INTERNATIONAL MONETARY FUND

Another Piece of the Puzzle:

Adding SWIFT Data on Documentary Collections to the Short-Term Forecast of World Trade

Prepared by Narek Ghazaryan, Alexei Goumilevski, Joannes Mongardini, and Aneta Radzikowski

WP/21/293

2021
DEC

WORKING PAPER

 WP/21/293

IMF Working Paper
Research Department

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Authorized for distribution by Benjamin Hunt
December 2021

ABSTRACT: This paper extends earlier research by adding SWIFT data on documentary collections to the short-term forecast of international trade. While SWIFT documentary collections accounted for just over one percent of world trade financing in 2020, they have strong explanatory power to forecast world trade and national trade in selected economies. The informational content from documentary collections helps improve the forecast of world trade, while a horse race with machine learning algorithms shows significant non-linearities between trade and its determinants during the Covid-19 pandemic.

RECOMMENDED CITATION: Ghazaryan, N. and A. Goumilevski, J.Mongardini, and A. Radzikowski (2021). “Another Piece of the Puzzle: Adding Swift Data on Documentary Collections to the Short-Term Forecast of World Trade”, IMF Working Paper No. 21/293, December 2021.

JEL Classification Numbers:	F17, F47
Keywords:	SWIFT; trade forecast; machine learning
Author’s E-Mail Address:	Narek.Ghazaryan@cba.am; agoumilevski@imf.org; jmongardini@imf.org; aradzikowski@imf.org

* Narek Ghazaryan was an economist in the Research Department of the International Monetary Fund when this research project was started. He is currently advisor to the Head of the Financial Supervision and Licensing Department at the Central Bank of Armenia. Alexei Goumilevski is a financial modeler in the Information Technology Department, and Joannes Mongardini and Aneta Radzikowski are deputy division chief and research officer, respectively, in the Research Department of the International Monetary Fund. We are grateful to Hayk Avetisyan, Hayk Karapetyan, Benjamin Hunt, Gevorg Minasyan, Armen Nurbekyan, Rafael Portillo, and Astrid Thorsen for useful comments on earlier drafts of this working paper.

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Introduction

This paper complements an earlier IMF working paper[1] published in November 2020 (hereinafter referred to as CHMMR) by adding SWIFT data on documentary collections to improve the short-term forecast of international trade. To the extent that SWIFT messages on documentary collections have strong explanatory power, they can provide an early indication of the short-term direction of world trade.

Documentary collections are a financial agreement between exporters, importers, and their respective financial institution, whereby the bank representing the importer, *the collecting bank,* agrees to release the importing documents to the importer only once the importer has paid for the imported goods. Under documentary collections, the exporter ships the goods and submits the shipping documents to its financial institution, called the *remitting bank*. The *remitting bank* then transfers the documents to the *collecting bank*, which will only release them to the importer once payment for the imported goods is collected.

Documentary collections are preferable to letters of credit as they are less costly and generally involve a single legal jurisdiction. If a legal dispute about documentary collections arises, the dispute can be handled in the importing economy without involving lengthy and complex international legal disputes associated with a letter of credit. However, documentary collections do not provide a financial guarantee of payment, like letters of credit do. Exporters therefore still face the risk of not being paid. As such, documentary collections are often used by trading partners with a well-established business relationship, and when trading partners have not yet moved to an open account system, namely a system of direct payments between the importer and the exporter without any form of bank financing or guarantee.

To the extent that the financing of international trade happens ahead of the actual movement of goods, documentary collections, like letters of credit, represent an early indicator of future trade activity. While documentary collections accounted for just over one percent of the financing of international trade in 2020, they have strong correlation with world trade and international trade in selected economies. They are particularly relevant for financing imports from Asia, where importers and financial institutions prefer to keep their legal arrangements within their legal jurisdiction rather than using a letter of credit.

This paper investigates the relevance of SWIFT messages on documentary collections (referred hereafter by their SWIFT identification code MT 400) to forecast international trade. Section II describes the financial and trade flows associated with documentary collections. Section III presents the regression results of world trade adding SWIFT MT 400 messages to the specification described in CHMMR. It then shows linear forecasts of world trade during the Covid-19 crisis using such specification and compares them to an alternative Dynamic Factor Model (DFM). Section IV discusses the linear regression forecasts for national trade for several economies. Section V assesses the horse race between linear regressions and machine learning algorithm. Section VI concludes.

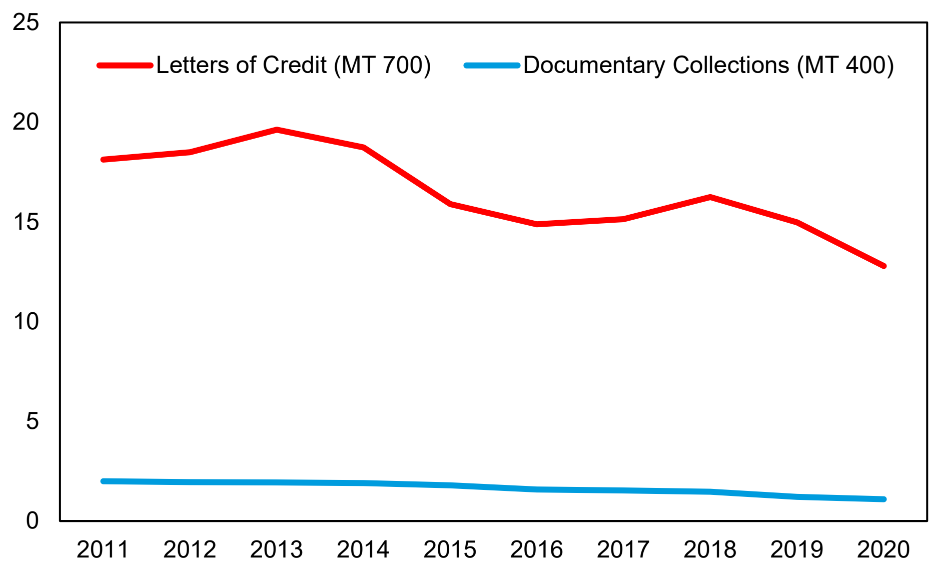
[1] Carton, B. and others (2020).

Documentary Collections

SWIFT is the main provider of secure financial messaging systems used by financial institutions around the world to settle international financial payments, securities, foreign exchange transactions, treasury operations, and trade flows.[2]

One common set of SWIFT messages used to finance international trade are letters of credit. Letters of credit are contracted by importers from their own banks (the *issuing bank*) to import merchandise goods against a fixed transaction fee and interest payments. The *issuing bank* sends the letter of credit to the exporter's bank (the *advising bank*) as a guarantee of payment. The payment is then effectuated once the exporter has shipped the goods to the importer. SWIFT messages on letters of credit (MT 700 messages) accounted for about 12 percent of world merchandise trade in 2020, while documentary collections (MT 400 messages) were used to finance just over 1 percent of world trade in 2020 (Figure 1). Niepmann and Schmidt-Eisenlohr (2017) and Carton and others (2020) provide more details about trade financing through letters of credit.

