WP/20/247

IMF Working Paper

Improving the Short-term Forecast of World Trade During the Covid-19 Pandemic Using SWIFT Data on Letters of Credit

by Benjamin Carton, Nan Hu, Joannes Mongardini, Kei Moriya, and Aneta Radzikowski

INTERNATIONAL MONETARY FUND

 WP/20/247

IMF Working Paper

Research Department

Improving the Short-term Forecast of World Trade During the Covid-19 Pandemic Using SWIFT Data on Letters of Credit

Prepared by Benjamin Carton, Nan Hu, Joannes Mongardini,
Kei Moriya, and Aneta Radzikowski*

Authorized for distribution by Benjamin Hunt

November 2020

Abstract

An essential element of the work of the Fund is to monitor and forecast international trade. This paper uses SWIFT messages on letters of credit, together with crude oil prices and new export orders of manufacturing Purchasing Managers' Index (PMI), to improve the short-term forecast of international trade. A horse race between linear regressions and machine-learning algorithms for the world and 40 large economies shows that forecasts based on linear regressions often outperform those based on machine-learning algorithms, confirming the linear relationship between trade and its financing through letters of credit.

JEL Classification Numbers: F17, F47

Keywords: SWIFT; trade forecast; machine learning

Author's E-Mail Addresses: bcarton@imf.org nhu@hkma.gov.hk; jmongardini@imf.org; kmoriya@imf.org; aradzikowski@imf.org

---

* Benjamin Carton, Joannes Mongardini, and Aneta Radzikowski are, respectively, senior economist, deputy division chief, and research officer in the IMF Research Department. Kei Moriya is an economic system engineer at the IMF. Nan Hu was an IMF project officer during February-July 2019 when she took part in this research project. She is now an economist at the Hong Kong Institute for Monetary and Financial Research We are grateful to the IMF Innovation Lab for funding to undertake this project, and to Astrid Thorsen, Benjamin Hunt, Sonali Das, Pragyan Deb, Bertrand Gruss, Daniel Garcia-Marcia, Gee Hee Hong, Alvar Kangur, Ivo Krznar, Louise Taylor-Digby, Aiko Mineshima, Rafael Portillo, and participants of a workshop on the digital economy during the IMF and World Bank Spring Meetings in April 2019 for useful comments. All remaining errors are our own.

Contents Page

Figures

Appendices

I. Introduction

An essential element of the work of the Fund is to monitor and forecast international trade. Trade is a leading indicator of global economic activity and a key channel of spillovers. An accurate and timely reading of trade developments can therefore provide useful insights into global economic activity and an economy's short-term growth dynamics. This is particularly relevant during the current conjuncture as the decline in world trade in the first half of 2020 was an early indicator of the contraction in global economic activity due to the lockdowns and social distancing associated with the ongoing Covid-19 pandemic.

Trade financing can be an early indicator of international trade. Ahead of goods moving across countries, importers often arrange for trade financing, particularly in Asia. Banks provide letters of credit or trade advances that can be secured by the imported goods as collateral, and charge fees and interest until the importer has sold the goods and paid off the trade credit. Trade financing can therefore be a leading indicator of international trade by several weeks depending on the time needed to produce and transport the merchandise from the exporting country to the importing one.

SWIFT, the global provider of secure financial messaging services, provided the authors of this working paper with access to data on letters of credit.[1] The monthly SWIFT data are available a few business days following the end of the reported month, aggregated by country and on an anonymous basis. The associated metadata provide the country where the message originates from (normally the importing country), the country where the beneficiary resides (usually, the exporting country), and the total amount of transactions during the month (in USD and in the currency of settlement).

This paper uses the SWIFT data to improve the short-term forecast of international trade, together with Brent crude oil prices and the new export orders subcomponent of manufacturing Purchasing Managers' Index (PMI) where available. Both linear regressions and machine-learning algorithms are used to extract the lead information content of SWIFT trade messages to improve the short-term forecast of world and national trade for 40 large economies. In doing so, SWIFT trade messages are shown to have informational content to forecast world trade in the short run, and national trade in selected economies, particularly in Asia. In addition, a horse race between linear regression forecasts and machine-learning ones

[1] SWIFT stands for the Society for Worldwide Interbank Financial Telecommunication. It is a cooperative utility founded by international banks in 1973 to provide a secure communication platform. See SWIFT (2019a) for additional information. Data relating to SWIFT messaging flows is published with permission of S.W.I.F.T. SC. SWIFT © 2020. All rights reserved. Because financial institutions have multiple means to exchange information about their financial transactions, SWIFT statistics on financial flows do not represent complete market or industry statistics. SWIFT disclaims all liability for any decisions based, in full or in part, on SWIFT statistics, and for their consequences.

show that linear regression forecasts often outperform other forecasts. This likely reflects the linear relationship between trade data and its financing through SWIFT.

This paper is organized as follows. Section II provides a brief introduction to SWIFT messages and trade financing. Section III describes the forecast of world trade using SWIFT messages and the recent performance during the Covid-19 pandemic compared with other forecasts of world trade. The relationship between SWIFT messages and national trade is discussed in Section IV. Section V presents the horse race between forecasts based on linear regressions and those based on machine-learning algorithms. The main conclusions are summarized in Section VI.

II. SWIFT Messages and International Trade

SWIFT is a provider of secure financial messaging services. Its services are used by over 11,000 financial institutions in more than 200 countries and territories around the world. To this day, SWIFT represents the primary communication channel for corporates, financial institutions, and market infrastructures to settle international financial payments, securities, foreign exchange transactions, treasury operations, and trade flows.[2]

SWIFT messages and reference data are standardized, which ensures that data exchanged between financial institutions is unambiguous. SWIFT messages are classified into nine categories such as customer payments and checks, financial institution transfers, treasury markets, and documentary credits and guarantees. Each of these categories contains several types of messages. A SWIFT message starts with an identifier (MT) and is followed by a 3-digit number that represents category, group, and type.

The Fund acquired a proprietary database of SWIFT messages several years ago going back to 2010 and receives monthly updates a few business days after the end of the month. SWIFT data are aggregated by country at a monthly frequency and are anonymous. Each data point contains the message type code, message name, the code and name of the originating country, the code and name of the counterparty country, the currency used, the total number of SWIFT transactions sent and received during the month, and the total net amount sent and received in the original currency and US dollar equivalent.

SWIFT messages used in this paper are MT 700 messages and represent documentary credits, more commonly known as letters of credit.[3] Importers usually contract a letter of credit from a bank to import merchandise goods against a fixed transaction fee and interest

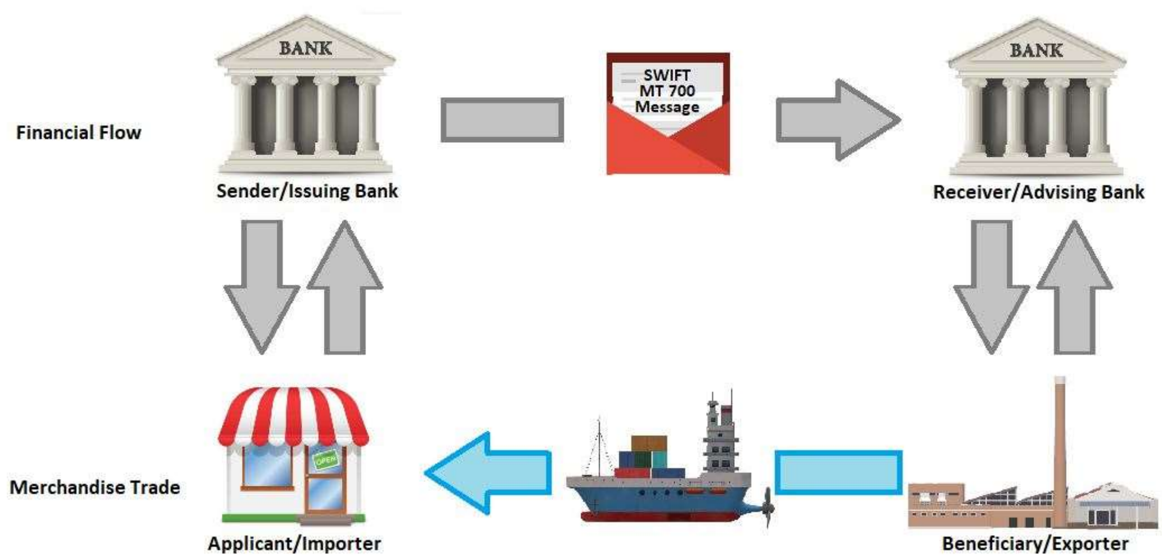
[2] SWIFT (2019b).

[3] Another less common form of SWIFT trade financing is documentary collections (MT 400 messages), where the shipping/ownership documents are transferred to the importer's bank, which releases them to the importer only once the importer has paid the exporter for the imported goods. According to Niepmann and Schmidt-Eisenlohr (2017), documentary collections (MT 400 messages) financed 1.8% of world trade, compared with 13.0% of letters of credit (MT 700 messages) in 2013.

payments. When the letter of credit is obtained, the issuing bank sends an MT 700 message to the bank of the exporter (the advising bank) to indicate the terms and conditions of the letter of credit. Against this guarantee, the exporter then produces and ships the merchandise goods to the importer and produces the necessary shipping documentation (e.g., bill of laden) representing title to the goods. The issuing bank then checks the shipping documentation against the requirements under the letter of credit before making the payment to the advising bank. Letters of credit and associated obligations to handle documents under documentary credits are governed by the Uniform Customs and Practice for Documentary Credits rules established by the International Chamber of Commerce (ICC).[4]

SWIFT MT 700 messages can be a leading indicator of world trade. Since the letter of credit is sent before exporters ship their merchandise goods, the dollar amount of the letter of credit provides an early indicator of the nominal value of the trade that will take place. Figure 1 provides a graphical representation of the financial flows under a letter of credit (top row) before the actual movement of goods takes place (bottom row). It is worth noting that SWIFT MT 700 messages go in the opposite direction of the trade flow.

Figure 1. Financial Flow and Merchandise Trade



Source: Authors' representation.

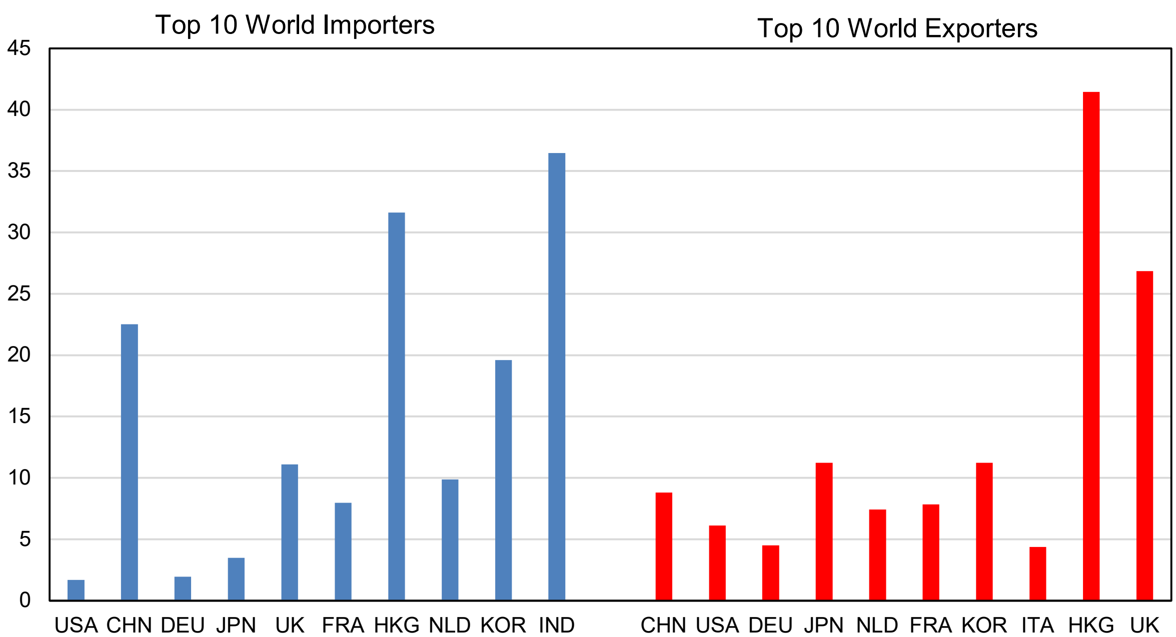
The extent to which a SWIFT trade message is a leading indicator of bilateral trade varies across countries. The time it takes from the moment the MT 700 message is sent and the goods are recorded by the customs authorities of the importing country largely depends on the production time, the proximity between the trading partners, and the type of transportation method. For example, the lead time between the United States and Mexico

[4] Danske Bank (2019).

may be very short (a week or two), while the lead time between China and Germany may be longer (one to two months), unless goods are already produced and shipped by plane. Thus, the lead time between SWIFT trade messages and bilateral trade will vary depending on the physical distance and method of transportation used for the merchandise to be shipped between countries. According to the ICC, the average maturity of a letter of credit is 60 days.[5]

The share of trade financed through SWIFT trade messages varies significantly across economies. Amongst the top 10 importers in the world, India, Hong Kong SAR, and China were the largest users of SWIFT MT 700 trade messages in 2019 with a share over 20 percent of their total merchandise trade (Figure 2). Amongst the largest 10 exporters, Hong Kong SAR and United Kingdom stand out as the largest user of SWIFT trade messages at over 25 percent, followed by Korea, Japan, and China. The relatively large shares for Hong Kong SAR, Japan, the United Kingdom, and the United States may, however, partly reflect the fact that banks located in these countries receive SWIFT trade messages on behalf of exporting clients in other parts of the world. Unfortunately, this cannot be verified through available data.

Figure 2. Share of Merchandise Trade Financed by SWIFT Trade Messages For the 10 Largest Importers and Exporters in the World, 2019



Sources: National customs' data, SWIFT, and authors' calculations.

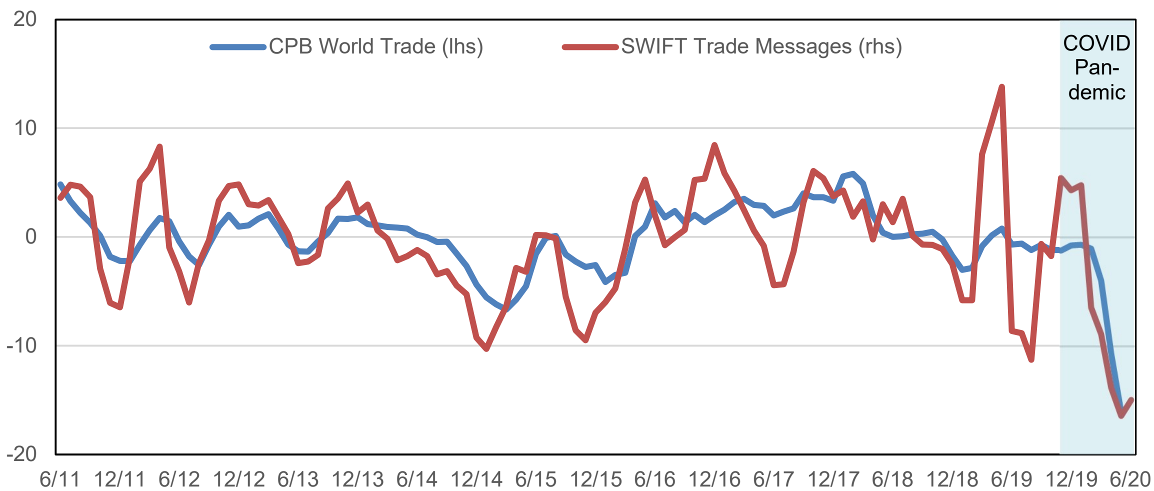
[5] ICC (2018).

III. A Forecast of World Trade Using SWIFT Messages

SWIFT MT 700 messages financed about 15 percent of world trade in 2019. The relatively small share of trade financed through SWIFT is explained by the fact that letters of credit are mainly used by new customers, customers without payment record, in jurisdictions that are unfamiliar to the importer, or in countries where international contracts are difficult to enforce. Niepmann and Schmidt-Eisenlohr (2017) show that the use of letters of credit is mostly prevalent in bilateral trade with emerging markets, most notably in Asia, while open contracts are more prevalent in bilateral trade between advanced economies, and cash-in-advance amongst low-income and developing countries that do not have access to trade financing (Appendix I). This evidence is also confirmed by the forecasts below. Moreover, trade can be financed by a global bank or a multinational enterprise with subsidiaries or branches in both the exporting and importing country, which may require a simple crediting and debiting of the balance sheet within different units of the global bank or enterprise.

SWIFT trade messages have a strong correlation with world trade. Figure 3 shows the co-movement of the growth rate of SWIFT trade messages and world trade as measured by the Netherlands' Bureau of Economic Policy Analysis (CPB).[6] A visual inspection shows that SWIFT trade messages generally move broadly in line with world trade, while being more volatile and subject to unusual spikes and corrections that are unrelated to the underlying trade flows (see for example the large spikes and corrections in 2019). Most recently, SWIFT trade messages have closely mirrored the decline in world trade during the COVID pandemic, shown in the shaded blue area.

Figure 3. World Trade and SWIFT Trade Messages
(Percentage Change in US dollars; 3-month moving average, seasonally adjusted)



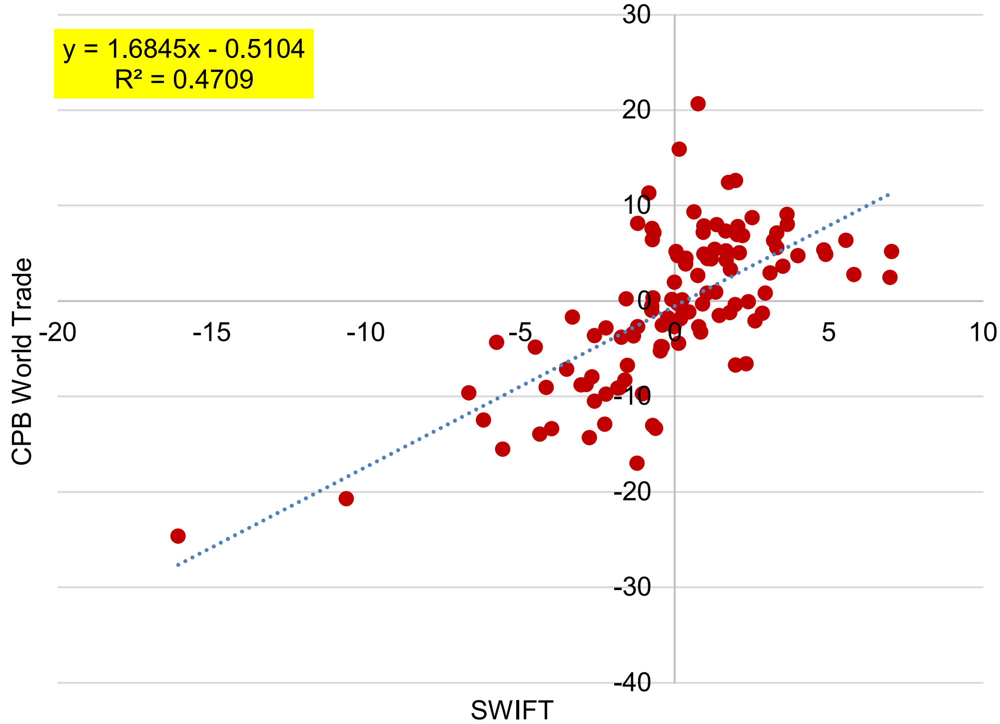
Source: CPB, SWIFT, and authors' calculations.

[6] See CPB Netherlands' Bureau for Economic Policy Analysis (2019). The use of a 3-month moving average is appropriate given the diverse lag structure between SWIFT trade messages and bilateral trade as explained in the previous section. For similar charts for selected individual countries in the sample, please refer to Appendix II.

Another way to visualize this co-movement is through a scatterplot (Figure 4). The simple regression shown in the scatterplot has an R^2 of 47 percent. The recent large declines in world trade associated with the COVID pandemic (the dots on the bottom left quadrant of the scatter plot) are broadly in line with the estimated regression, suggesting a stable linear relationship between the two variables, even during the current pandemic.

Figure 4. World Trade and SWIFT Trade Messages

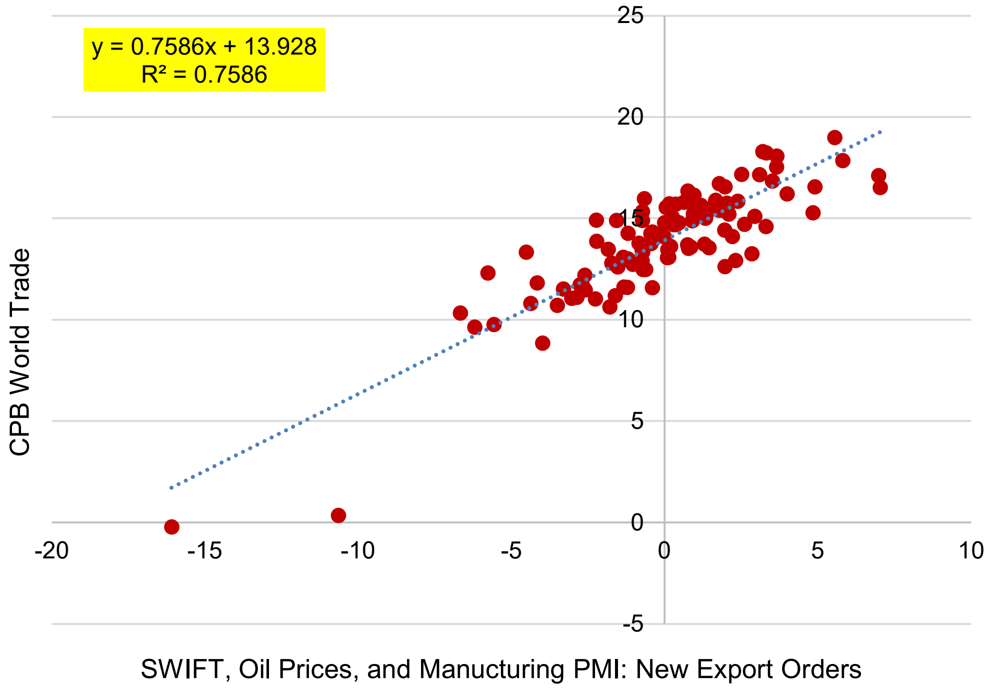
(Percentage change; 3-month moving average; seasonally adjusted; December 2010-May 2020)



Sources: CPB, SWIFT, and authors' regression.

Other variables, beyond SWIFT trade messages, are useful to explain the variation in world trade. In this paper, SWIFT trade messages are therefore complemented by Brent crude oil prices and a proxy for manufacturing exports to produce a more comprehensive forecast of world trade. Brent crude oil prices are generally a volatile determinant of the value of world trade in nominal terms as they capture both the value of traded hydrocarbons (as part of the world trade deflator) and the expectations of future global energy demand (and thus global economic activity) in volume terms. Global manufacturing activity also has a strong correlation with the volume of world trade as it is generally driven by global investment spending, which is highly trade intensive as evidenced during the Global Financial Crisis (see IMF 2016). Adding these two explanatory variables, in the form of Brent crude oil prices and the new export orders of the Global Manufacturing Purchasing Managers' Index (PMI), significantly improves the fit in the scatterplot above and raises the R^2 to 76 percent (Figure 5).

Figure 5. World Trade and SWIFT Trade Messages, Manufacturing PMI: New Export Orders, and Oil Prices
(Percentage change; 3-month moving average; seasonally adjusted; December 2010-May 2020)



Sources: CPB, Haver, IHS Markit, JP Morgan, SWIFT, and authors' regression.

