Switzerland	0.014	0.572***	NA	0.013	0.458***	NA
Export	UK	0.012	0.506***	0.520***	0.013	0.492***	0.492***
Export	USA	0.037	0.505**	0.552***	0.039	0.511**	0.519***
Import	Austria	0.027	0.644**	0.589**	0.028	0.630**	0.633**
Import	Belgium	0.045	0.584***	0.617***	0.046	0.466***	0.462***
Import	China, P.R.	0.050	0.751*	NA	0.051	0.831**	NA
Import	Czech Rep.	0.040	0.841*	NA	0.038	0.668**	NA
Import	France	0.040	0.681	0.800	0.043	0.723	0.701
Import	Italy	0.046	0.808***	0.958	0.039	0.655**	0.692*
Import	Netherlands	0.021	0.731***	0.900	0.024	0.664**	0.662**
Import	Poland	0.034	0.874**	1.206	0.030	0.788*	0.760**
Import	Switzerland	0.029	0.479***	NA	0.031	0.429***	NA
Import	USA	0.025	0.626***	0.591***	0.029	0.684***	0.681***

PLS RMSFE refers to the root means squared forecast error of the ARX-PLS model. rRMSFE refers to the relative RMSFE of ARX-PLS against ARX-ifo indicator and ARX-Partner indicator. Ifo-indicator refers to ifo export expectations for German exports and ifo import climate for German imports. Partner indicators are the EU industrial confidence indicator and the US industrial production index. Relativ RMSFE values above one marked in grey. Significance levels calculated using Diebold-Mariano test.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01