Figure 1. Share of World Trade Financed by SWIFT Letters of Credit and Documentary Collections, 2011-20



Sources: CPB, SWIFT, and authors' calculations.

Documentary collections are a less common type of SWIFT messages used to finance international trade. Documentary collections are a contractual arrangement between the exporter's bank (the *remitting bank*) and the importer's bank (the *collecting bank*) to effectuate payment once the importer has paid for the imported goods (Figure 2).[3] This method offers an exporter some degree of security as the payment is facilitated through the banks. The title documents are transferred from the *collecting bank* to the importer only after payments for

2 SWIFT (2021). 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 (2019) for additional information. Data relating to SWIFT messaging flows is published with permission of S.W.I.F.T. SC. SWIFT © 2021. 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.

3 International Trade Administration (2021).

the goods are received. Once the exporter and importer decide to use documentary collections as a financing method, the exporter sends the bill of sale and other exporting documents to the *remitting bank*. The documents are then forwarded to the *collecting bank*, which releases them to the importer only once payment for the imported goods is made or the importer agrees to make a payment on a due date.[4]

Figure 2. Documentary Collections: Financial Flows and Merchandise Trade

Source: Authors' representation.

Letters of credit and documentary collections are thus quite different financial contracts. First, while letters of credit are essentially a financial guarantee by the *issuing bank* to the *advising bank*, no financial guarantee is provided in documentary collections. The only agreement is that the *collecting bank* will not release the importing documents to the importer until payment is effectuated (or similar arrangement). Second, while there can still be disputes between the exporter and importer in terms of the delivery or the quality of the goods shipped, financial disputes in documentary collections generally occur between the *collecting bank* and the importer as to the release of the import documents. In this respect, documentary collections imply less of a risk of a cumbersome international legal dispute usually associated with letters of credit as the *collecting bank* and the importer usually reside in the same legal jurisdiction. Finally, the cost to the importer of a letter of credit (given the financial guarantee involved) is usually significantly higher than that of a documentary collection. Documentary collections are therefore most often used among existing trading partners, which have a well-established business relationship, but have not yet moved to an open-account system, namely a system of direct payments between the importer and the exporter without the need for a letter of credit or a documentary collection. [5]

The use of letters of credit and documentary collections varies by export destination. Letters of credit are generally used more than documentary collections for exports to economies with weaker contract enforcement.[6] As shown in Figure 3 below, the main export flows financed by letters of credit (MT 700 messages) are within the triangle between China, Hong Kong SAR, and Singapore. On the contrary, the main

[4] Danske Bank (2021).

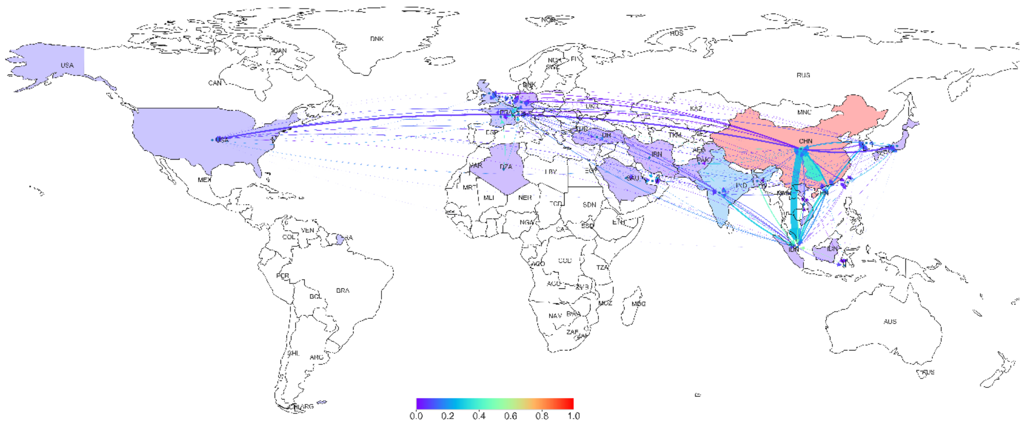
[5] International Trade Administration (2021).

[6] Niepmann and Schmidt-Eisenlohr (2017).

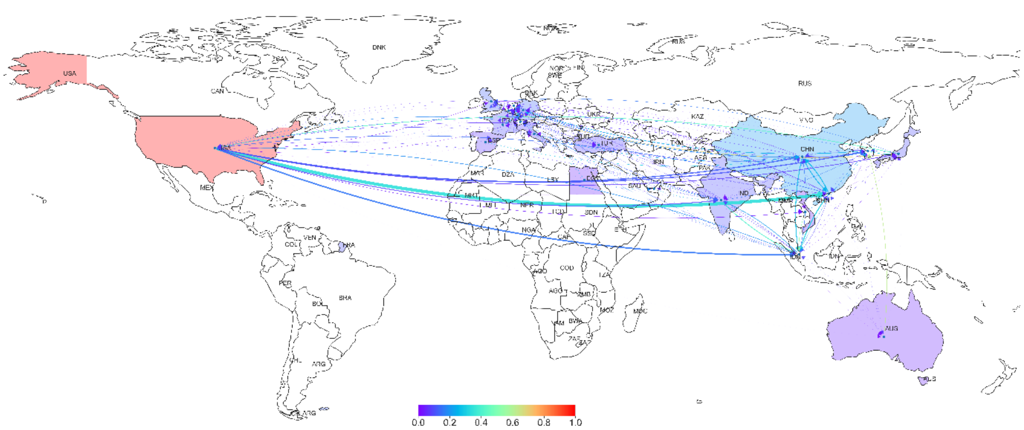
export flows associated with documentary collections (MT 400 messages) are between Asia (notably China, India, Korea, and Singapore) and the United States.