Based on these preliminary results, a complete regression is posited in Equation 1. World trade (*WT*) is regressed against its own lags, SWIFT trade messages (*SWIFT*), Brent crude oil prices (*Brent*), and the new export orders subcomponent of the global manufacturing PMI (*PMI*). All variables have up to four lags and are expressed in log differences except *PMI*, which is expressed in its original diffusion index form but re-centered around zero. The reduced-form equation is then as follows:

$$dlog(WT_t) = \alpha + \beta_i dlog(WT_{t-i}) + \gamma_j dlog(SWIFT_{t-j}) + \delta_j dlog(Brent_{t-j}) + \vartheta_j PMI_{t-j} + \varepsilon_t \qquad (1)$$

where the lag index i goes from 1 to 4 and the lag index j goes from 0 to 4.

The regression results of different specifications of equation (1) show that SWIFT trade messages, Brent crude oil prices, and manufacturing activity are all significant determinants of world trade (Table 1). The coefficients on lags of world trade are mostly insignificant, except under the two specifications in the center of Table 1 with *Brent*, and *Brent* and *PMI* as explanatory variables. The contemporaneous coefficients on SWIFT are positive as expected, (higher SWIFT financing should lead to higher trade activity), and highly significant in all specifications, while SWIFT lags are significant only in the specification without *Brent* and *PMI*. As expected, the coefficients on *Brent* and on *PMI* are positive (higher oil prices and more manufacturing activity lead to higher world trade) and highly significant, including in their first lags. When SWIFT is omitted from the regressions (the two right-hand columns of Table 1), coefficients on OIL and PMI (and some of their lags) continue to be significant and the R^2 is high (0.673-0.768). This suggests that OIL explains most of the variation in world trade. Specifically, OIL and SWIFT seem to be non-orthogonal, and the contribution of SWIFT is smaller when OIL is included in the specification.

Overall, the regressions confirm the economic theory of positive signs on the coefficients of the explanatory variables and their statistical significance. The specification with all explanatory variables has an R^2 of close to 80 percent (adjusted R^2 of 75 percent), which provides a good basis to use this reduced-form equation to forecast world trade in the section below.

Forecast of World Trade

The predictive power of the regressions above is evident by forecasts of world trade. An initial forecast was undertaken on January 15, 2019, based on data available at the time, namely CPB world trade data up to October 2018 and SWIFT messages up to December 2018. A simple autoregressive process at the time predicted world trade to continue growing at a constant rate in late 2018/early 2019, as shown by the green line in Figure 6. The forecast with only SWIFT messages up to December 2018 instead predicted a gradual decline in world trade in the latter part of 2018 and early 2019 as shown by the blue line. Adding Brent crude oil prices extended by oil futures available on January 15, 2019, produced a forecast that was even more negative as shown by the purple line. In fact, as shown by the red line, world merchandise trade declined rapidly in November and December, and stabilized in the first four months of 2019, broadly in line with the forecast with oil prices.

Repeating the same forecast exercise above on a regular basis for 2019 and the first eight months of 2020 shows that these forecasts are close to the realized data (Figure 7). During the current pandemic, the April 16, 2020 forecast correctly pointed to a significant decline in world trade, albeit not as sharp as it finally occurred. In contrast, CPB data was available only up to January 2020 and indicated only a stabilization in world trade. The latest SWIFT forecast as of August 17, 2020, predicts a moderate rebound in world trade in the third and fourth quarter of 2020. The CPB data for June 2020, which became available in late August, confirmed the rebound, albeit stronger than predicted by the August 17 forecast.

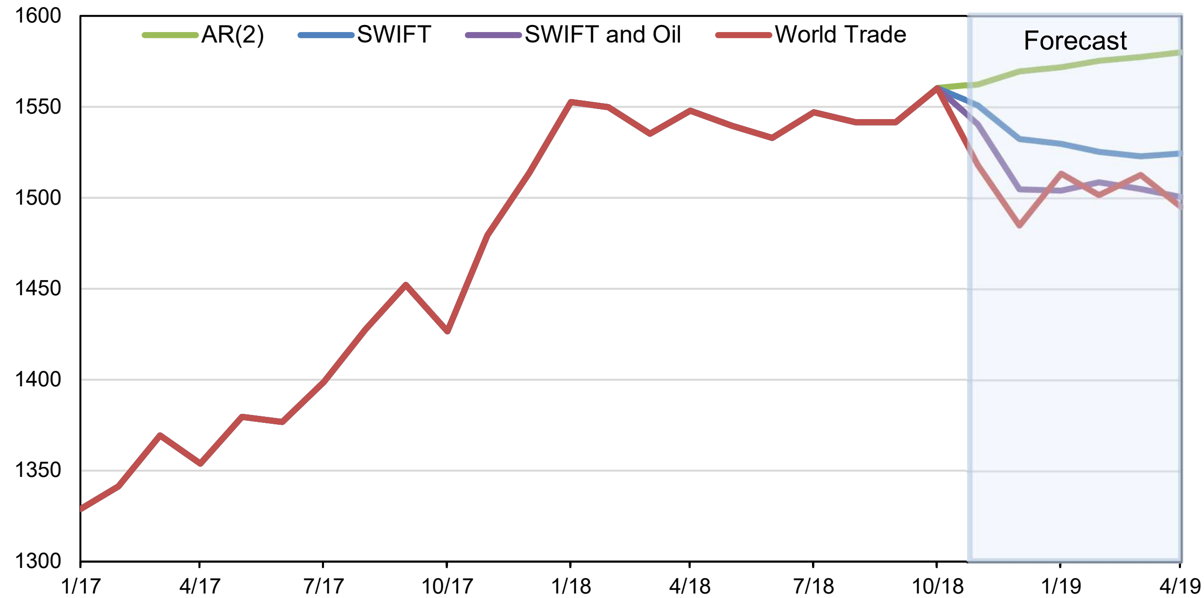
Table 1. World Trade: Comparison of Different Regression Specifications
Dependent Variable: World Trade
Sample: April 2011-May 2020 (110 observations)
(Coefficients and Standard Errors in Parenthesis)*

	World Trade	+ SWIFT	+ OIL	+ PMI	- SWIFT	- PMI
Constant	-0.0019	-0.0006	0.0011	0.0009	0.0009	0.0010
	(0.002)***	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
World Trade (-1)	0.0717	-0.2124	-0.3342	-0.4271	-0.3943	-0.3036
	(0.150)	(0.134)	(0.093)***	(0.087)***	(0.082)***	(0.084)***
World Trade (-2)	0.2548	0.0859	0.0110	-0.0672	-0.0660	-0.0207
	(0.124)**	(0.127)	(0.117)	(0.104)	(0.097)	(0.106)
World Trade (-3)	0.0869	0.1158	0.1176	0.0659	0.0861	0.0998
	(0.114)	(0.145)	(0.123)	(0.100)	(0.109)	(0.116)
World Trade (-4)	0.1078	0.0989	0.1926	0.2439	0.2526	0.2388
	(0.122)	(0.179)	(0.102)	(0.092)**	(0.091)***	(0.087)***
SWIFT		0.1329	0.0392	0.0413		
		(0.048)***	(0.015)**	(0.012)***		
SWIFT (-1)		0.1145	0.0008	0.0210		
		(0.037)***	(0.023)	(0.017)		
SWIFT (-2)		0.0823	-0.0232	-0.0030		
		(0.029)***	(0.027)	(0.022)		
SWIFT (-3)		0.0654	-0.0155	-0.0030		
		(0.032)**	(0.021)	(0.021)		
SWIFT (-4)		0.0222	-0.0058	-0.0154		
		(0.038)	(0.011)	(0.010)		
Brent			0.1124	0.0767	0.0878	0.1176
			(0.021)***	(0.011)***	(0.011)***	(0.018)***
Brent (-1)			0.1100	0.0679	0.0748	0.1135
			(0.032)***	(0.021)***	(0.020)***	(0.032)***
Brent (-2)			0.0276	0.0279	0.0216	0.0198
			(0.024)	(0.020)	(0.018)	(0.022)
Brent (-3)			0.0435	0.0357	0.0330	0.0398
			(0.021)**	(0.020)*	(0.018)*	(0.019)**
Brent (-4)			0.0130	0.0087	-0.0026	0.0045
			(0.018)	(0.015)	(0.018)	(0.020)
PMI				0.0046	0.0043	
				(0.001)***	(0.001)***	
PMI (-1)				-0.0023	-0.0017	
				(0.001)*	(0.001)	
PMI (-2)				-0.0003	-0.0002	
				(0.002)	(0.002)	
PMI (-3)				0.0001	-0.0002	
				(0.002)	(0.002)	
PMI (-4)				-0.0005	-0.0005	
				(0.001)	(0.001)	
Diagnostics						
R^2	0.068	0.320	0.701	0.793	0.768	0.673
Adjusted R^2	0.033	0.258	0.657	0.749	0.733	0.644
F-Statistic	2.846	4.529	11.15	32.69	40.2	9.234
Prob. (F-Statistic)	0.0276	5.19e -05	1.34e -14	2.85e -32	1.18e -33	4.45e -10
Log-likelihood	266.61	283.91	329.13	349.34	342.96	324.26
Durbin-Watson	1.962	2.038	1.983	2.019	1.994	1.978

* Standard errors are heteroscedasticity and autocorrelation robust (HAC) using 1 lags and without small sample correction. Asterisks indicate significance at 10 percent (*), 5 percent (**), and 1 percent level (***).

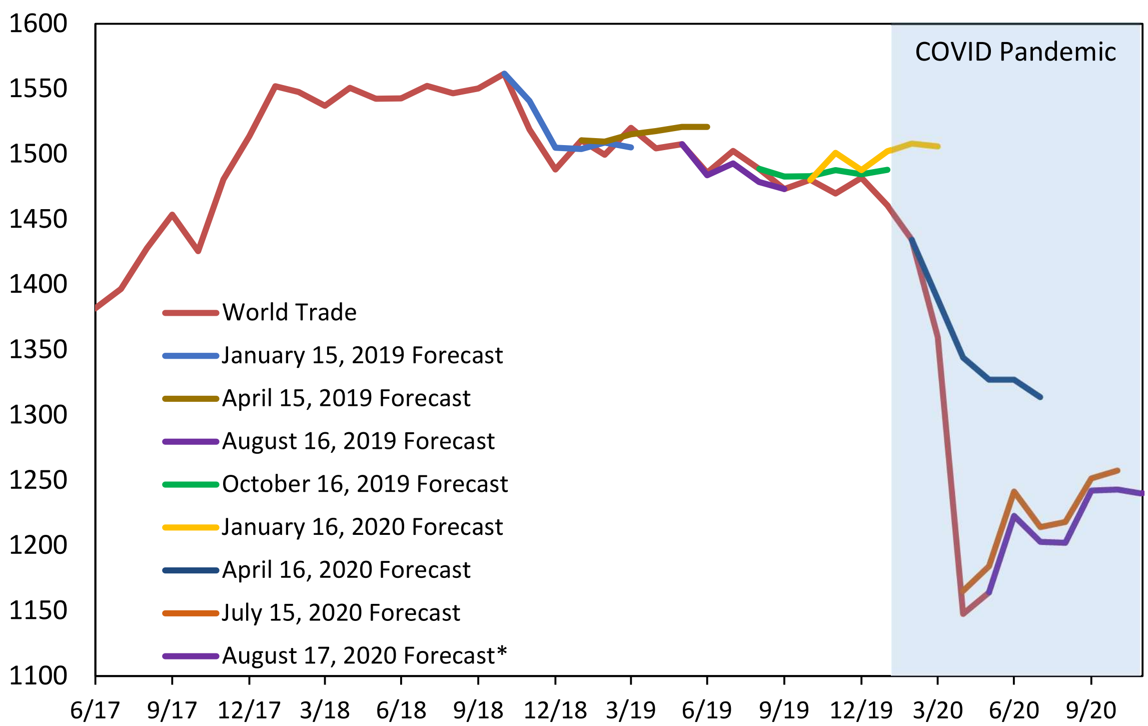
Source: Authors' regression results.

Figure 6. Forecast of World Trade, January 15, 2019
(Billions of US dollars; seasonally adjusted)



Sources: CPB, Haver, SWIFT, and authors' regression and forecast.

Figure 7. Rolling Forecasts of World Trade
(Billions of US dollars; seasonally adjusted)



Sources: CPB, Haver, IHS Markit, JP Morgan, SWIFT, and authors' regressions and forecasts. All forecasts are based on the regression specification with lagged world trade, SWIFT trade data, and Brent crude oil prices, except for the August 17, 2020 forecast which includes the new export orders subcomponent of the global manufacturing PMI.

Comparison with Other Forecasts of World Trade

It is useful to compare the forecasts above with other potential forecasts of world trade. Specifically, this section compares the SWIFT forecast with a forecast based on the Baltic Dry Index and a statistical forecast based on an autoregressive model.

The Baltic Dry Index provided a good early indicator of developments in world trade in the past. During the Global Financial Crisis, it foretold the collapse in world trade that occurred in late 2008-early 2009. A formal regression of CPB world trade, based on a similar specification in log differences as in Equation 1 above, confirms that the coefficients on the Baltic Dry Index (BDI_t) and its lags are statistically significant and are able to explain about a quarter of the variation in world trade (Table 2).

A comparison of the SWIFT and the BDI forecasts provides interesting insights. For the comparison purposes, both forecasts were built based on the information available on April 16, 2020, namely world trade data up to January 2020, SWIFT data up to March 2020, and the BDI data available until mid-April. Specifically, the BDI showed a significant decline in February/March followed by a rebound in early April. Accordingly, the forecast, based on the regression in Table 2, predicated a significant decline in world trade until May 2020, followed by a rapid rebound in June and July (blue line in Figure 8). The SWIFT forecast instead predicted a slower decline in world trade until March 2020, followed by a more rapid decline until July 2020 (red line in Figure 8). The actual world trade data through May shows a rapid decline in February/March, closely matching the BDI forecast, followed by a much sharper decline in April than either the BDI or the SWIFT forecast predicted (green line in Figure 8). Overall, the BDI forecasts performed better one- to two-months ahead, while the SWIFT forecast performed better over the longer forecast horizon. The better short-term performance of the BDI forecast may, in part, reflect the fact that the BDI forecast includes additional information up to mid-April 2020, while the SWIFT data only covered trade developments up to March 2020.

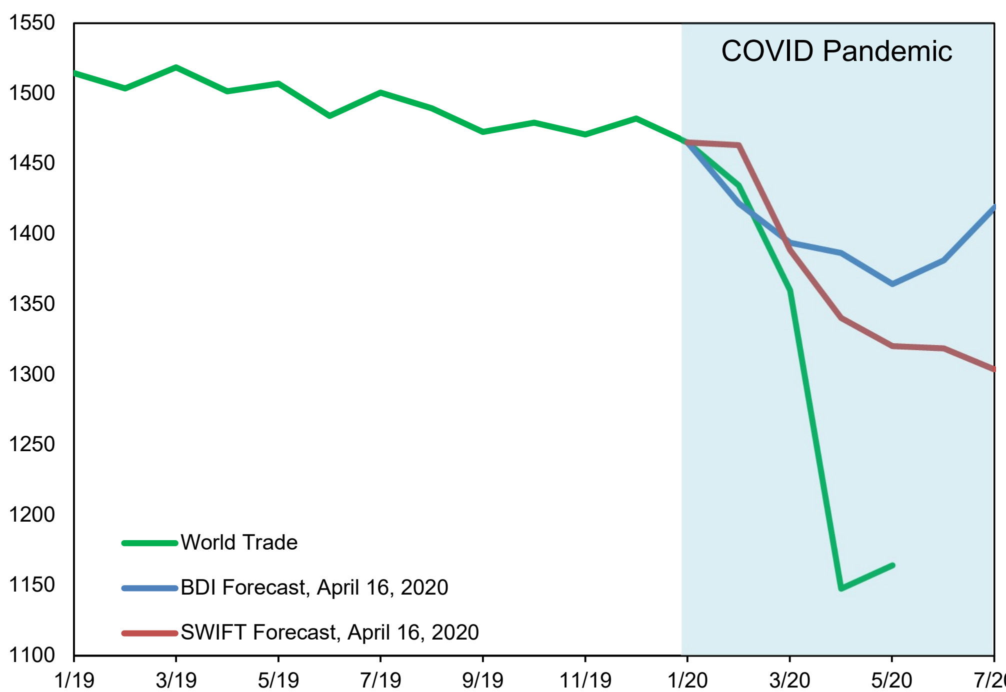
A similar comparison can be undertaken with the statistical model. The statistical model is based on a simple autoregressive process of order 2 (AR(2)) with a slow-moving long-term mean. As such, the AR(2) forecast relies only on past lags of world trade data and does not consider other explanatory variables, like Brent crude oil prices, SWIFT trade messages, or new export orders for the SWIFT forecast. The AR(2) forecast does not cover all countries in the world and excludes about 9 percent ($1.5 trillion annually on the import side) of world trade compared with the CPB measure.

Table 2. World Trade: Regression Results, Baltic Dry Index (BDI)
Dependent Variable: World Trade
Sample: May 2006-January 2020 (165 observations)
(Coefficients and Standard Errors in Parenthesis)*

Variable	
Constant	0.0030
	(0.0016)*
BDI	0.0240
	(0.0070)***
BDI(-1)	0.0180
	(0.0074)**
BDI(-2)	0.0228
	(0.0075)***
BDI(-3)	0.0077
	(0.0075)
BDI(-4)	0.0240
	(0.0073)***
Diagnostics	
R^2	0.2424
Adjusted R^2	0.2186
F-Statistic	10.1751
Prob. (F-Statistic)	0.0001
Durbin-Watson	1.3500

* Asterisks indicate significance at 10 percent (*), 5 percent (**), and 1 percent level (***).
Sources: Bloomberg, CPB, and authors' regression results.

Figure 8. BDI and SWIFT Forecasts of World Trade
(Billions of US dollars; seasonally adjusted)



Sources: Bloomberg , CPB, Haver, IHS Markit, JP Morgan, SWIFT, and authors' regression results and forecasts.

A visual comparison of the SWIFT and AR(2) forecasts during the current COVID pandemic shows that the SWIFT forecast generally picks up turning points earlier than the AR(2) forecasts (Figure 9). In January and February 2020, both forecasts were showing a relatively flat projection of world trade. In March, April, and May 2020, however, the SWIFT forecast was predicting a significant decline in world trade, while the AR(2) forecast was still signaling a relatively flat world trade forecast, notwithstanding an initial decline. In June 2020, on the contrary, the AR(2) forecast was significantly more pessimistic than the SWIFT forecast, and correctly predicted the steep decline in global trade that happened in April 2020. In July and August, the SWIFT forecast signals a moderate rebound in global trade, while the AR(2) forecast predicts a continued decline, despite a correction in June. The CPB data for June, instead, showed a larger rebound in world trade than predicted by the SWIFT forecast. The AR(2) forecast also generally provides a forecast over two to three months, while the SWIFT forecast provides a longer forecast up to six months.

Overall, the AR(2) forecast generally provides a relatively good forecast during normal times. It picks well the trend growth in world trade. However, given that the AR(2) forecast is purely backward looking, it is unable to pick up turning points the way the BDI or SWIFT forecast can.

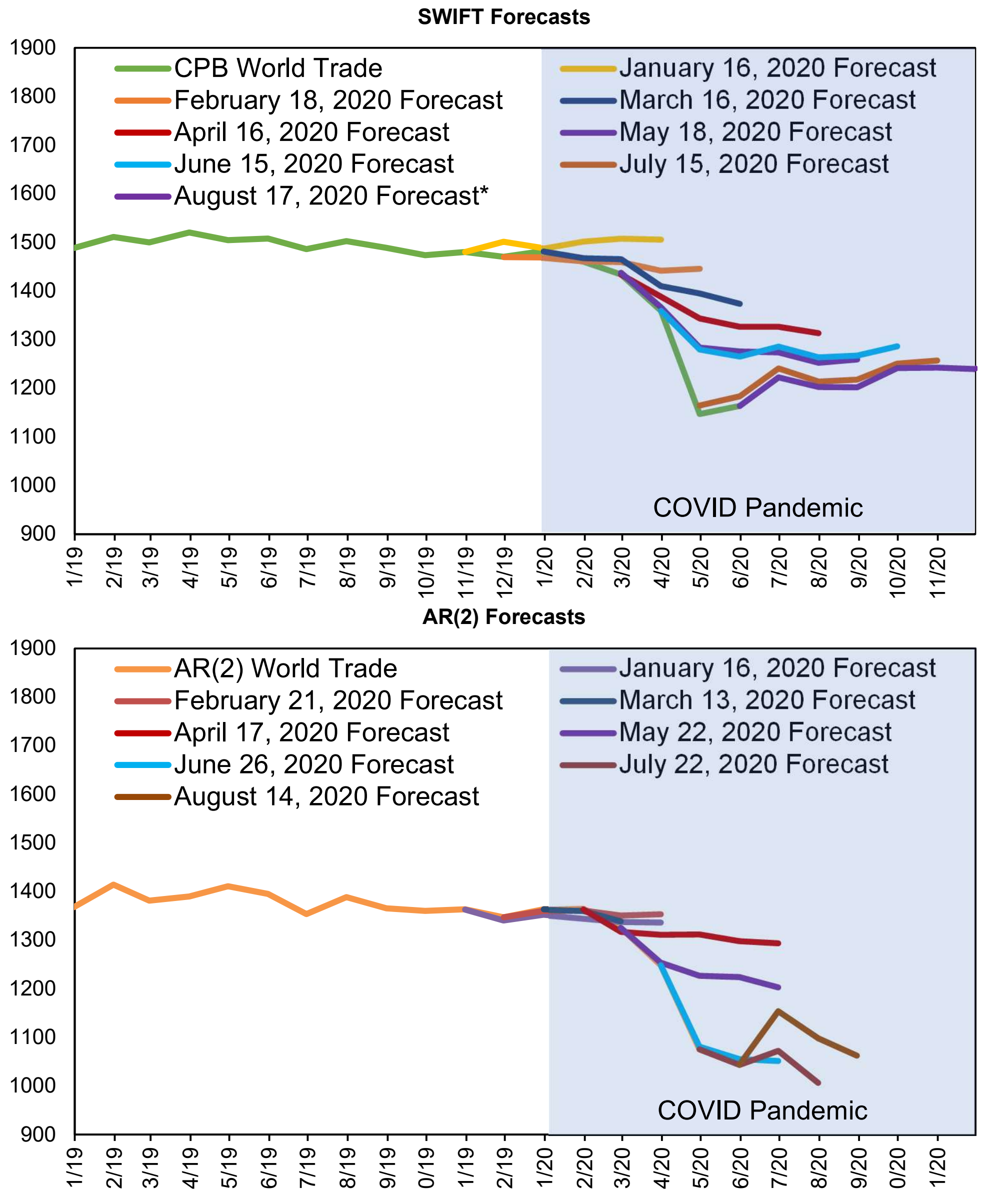
It is unfortunately not possible at this stage make a statistical comparison of the accuracy of each forecast, given the short overlap of SWIFT and AR(2) forecasts. An accurate statistical comparison would require at least 40 overlapping forecasts, while for now there are only 12 overlapping forecasts. A formal statistical comparison will therefore need to be undertaken as part of future research work.

IV. SWIFT AND NATIONAL CUSTOMS TRADE

The ability to forecast world trade with SWIFT trade messages derives from its use to finance national trade, particularly in Asia. However, the relationship between SWIFT trade messages and national trade flows is blurred by the fact that SWIFT trade messages are often handled by international banks located in a different country from the one where the merchandise trade originates from or is destined to. While this is not a problem at a world level, it is an issue at a national level because it reduces the correlation between SWIFT trade messages and the underlying merchandise trade flows. As indicated before, this is particularly relevant for economies that host financial centers, like Hong Kong SAR, Japan, the United Kingdom, and the United States, where most of the international banks that handle SWIFT trade messages are located. Unfortunately, no data are available to verify or correct this blurred relationship.[7]

[7] SWIFT will shortly introduce new fields in MT 700 messages that will identify the port of origin and destination of the underlying merchandise trade being financed by letters of credit. Once available, these fields will greatly improve the correlation between SWIFT data and the underlying merchandise trade, and thus the usefulness of SWIFT data in forecasting national trade.