Figure 3. Global Map of SWIFT Trade Messages for Merchandise Exports, August 2021
(Percent of Total)

A. Letters of Credit (MT 700 Messages)



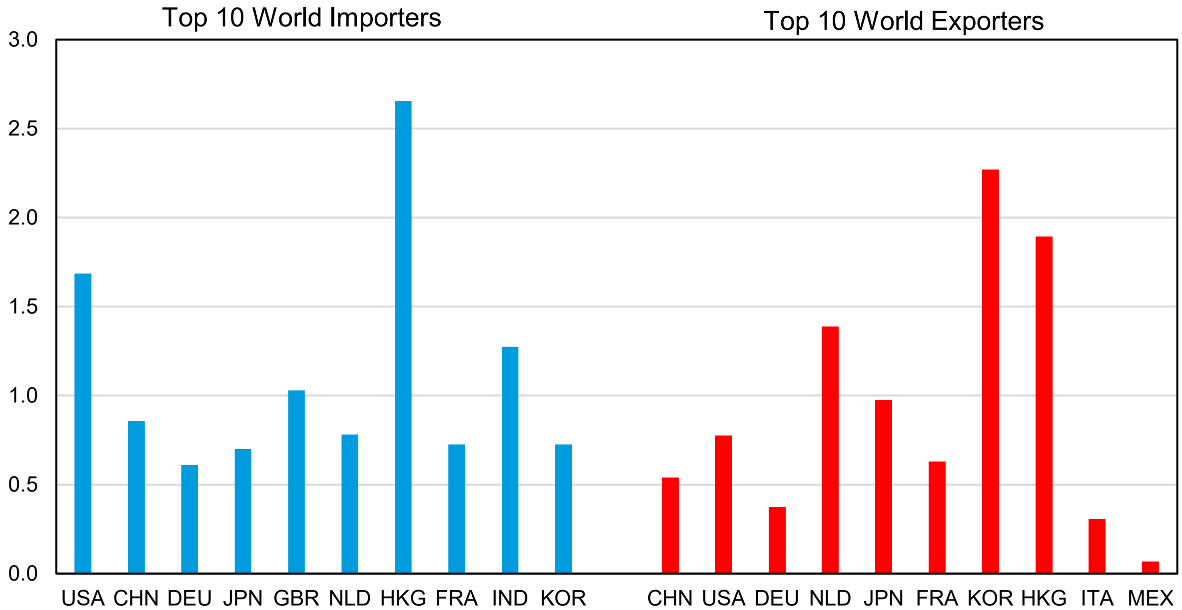
B. Documentary Collections (MT 400 Messages)



Source: SWIFT and authors' representation.

Amongst the top 10 importers in the world, the main users of SWIFT MT 400 messages in 2020 were Hong Kong SAR, the United States, and India (Figure 4). Amongst the top 10 exporters, documentary collections were used the most by Korea, Hong Kong SAR, and the Netherlands. However, as discussed below, these results may reflect the fact that most international banks associated with SWIFT MT 400 messages reside in Hong Kong SAR, the Netherlands, and the United States, and may not be directly related to the trade flows of these economies.

Figure 4. Share of Merchandise Trade Financed by SWIFT MT 400 Messages For the 10 Largest Importers and Exporters in the World, 2020



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

Both SWIFT MT 700 and MT 400 messages can be used as leading indicators of world trade, as they are typically sent before the title documents are transferred to the importer and cleared through customs. The lead time varies across economies and merchandise, and it mainly depends on the exporters' production and export lags, the geographical distance between the trading partners, and the time it takes to clear the goods through customs in the importing economy.

Documentary Collections and World Trade

This section presents the results of including SWIFT documentary collections in the regression of world trade. As in CHMMR, a simple regression is posited (Equation 1). World trade (*WT*) is regressed against its own lags, SWIFT MT 400 messages (*SWIFT4*), SWIFT MT 700 messages (*SWIFT7*), Brent crude oil prices (*Brent*), and the new export orders subcomponent of the global manufacturing Purchasing Managers' Index (*PMI*).[7] All variables have up to four lags and are expressed in log differences except *PMI*, which is expressed in its original diffusion index form re-centered around zero. The reduced-form equation is then as follows:

$$dlog(WT_t) = \alpha + \beta_i dlog(WT_{t-i}) + \gamma_j dlog\left(SWIFT4_{t-j}\right) + \delta_j dlog\left(SWIFT7_{t-j}\right) + + \vartheta_j dlog(Brent_{t-j}) + \mu_j PMI_{t-j} + \varepsilon_t \qquad (1)$$

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

The regression results confirm the significance of SWIFT MT 400 (*SWIFT4*) and MT 700 (*SWIFT7*) messages, together with Brent crude oil prices and new export orders, in determining the value of world trade (Table 1). In the specification with only SWIFT messages (third column), the contemporaneous coefficients on *SWIFT4* and *SWIFT7* and some of their lags are positive as expected and highly significant, with an R^2 of just over 50

[7] The sources and definitions of the variables are summarized in Appendix I. Brent crude oil prices affect internal trade both directly as an important nominal share of world trade and, indirectly, as a good proxy for real global economic activity.

percent. Once *Brent* crude oil prices and *PMI* are included, the contemporaneous coefficient on *SWIFT4* remains highly significant, but *SWIFT7* coefficients become insignificant. This result is consistent with those in CHMMR. *SWIFT7* and *Brent* seem to be non-orthogonal, and the contribution of *SWIFT7* messages is diminished when *Brent* is included. A possible explanation of this result is that *SWIFT7* messages are partly used to finance a significant portion of hydrocarbon trade in Asia.

Overall, the regression results 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 next section.

Forecast of World Trade

This section describes the forecast of world trade using the specification with all explanatory variables in equation (1). Specifically, it focuses on the period of the Covid-19 crisis starting in January 2020 and its aftermath to gauge how well the SWIFT trade forecast performed during that period. This will then set the stage for a comparison with a different forecast method, the Dynamic Factor Model, in the next section.

The impact of the Covid-19 pandemic on the global economy has been unique, both in terms of the depth of its trough in April/May 2020 and its rapid recovery, following the lifting of lockdown measures around the world. World real GDP is estimated to have contracted by 3.1 percent in 2020, while it is projected to rebound by 5.9 percent in 2021.[8] Supply chain disruptions, the unprecedented decline in cross-country social mobility, the containment measures introduced by governments, falling commodity prices, and the tightening of financial conditions hit global trade severely (Espitia et al. (2021)). As a result, world trade contracted by more than 20 percent in the first four months of 2020, reaching its lowest level in April/May 2020 (Figure 5).

Starting from June 2020, world trade showed strong growth, supported by unprecedented monetary and fiscal stimuli across the globe, a gradual relaxation of containment measures, and adjustment of households and businesses to the so-called new normal. As a result, world trade surpassed the pre-pandemic levels in October 2020. By contrast, the Global Financial Crisis (GFC) of 2008-10 had a much sharper contraction over the first 10 months, followed by a gradual recovery over the following 20 months.

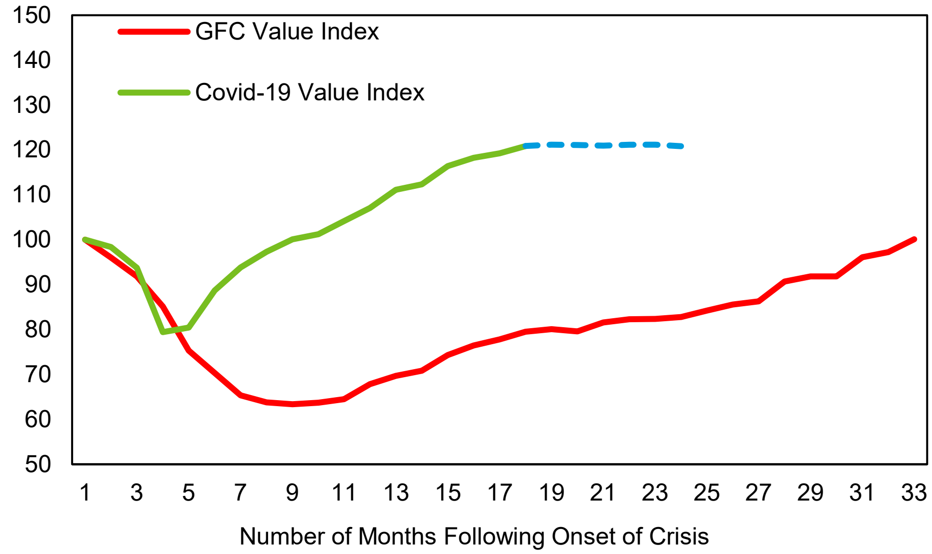
[8] IMF (2021).

Table 1. World Trade: Comparison of Different Regression Specifications
Sample: April 2011-June 2021 (123 observations)
(Coefficients and Standard Errors in Parenthesis)*

	World Trade	+ SWIFT4	+ SWIFT7	+ OIL	+ PMI	- SWIFT4-7	- PMI
Constant	0.0012	0.0051	0.0043	0.0035	0.0023	0.0018	0.0028
	(0.002)	(0.002)***	(0.002)**	(0.001)***	(0.001)**	(0.001)	(0.001)**
World Trade (-1)	0.3205	0.1371	-0.0858	-0.1223	-0.2323	-0.2055	-0.1034
	(0.133)**	(0.088)	(0.106)	(0.099)	(0.085)***	(0.078)***	(0.106)
World Trade (-2)	-0.0582	-0.1090	-0.0865	0.0483	0.0452	0.0455	-0.0141
	(0.218)	(0.153)	(0.141)	(0.105)	(0.089)	(0.089)	(0.108)
World Trade (-3)	-0.0359	-0.1972	-0.1498	-0.0598	0.0648	0.1205	-0.0252
	(0.079)	(0.090)**	(0.106)	(0.119)	(0.104)	(0.097)	(0.096)
World Trade (-4)	0.0437	-0.1748	-0.1976	0.0140	0.2005	0.2454	0.1166
	(0.096)	(0.103)*	(0.128)	(0.108)	(0.077)**	(0.067)***	(0.088)
SWIFT4		0.3448	0.2371	0.1379	0.0770		
		(0.110)***	(0.070)***	(0.045)***	(0.036)**		
SWIFT4 (-1)		0.2062	0.1586	0.0525	0.0489		
		(0.071)***	(0.062)**	(0.040)	(0.032)		
SWIFT4 (-2)		0.0193	-0.0463	-0.0723	-0.0278		
		(0.064)	(0.075)	(0.051)	(0.036)		
SWIFT4 (-3)		0.1330	0.0447	0.0384	0.0413		
		(0.056)**	(0.050)	(0.053)	(0.044)		
SWIFT4 (-4)		0.1873	0.1432	0.0675	0.0225		
		(0.083)**	(0.066)**	(0.047)	(0.038)		
SWIFT7			0.1561	0.0186	0.0219		
			(0.055)***	(0.025)	(0.025)		
SWIFT7 (-1)			0.1207	-0.0135	0.0174		
			(0.033)***	(0.031)	(0.027)		
SWIFT7 (-2)			0.0348	-0.0385	0.0027		
			(0.037)	(0.036)	(0.029)		
SWIFT7 (-3)			0.0531	-0.0171	0.0079		
			(0.029)	(0.035)	(0.026)		
SWIFT7 (-4)			0.0175	0.0048	-0.0138		
			(0.029)	(0.014)	(0.012)		
Brent				0.1010	0.0622	0.0804	0.1205
				(0.018)***	(0.016)***	(0.015)***	(0.020)***
Brent (-1)				0.1030	0.0577	0.0638	0.1068
				(0.021)***	(0.019)***	(0.020)***	(0.022)***
Brent (-2)				0.0194	-0.0078	-0.0029	0.0127
				(0.023)	(0.019)	(0.020)	(0.023)
Brent (-3)				0.0258	0.0128	0.0152	0.0308
				(0.025)	(0.024)	(0.018)*	(0.019)
Brent (-4)				-0.0003	-0.0221	-0.0259	-0.0063
				(0.017)	(0.014)	(0.016)*	(0.019)
PMI					0.0047	0.0048	
					(0.001)***	(0.001)***	
PMI (-1)					-0.0019	-0.0019	
					(0.001)	(0.001)	
PMI (-2)					-0.0017	-0.0017	
					(0.002)	(0.001)	
PMI (-3)					-0.0017	-0.0016	
					(0.001)	(0.001)	
PMI (-4)					0.0003	0.0001	
					(0.001)	(0.001)	
Diagnostics							
R^2	0.097	0.376	0.507	0.706	0.801	0.779	0.661
Adjusted R^2	0.066	0.326	0.443	0.652	0.753	0.75	0.634
F-Statistic	1.573	2.807	4.151	9.230	29.33	45.00	10.72
Prob. (F-Statistic)	0.186	0.005	9.12e-06	7.87e-15	1.56e-34	1.67E-38	6.79E-12
Log-likelihood	289.45	312.15	326.71	358.46	382.54	375.90	349.65
Durbin-Watson	2.002	2.065	2.060	1.974	1.982	1.976	1.951

Source: Authors' regression results.
* Standard errors are heteroscedasticity and autocorrelation robust (HAC) using 1 lag and without small sample correction. Asterisks indicate significance at 10 percent (*), 5 percent (**), and 1 percent level (***).

Figure 5. Comparison of World Trade During Covid-19 and Global Financial Crisis (CPB World Trade, Value Index = 100 at Beginning of COVID-19 [January 2020] and Global Financial [July 2008] Crises)



Sources: CPB and authors' calculations and forecasts.