Figure 9. Comparison of SWIFT and AR(2) Forecasts of World Trade
(Billions of US dollars; seasonally adjusted)



Sources: Bloomberg, CPB, IHS Markit, JP Morgan, SWIFT, and authors' regression results and forecasts.

Figure 10 shows the simple contemporaneous correlation between SWIFT messages and total merchandise exports and imports, as reported by the national customs authorities of each of the 40 countries in the sample.[8] It shows that the highest correlation is driven by Turkey and Asian countries (Korea, China, Vietnam, Bangladesh, Indonesia, Malaysia, and Thailand),

[8] The 40 economies in the sample are Bangladesh, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Estonia, France, Germany, Ghana, Hong Kong SAR, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Malaysia, Mexico, Netherlands, Nigeria, Norway, Philippines, Poland, Portugal, Russia, South Africa, Spain, Sweden, Taiwan Province of China, Thailand, Turkey, United Kingdom, United States, Vietnam.

while the lowest correlation is for several advanced economies (Ireland, Sweden, Belgium, Norway, Japan, and the US) and several emerging markets (Colombia, Philippines, South Africa, and Poland). Moreover, the contemporaneous correlation is likely to understate the overall correlation, given the lagged correlation between SWIFT trade messages and national trade mentioned above. The significance of the contemporaneous coefficient on the SWIFT variable in the regression results below is shown by the number of asterisks next to the name of the national customs data in Figure 10.

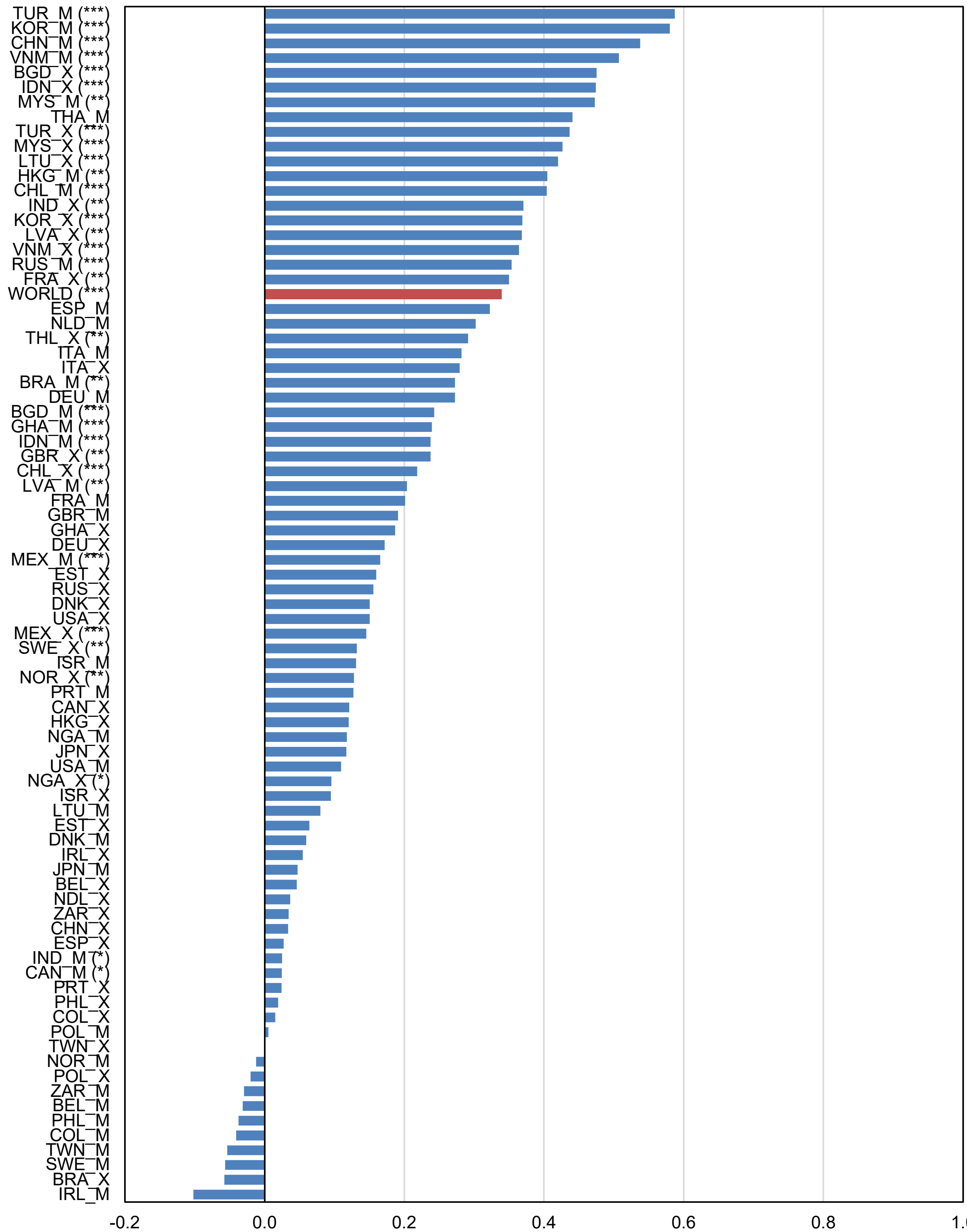
To build a linear forecast of national trade based on SWIFT trade messages, a simple regression is estimated for both exports and imports for the 40 countries in the sample, based on Equation 1 in the previous section. The equation is estimated in log differences for both exports and imports (cus_x and cus_m) as reported by the national customs authorities for each country (80 regressions) using lagged customs data, Brent crude oil prices and the new export orders subcomponent of the national manufacturing PMI where available. The equation is estimated using ordinary least squares with heteroskedastic-consistent and autocorrelated robust (HAC) standard errors.[9]

As expected, the regression results vary broadly in line with the correlation structure shown in Figure 8 (see Appendix II for selected regression results). The overall fit of the regression results for the countries in the sample broadly match the contemporaneous correlation structure, except for countries where the coefficients on SWIFT are insignificant while the ones on Brent crude oil prices and PMIs are highly significant. For those regressions where SWIFT coefficients are significant, they are also positive, indicating that higher trade financing is associated with higher trade activity. The magnitude of the coefficients on SWIFT vary in line with the contribution of SWIFT trade messages in explaining the variation of national trade. The contemporaneous coefficients on Brent crude oil prices and PMIs are also generally positive as expected.

In Asia, the regression results for Bangladesh, India and Korea, Thailand, and Vietnam exports; and China, Indonesia, Korea, Malaysia, and Vietnam imports show a relatively high R^2 (0.60-0.79) and positive and significant coefficients on SWIFT trade messages. On the other hand, the coefficient on SWIFT trade messages for Hong Kong SAR, Japan, the Philippines, Taiwan Province of China, (both exports and imports) are insignificant or of the wrong sign. In the case of Hong Kong SAR and Japan, this probably reflects the fact that banks domiciled in Hong Kong SAR and Japan intermediate significant SWIFT trade messages unrelated to their trade flows as discussed above. Overall, the regression results confirm the relevance of letters of credit in financing selected Asian trade.

[9] The regressions are run using the statsmodels in python. See Seabold S. and J. Perktold (2010).

Figure 10. Correlation Between SWIFT Messages and National Customs Data
(Contemporaneous Correlation in log difference, after adjusting for outliers)



Sources: CPB, national customs data, SWIFT, and authors' calculations. Asterisks next to the name of the country indicate the significance level of the contemporaneous coefficient on SWIFT in the regression results at the 10 percent (*), 5 percent (**), and 1 percent (***) levels when the coefficient is positive.

In Europe, results are mixed. The coefficients on SWIFT trade messages are significant for France, Italy, Latvia, Lithuania, Norway, and Sweden exports; and for Latvia, Lithuania, and Russia imports, with a relatively high R^2 (0.49-0.78). On the other hand, the coefficients on SWIFT trade messages are insignificant for the regressions for Belgium, Denmark, Estonia, Germany, Ireland, Netherlands, Poland, Portugal, Spain, and the United Kingdom (both exports and imports). This suggests that SWIFT trade messages mostly finance imports to Eastern Europe (Latvia, Lithuania, and Russia) and significant portion of exports for selected European countries. In the case of the United Kingdom, the London financial center acts as a significant financial intermediary for SWIFT trade messages and as such blurs the relationship between SWIFT trade messages and United Kingdom trade.

In the Western Hemisphere, the results are also mixed. The coefficients on SWIFT trade messages are significant for Mexico exports, and Brazil, Chile, and Mexico imports, with a relatively high R^2 (0.54-0.88). However, the coefficients are insignificant for Canada, Colombia and the United States (both exports and imports). The results for the United States again may reflect the significant activity of U.S. banks in intermediating SWIFT trade messages on behalf of exporters and importers outside of the United States.

In the Middle East, the results confirm the significant use of SWIFT trade messages to finance trade in Israel and Turkey. For Israel, the coefficients on SWIFT trade messages are significant both on the export and the import side and the R^2 is relatively high (0.62 on the export side and 0.72 on the import side). For Turkey, the coefficients on SWIFT trade messages are highly significant both in the export and import regression and the R^2 is among the highest in the sample (0.70 on the export side and 0.72 on the import side).

In Africa, the results are significant for Ghana and Nigeria, but not for South Africa. For Ghana, the coefficients on SWIFT trade messages are significant for the import equation, namely the contemporaneous coefficient and the ones on 1 and 3 lags, while the R^2 is 0.50. For Nigeria, the coefficients on SWIFT trade messages are significant on the export side, namely on both the contemporaneous coefficient and the ones on 1 and 2 lags, with an R^2 of 0.41. On the other hand, the coefficients on SWIFT trade messages for South Africa are insignificant both in the export and import regressions, suggesting that banks in South Africa may also be intermediating SWIFT trade messages for other countries, thus blurring the relationship with national trade.

V. Horse Race Between Linear Regression and Machine-Learning Forecasts

It is useful to compare the linear regressions forecasts with machine-learning forecasts in order to rule out significant non-linearities in the relationship between SWIFT trade messages and the underlying trade flows. For this purpose, this section presents a horse race between linear regression and machine-learning forecasts for world trade and the 40 countries in the sample. It provides an overview of the linear regression and machine-learning forecasts, and an overall assessment of the forecasts. For a detailed description of the machine-learning algorithms (MLAs) used in this paper, together with the advantages and disadvantages of linear regressions vs. machine–learning algorithms, please refer to Appendix III. Appendix IV provides a description of the forecast methodology used.

Linear Regression Forecasts

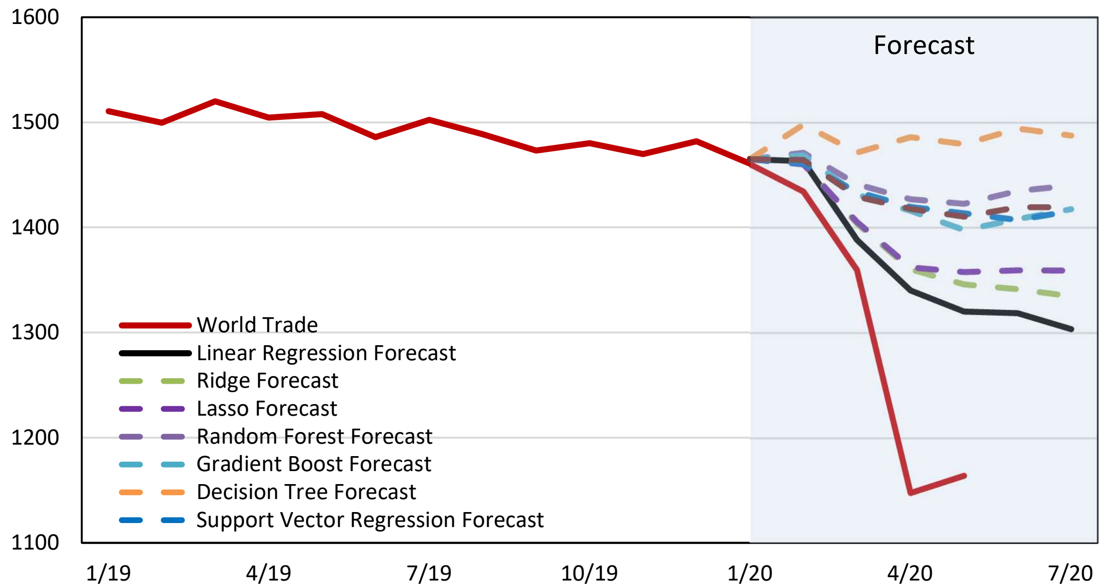
This section discusses linear regression forecasts. Linear regression forecasts are built using the estimated regressions of equation (1) to forecast one-step ahead and then recursively forecasting longer horizons.[10] Customs data are extended using the one-step ahead forecast. SWIFT data are generally available one to three months ahead of the customs data. For the remainder, SWIFT data are extended through an AR(1) process. Brent crude oil prices are extended through the closing futures prices on the date of the forecast for the one-, three-, and six-month contracts, while interpolating the other months. The new export orders subcomponent of the PMI is usually available one to three months ahead of customs data. For the remainder of the forecast horizon, it is extended through an AR(1) process.

A good example of a linear regression forecast is the one for world trade as of April 16, 2020. At the time, the CPB world trade data was only available up to January 2020, while SWIFT data up to March 2020 already indicated a significant decline in global trade activity. Brent crude oil prices had plummeted from $68 per barrel in early January to $27 per barrel on April 16, and Brent futures indicated a further decline in the months ahead. The new export orders subcomponent of the global manufacturing PMI for March had fallen from 49.5 in January to 43.0 in March, signaling a significant contraction in manufacturing exports going forward.

Based on these explanatory variables, the linear regression forecast on April 16, 2020 indicated a significant decline in world trade going forward (black line in Figure 11). Other machine-learning forecasts indicated a smaller decline and possibly a stabilization in world trade (e.g., Decision Tree). World trade (red line) turned out close to the linear regression forecast for February and March 2020, before collapsing in April 2020.

[10] An alternative approach is a direct forecast, where a different model is selected to forecast customs data 1 to 6 months ahead. The results of this alternative approach are available from the authors. Forecasts based on this direct method, rather than the recursive method, however, have proven consistently less accurate than the recursive method as they do not use all the lead informational content available from SWIFT trade messages.

Figure 11. World Trade: Forecasts Based on Linear Regression and MLAs, April 16, 2020
(Billions of US dollars, Seasonally Adjusted)



Sources: CPB, SWIFT, Brent crude oil prices and futures, JP Morgan Global Manufacturing PMI and authors' regressions and forecast results.

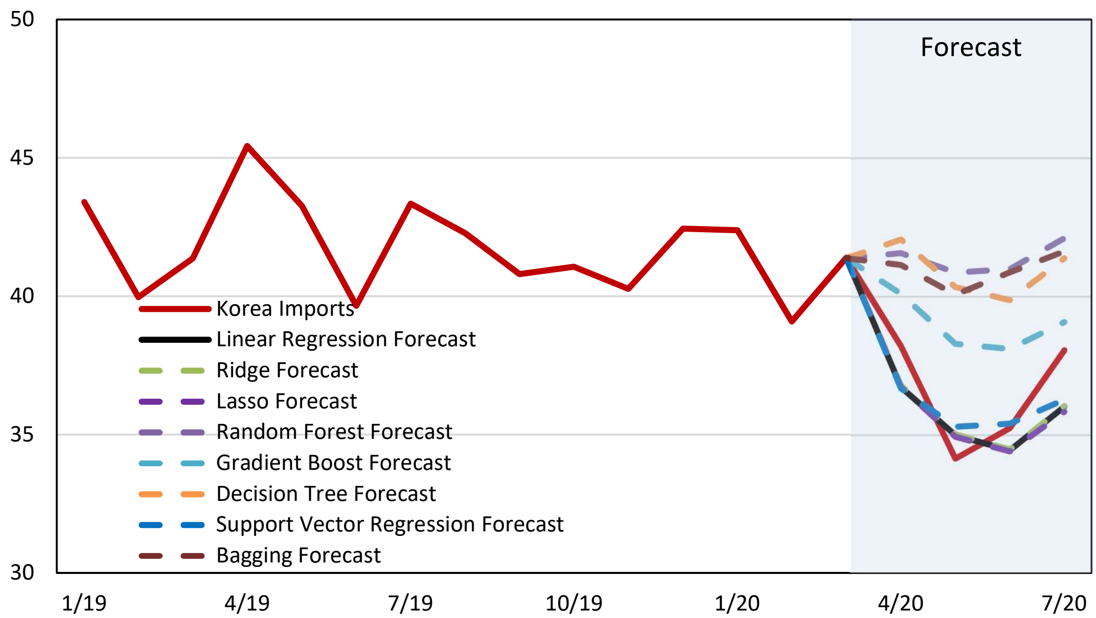
Machine-learning forecasts[11]

Three categories of MLAs are used in this paper, namely linear, single nonparametric, and ensemble nonparametric MLAs. Linear MLAs comprise Lasso and Ridge regressions, which are variations of a linear regression that weigh regressors based on their significance. Single nonparametric MLAs comprise Decision Tree Regression and Support Vector Regression. Ensemble MLAs are built based on regression trees to identify non-linearities in subsamples of the dataset. The tree-based ensemble MLAs comprise Bagging, Gradient Boost, and Random Forest. Each MLA is *trained* over the full sample period. Based on this training, each MLA is then used to produce a forecast one to six-month ahead based on the same one-step ahead forecast as for linear regression forecast.

A good example of an MLA forecast that is superior to a linear regression one is in the case of Korea imports (Figure 12). As of April 16, 2020, Korea merchandise import data for March 2020 were already available and signaled a rebound from the decline experienced the previous month. However, with SWIFT, Brent crude oil prices and futures, and Korea's new export orders of the manufacturing PMI all signaling a decline in imports in the near future, the linear regression forecast as of April 16, 2020 pointed to a steep decline up to May 2020, before a rebound in June and July. Customs data released subsequently turned out to follow a similar pattern with the exception that the trough was in April instead of May. The Lasso forecast in this respect did marginally better at capturing this pattern than the linear regression forecast, but the difference in forecast errors between the two is marginal.

[11] The machine-learning algorithms are coded in python based on Pedregosa et al. (2011).

Figure 12. Korea Imports: Forecasts Based on Linear Regression and MLAs, April 16, 2020
(Billions of US dollars, Seasonally Adjusted)



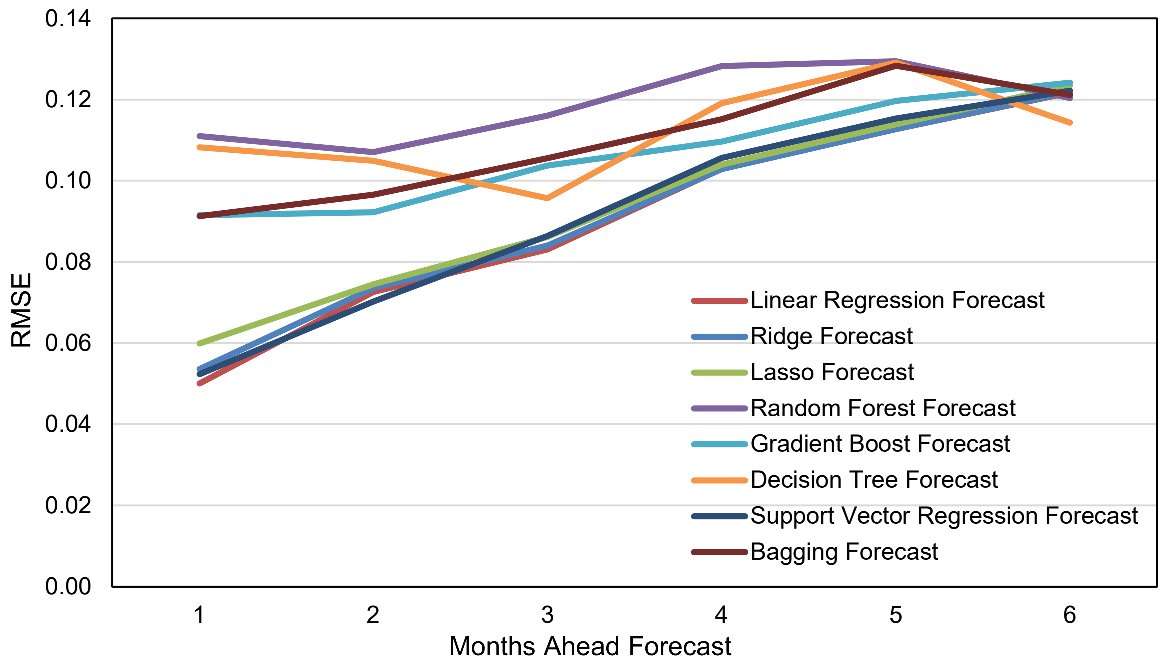
Sources: Brent crude oil prices and futures, IHS Markit, national customs data, SWIFT, and authors' regressions and forecast results.

Evaluation of linear and machine-learning forecasts

The evaluation of linear and machine-learning forecasts is based on the root mean squared error (RMSE) of the two forecast methods. To calculate the RMSEs, the forecasts are computed based on a subsample up to May 2019 (the training set). The forecasts thus computed are then evaluated over the data between June 2019 and May 2020 (the test set), based on monthly rolling forecasts, and then calculating the RMSE over the one-, two-, three-, four-, five-, and six-month ahead forecasts.

The RMSEs for Latvia imports provide a useful example of this evaluation (Figure 13). They are relatively small, ranging between 5 and 14 percent, with longer forecast horizons having larger RMSEs as expected. Most notably, there is a clear difference in performance in the shorter forecast horizons, with the linear regression, ridge, support vector regression, and lasso forecasts having much smaller RMSEs than the other forecasts. This advantage then disappears over the longer forecast horizons. This suggests that linear regression methods have a clear advantage in forecasting Latvia's imports over the short run, while over five to six months this advantage disappears.

Figure 13. Latvia Exports: RMSEs for Different Forecasts



Sources: Authors' forecasts and calculations.

The best-performing forecasts based on the lowest RMSE for the world and the 40 countries are presented in Table 3. It is worth noting that the linear regression forecasts perform the best over a 1-month ahead forecast in nearly half the sample. The ratio increases to two thirds when Lasso and Ridge forecasts (which are more parsimonious version of linear regression forecasts) are added. This means that linear forecasts generally outperform other non-linear MLAs, which confirms a linear relationship between SWIFT trade messages and the underlying merchandise trade as expected by economic theory.

All forecasts are also evaluated formally using the Diebold-Mariano (DM) test.[12] The DM test assesses the statistical significance of the differences in RMSEs of each forecast against a so-called naïve forecast, which is based on the simple average growth rate of exports/imports over the sample period. The results of the DM tests for the best one-step ahead forecast are also shown in Table 3, together with the corresponding P-statistics and RMSEs. The results show that a few countries have statistically significant forecasts that are different than a naïve forecast. This suggests that more needs to be done to improve the quality of the forecasts, possibly by considering additional explanatory variables.

VI. Conclusions

This paper has documented the usefulness of using SWIFT trade messages, Brent crude oil prices, and the new export orders subcomponent of manufacturing PMI (where available) to forecast short-term merchandise trade. While SWIFT trade messages only finance 15 percent of world trade, they have predictive power to forecast world trade. They can help forecast

[12] Diebold and Mariano (1995).

turning points in world trade and are particularly relevant to forecast trade in Asia. However, the relationship at a national level between SWIFT trade messages and the underlying merchandise trade becomes blurred, particularly in economies that host financial centers, like Hong Kong SAR, Japan, the United Kingdom, and the United States. SWIFT trade messages are therefore less reliable in forecasting national trade particularly in those countries.

A horse race between linear regression forecasts and other forecasts based on machine-learning algorithms has also shown that linear regression forecasts, together with its Lasso and Ridge variants, are superior in about two thirds of the sample, which suggests that the underlying relationship between SWIFT messages and merchandise trade for most countries is likely to be linear. Future research will need to assess whether SWIFT forecasts perform statistically better than forecasts based on the Baltic Dry Index or on a simple autoregressive process.

Table 3. Diebold-Mariano Tests of One-Step Ahead Forecast[13]

Economies	Exp/Imp	Best Forecast	DM Statistic	P-Value	RMSE	Naïve RMSE
World		Linear Regression	-1.2926	0.1961	0.0235	0.0539
Bangladesh	Imp.	Ridge	-0.1643	0.8695	0.1721	0.1746
	Exp.	Linear Regression	-0.9631	0.3355	0.4731	0.5306
Belgium	Imp.	Support Vector Regression	-1.1798	0.2381	0.0445	0.0791
	Exp.	Linear Regression	-1.2860	0.1984	0.0524	0.0797
Brazil	Imp.	Linear Regression	-1.8878	0.0591	0.0881	0.1186
	Exp.	Lasso	-1.2256	0.2203	0.0554	0.0622
Canada	Imp.	Linear Regression	-1.3884	0.1650	0.0804	0.1099
	Exp.	Linear Regression	-1.5073	0.1317	0.0615	0.1189
Chile	Imp.	Linear Regression	-1.3230	0.1858	0.0769	0.0855
	Exp.	**Random Forest**	3.7222	0.0002	0.0801	0.0709
China	Imp.	Lasso	-1.6141	0.1065	0.0467	0.0679
	Exp.	Random Forest	-1.4962	0.1346	0.2093	0.2158
Colombia	Imp.	**Linear Regression**	-2.6656	0.0077	0.0635	0.1186
	Exp.	Decision Tree	-1.6119	0.1070	0.1216	0.1525
Denmark	Imp.	Linear Regression	-1.0953	0.2734	0.0279	0.0427
	Exp.	**Linear Regression**	-2.1452	0.0319	0.0252	0.0451
Estonia	Imp.	**Support Vector Regression**	-2.3012	0.0214	0.0582	0.1061
	Exp.	Support Vector Regression	-1.5127	0.1304	0.0431	0.1031
France	Imp.	Linear Regression	-1.5814	0.1138	0.0803	0.1305
	Exp.	Linear Regression	-1.5346	0.1249	0.1024	0.1490
Germany	Imp.	Linear Regression	-1.5234	0.1277	0.0363	0.0683
	Exp.	Linear Regression	-1.5533	0.1203	0.0718	0.1067
Ghana	Imp.	**Linear Regression**	-4.0206	0.0001	0.1095	0.1443
	Exp.	Gradient Boost	-1.6623	0.0965	0.0887	0.1123
Hong Kong SAR	Imp.	**Decision Tree**	-2.0804	0.0375	0.0222	0.0255
	Exp.	Random Forest	-1.5271	0.1267	0.0669	0.0755
India	Imp.	Linear Regression	-1.3022	0.1928	0.1347	0.1984
	Exp.	Linear Regression	-1.5984	0.1100	0.2075	0.2634
Indonesia	Imp.	Support Vector Regression	-1.2995	0.1938	0.0969	0.1073
	Exp.	Random Forest	0.2499	0.8026	0.0849	0.0823
Ireland	Imp.	Bagging	-1.2987	0.1941	0.0735	0.0873
	Exp.	Support Vector Regression	-1.3380	0.1809	0.1457	0.1822
Israel	Imp.	Ridge	-1.0349	0.3007	0.0766	0.0861
	Exp.	**Lasso**	-2.6175	0.0089	0.0851	0.1211
Italy	Imp.	Support Vector Regression	-1.5592	0.1189	0.0489	0.0999
	Exp.	Linear Regression	-1.5483	0.1215	0.1318	0.1711
Japan	Imp.	**Ridge**	-1.9579	0.0502	0.0411	0.0511
	Exp.	**Gradient Boost**	-2.1288	0.0333	0.0391	0.0474
Korea	Imp.	**Lasso**	-2.3016	0.0214	0.0420	0.0611
	Exp.	Random Forest	-0.5655	0.5717	0.0877	0.0901
Latvia	Imp.	**Linear Regression**	-2.3876	0.0170	0.0501	0.1097
	Exp.	Support Vector Regression	-1.5119	0.1306	0.0393	0.0768
Lithuania	Imp.	Linear Regression	-1.5415	0.1232	0.0811	0.1141
	Exp.	Linear Regression	-1.5358	0.1246	0.0468	0.0776
Malaysia	Imp.	Linear Regression	-1.1789	0.2384	0.0712	0.1208
	Exp.	Support Vector Regression	-1.4992	0.1338	0.0828	0.1286
Mexico	Imp.	Linear Regression	-1.4536	0.1461	0.0805	0.1119
	Exp.	Linear Regression	-1.2095	0.2265	0.1832	0.2234
Netherlands	Imp.	Linear Regression	-1.3853	0.1660	0.0186	0.0431
	Exp.	Linear Regression	-1.4084	0.1590	0.0238	0.0588
Nigeria	Imp.	Ridge	-0.4627	0.6436	0.2343	0.2472
	Exp.	Lasso	-0.2401	0.8103	0.1752	0.1810

[13] Bolded forecasts are the ones with a Diebold-Mariano test that is significant at the 95th percentile. These tests were run with the DMARIANO Stata module. See Baum (2011).

Table 3. Diebold-Mariano Tests of One-Step Ahead Forecast (Continued)

Economies	Exp/Imp	Best Forecast	DM Statistic	P-Value	RMSE	Naïve RMSE
Norway	Imp.	Support Vector Regression	-1.5869	0.1125	0.0397	0.0676
	Exp.	**Decision Tree**	-2.6508	0.0080	0.0603	0.0968
Philippines	Imp.	Linear Regression	-1.0921	0.2748	0.2383	0.2711
	Exp.	Ridge	-1.4829	0.1381	0.1209	0.1890
Poland	Imp.	**Linear Regression**	-2.8293	0.0047	0.0578	0.0845
	Exp.	Linear Regression	-1.9250	0.0542	0.0528	0.0800
Portugal	Imp.	Support Vector Regression	-1.7814	0.0748	0.0875	0.1251
	Exp.	Linear Regression	-1.6064	0.1082	0.0983	0.1416
Russia	Imp.	**Ridge**	-2.0229	0.0431	0.0479	0.0680
	Exp.	Linear Regression	-1.1801	0.2380	0.0546	0.0859
Spain	Imp.	Ridge	-1.3743	0.1693	0.0695	0.1026
	Exp.	Ridge	-1.4077	0.1592	0.0467	0.1122
South Africa	Imp.	Random Forest	1.6057	0.1083	0.0867	0.0789
	Exp.	Linear Regression	-1.4415	0.1494	0.2336	0.3165
Sweden	Imp.	Linear Regression	-1.5648	0.1176	0.0368	0.0654
	Exp.	Lasso	-1.7551	0.0792	0.0366	0.0725
Taiwan Province of China	Imp.	**Bagging**	-2.6978	0.0070	0.0394	0.0555
	Exp.	Lasso	-0.1947	0.8457	0.0222	0.0230
Thailand	Imp.	**Gradient Boost**	-2.1814	0.0292	0.1023	0.1266
	Exp.	Lasso	-0.9224	0.3563	0.0928	0.0931
Turkey	Imp.	Lasso	-0.1956	0.8450	0.1389	0.1405
	Exp.	Bagging	1.6256	0.1040	0.2090	0.1679
United Kingdom	Imp.	Linear Regression	-1.7256	0.0844	0.0651	0.1077
	Exp.	**Bagging**	-2.2409	0.0250	0.0822	0.0878
United States	Imp.	Linear Regression	-1.4138	0.1574	0.0331	0.0500
	Exp.	Linear Regression	-1.4937	0.1352	0.0715	0.0976
Vietnam	Imp.	Bagging	0.6817	0.4954	0.1169	0.1100
	Exp.	**Linear Regression**	-2.1060	0.0352	0.1300	0.1785

Source: Authors' forecasts and calculations.

References

Basak, D., Srimanta Pal and Dipak C. Patranabis, D.C., 2007, "Support Vector Regression," *Neural Information Processing-Letters and Reviews* 11(10): 203–224.

Baum, C., 2011, "DMARIANO: Stata Module to Calculate Diebold-Marian Comparison of Forecast Accuracy," *EconPapers*, available at https://econpapers.repec.org/software/bocbocode/s433001.htm

Boehmke, B., & Brandon M. Greenwell, 2019, *Hands-On Machine Learning with R.* CRC Press.

Breiman, L., J.H. Friedman, R.A. Ohlsen, and C.J. Stone, C.J., 1984, "Classification and Regression Trees." *Wadsworth & Brooks/Cole*.

Breiman, L., 2001, "Random Forests." *Machine Learning* 45(1):5–32.

CPB Netherlands Bureau for Economic Policy Analysis, 2019, "CPB World Trade Monitor", January 2019, available at https://www.cpb.nl/en/worldtrademonitor.

Danske Bank (2019). *"Documentary Credits – Protecting Payments in International Trade,"* available at https://danskebank.com/en-gb/Corporate-Banking/Trade-and-Export-Finance/Documentary-Credits/Pages/The-Documentary-Credit-process.aspx.

Diebold, F.X. and R.S. Mariano, 1995, "Comparing Predictive Accuracy". *Journal of Business and Economic Statistics*, 13: 253–63.

Dietterich, T.G., 2000, "Ensemble Methods in Machine Learning." in *International Workshop on Multiple Classifier Systems*, 1–15. Berlin and Heidelberg: Springer.

Hayashi, F., 2000, *Econometrics,* Princeton University Press.

ICC, 2018, Global Trade–Securing Future Growth, 2018, Technical Report, International Chamber of Commerce.

IMF, 2016, "*Global Trade: What's Behind the Slowdown?*" Chapter 2 of "Subdued Demand: Symptoms and Remedies," World Economic Outlook, October 2016, International Monetary Fund.

Jones, S., David Johnstone, and Roy Wilson, 2015, "An Empirical Evaluation of the Performance of Binary Classifiers in the Prediction of Credit Ratings Changes." *Journal of Banking & Finance.* 56: 72–85.

Lantz, B., 2013, *Machine Learning with R.* Birmingham: Packt Publishing Ltd. (Second edition).

LeCun, Y., Yoshua Bengio, and Geoffrey Hinton, 2015, "Deep Learning." *Nature* 521(7553): 436.

Mahdevari, S., Kourosh Shahriar, Saffet Yagiz, and Mohsen A. Shirazi, 2014), "A Support Vector Regression Model for Predicting Tunnel Boring Machine Penetration Rates." *International Journal of Rock Mechanics and Mining Sciences* 72: 214–229.

McCulloch, W.S. and Pitts, W., 1943, "A Logical Calculus of the Ideas Immanent in Nervous Activity," *The Bulletin of Mathematical Biophysics* 5(4):,115–133.

Moustapha, M., Jean Marc Bourinet, J., Benoît Guillaume, and Sudret, Bruno, 2018, Comparative study of Kriging and support vector regression for structural engineering applications. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems*, Part A: Civil Engineering, 4(2), 04018005.

Mullainathan, S. and Jann Spiess, 2017), "Machine Learning: An Applied Econometric Approach." *Journal of Economic Perspectives,* 31(2): 87–106.

Niepmann, F. and Tim Schmidt-Eisenlohr, 2017, "International Trade, Risk and the Role of Banks," in *Journal of International Economics* 107: 111–26.

Pedregosa, F., Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, and Jake Vanderplas, J., 2011, "Scikit-learn: Machine Learning in Python." *Journal of Machine Learning Research,* 12(10): 2825–2830.

Russell, S.J. and Peter Norvig, 2016, "Artificial Intelligence: A Modern Approach." Malaysia: Pearson Education Limited.

Seabod, S. and Josef Perktold, 2010, "Statsmodels:Econometric and Statistical Modeling with Python," *Proceedings of the 9th Python in Science Conference.*

SWIFT (2019a), "SWIFT History", available at https://www.swift.com/about-us/history.

SWIFT (2019b), "*Messaging Standards*," available at https://www.swift.com/about-us/discover-swift/messaging-standards.

Verikas, A., Evaldas Vaiciukynas, Adas Gelzinis, James Parker, and M. Charlotte Olsson, 2016, "Electromyographic patterns during golf swing: Activation sequence profiling and prediction of shot effectiveness," *Sensors*, 16(4), 592.

Appendix I—International Trade Financing

This appendix summarizes the four main ways in which international trade can be financed. It draws heavily from earlier work by Niepmann and Schmdt-Eisenlohr (2017).

International trade is usually financed in four ways. These are: cash-in-advance, open account, letter of credit, and documentary collection. Each of these methods has tradeoffs in terms of risks and financial costs for the exporter and importer. Table 1 summarizes these tradeoffs, which are explained below.

Table I.1. Tradeoffs in Trade Financing

	Risks	Financial Costs
A. Cash-in-advance		
Exporter	None	None
Importer	Large	Medium
B. Open account		
Exporter	Large	Medium
Importer	None	None
C. Letter of credit		
Exporter	None	Medium
Importer	None	Medium
D. Documentary collection		
Exporter	Medium	Large
Importer	None	None

Source: Niepmann and Schimdt-Eisenlohr (2017)

A. Cash-in-advance

Cash-in-advance financing requires the importer to prepay the exporter for the delivery of imported goods. As such, the importer will normally draw on a credit from a domestic bank to finance the imported goods in advance of their delivery. Once sold, the importer will repay the credit line with interest.

Risks and financial costs of cash-in-advance financing fall exclusively on the importer. The importer carries the risk that the imported goods will not be delivered on time or will be of a substandard quality. S/he also bears the financial costs of paying interest on its credit line. The exporter will not bear risks or financial costs given that it receives the payment in advance of exporting the goods. S/he also does not incur any risks, unless the importer sues in court for breach of contract, which is likely to be an expensive proposition across international borders.

Cash-in-advance financing is most prevalent in low-income countries, where importers do not have access to other forms of trade financing or where the cost of this financing is prohibitive.

B. Open account

An open account is a legal contract requiring the importer to pay the exporter once goods are received. Accordingly, the importer can verify the quality of the goods received and charge penalty for delays ahead of making a payment.

With open accounts, the risk and financial costs fall exclusively on the exporter. It is the exporter that assumes all the risks of producing and shipping the goods ahead of being paid by the importer. In addition, the financial costs also fall on the exporter as s/he will need working capital to produce the goods and ship them until payment is received.

Open accounts are very common in international trade amongst advanced economies. The reason is that it is easier for contracts to be legally enforced and relations between exporters are importers are long-standing and well-established, leading to a higher degree of trust that open accounts will be honored.

C. Letters of credit

A letter of credit (also called documentary credit) is a financial instrument that allows exporters and importers to mitigate the risk and share the financial cost of international trade. A letter of credit is a guarantee by the bank servicing the importer to make a payment to the exporter once the exporter produces documents (normally a bill of laden) that prove that the goods have been shipped. The letter of credit is usually presented to the exporter once the goods are ordered and extinguished once the goods are shipped. For the exporter, the letter of credit can be used as collateral to request a credit line from its own bank to produce the goods and ship them to the importer. For the importer, the letter of credit can turn into a credit line from its own bank once the goods are shipped until they are sold. The importing bank usually charges the importer a fixed fee and interest on a letter of credit.

With letters of credit, risks and financial costs are shared between the importer and the exporter. The risk is borne by the exporter until the goods are shipped, and they fall to the importer after that. The financial costs are shared. The exporter pays interest for the working capital until the goods are shipped. The importer pays for the credit line after the goods have been shipped. The fees for the letter of credit are often split between the importer and the exporter, but this varies from case to case.

Letters of credit are most frequently used for trade with emerging markets, particularly in Asia. They mitigate the risks between exporters and importers and share the financial burden, while generating fees and interest income for banks producing the letters of credit. They also mitigate the likelihood of legal disputes as letters of credit are usually governed by rules and regulations established by the International Chamber of Commerce (ICC).

D. Documentary collection

A documentary collection involves the transfer of the shipping/ownership documents from the exporter (or his/her bank) to the importer's bank. The importer's bank will then transfer the shipping/ownership documents to the importer only after payment is made to the exporter. There is no guarantee of payment involved (like in the case of a letter of credit). Rather, a documentary collection is more of a form of insurance for the exporter that the importer will pay for the goods upon receipt.

With a documentary collection, it is still the exporter who carries the risk and the financial cost. The only advantage compared with an open account is that the documentary collection ensures prompt payment by the importer once the goods are received. However, the risk and financial cost are borne by the exporter.

Documentary collections are a relatively new means of financing global trade. According to the ICC, documentary collections accounted for about one tenth the volume of letters of credit in 2017 and their use declined significantly that year.

Appendix II—Charts and Linear Regression Results[14]

Figure II.1. Bangladesh Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

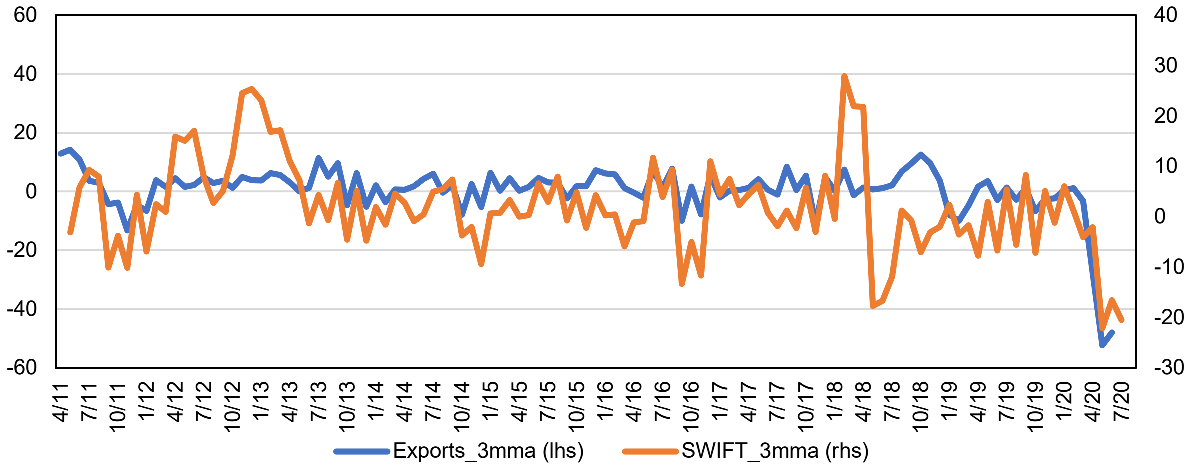


Table II.1. Regression Results for Bangladesh Exports

Variables		Diagnostics	
Constant	0.0056 (0.009)	Observations	111
Exports (-1)	-0.5812 (0.093)***	R^2	0.686
Exports (-2)	-0.3896 (0.144)***	Adjusted R^2	0.64
Exports (-3)	-0.2865 (0.165)*	F-Statistic	36.64
Exports (-4)	-0.1391 (0.129)	Prob. (F-Statistic)	2.92e-32
SWIFT	0.4586 (0.115)***	Log-likelihood	78.107
SWIFT (-1)	0.2195 (0.13)*	Durbin-Watson	1.953
SWIFT (-2)	0.2065 (0.11)*		
SWIFT (-3)	0.0532 (0.12)		
SWIFT (-4)	-0.0618 (0.073)*		
BRENT	0.4256 (0.232)**		
BRENT (-1)	0.7672 (0.369)**		
BRENT (-2)	-0.1829 (0.152)		
BRENT (-3)	0.0761 (0.131)		
BRENT (-4)	0.1405 (0.131)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, national customs data, SWIFT, and authors' regressions.

[14] The full set of charts and regression results are available from the authors.

Figure II.2. Brazil Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

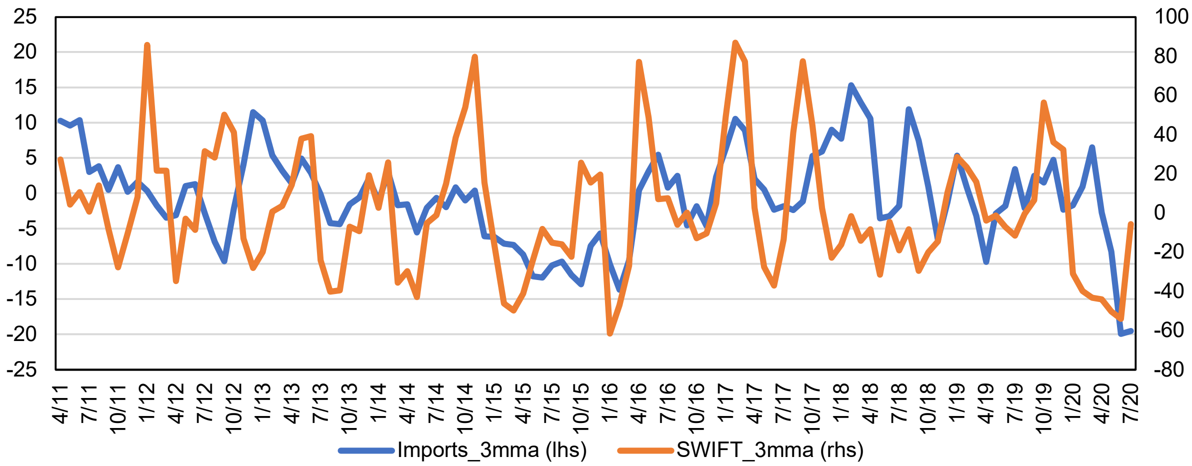


Table II.2. Regression Results for Brazil Imports

Variables		Diagnostics	
Constant	0.002 (0.006)	Observations	112
Imports (-1)	-0.7196 (0.082)***	R^2	0.546
Imports (-2)	-0.5384 (0.104)***	Adjusted R^2	0.452
Imports (-3)	-0.0805 (0.119)	F-Statistic	12.57
Imports (-4)	0.0392 (0.095)	Prob. (F-Statistic)	4.72e-18
SWIFT	0.041 (0.016)**	Log-likelihood	151.45
SWIFT (-1)	0.0283 (0.019)	Durbin-Watson	2.035
SWIFT (-2)	0.0422 (0.021)**		
SWIFT (-3)	0.0123 (0.022)		
SWIFT (-4)	-0.0116 (0.018)		
BRENT	0.0854 (0.067)		
BRENT (-1)	0.0721 (0.06)		
BRENT (-2)	0.0984 (0.061)		
BRENT (-3)	0.313 (0.098)***		
BRENT (-4)	0.1456 (0.108)		
PMI	0.003 (0.003)		
PMI (-1)	-0.0057 (0.005)		
PMI (-2)	0.009 (0.005)*		
PMI (-3)	-0.0067 (0.005)		
PMI (-4)	0.0008 (0.004)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.3. Chile Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