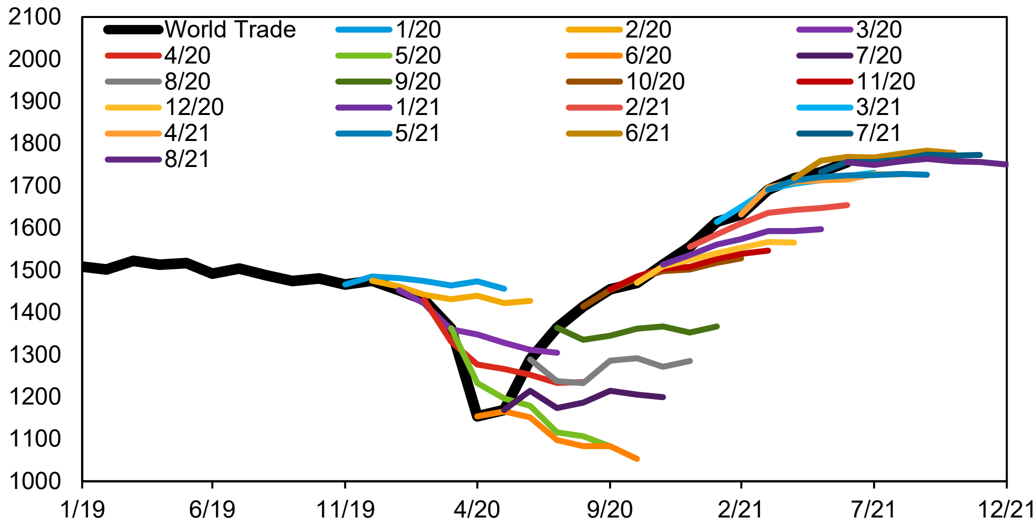
During the Covid-19 crisis, SWIFT linear forecasts of world trade performed well in predicting the turning point of the crisis (Figure 6). Specifically, by end-March 2020, the forecast was already indicating a significant decline in world trade, at a time when CPB data on world trade was only available for January 2020 (light green line). By July 2020, the forecast was already pointing to a recovery in global trade (dark green line), albeit not as rapid as it turned out to be. Starting in October 2020, the forecast was indicating a rapid recovery well above pre-pandemic levels (brown line), while the more recent forecasts point to a stabilization of global trade in the second half of 2021, albeit still well above pre-pandemic levels. This stabilization probably reflects supply disruptions currently affecting major global supply chains and limited shipping capacity around the world.

Overall, the linear regression forecasts have done a relatively good jobs at picking up the turning points of world trade during the Covid-19 crisis. Nevertheless, this leaves open the question whether other models of world trade, like a Dynamic Factor Model, or machine-learning algorithms could have done better at forecasting world trade during the crisis, something that will be examined in the sections below.

A Comparison with a Dynamic Factor Model

This section presents an alternative Dynamic Factor Model (DFM) of world trade and out-of-sample DFM forecasts from January 2020 to December 2020. The DFM forecasts are then compared with the SWIFT linear regression forecasts above. Appendix II describes the methodology and the macroeconomic time series used for the estimation of the DFM.

Figure 6. Out-of-Sample Linear Regression Forecasts of World Trade During Covid-19



Sources: CPB, Haver, JP Morgan, Markit, SWIFT, and authors' forecasts at end of each month.

Each DFM forecast is based on the same cut-off date and the same sample size as the SWIFT linear regression forecasts in the previous section to ensure an appropriate comparison. For example, the forecast done in January 2020 for both models uses the dataset available as of January 31, 2020, for February 2020 the dataset available on February 28, 2020, and so on. The DFM uses a wider set of 28 macroeconomic time series covering different aspects of the global economy, such as global financial conditions, economic sentiment, manufacturing output, commodity prices and trade related indicators such as the Baltic Dry and Container throughput indices.

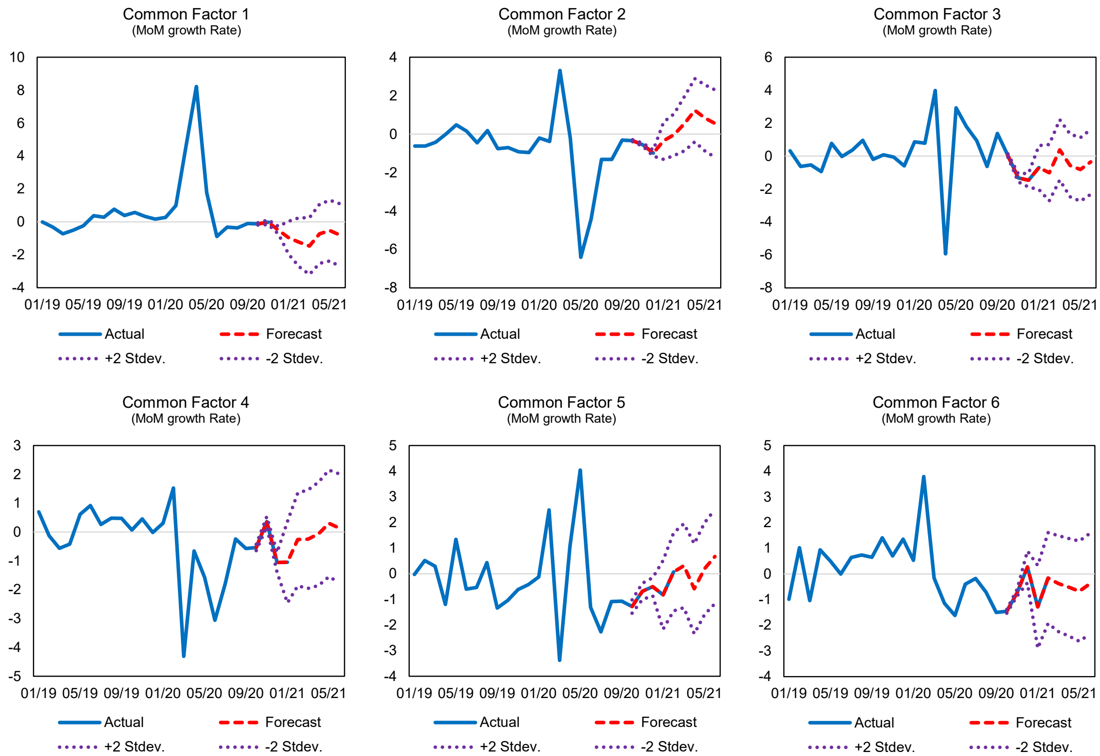
Using a two-step estimation procedure for the DFM model, six common factors are estimated. These can be interpreted as major forces defining global economic developments, which in turn influence world trade. Specifically, CPB world trade (in value terms) can be represented as a linear combination of these six common factors, estimated based on the available dataset. Figure 7 below shows the historic values of the estimated common factors and their forecasts up to June 2021, together with a 95 percent confidence interval around the forecast.

The DFM forecasts based on the six common factors shown above also performed relatively well at predicting the Covid crisis (Figure 8). Already in February 2020, the DFM forecast was pointing to a significant decline in world trade (blue line), which became more acute with the March and April forecasts. On the other hand, the DFM forecasts from May to August 2020 significantly underestimated the recovery in global trade. Only starting with the September forecast, did the forecast correctly anticipate the rapid recovery, well above pre-pandemic level.

The benefit of DFM forecasts is that they can be updated as soon as new data become available. For example, the DFM forecast can be updated as soon as PMI data are published at the beginning of the month. The same is true for all other variables shown in Table II.1 in the appendix. This allows for forecasts to be updated on a more frequent basis than SWIFT forecasts.

Figure 7. Common Factors of the DFM Forecast of World Trade

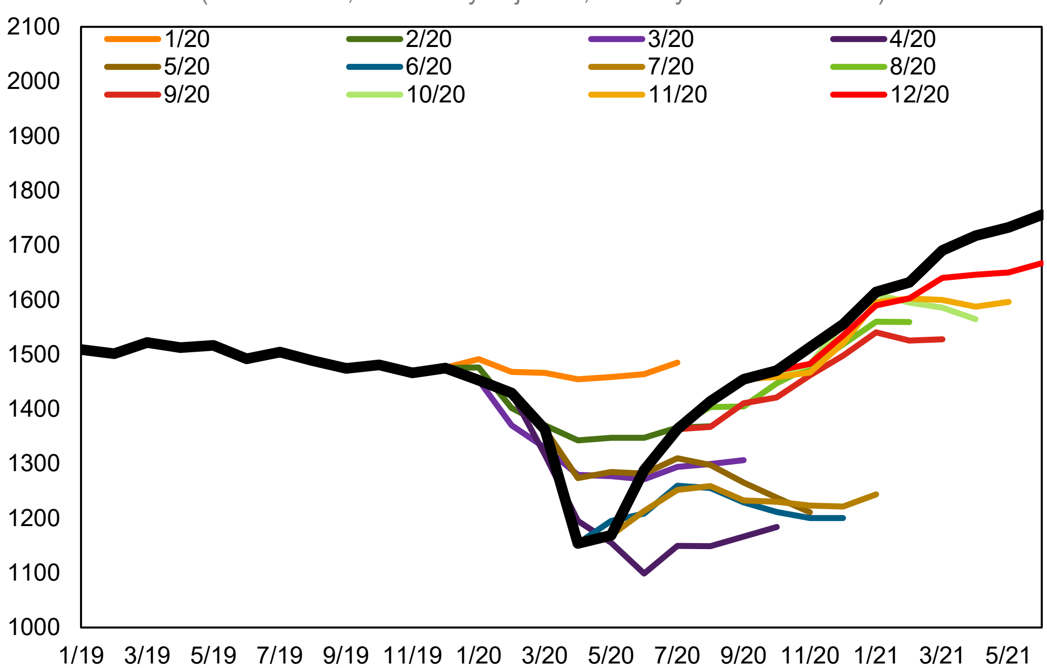
(Month over month normalized growth rates)



Sources: CPB and authors' calculations and forecasts.

Figure 8. DFM: Out-of-Sample Forecasts of World Trade

(USD billions; seasonally adjusted; January 2020-June 2021)



Sources: CPB and authors' calculations and forecasts.

A comparison of forecast performance shows that SWIFT linear regression forecasts and the DFM forecasts were broadly similar (Table 2). The root mean squared errors (RMSEs) for 2020 on average over the one-month ahead forecasts were better for the SWIFT linear regression forecasts, but this advantage was reversed over longer time horizons up to five-months ahead. On average over the one- to six-month forecast horizon, the DFM forecast did somewhat better, possibly reflecting the use of a larger sample of dependent variables, including financial variables, to explain world trade.

Table 2. SWIFT and DFM Forecasts: Average Out-of-Sample Root Mean Squared Errors

(Log difference; January to December 2020)

Forecast Horizon (Months ahead)	1	2	3	4	5	6	Horizon Avg.
SWIFT Linear Regression Forecast RMSEs	4.2	5.8	6.6	7.1	6.8	4.3	5.8
DFM RMSEs	4.5	4.1	6.6	6.2	5.7	6.1	5.6

Sources: Authors' calculations and forecasts.

Documentary Collections and National Trade

SWIFT trade messages are correlated with world trade because they finance national trade flows. However, the correlation between SWIFT trade messages and national trade flows is blurred by the fact that SWIFT trade messages are often sent and received by large 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 when forecasting world trade, it becomes an issue in forecasting national trade, because it blurs the correlation between SWIFT trade messages and the underlying merchandise trade flows. As indicated in CHMMR, this is particularly relevant for economies that host international financial centers, like Hong Kong SAR, Japan, Netherlands, the United Kingdom, and the United States. Unfortunately, no data are yet available to correct for this blurred relationship.[9]

The use of SWIFT documentary collections (MT 400) varies across economies and is mostly prevalent in trade with Asia as shown in Section II. Figure 9 shows the simple contemporaneous correlation between MT 400 messages and total merchandise exports and imports, as reported by the national customs authorities of the 60 economies in the sample. [10] The highest correlation coefficients are for Vietnam and Egypt imports, followed by Malaysia exports, Hong Kong SAR imports, and Portugal, Spain, and Singapore exports. The contemporaneous coefficients in the regressions for these trade flows are all highly significant as expected. It is worth noting that this correlation pattern across economies is different from the one for MT 700 messages in CHMMR. While for MT 700 messages, the correlation was highest for Turkey and Asian economies, for MT 400 messages, the highest correlation includes a mix of imports from emerging markets and exports from advanced economies, suggesting that MT 400 messages are more widely used geographically, including in advanced economies.

[9] SWIFT is planning to introduce new fields in the MT 400 and MT 700 messages that will identify the port of origin and destination of the underlying merchandise trade being financed through letters of credit or documentary collections. Once available, these fields will greatly improve the correlation between SWIFT data and the underlying merchandise trade, and thus the usefulness of SWIFT data to forecast national trade.

[10] The sample comprises Argentina, Australia, Austria, Belgium, Bangladesh, Brazil, Bulgaria, Canada, Chile, China, Colombia, Cyprus, Denmark, Egypt, Estonia, Finland, France, Germany, Ghana, Greece, Hong Kong SAR, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Korea, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Nigeria, Netherlands, Norway, New Zealand, Pakistan, Peru, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, Taiwan Province of China, United Kingdom, United States, and Vietnam.

A simple regression is estimated for both exports and imports for the 60 economies in the sample based on Equation 1 above. 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 economy (120 regressions) using lagged customs data, the relevant SWIFT MT 700 and MT 400 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.[11]

The regression results vary broadly in line with the correlations structure shown in Figure 9 (Appendix III presents selected regression results). The overall fit of the regression results broadly match the contemporaneous correlation structure. For some economies, the coefficients on MT 700 messages are positive and significant while the ones on MT 400 messages are not. In others, the opposite is true. A few economies have positive and significant coefficients on both, suggesting that both letters of credit and documentary collections are used to finance international trade in those economies (e.g., Bangladesh, Hong Kong SAR, Korea, Saudi Arabia, and Vietnam imports; Indonesia, Israel, and Turkey exports).