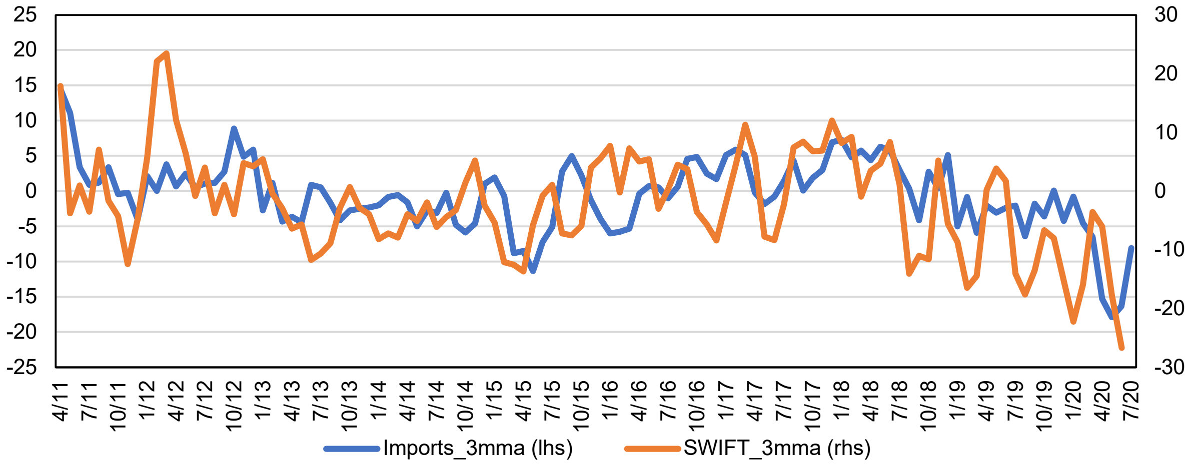


Table II.3. Regression for Results Chile Imports

Variables		Diagnostics	
Constant	-0.0008 (0.006)	Observations	112
Imports (-1)	-0.8498 (0.07)***	R^2	0.641
Imports (-2)	-0.5898 (0.106)***	Adjusted R^2	0.567
Imports (-3)	-0.0821 (0.126)	F-Statistic	17.58
Imports (-4)	-0.0552 (0.103)	Prob. (F-Statistic)	8.23e-23
SWIFT	0.1739 (0.048)***	Log-likelihood	184.15
SWIFT (-1)	0.1403 (0.053)***	Durbin-Watson	2.087
SWIFT (-2)	0.1347 (0.075)*		
SWIFT (-3)	0.0801 (0.055)		
SWIFT (-4)	0.1312 (0.051)**		
BRENT	0.1241 (0.049)**		
BRENT (-1)	0.029 (0.046)		
BRENT (-2)	0.1824 (0.049)***		
BRENT (-3)	-0.0373 (0.077)		
BRENT (-4)	0.052 (0.083)		
PMI	0.0009 (0.001)		
PMI (-1)	0.0006 (0.001)		
PMI (-2)	-0.003 (0.002)		
PMI (-3)	0.0031 (0.003)		
PMI (-4)	-0.0007 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.4. China Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

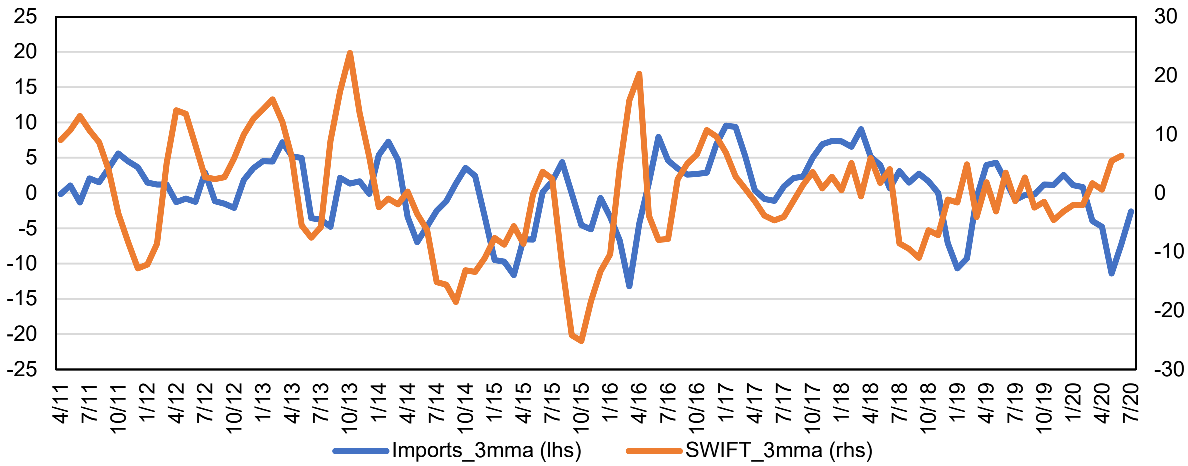


Table II.4. Regression Results for China Imports

Variables		Diagnostics	
Constant	0.0105 (0.004)***	Observations	112
Imports (-1)	-0.6309 (0.105)***	R^2	0.62
Imports (-2)	-0.4429 (0.111)***	Adjusted R^2	0.541
Imports (-3)	-0.285 (0.105)***	F-Statistic	22.21
Imports (-4)	-0.0589 (0.091)	Prob. (F-Statistic)	2.18e-26
SWIFT	0.1699 (0.056)***	Log-likelihood	205.98
SWIFT (-1)	-0.0124 (0.05)	Durbin-Watson	2.008
SWIFT (-2)	0.0878 (0.048)*		
SWIFT (-3)	0.1578 (0.059)***		
SWIFT (-4)	0.0087 (0.048)		
BRENT	0.1033 (0.038)***		
BRENT (-1)	0.1573 (0.044)***		
BRENT (-2)	0.1007 (0.046)**		
BRENT (-3)	0.0384 (0.051)		
BRENT (-4)	0.0828 (0.062)		
PMI	0.0008 (0.002)		
PMI (-1)	0.004 (0.002)*		
PMI (-2)	-0.0041 (0.002)**		
PMI (-3)	-0.0004 (0.002)		
PMI (-4)	0.0029 (0.003)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.5. France Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

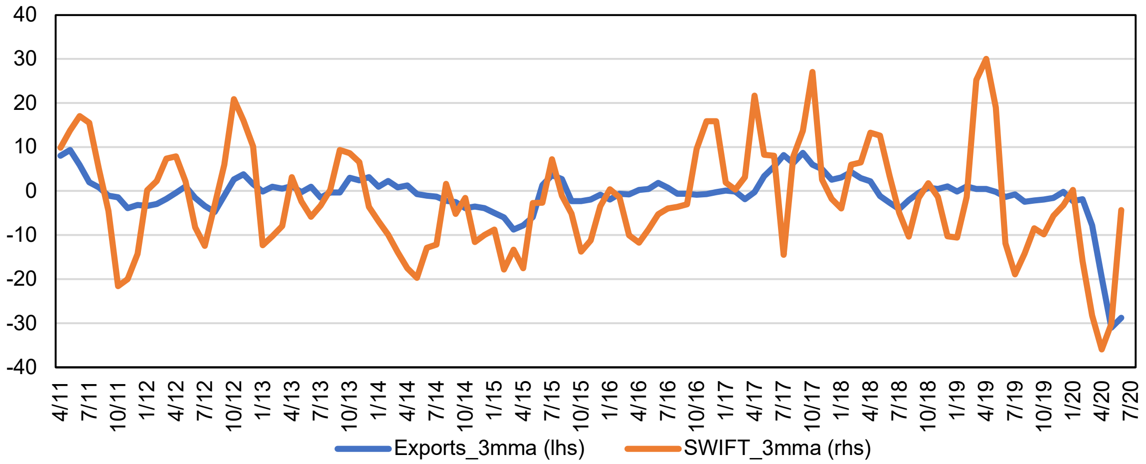


Table II.5. Regression Results for France Exports

Variables		Diagnostics	
Constant	0.0014 (0.003)	Observations	111
Exports (-1)	-0.5291 (0.082)***	R^2	0.725
Exports (-2)	-0.439 (0.076)***	Adjusted R^2	0.667
Exports (-3)	0.0817 (0.105)	F-Statistic	11.99
Exports (-4)	0.1638 (0.123)	Prob. (F-Statistic)	2.50e-17
SWIFT	0.0633 (0.029)**	Log-likelihood	230.24
SWIFT (-1)	0.0242 (0.029)	Durbin-Watson	2.005
SWIFT (-2)	0.0306 (0.032)		
SWIFT (-3)	0.017 (0.028)		
SWIFT (-4)	-0.0019 (0.027)		
BRENT	0.1247 (0.032)***		
BRENT (-1)	0.0401 (0.045)		
BRENT (-2)	0.0511 (0.042)		
BRENT (-3)	0.0266 (0.034)		
BRENT (-4)	-0.0325 (0.045)		
PMI	0.0068 (0.002)***		
PMI (-1)	0.0019 (0.002)		
PMI (-2)	-0.0035 (0.002)*		
PMI (-3)	-0.0024 (0.002)		
PMI (-4)	0.0005 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.6. Ghana Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

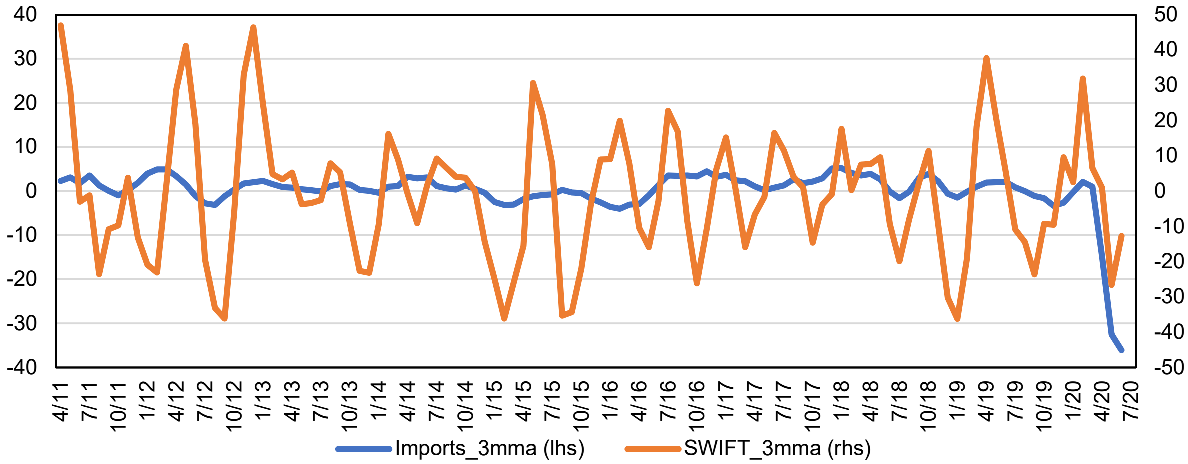


Table II.6. Regression Results for Ghana Imports

Variables		Diagnostics	
Constant	0.0002 (0.006)	Observations	111
Imports (-1)	-0.675 (0.098)***	R^2	0.496
Imports (-2)	-0.1287 (0.125)	Adjusted R^2	0.422
Imports (-3)	0.0369 (0.126)	F-Statistic	7.751
Imports (-4)	-0.0479 (0.093)	Prob. (F-Statistic)	1.10e-10
SWIFT	0.095 (0.03)***	Log-likelihood	146.37
SWIFT (-1)	0.1051 (0.033)***	Durbin-Watson	2.092
SWIFT (-2)	0.0159 (0.033)		
SWIFT (-3)	0.0962 (0.039)**		
SWIFT (-4)	0.0453 (0.035)		
BRENT	-0.0655 (0.051)		
BRENT (-1)	0.0047 (0.058)		
BRENT (-2)	-0.0565 (0.076)		
BRENT (-3)	-0.0498 (0.091)		
BRENT (-4)	0.1115 (0.094)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, national customs data, SWIFT, and authors' regressions.

Figure II.7. India Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

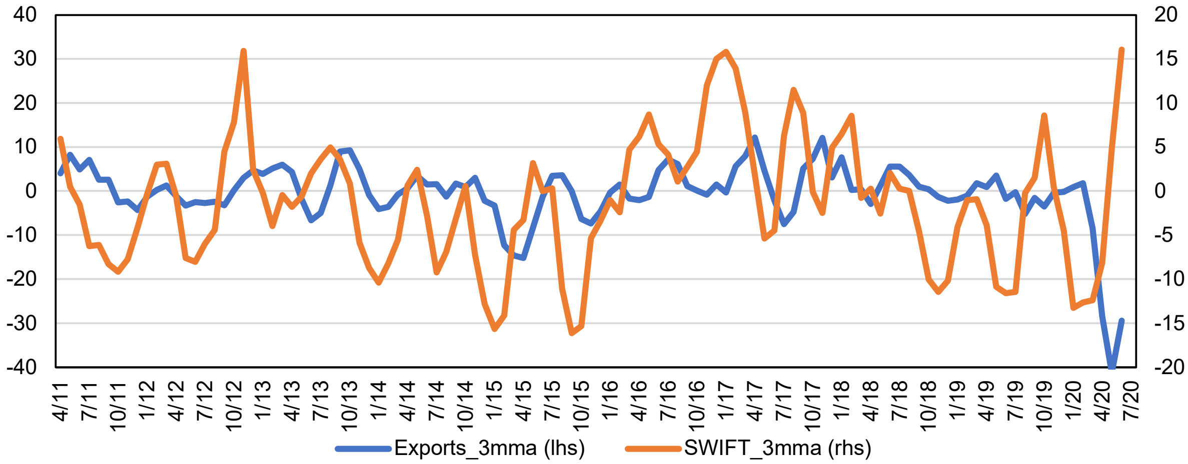


Table II.7. Regression Results for India Exports

Variables		Diagnostics	
Constant	-0.0091 (0.007)	Observations	111
Exports (-1)	-0.6641 (0.104)***	R^2	0.789
Exports (-2)	-0.3341 (0.092)***	Adjusted R^2	0.745
Exports (-3)	-0.2617 (0.109)**	F-Statistic	32.49
Exports (-4)	-0.1723 (0.082)**	Prob. (F-Statistic)	2.16e-32
SWIFT	0.1388 (0.06)**	Log-likelihood	182.92
SWIFT (-1)	0.1566 (0.077)**	Durbin-Watson	2.011
SWIFT (-2)	0.12 (0.078)		
SWIFT (-3)	0.1717 (0.078)**		
SWIFT (-4)	0.1028 (0.073)		
BRENT	0.2737 (0.075)***		
BRENT (-1)	-0.0199 (0.061)		
BRENT (-2)	0.2373 (0.061)***		
BRENT (-3)	0.1086 (0.061)*		
BRENT (-4)	0.0026 (0.054)		
PMI	0.0142 (0.002)***		
PMI (-1)	-0.0132 (0.003)***		
PMI (-2)	-0.0022 (0.003)		
PMI (-3)	0.0112 (0.004)***		
PMI (-4)	-0.0036 (0.003)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.8. Indonesia Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

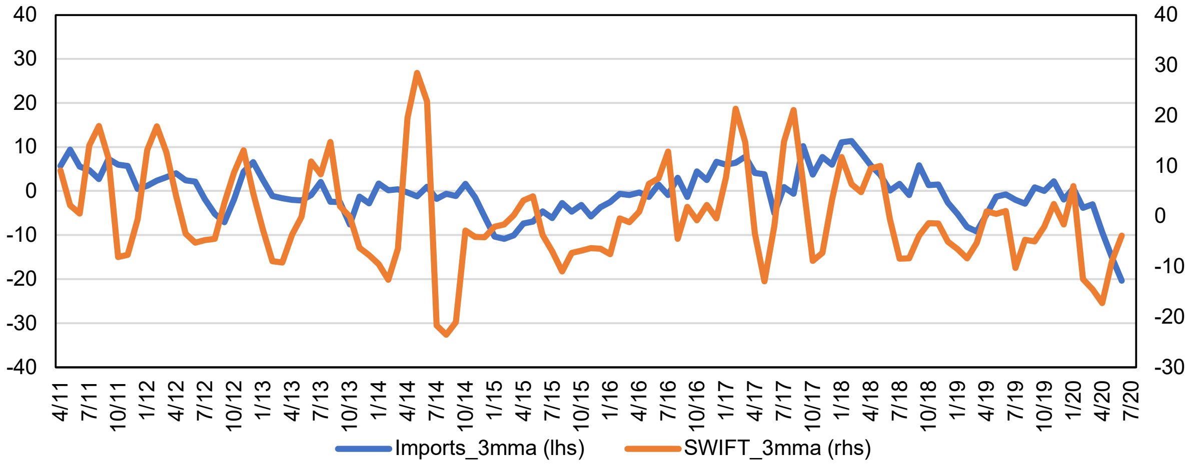


Table II.8. Regression Results for Indonesia Imports

Variables		Diagnostics	
Constant	0.0034 (0.006)	Observations	107
Imports (-1)	-1.0373 (0.101)***	R^2	0.698
Imports (-2)	-0.5353 (0.13)***	Adjusted R^2	0.632
Imports (-3)	0.1106 (0.133)	F-Statistic	16.58
Imports (-4)	0.1642 (0.087)*	Prob. (F-Statistic)	2.72e-21
SWIFT	0.1133 (0.04)***	Log-likelihood	178.44
SWIFT (-1)	0.0803 (0.053)	Durbin-Watson	1.967
SWIFT (-2)	0.0411 (0.058)		
SWIFT (-3)	-0.0134 (0.046)		
SWIFT (-4)	-0.0201 (0.033)		
BRENT	0.0662 (0.051)		
BRENT (-1)	0.189 (0.047)***		
BRENT (-2)	0.1532 (0.046)***		
BRENT (-3)	0.1269 (0.06)**		
BRENT (-4)	0.064 (0.077)		
PMI	-0.0017 (0.002)		
PMI (-1)	0.003 (0.002)		
PMI (-2)	0.0034 (0.002)		
PMI (-3)	-0.004 (0.003)		
PMI (-4)	0.0002 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.9. Israel Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

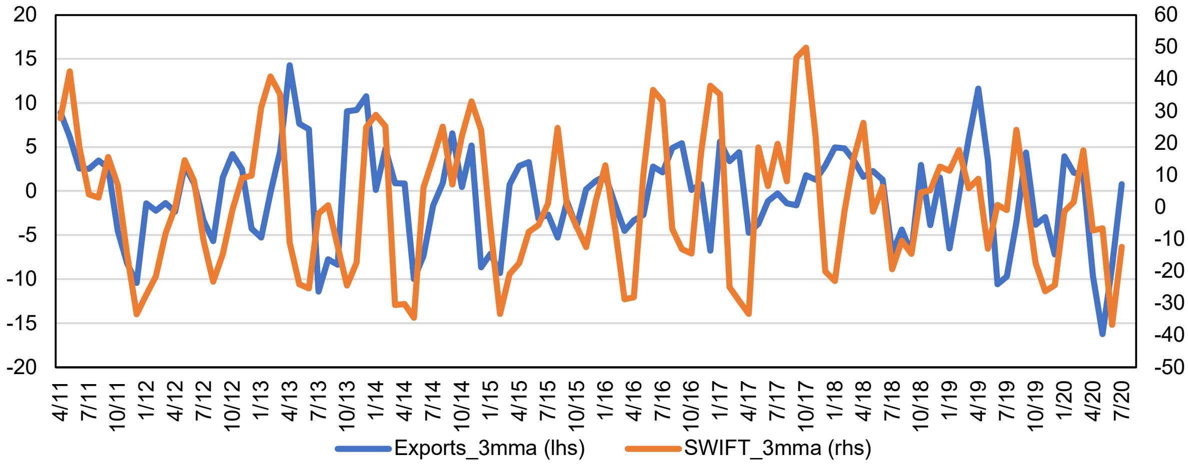


Table II.9. Regression Results for Israel Exports

Variables		Diagnostics	
Constant	0.0004 (0.007)	Observations	111
Exports (-1)	-0.9916 (0.079)***	R^2	0.62
Exports (-2)	-0.8086 (0.092)***	Adjusted R^2	0.541
Exports (-3)	-0.5187 (0.1)***	F-Statistic	17.92
Exports (-4)	-0.2679 (0.072)***	Prob. (F-Statistic)	5.94e-23
SWIFT	0.04 (0.029)	Log-likelihood	139.27
SWIFT (-1)	0.0539 (0.025)**	Durbin-Watson	2.168
SWIFT (-2)	0.0565 (0.03)*		
SWIFT (-3)	0.0703 (0.031)**		
SWIFT (-4)	0.0517 (0.026)*		
BRENT	0.1301 (0.044)***		
BRENT (-1)	0.1434 (0.051)***		
BRENT (-2)	0.1115 (0.067)		
BRENT (-3)	-0.0198 (0.08)		
BRENT (-4)	-0.0787 (0.073)		
PMI	0.0004 (0.001)		
PMI (-1)	0.0014 (0.002)		
PMI (-2)	-0.0024 (0.002)		
PMI (-3)	0.0036 (0.001)***		
PMI (-4)	-0.0013 (0.001)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.10. Israel Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

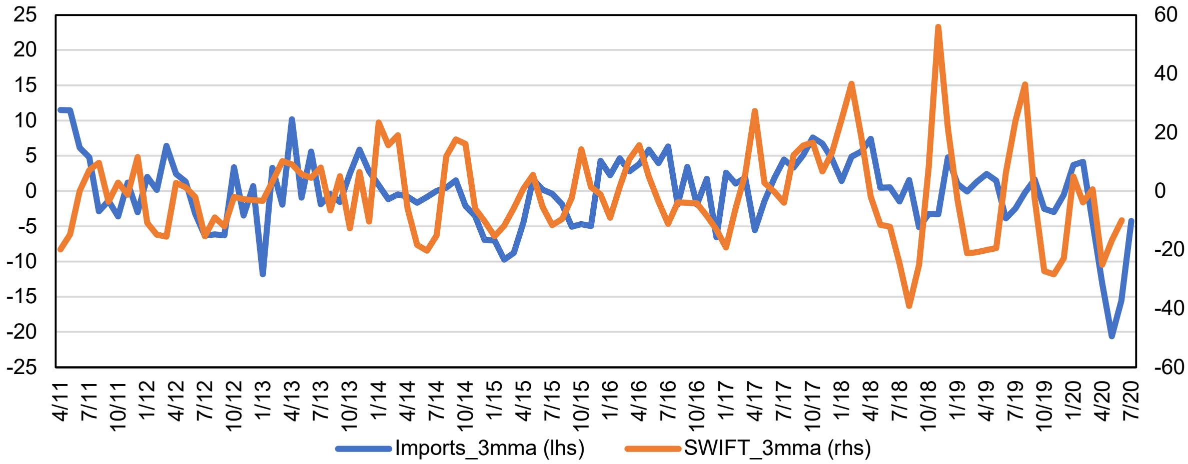


Table II.10. Regression Results for Israel Imports

Variables		Diagnostics	
Constant	0.0084 (0.005)	Observations	111
Imports (-1)	-1.1307 (0.117)***	R^2	0.721
Imports (-2)	-0.8431 (0.17)***	Adjusted R^2	0.663
Imports (-3)	-0.2049 (0.173)	F-Statistic	21.98
Imports (-4)	0.0835 (0.129)	Prob. (F-Statistic)	4.58e-26
SWIFT	0.0294 (0.026)	Log-likelihood	163.9
SWIFT (-1)	0.0698 (0.031)**	Durbin-Watson	1.99
SWIFT (-2)	0.1068 (0.036)***		
SWIFT (-3)	0.0334 (0.04)		
SWIFT (-4)	-0.0066 (0.026)		
BRENT	0.127 (0.042)***		
BRENT (-1)	0.2706 (0.05)***		
BRENT (-2)	0.1253 (0.069)*		
BRENT (-3)	0.0792 (0.093)		
BRENT (-4)	-0.1411 (0.08)*		
PMI	0.0003 (0.001)		
PMI (-1)	0.0028 (0.001)**		
PMI (-2)	-0.002 (0.001)		
PMI (-3)	0.0013 (0.001)		
PMI (-4)	-0.0001 (0.001)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.11. Italy Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

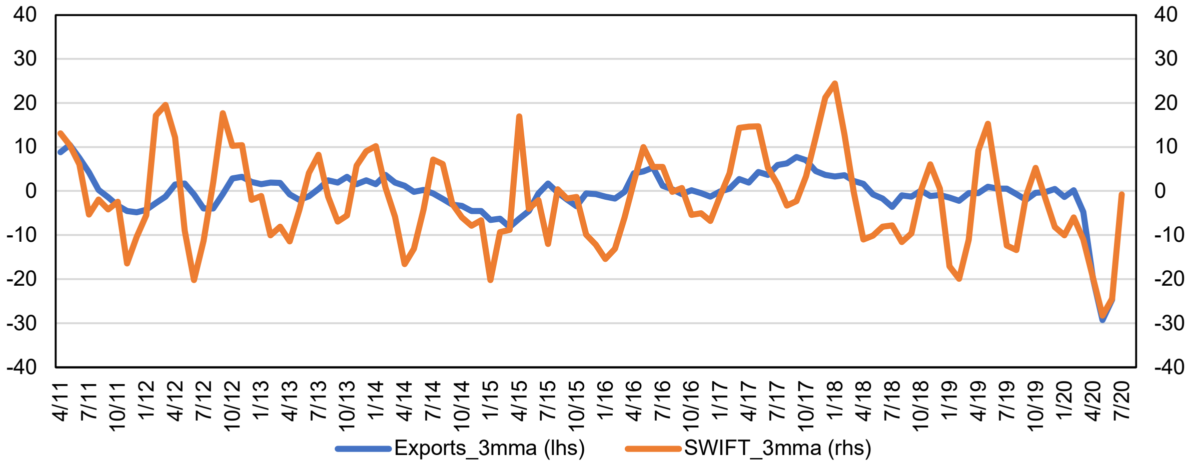


Table II.11. Regression Results for Italy Exports

Variables		Diagnostics	
Constant	-0.0021 (0.003)	Observations	111
Exports (-1)	-0.4547 (0.1)***	R^2	0.784
Exports (-2)	-0.2591 (0.086)***	Adjusted R^2	0.739
Exports (-3)	0.0012 (0.105)	F-Statistic	13.13
Exports (-4)	0.2644 (0.116)**	Prob. (F-Statistic)	1.53e-18
SWIFT	-0.0075 (0.027)	Log-likelihood	237.36
SWIFT (-1)	-0.0304 (0.032)	Durbin-Watson	2.066
SWIFT (-2)	0.0654 (0.03)**		
SWIFT (-3)	0.054 (0.028)*		
SWIFT (-4)	0.0335 (0.027)		
BRENT	0.1412 (0.037)***		
BRENT (-1)	0.1853 (0.049)***		
BRENT (-2)	-0.0768 (0.043)*		
BRENT (-3)	0.0803 (0.047)*		
BRENT (-4)	-0.0047 (0.037)		
PMI	0.0088 (0.002)***		
PMI (-1)	-0.0041 (0.002)**		
PMI (-2)	-0.0016 (0.002)		
PMI (-3)	-0.0019 (0.002)		
PMI (-4)	0.0012 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.12. Korea Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

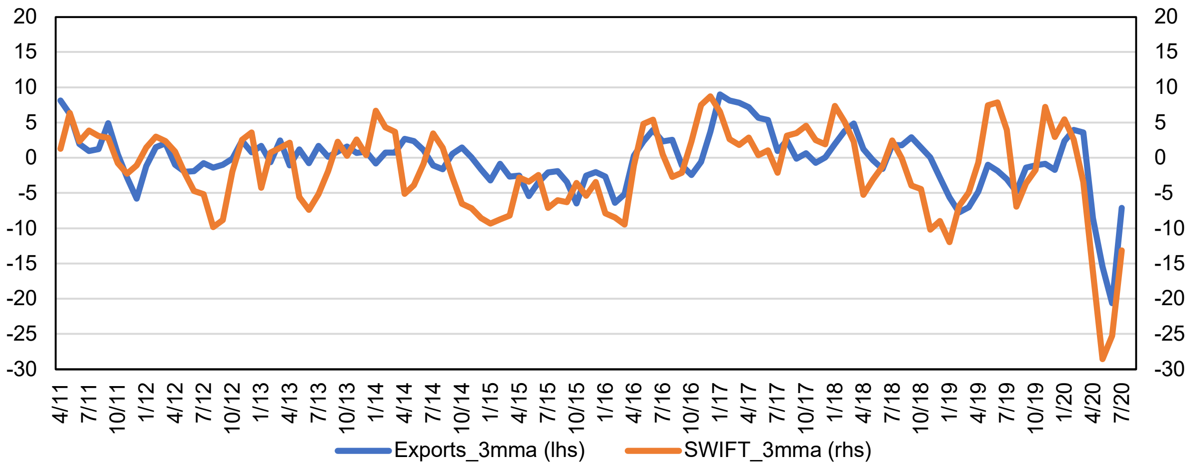


Table II.12. Regression Results for Korea Exports

Variables		Diagnostics	
Constant	0.0069 (0.003)**	Observations	112
Exports (-1)	-0.7331 (0.098)***	R^2	0.595
Exports (-2)	-0.4508 (0.125)***	Adjusted R^2	0.511
Exports (-3)	-0.2487 (0.13)*	F-Statistic	10.74
Exports (-4)	-0.0754 (0.123)	Prob. (F-Statistic)	5.35e-16
SWIFT	0.1608 (0.059)***	Log-likelihood	227.68
SWIFT (-1)	0.1579 (0.072)**	Durbin-Watson	2.035
SWIFT (-2)	0.1349 (0.082)		
SWIFT (-3)	0.1849 (0.064)***		
SWIFT (-4)	0.1138 (0.055)**		
BRENT	0.0028 (0.048)		
BRENT (-1)	0.1348 (0.041)***		
BRENT (-2)	0.0322 (0.037)		
BRENT (-3)	-0.0467 (0.042)		
BRENT (-4)	0.0227 (0.05)		
PMI	0.0047 (0.002)**		
PMI (-1)	-0.0015 (0.003)		
PMI (-2)	0.0017 (0.003)		
PMI (-3)	-0.0042 (0.002)*		
PMI (-4)	0.0042 (0.002)**		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.13. Korea Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

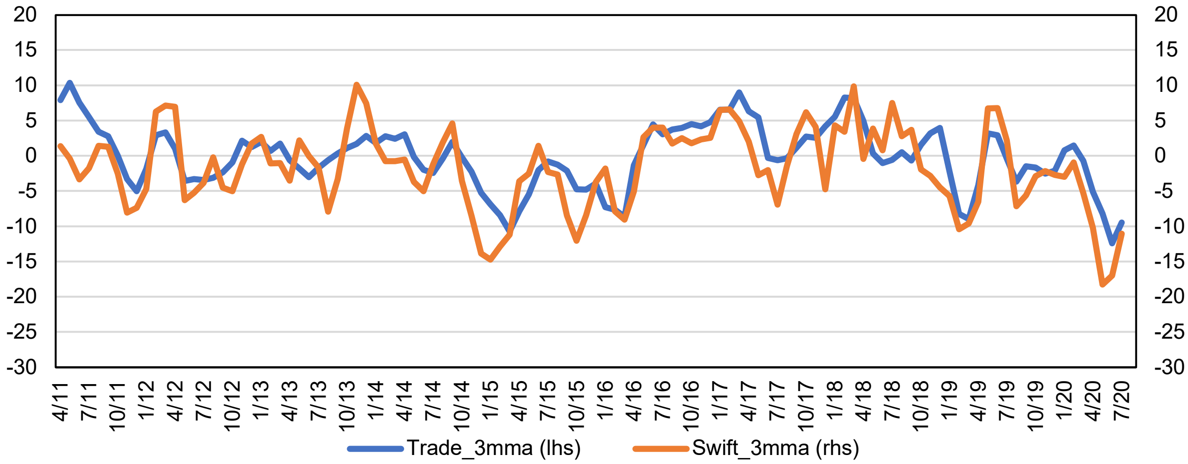


Table II.13. Regression Results for Korea Imports

Variables		Diagnostics	
Constant	0.0059 (0.003)**	Observations	112
Imports (-1)	-0.6912 (0.087)***	R^2	0.663
Imports (-2)	-0.3849 (0.113)***	Adjusted R^2	0.594
Imports (-3)	-0.0624 (0.11)	F-Statistic	21.53
Imports (-4)	0.0392 (0.115)	Prob. (F-Statistic)	6.66e-26
SWIFT	0.2637 (0.053)***	Log-likelihood	246.31
SWIFT (-1)	0.1838 (0.072)**	Durbin-Watson	1.99
SWIFT (-2)	0.108 (0.08)		
SWIFT (-3)	0.1002 (0.072)		
SWIFT (-4)	0.0269 (0.064)		
BRENT	0.0254 (0.032)		
BRENT (-1)	0.104 (0.029)***		
BRENT (-2)	0.1072 (0.029)***		
BRENT (-3)	0.1168 (0.039)***		
BRENT (-4)	-0.0408 (0.051)		
PMI	-0.0011 (0.002)		
PMI (-1)	-0.0002 (0.002)		
PMI (-2)	0.0006 (0.001)		
PMI (-3)	0.0002 (0.002)		
PMI (-4)	0.0026 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.14. Latvia Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

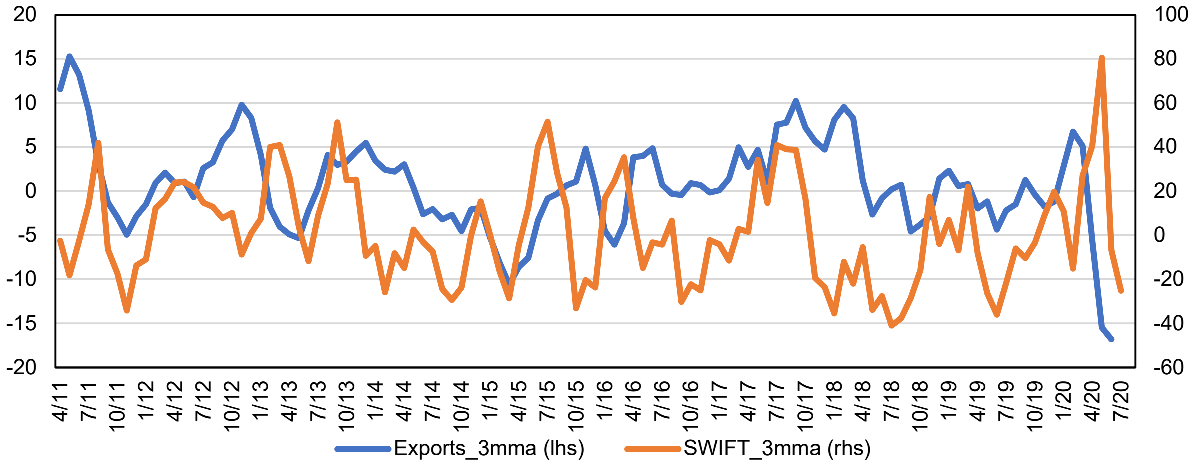


Table II.14. Regression Results for Latvia Exports

Variables		Diagnostics	
Constant	0.0077 (0.004)*	Observations	111
Exports (-1)	-0.4863 (0.089)***	R^2	0.524
Exports (-2)	-0.2437 (0.094)**	Adjusted R^2	0.454
Exports (-3)	0.0599 (0.099)	F-Statistic	15.94
Exports (-4)	-0.1062 (0.079)	Prob. (F-Statistic)	2.87e-19
SWIFT	0.0384 (0.015)**	Log-likelihood	199.08
SWIFT (-1)	0.0087 (0.019)	Durbin-Watson	2.063
SWIFT (-2)	0.0255 (0.02)		
SWIFT (-3)	0.046 (0.019)**		
SWIFT (-4)	0.0264 (0.014)***		
BRENT	0.1343 (0.03)***		
BRENT (-1)	0.1206 (0.036)***		
BRENT (-2)	0.1081 (0.036)***		
BRENT (-3)	0.0293 (0.052)		
BRENT (-4)	0.0435 (0.058)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.15. Lithuania Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

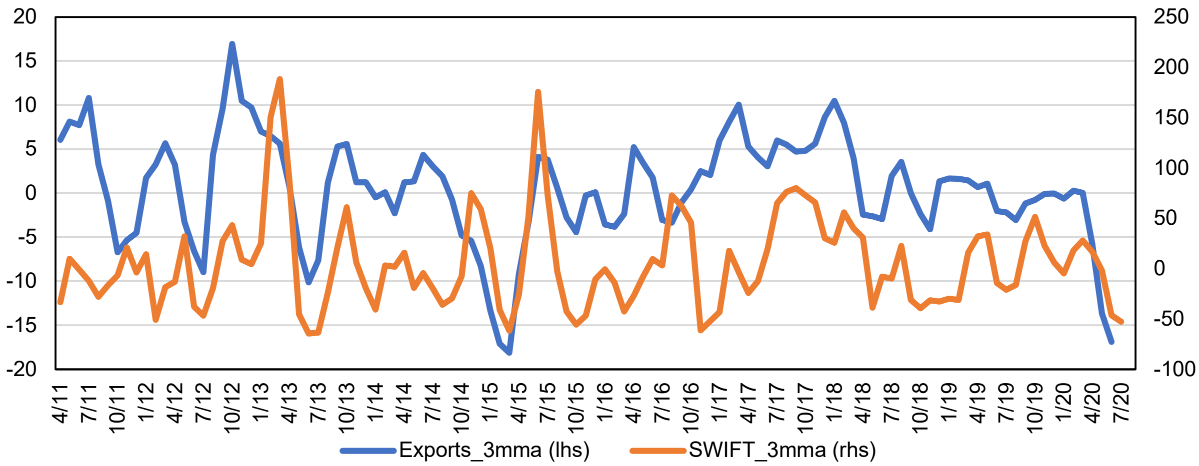


Table II.15. Regression Results for Lithuania Exports

Variables		Diagnostics	
Constant	0.0058 (0.004)	Observations	111
Exports (-1)	-0.5104 (0.091)***	R^2	0.492
Exports (-2)	-0.2159 (0.097)**	Adjusted R^2	0.417
Exports (-3)	-0.0204 (0.107)	F-Statistic	11.51
Exports (-4)	-0.0184 (0.088)	Prob. (F-Statistic)	4.88e-15
SWIFT	0.0377 (0.011)***	Log-likelihood	188
SWIFT (-1)	0.0146 (0.011)	Durbin-Watson	2.016
SWIFT (-2)	0.0042 (0.01)		
SWIFT (-3)	-0.0109 (0.009)		
SWIFT (-4)	-0.0142 (0.009)***		
BRENT	0.1338 (0.034)***		
BRENT (-1)	0.186 (0.042)***		
BRENT (-2)	0.0236 (0.044)		
BRENT (-3)	0.0629 (0.051)		
BRENT (-4)	0.0785 (0.06)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.16. Malaysia Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

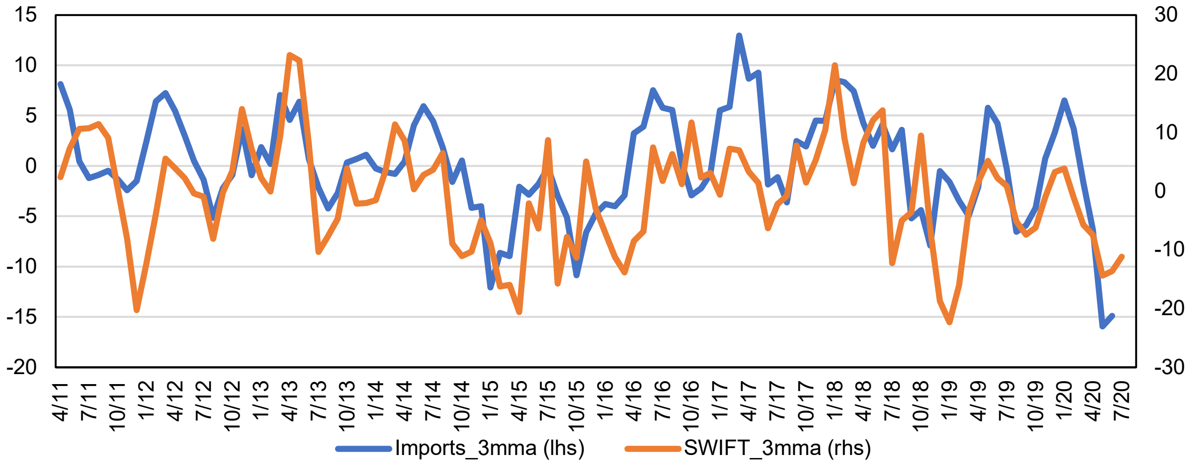


Table II.16. Regression Results for Malaysia Imports

Variables		Diagnostics	
Constant	0.0063 (0.004)	Observations	92
Imports (-1)	-0.7635 (0.072)***	R^2	0.74
Imports (-2)	-0.3948 (0.11)***	Adjusted R^2	0.671
Imports (-3)	-0.2767 (0.106)**	F-Statistic	92.71
Imports (-4)	-0.1119 (0.102)	Prob. (F-Statistic)	7.01e-43
SWIFT	0.1041 (0.043)**	Log-likelihood	171.37
SWIFT (-1)	0.1175 (0.057)**	Durbin-Watson	1.969
SWIFT (-2)	0.1544 (0.058)**		
SWIFT (-3)	0.1626 (0.051)***		
SWIFT (-4)	0.1047 (0.054)*		
BRENT	0.1343 (0.04)***		
BRENT (-1)	0.1553 (0.057)***		
BRENT (-2)	0.0339 (0.054)		
BRENT (-3)	0.1982 (0.07)***		
BRENT (-4)	-0.0808 (0.069)		
PMI	-0.0041 (0.001)***		
PMI (-1)	0.0081 (0.002)***		
PMI (-2)	-0.0024 (0.002)		
PMI (-3)	-0.0045 (0.003)		
PMI (-4)	0.0051 (0.003)*		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.17. Mexico Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

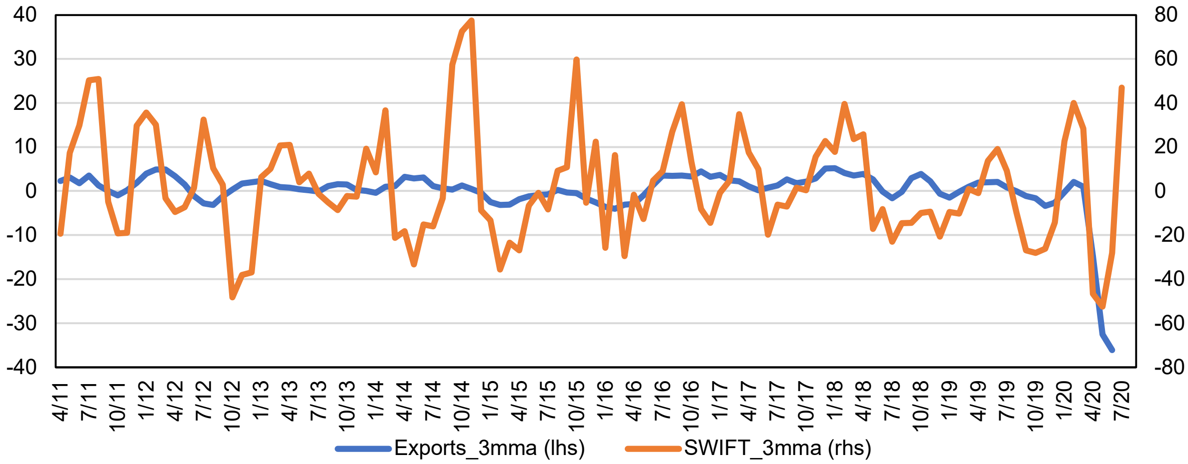


Table II.17. Regression Results for Mexico Exports

Variables		Diagnostics	
Constant	0.0017 (0.004)	Observations	107
Exports (-1)	-0.1959 (0.107)*	R^2	0.876
Exports (-2)	-0.8845 (0.115)***	Adjusted R^2	0.849
Exports (-3)	-0.223 (0.155)	F-Statistic	47.4
Exports (-4)	-0.147 (0.144)	Prob. (F-Statistic)	1.01e-37
SWIFT	0.0338 (0.006)***	Log-likelihood	234.46
SWIFT (-1)	0.0482 (0.011)***	Durbin-Watson	1.874
SWIFT (-2)	0.0367 (0.014)***		
SWIFT (-3)	0.0055 (0.01)		
SWIFT (-4)	-0.0105 (0.009)		
BRENT	0.0356 (0.029)		
BRENT (-1)	0.2468 (0.049)***		
BRENT (-2)	0.0096 (0.037)		
BRENT (-3)	0.0304 (0.034)		
BRENT (-4)	0.1202 (0.035)***		
PMI	0.0099 (0.003)***		
PMI (-1)	0.0006 (0.002)		
PMI (-2)	-0.0046 (0.002)**		
PMI (-3)	0.0001 (0.002)		
PMI (-4)	-0.0005 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.18. Nigeria Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

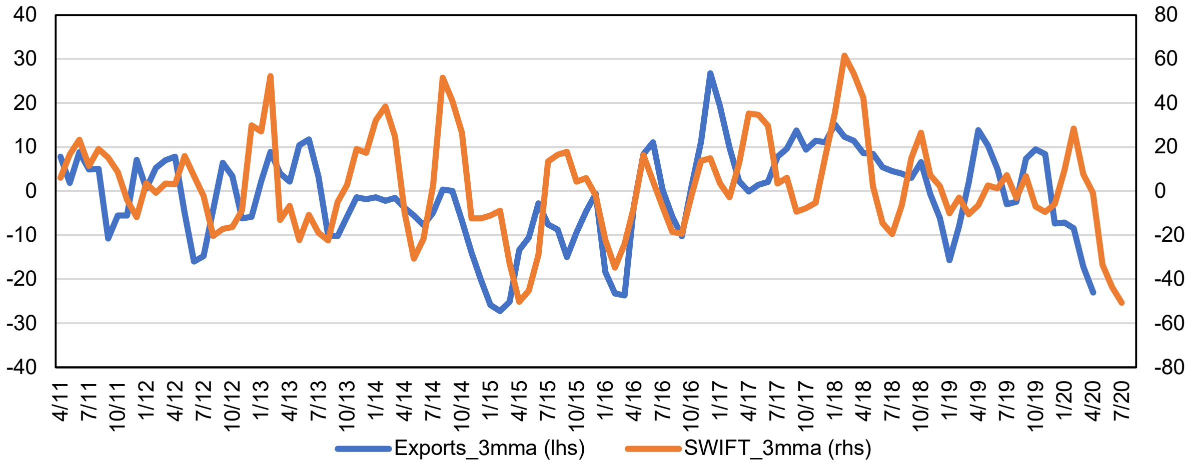


Table II.18. Regression Results for Nigeria Exports

Variables		Diagnostics	
Constant	-0.004 (0.008)	Observations	109
Exports (-1)	-0.5834 (0.114)***	R^2	0.408
Exports (-2)	-0.3401 (0.111)***	Adjusted R^2	0.32
Exports (-3)	-0.1528 (0.119)	F-Statistic	9.18
Exports (-4)	0.0235 (0.091)	Prob. (F-Statistic)	2.41e-12
SWIFT	0.0706 (0.039)*	Log-likelihood	109.77
SWIFT (-1)	0.0917 (0.045)**	Durbin-Watson	1.857
SWIFT (-2)	0.1066 (0.045)**		
SWIFT (-3)	0.0217 (0.039)		
SWIFT (-4)	-0.0105 (0.035)***		
BRENT	0.5683 (0.128)		
BRENT (-1)	0.005 (0.222)		
BRENT (-2)	0.0632 (0.131)		
BRENT (-3)	0.0186 (0.129)		
BRENT (-4)	0.016 (0.103)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, national customs data, SWIFT, and authors' regressions.