In Asia, the regression results show letters of credit (MT 700) and, to a lesser extent, documentary collections (MT 400) are significant in explaining the variation of national trade (Figure 10). The coefficient on MT 700 messages is positive and significant in the regressions for Bangladesh imports and exports, China and Hong Kong SAR imports, Indonesia and India imports and exports, Japan and Korea imports, Philippines exports, Taiwan Province of China imports and exports, and Vietnam imports. In contrast, the coefficient on MT 400 messages is positive and significant in the regressions for Bangladesh imports, China exports, Hong Kong SAR imports, Indonesia exports, Korea imports, Malaysia and Singapore exports, Thailand imports and exports, and Vietnam imports. Overall, the results suggest that both letters of credit and documentary collections are used extensively in Asia to finance national trade, but probably for different goods and with different origins and/or destinations.

A similar pattern is also true in Australia and New Zealand. The coefficient on MT 700 messages is positive and highly significant in the regressions for Australia exports and New Zealand imports, while the coefficient on MT 400 messages is positive and significant only in the regression for Australia exports. The coefficient on both MT 700 and MT 400 messages are insignificant for Australia imports and New Zealand exports.

In Europe, results are mixed. The coefficient on MT 700 messages is positive and significant in the regressions for Belgium, Estonia, Finland, France, Greece, Latvia, Lithuania, Slovenia, Sweden, and UK exports, and in the regressions for Latvia, Portugal, Russia, and Slovenia imports. In contrast, the coefficient on MT 400 messages is positive and significant in the regressions for France, Hungary, Lithuania, Netherlands, Portugal, Spain, and Sweden exports, and in the regression for Russia imports. The coefficient on both SWIFT messages is insignificant in the regressions for Austria, Bulgaria, Cyprus, Germany, Denmark, Ireland, Italy, Luxembourg, Malta, Norway, Poland, Slovakia, and Switzerland (both exports and imports). Overall, the results suggest limited use of letters of credit and documentary collections in financing international trade in Europe.

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

Figure 9. Correlation Between SWIFT MT 400 Messages and National Customs Data

(Contemporaneous Correlation in log difference, after adjusting for outliers)

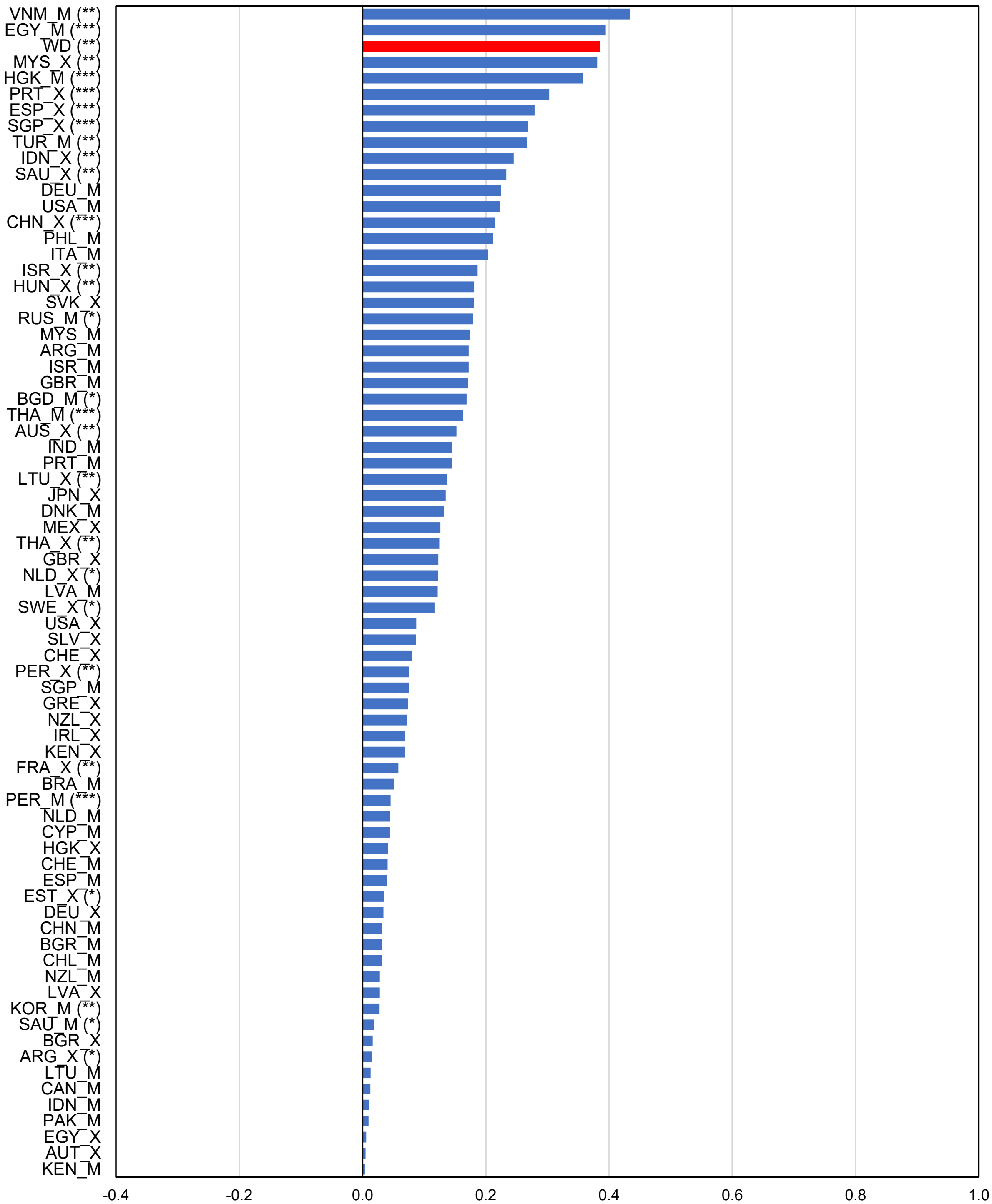
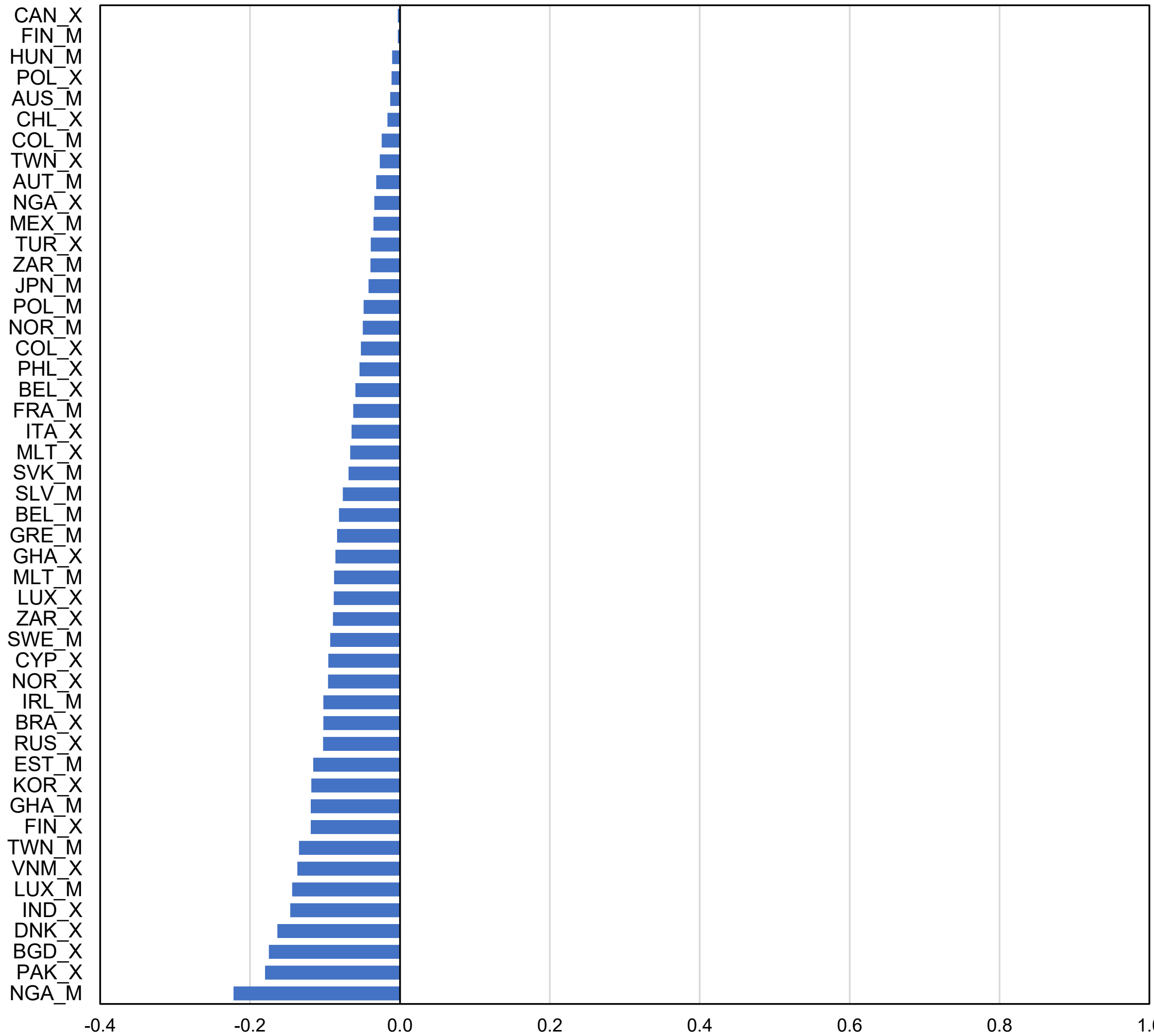