Figure II.19. Norway Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

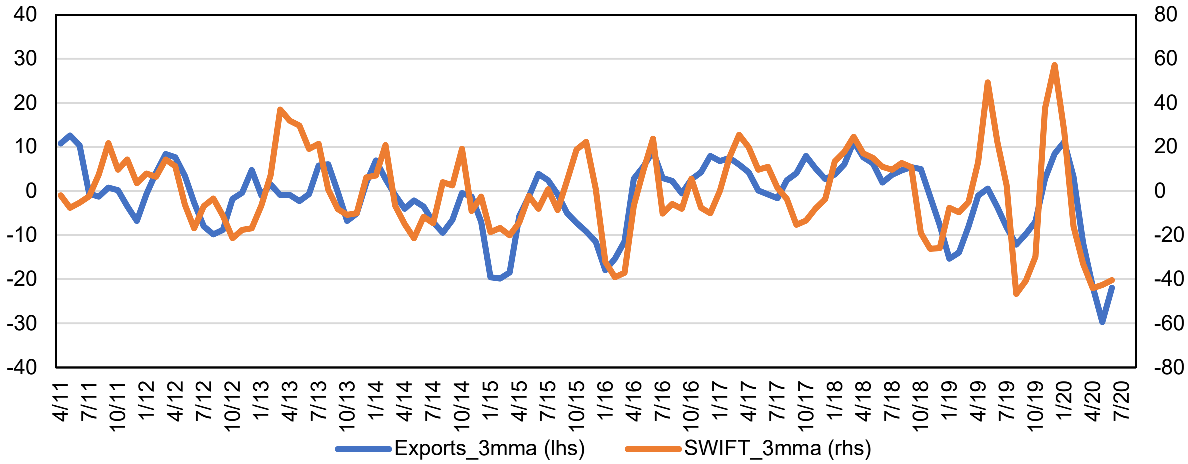


Table II.19. Regression Results for Norway Exports

Variables		Diagnostics	
Constant	-0.0032 (0.005)	Observations	111
Exports (-1)	-0.6266 (0.082)***	R^2	0.53
Exports (-2)	-0.3882 (0.093)***	Adjusted R^2	0.432
Exports (-3)	-0.2189 (0.1)**	F-Statistic	9.421
Exports (-4)	-0.21 (0.096)**	Prob. (F-Statistic)	2.58e-14
SWIFT	0.0489 (0.02)**	Log-likelihood	177.77
SWIFT (-1)	0.0539 (0.027)*	Durbin-Watson	2.034
SWIFT (-2)	0.058 (0.032)*		
SWIFT (-3)	-0.0066 (0.032)		
SWIFT (-4)	0.0035 (0.024)		
BRENT	0.3253 (0.06)***		
BRENT (-1)	0.2401 (0.053)***		
BRENT (-2)	0.1691 (0.054)***		
BRENT (-3)	0.1284 (0.07)*		
BRENT (-4)	0.1893 (0.069)***		
PMI	-0.0005 (0.001)		
PMI (-1)	-1.136e (-6)***		
PMI (-2)	0.0019 (0.002)		
PMI (-3)	0.0009 (0.001)		
PMI (-4)	-0.0027 (0.001)*		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.20. Russia Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

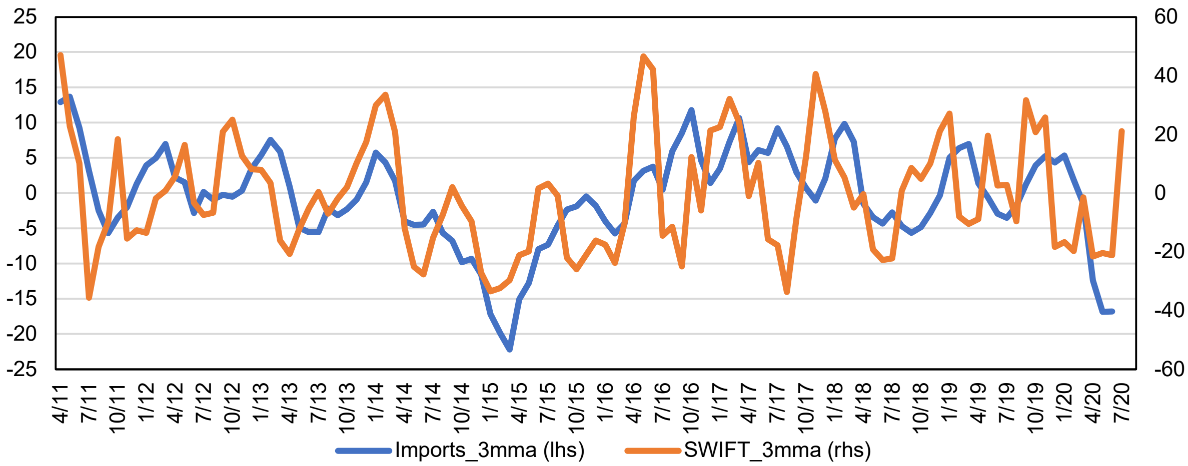


Table II.20. Regression Results for Russia Imports

Variables		Diagnostics	
Constant	0.0015 (0.005)	Observations	111
Imports (-1)	-0.383 (0.083)***	R^2	0.506
Imports (-2)	-0.0549 (0.074)	Adjusted R^2	0.403
Imports (-3)	0.2489 (0.084)***	F-Statistic	12.73
Imports (-4)	-0.1481 (0.087)*	Prob. (F-Statistic)	4.04e-18
SWIFT	0.0723 (0.016)***	Log-likelihood	197.06
SWIFT (-1)	0.0505 (0.024)**	Durbin-Watson	2.086
SWIFT (-2)	0.0739 (0.028)**		
SWIFT (-3)	0.0496 (0.023)**		
SWIFT (-4)	0.0165 (0.019)		
BRENT	0.1727 (0.043)***		
BRENT (-1)	0.0686 (0.053)		
BRENT (-2)	-0.0226 (0.063)		
BRENT (-3)	0.0039 (0.061)		
BRENT (-4)	0.1481 (0.053)***		
PMI	-0.001 (0.002)		
PMI (-1)	0.0035 (0.002)		
PMI (-2)	-0.0024 (0.002)		
PMI (-3)	0.0023 (0.003)		
PMI (-4)	-0.0024 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.21. Thailand Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

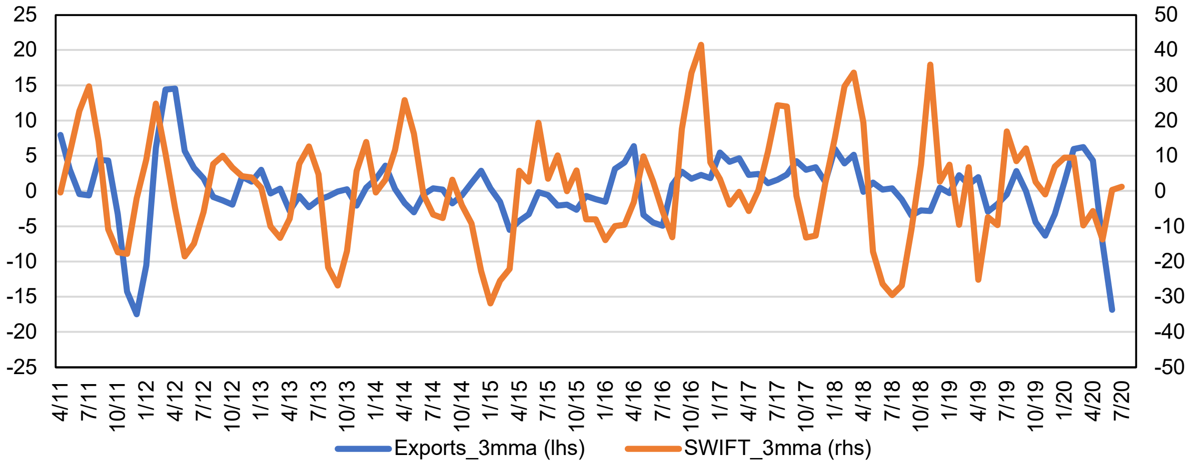


Table II.21. Regression Results for Thailand Exports

Variables		Diagnostics	
Constant	0.0105 (0.005)*	Observations	51
Exports (-1)	-0.7136 (0.127)***	R^2	0.703
Exports (-2)	-0.4078 (0.144)***	Adjusted R^2	0.522
Exports (-3)	-0.0816 (0.134)	F-Statistic	16.73
Exports (-4)	-0.0008 (0.124)	Prob. (F-Statistic)	2.42e-11
SWIFT	0.1461 (0.057)**	Log-likelihood	102.68
SWIFT (-1)	0.261 (0.069)***	Durbin-Watson	1.966
SWIFT (-2)	0.1582 (0.08)*		
SWIFT (-3)	0.1141 (0.091)		
SWIFT (-4)	0.0184 (0.062)		
BRENT	-0.1863 (0.062)***		
BRENT (-1)	-0.0948 (0.085)		
BRENT (-2)	0.0432 (0.088)		
BRENT (-3)	-0.056 (0.086)		
BRENT (-4)	0.0585 (0.082)		
PMI	0.0073 (0.003)**		
PMI (-1)	-0.0006 (0.005)		
PMI (-2)	-0.0026 (0.007)		
PMI (-3)	-0.002 (0.005)		
PMI (-4)	-0.0065 (0.007)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.

Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.22. Turkey Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

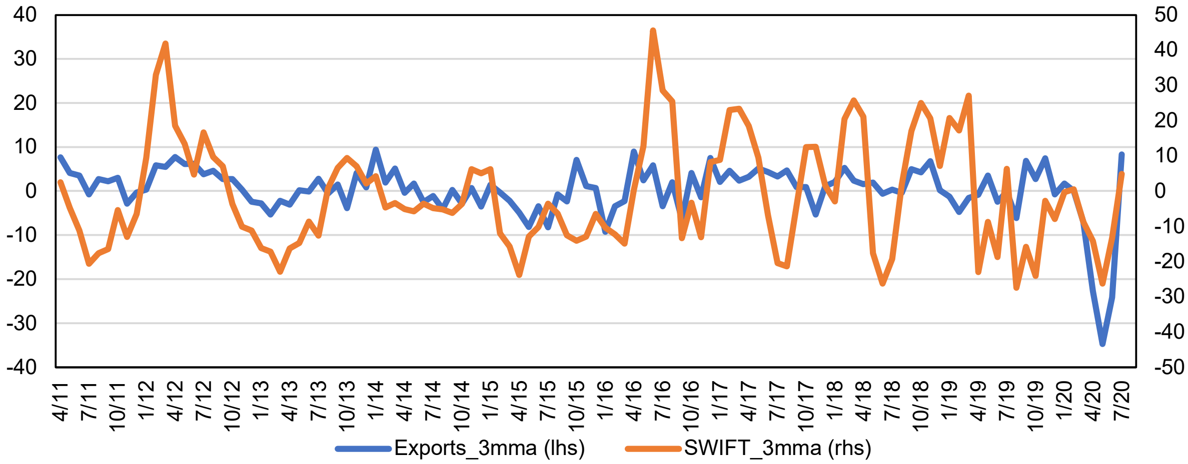


Table II.22. Regression Results for Turkey Exports

Variables		Diagnostics	
Constant	0.006 (0.005)	Observations	112
Exports (-1)	-0.8792 (0.091)***	R^2	0.696
Exports (-2)	-0.5197 (0.14)***	Adjusted R^2	0.634
Exports (-3)	-0.3124 (0.143)**	F-Statistic	19.02
Exports (-4)	-0.0384 (0.092)	Prob. (F-Statistic)	5.45e-24
SWIFT	0.1045 (0.039)***	Log-likelihood	166.42
SWIFT (-1)	0.0704 (0.042)*	Durbin-Watson	2.002
SWIFT (-2)	0.0407 (0.039)		
SWIFT (-3)	0.0624 (0.041)		
SWIFT (-4)	0.07 (0.043)		
BRENT	0.1741 (0.062)***		
BRENT (-1)	0.0828 (0.072)		
BRENT (-2)	0.0401 (0.077)		
BRENT (-3)	-0.1321 (0.082)		
BRENT (-4)	-0.042 (0.073)		
PMI	0.0078 (0.002)***		
PMI (-1)	0.0059 (0.002)**		
PMI (-2)	-0.0054 (0.002)**		
PMI (-3)	0.0002 (0.002)		
PMI (-4)	-0.0007 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.23. Turkey Exports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

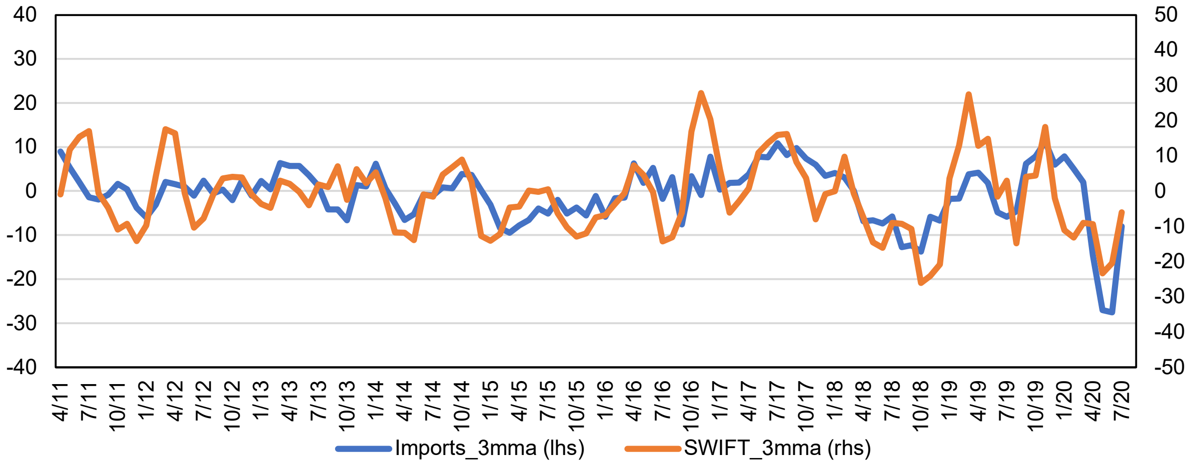


Table II.23. Regression Results for Turkey Imports

Variables		Diagnostics	
Constant	0.0002 (0.005)	Observations	112
Imports (-1)	-0.6913 (0.116)***	R^2	0.718
Imports (-2)	-0.1047 (0.123)	Adjusted R^2	0.66
Imports (-3)	0.0283 (0.114)	F-Statistic	31.47
Imports (-4)	0.0264 (0.116)	Prob. (F-Statistic)	4.43e-32
SWIFT	0.2715 (0.044)***	Log-likelihood	186.46
SWIFT (-1)	0.1173 (0.055)**	Durbin-Watson	2.041
SWIFT (-2)	0.0333 (0.046)		
SWIFT (-3)	0.0997 (0.047)**		
SWIFT (-4)	0.1089 (0.056)*		
BRENT	0.1508 (0.041)***		
BRENT (-1)	0.0273 (0.061)		
BRENT (-2)	-0.0413 (0.046)		
BRENT (-3)	-0.0172 (0.079)		
BRENT (-4)	-0.0259 (0.066)		
PMI	0.0043 (0.002)**		
PMI (-1)	0.0054 (0.003)**		
PMI (-2)	-0.0039 (0.002)*		
PMI (-3)	-0.0025 (0.002)		
PMI (-4)	0.0001 (0.002)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Figure II.24. Vietnam Imports and SWIFT Trade Messages
(Percentage change; 3-month moving average, seasonally adjusted)

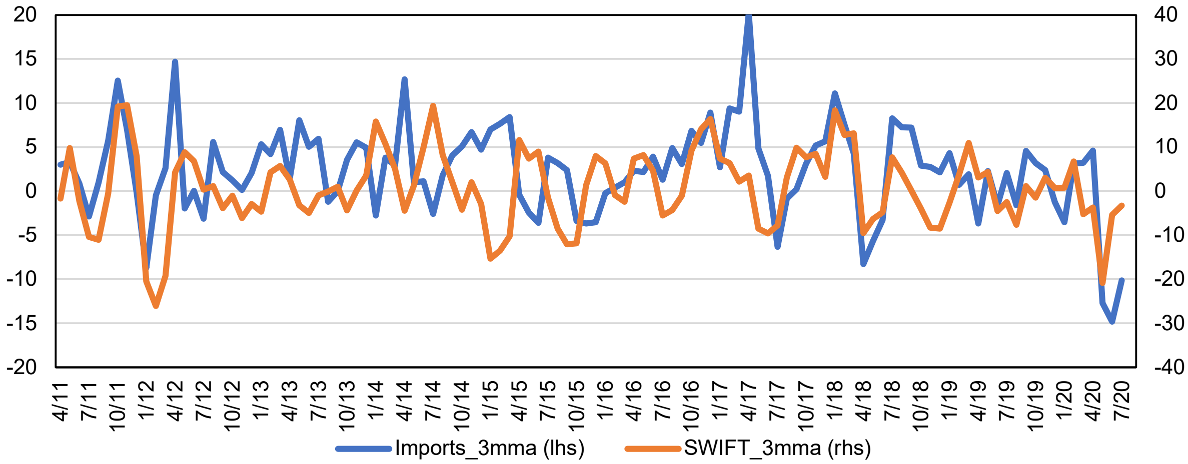


Table II.24. Regression Results for Vietnam Imports

Variables		Diagnostics	
Constant	0.0236 (0.007)***	Observations	109
Imports (-1)	-0.9585 (0.121)***	R^2	0.683
Imports (-2)	-0.6208 (0.132)***	Adjusted R^2	0.616
Imports (-3)	-0.3946 (0.121)***	F-Statistic	9.613
Imports (-4)	-0.2326 (0.08)***	Prob. (F-Statistic)	2.07e-14
SWIFT	0.3278 (0.069)***	Log-likelihood	158.7
SWIFT (-1)	0.1917 (0.079)**	Durbin-Watson	2.085
SWIFT (-2)	-0.0175 (0.083)		
SWIFT (-3)	0.0011 (0.074)		
SWIFT (-4)	0.0881 (0.061)		
BRENT	-0.1712 (0.066)**		
BRENT (-1)	-0.01 (0.087)		
BRENT (-2)	0.0888 (0.095)		
BRENT (-3)	0.0553 (0.081)		
BRENT (-4)	-0.0096 (0.095)		
PMI	0.005 (0.002)**		
PMI (-1)	0.0018 (0.003)		
PMI (-2)	-0.0005 (0.003)		
PMI (-3)	-0.0026 (0.003)		
PMI (-4)	-0.0018 (0.003)		

Standard errrors (in parenthesis) are heteroskedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at the 10 percent (*), 5 percent (**), and 1 percent (***) levels.
Sources: Haver, IHS Markit, national customs data, SWIFT, and authors' regressions.

Appendix III—Machine-Learning Algorithms

Machine-learning algorithms (MLAs) have grown in importance in recent years to establish correlation structures within big data. With ever-increasing computing power, the use of MLAs has spread widely to identify both linear and non-linear correlations in large data sets. In computer science, for example, MLAs are often used to solve highly complex tasks, like voice or face recognition.[15] In economics, MLAs have gained in importance to do text search analysis to analyze economic commentary or as alternative methods to traditional regression estimations to identify correlation structures in economic data.[16]

In this paper, we use MLAs to provide alternative methods to identify correlation structures. The main idea is that MLAs can provide insights into non-linear correlation structures between SWIFT and trade data that cannot be captured from a linear regression. This appendix explains the main characteristics of the MLAs used in the paper.

One contribution of this paper is to investigate whether the complex method is always better than the simple and interpretable linear regression in predicting trade. Because complex algorithms have more hyper-parameters to estimate, they sacrifice more degrees of freedom compared with linear regressions. This may lead to unreliable estimates if the data are not sufficiently large. The results show that in this case, linear regression is generally more suitable.

MLAs can be classified into parametric and non-parametric methods, based on whether the algorithm estimates a correlation parameter between the data. In this paper, we use two parametric MLAs (Ridge and LASSO) and six nonparametric MLAs (Decision Tree Regression, Support Vector Regression, Bagging, Random Forest, and Gradient Boost). Amongst the non-parametric MLAs, Decision Tree Regression, Support Vector Regression, and Neural Network are single methods, while Gradient Boost, Bagging, and Random Forest are ensembled methods, namely methods that combine two or more single-method algorithms.

Parametric MLAs

Parametric MLAs are alternative regression methods, which help improve the fit under specific correlation structures. Ridge and LASSO regressions are two most common parametric MLAs and have been developed to solve the problem of multi-collinearity in datasets with many variables. They are based on a standard linear regression methodology plus a regular regulation to reduce the variance of model. Both Ridge and LASSO regression use all the variables in the dataset, and adjusts the coefficient estimates of non-significant variables to *shrink* the number of regressors towards the zero. The difference between the two methods is that the Ridge regression keeps all regressors, while the LASSO regression

[15] LeCun, Bengio, and Hinton (2015).

[16] Mullainathan and Spiess (2017).

allows some regressors to be dropped by assigning a zero coefficient to statistically non-significant regressors. Thus, the LASSO regression produces a more parsimonious regression model.

The difference with the standard ordinary least square (OLS) regression method is best shown in terms of the loss functions. The standard OLS loss function is given by [17]:

$$f(\omega) = \sum_{i=1}^{m} (y_i - x_i^T \omega)^2$$

where y_i is the dependent variable, x_i^T is the vector of regressors, and ω is the vector of coefficients. In the Ridge regression, the loss function is modified as follows [18]:

$$f(\omega) = \sum_{i=1}^{m} (y_i - x_i^T \omega)^2 + \lambda \sum_{j=1}^{n} {\omega_j}^2$$

where the hyperparameter (λ) is the regularization penalty degree. The higher λ, the more penalty is associated with a larger number of regressors being kept in the regression model. In the LASSO regression, the loss function is further modified as follows:

$$f(\omega) = \sum_{i=1}^{m} (y_i - x_i^T \omega)^2 + \lambda \sum_{j=1}^{n} |\omega_j|$$

and the value of ω_i can be zero for statistically insignificant regressors.

Ridge and Lasso regressions are useful MLAs in data sets with large potential regressors with no clear ex-ante correlation structure. Specifically, Lasso regressions are useful in large data sets to home in a linear parsimonious model that is statistically significant.

Non-parametric MLAs

Non-parametric MLAs do not assume a particular correlation structure in the dataset. They instead derive the correlation structure from a series of operations to divide data into subsets (e.g., Decision Tree Regression) or derive bimodal distributions to the correlation structure (e.g., Neural Network).

Non-parametric MLAs can be divided into single-method and ensemble MLAs. Single-method MLAs use a single MLA method to derive the results, while ensemble MLAs calculate the average of single-method MLAs. Decision Tree Regression, and Support Vector

[17] Hayashi (2000).

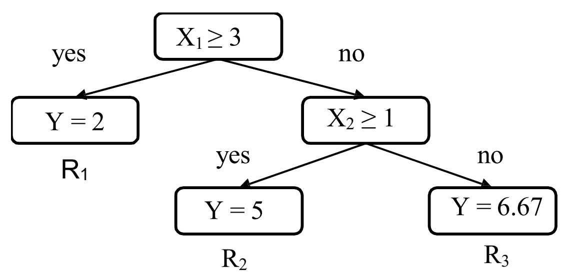
[18] Pedregosa et al. (2011).

Regression are single methods, while Gradient Boost, Bagging, and Random Forest are ensembled methods.

The Decision Tree Regression is a single-method MLA that captures the nonlinearity inside data sets by dividing data into homogeneous subsets to minimize the overall standard deviation.[19] This method seeks recursively to split the data into subsets so as to find linear solutions within the subset that can improve the overall fit. This method uses a top-down binary approach to choose the best attribute to divide the space. The best attribute will lead to the largest standard deviation reduction in all generated subsets.

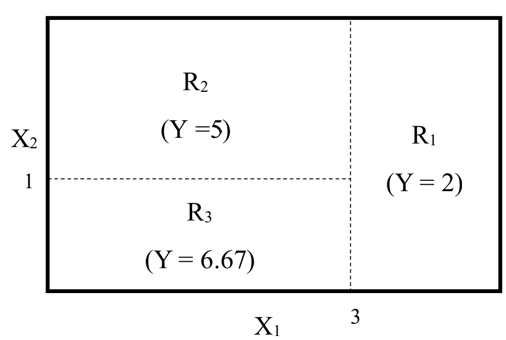
The following example provides an illustration of the Decision Tree Regression method. Suppose we want to predict Y from regressor X_1 and X_2 using a Decision Tree Regression MLA. This method will split the dataset into interval to reduce the standard error within the subsets as in Figure 1.

Figure III.1. The Decision Tree Regression[20]



The data set is correspondingly divided into three subsets as in Figure 2. All the observations in a subset minimize the standard error in the linear estimation of the mean value of Y.

Figure III.2. Partition of the Dataset



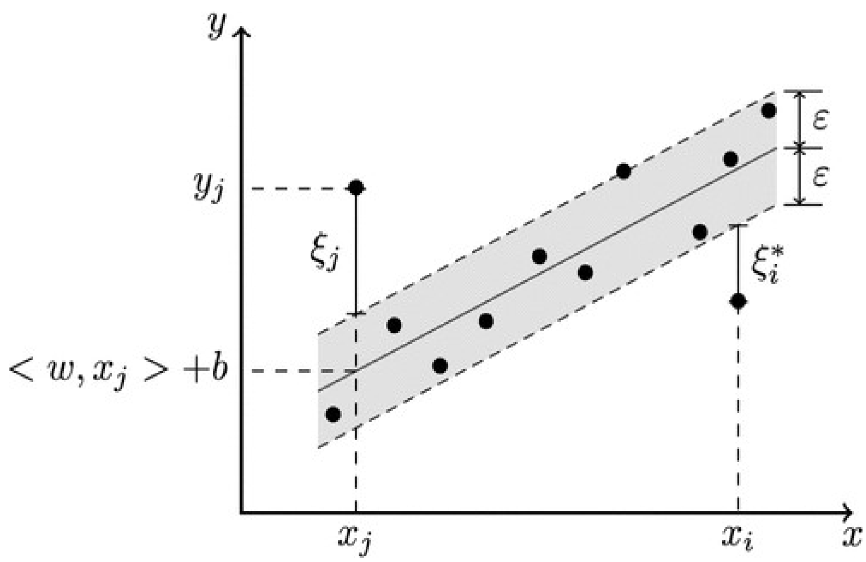
[19] Breiman, Friedman, Ohlsen, and Stone (1984).

[20] Lantz (2013).

The Decision Tree Regression MLA is therefore able to capture non-linearities in the data. In the example above, this method found locally linear means of the dependent variable (Y) in each subset, but the global mean of Y is clearly highly non-linear. The effectiveness of the Decision Tree Regression method is based on the homogeneity in each subset. The tradeoff is between the size of each subset and the minimization of the standard error.

Support Vector Regression (SVR) use a *fixed-width stripe* to fit the observations, instead of a *line* as linear regression. SVR seeks to identify such a stripe to cover as many sample observations as possible to minimize the aggregate standard error[21]. Unlike linear regressions, the stripe can be a non-linear curve.

Figure III.3. The Fitting Process of the Support Vector Regression



Source: Moustapha et al. (2018).

SVR can turn a nonlinear problem into a linear one (Figure 4). This method deals with nonlinearities in the dataset by reflecting the regressor space into a higher dimensional space using a kernel function. For example, suppose the true non-linear data-generating process is

$$f(x) = 2X^2 + \varepsilon, \ \varepsilon \in (0,1) \ .$$

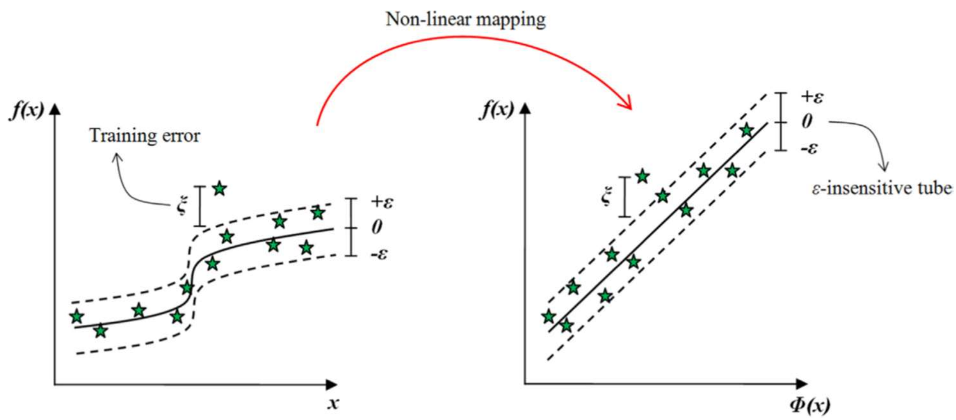
To convert this process into a linear one, we transform the function using the kernel function $\Phi(x) = X^2$ as follows:

[21] Basak and Patranabis (2007).

$$f(x) = 2\Phi(x) + \varepsilon,\ \varepsilon \in (0,1).$$

which then become a linear problem in the space of $\Phi(x)$. As this example shows, SVRs will be effective in capturing complex polynomial correlation structures in the data. However, non-linearities are not always of a polynomial nature. Likewise, SVRs can use a multitude of of kernel functions to capture different type of non-linearities in the data, including linear, polynomial, radial basis function, and sigmoid.

Figure III.4. Mapping Non-Linear SVR into High-Dimension Regressor Space [22]



Source: Mahdevari et al. (2014).

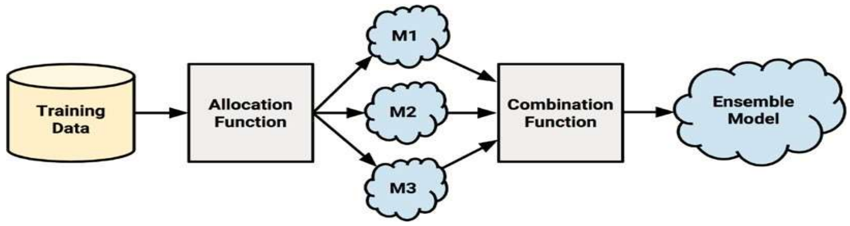
Non-parametric ensemble MLAs

Non-parametric ensemble MLAs combine predictions from multiple single method to generate a more accurate forecast (Figure 5).[23] The allocation functions of bootstrap aggregating (Bagging) is choosing different subsamples for M1 – M3 from the original dataset, Gradient Boosting is iteratively adjusting the weights for observations in dataset, and Random Forest is using different subsets. In practice, the most frequently used single method is the Decision Tree Regression.

[22] Mahdevari, Shahriar, Yagiz, and Shirazi (2015).

[23] Russell and Norvig (1943).

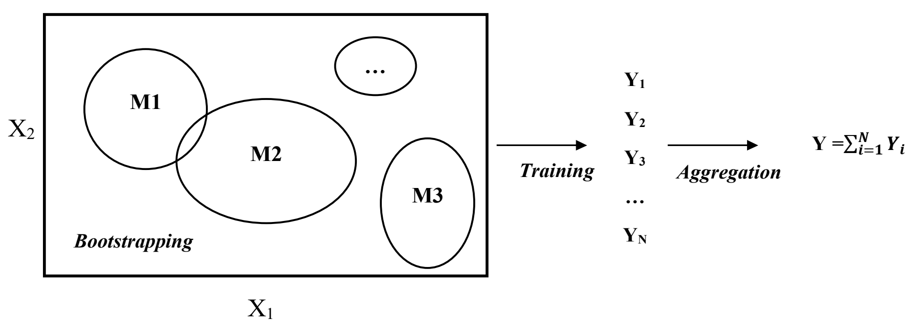
Figure III.5. Process of Ensemble Method [24]



Source: Pedregosa et al. (2011).

Bagging parallelly estimates the base method on subsamples of the original data sets and averages the outcomes of all models as the final output (Figure 6). Bagging starts by extracting the subsample from the original sample set using bootstrapping, resulting in N independent training sets. Each time, a training set is used to obtain a model, generating a total of N models. For the regression problem, the mean value of the above model is calculated as the result, with all models having the same importance.

Figure III.6. Bagging Method

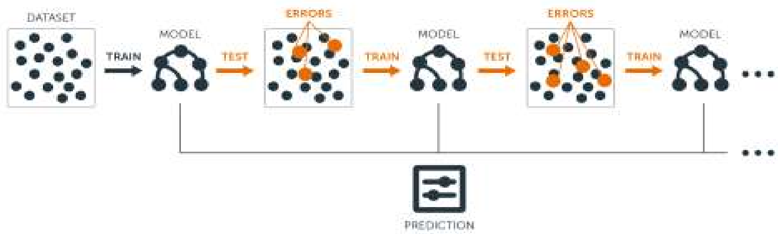


The Gradient Boosting method approaches the *true* model by iteratively estimating every model using the residuals of all previous models (Figure 7). The residual is the difference between true value and the predicted value for each model. [25] For example, suppose the true value is 10, and the prediction of the first model is 6. The training set for the second model will be 10 - 6 = 4. If the prediction of the second models is 3, the residual to train the third model will be 4 – 3 =1. The final prediction is to aggregate the output of all models: 6 + 3 + ...

[24] Lantz (2013).

[25] Dietterich (2001).

Figure III.7. Gradient Boosting Method[26]

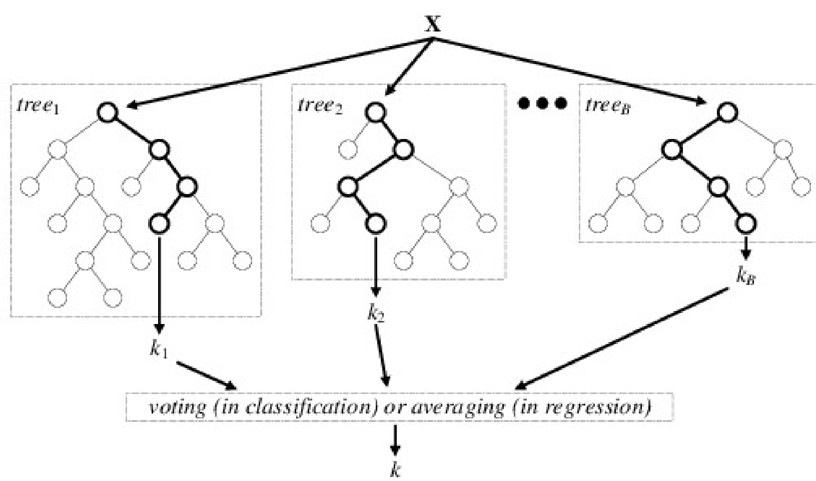


Source: Boehmke and Greenwell (2019).

The Gradient Boosting method used in the paper follows the process above and efficiently chooses the fastest direction to reduce the residuals during iterations. During each iteration, the method shrinks the learning rate from the residual to maintain a balanced performance to avoid overfitting.

The Random Forest method parallelly selects a random subset of the input variables to train the Decision Tree Regression and average the results for all trees (Figure 8). For example, suppose there are five input variables $X = \{X_1, X_2, X_3, X_4, X_5\}$ and three trees are estimated in Random Forest. The random variable sample allocated to tree 1 contains all five variables X, the sample to tree 2 has four variables $\{X_1, X_2, X_4, X_5\}$, and to tree 3 has three $\{X_2, X_3, X_5\}$. Correspondingly, the trees generate three predictions k_1, k_2, and k_3. The final output is the average $k = (k_1 + k_2 + k_3)/3$.

Figure III.8. Random Forest Method[27]



Source: Verikas et al. (2016).

[26] LeCun, Bengio, and Hinton (2015).

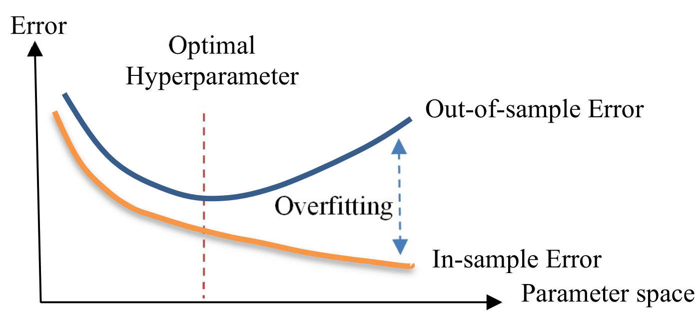
[27] *Ibidem*.

Under- and over-fitting

Two issues that strongly influence the out-of-sample forecast ability of the models is under- and over-fitting. Underfitting happens when a model fails to adequately capture the underlying structure of the data. The typical example is fitting a linear model to non-linear data. Since trade and SWIFT data are volatile and influenced by highly non-linear factors and shocks, including crisis and geopolitical incidence, such non-linearities are not likely to be captured by linear model, which would lead to underfitting. In contrast, MLAs have more flexible structures and can thus capture highly non-linear relationship in the data. However, MLAs may inadvertently fit *noise* as well as *signal* during the estimation, and thus lead to overfitting. Overfitting indicates that the model fits well in the in-sample training set but performs poorly in the out-of-sample forecast, since the *noise* in the in-sample training set may not be present in the out-of-sample test set.

An outstanding difference between linear regressions and MLAs is that MLAs have hyperparameters that determine their structures, enable them to capture the complexity in-sample, and avoid overfitting out-of-sample. The hyperparameters of the MLAs strongly influence the performance of the forecast, as well as the degree to which the model overfits the data. For example, the hyperparameter for a Ridge Regression is the penalty degree that controls the speed that the coefficients shrink towards zero. To avoid overfitting, optimal hyperparameters are determined to achieve a balanced performance for both in-sample and out-of-sample prediction. A commonly used method to avoid overfitting is the K-fold cross-validation method, which adjusts the hyperparameters to minimize the out-of-sample forecast error as shown in Figure 9.[28]

Figure III.9. Overfitting and Optimal Hyperparameter

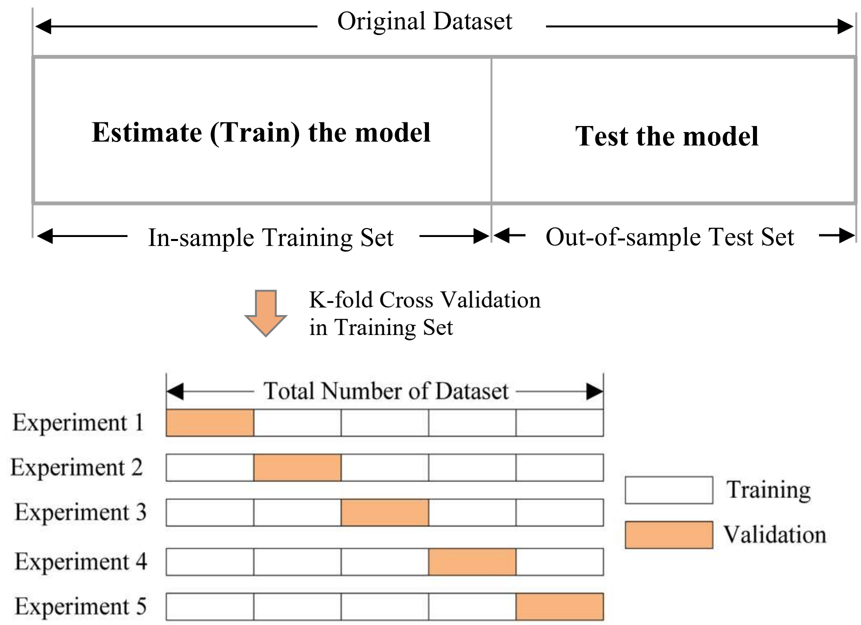


Choosing optimal hyperparameters for MLAs using the K-fold cross-validation can avoid overfitting and decrease out-of-sample forecast error. In estimation, the selection of hyperparameters is already targeted at minimizing out-of-sample error. For example, when K=5, the original in-sample training set is randomly partitioned into 5 equally sized subsets. Each time one of the subsets is used as out-of-sample validation set, with the 4 remaining subsets combined into one in-sample training set to estimate the model. The hyperparameters

[28] Lantz (2013).

are validated during the process and achieve a balance between in- and out-of-sample performance (Figure 10).

Figure III.10. K-Fold Cross Validation in Estimation Process (K=5)



MLAs can overcome the underfitting problem of OLS method and avoid overfitting by finetuning the hyperparameters, thus generate relatively lower forecast errors.

Advantages and disadvantages of MLAs over linear regressions

Compared with linear regressions, MLAs do not impose an ex-ante parametric structure to the dataset. A linear regression relies on a set of strong assumptions on the data-generating process to estimate a reduced-formed parametric structure. MLAs instead seek to identify an underlying correlation structure that is validated through subsequent observations by extracting signal from noise, thus allowing for a linear or nonlinear correlation structures in the dataset. Such difference in the estimation procedures between the two methods creates advantages and disadvantages.

Linear regressions require a series of strong assumptions on the data generating process. The five main assumptions of linear regressions are a linear (or log-linear) relationship, multivariate normality, limited multicollinearity, no autocorrelation and homoscedasticity. Such assumptions can erroneously define the data-generating process, make the statistical estimation meaningless, and lead to misleading out-of-sample forecasts. However, if the assumptions hold, linear regressions can provide parameter estimation results and produce a globally valid forecast. Thus, the advantage of a linear regression is that it provides a parametric estimation that has explanatory power.

MLAs can cover wide array of functional forms and select features to capture a non-linear correlation in the dataset. MLAs can identify complex patterns and hidden relationships, including highly nonlinear and contextual relationships that are often difficult to uncover with linear regressions. MLAs are also more effective than linear regressions in the presence of multicollinearity. For instance, MLAs can detect suitable interaction terms automatically, but such terms need to be identified manually in linear regression. The main advantage of MLAs is therefore their flexibility in identifying complex data-generating structures. However, MLAs may suffer from overfitting or identify wrong functional forms. Existing dataset contains both signal and noise. MLAs try to approximate the existing dataset with certain functional form, which can be plausible and highly relevant in training sets but may not represent the correct data-generating structure. Different functional forms could also possibly generate similar data patterns. In addition, the lack of a parametric representation (except for Lasso and Ridge regressions) makes the interpretation of the results more difficult.

Appendix IV—Methodology for SWIFT Forecasts

This appendix summarizes the methodology used in this paper for SWIFT forecasts. It describes data sources and variable descriptions, the one-month ahead forecast, the recursive method, the evaluation of the algorithms, and the methodology to eliminate outliers.

Data source and variable description

The dependent variable is the seasonally adjusted monthly merchandise exports and imports of a given country or the whole world (Table 1). The explanatory variables are lags of the dependent variables, the corresponding SWIFT MT 700 message, the Brent crude oil price, and their lags. All variables are expressed in log differences. The precise definition of variables appearing in the different models are summarized below.

Variable	Data description and source	Transformation
MG_t	Total monthly merchandise imports (or exports) of a given country in USD, World trade in USD, seasonally adjusted. Source: Netherlands Bureau for Economic Policy Analysis (CPB) for world trade and national customs departments/Haver Analytics for merchandise exports and imports for a single country.	$x_t = \log(MG_t) - \log(MG_{t-1})$
$SWIFT_t$	Corresponding USD amount of total monthly SWIFT MT 700 messages, seasonally adjusted. Source: SWIFT.	$y_t^1 = \log(SWIFT_t) - \log(SWIFT_{t-1})$
OIL_t	Average monthly Brent oil price in USD and Brent Oil Futures Prices at 1-month, 3-month, and 6-month maturity (interpolated). Source: Energy Information Administration, Intercontinental Exchange/Haver Analytics.	$y_t^2 = \log(POIL_t) - \log(POIL_{t-1})$
PMI_t	New export orders subcomponent of manufacturing PMI. Centered around zero instead of fifty. Available for the world and for 30 out of 40 countries in the sample. Where not available, this explanatory variable is dropped. Sources: Markit, JP Morgan, Haver.	$y_t^3 = PMI_t - 50$

Dataset and estimation

The dataset spans the period November 2010 to May 2020. The dataset for the dependent variable is t=5 to 117 and is split into (a) a training set ($\mathcal{A}$): t=5 to 105 (100 monthly observations), and (b) an out-of-sample test set ($\mathcal{T}$): t=106 to t=117 (12 monthly observations). (Y_t) is available from 2010:11 (t=1) to 2020:05 (t=115). The estimated model on the training set is given by:

$$\hat{x}_t = f(x_{t-1}, \dots, x_{t-4}, Y_t, \dots, Y_{t-4})$$

One-month ahead forecast model

The one-month ahead forecast is derived from a functional form of lagged variables of the dependent and explanatory variables. In the notation below, t stands for the last month for which custom data x is available. The one-month ahead forecast $\hat{x}_{t+1}$ is given by the following estimated model:

$$\hat{x}_{t+1} = f(x_t, \dots, x_{t-3}, Y_{t+1}, \dots, Y_{t-3})$$

where vector Y contains any subset of the three additional explanatory variables included in the vector Y (SWIFT, oil price), and f depends on the algorithm (i.e. linear, Ridge, Lasso, etc.) and the vector Y. In general, explanatory variables are available before customs data are released, so Y appears with a lead in the model.

Recursive method

The recursive method is built by using the one-month ahead forecast model for subsequent months. The recursive method consists of: (a) deriving the explanatory variables over the forecast horizon using an AR process, or the futures curve for oil prices, and (b) forecasting the dependent variable using recursively the one month ahead forecast algorithm estimated above. The projection model for additional explanatory variables is an AR(1) model used recursively to the end of the forecast horizon as shown below:

$$y_t = \sum_{i=1}^{3} \alpha_i \, y_{t-i} + \beta + \epsilon_t$$

The following illustrates the recursive method. The two-month ahead forecast is based on the one-month ahead algorithm feed with the following explanatory variables set that include the one-month ahead forecast plus the projection of the additional explanatory variables:

$$\hat{x}^{(2)}_{t+2} = f(Z^{(2)}_{t+1})$$

where

$$Z^{(2)}_{t+2} = \left[\hat{x}^{(1)}_{t+1}, x_t, x_{t-1}, x_{t-2}, \hat{Y}^{(1)}_{t+2}, Y_{t+1}, Y_t, Y_{t-1}, Y_{t-2}\right]$$

Recursively, the three-month ahead forecast is given by

$$\hat{x}^{(3)}_{t+3} = f(Z^{(3)}_{t+2})$$

where

$$Z_{t+3}^{(3)} = \left[\hat{x}_{t+2}^{(2)}, \hat{x}_{t+1}^{(1)}, x_t, x_{t-1}, \hat{Y}_{t+3}^{(2)}, \hat{Y}_{t+2}^{(1)}, Y_{t+1}, Y_t, Y_{t-1}\right]$$

and so on until the five-month ahead forecast is constructed.

Evaluation

The accuracy of the forecast algorithm is evaluated from the comparison between i-months ahead RMSE over the test set:

$$RMSE^i = \left[\frac{1}{N(\mathcal{T})}\sum_{t\in\mathcal{T}}\left(x_t - \hat{x}_t^{(i)}\right)^2\right]^{1/2}$$

and the naïve RMSE ($RMSE^n$) over the same test set where forecasted value is equal to the mean of the forecasted variable over the full sample.

$$RMSE^n = \left[\frac{1}{N(\mathcal{T})}\sum_{t\in\mathcal{T}}\left(x_t - \hat{x}\right)^2\right]^{1/2} \qquad \text{where} \qquad \hat{x} = \frac{\sum_{t\in\mathcal{A}}\hat{x}_t}{N(\mathcal{A})}$$

Outlier methodology

The SWIFT database includes some outliers in level. To test the robustness of our methodology, the models above are estimated using both raw and data cleaned of outliers. Specifically, an ARIMA(1,1,1) model is used on SWIFT data in log (here, u stands for log($SWIFT_t$)) to eliminate outliers as follows:

$$u_t - (1+\alpha)u_{t-1} + \alpha u_{t-2} = \varepsilon_t + \theta_1\varepsilon_{t-1} + c$$

The series of residuals ε_t is cleaned such that every value higher than 3 times the standard deviation is replaced by zero and the cleaned $\tilde{u}_t$ series is recalculated from the estimated ARIMA equation.