Figure 9 (Cont.). Correlation Between SWIFT MT 400 Messages and National Customs Data

(Contemporaneous Correlation in log difference, after adjusting for outliers)

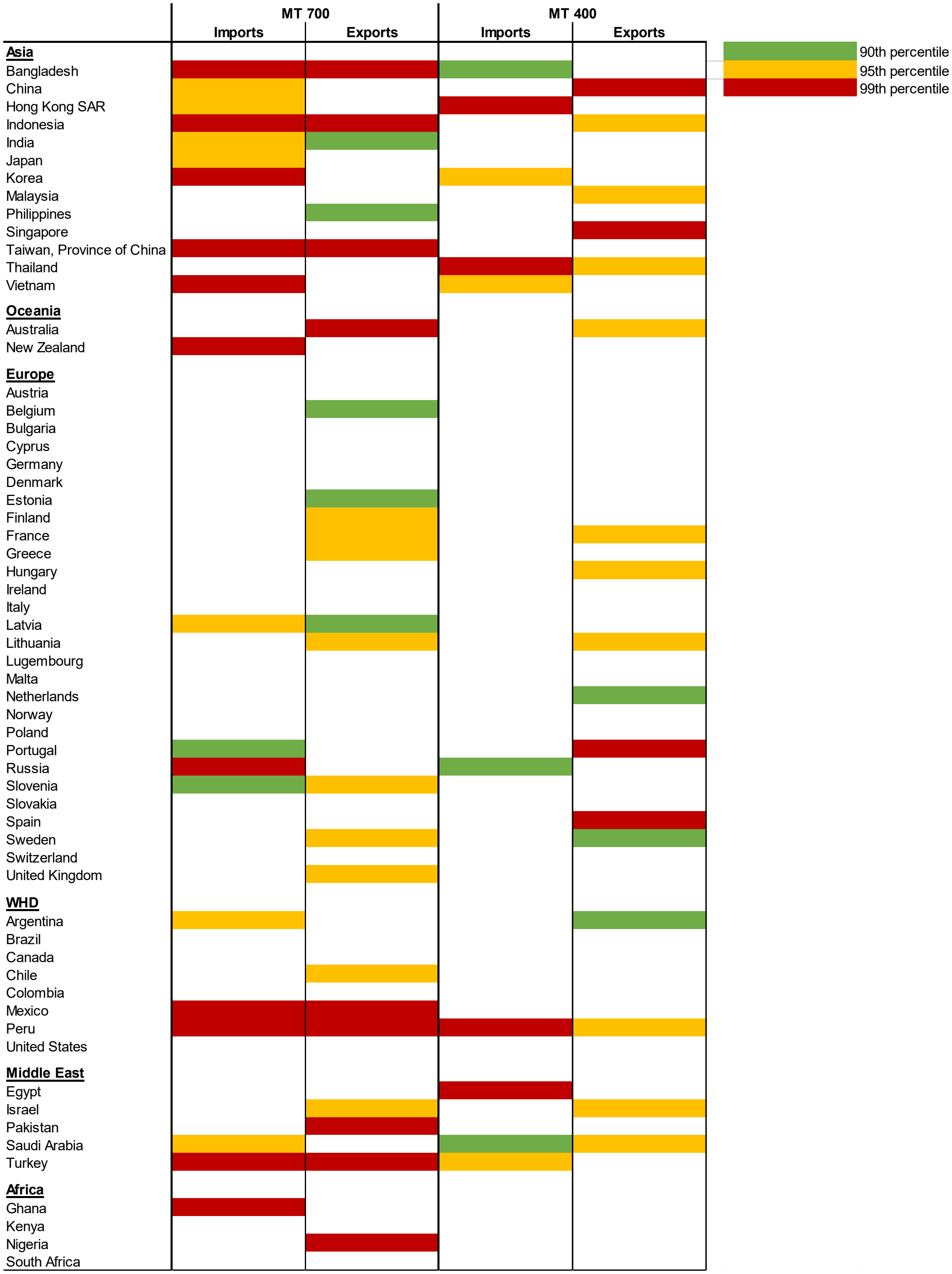


Sources: CPB, national customs data, SWIFT, and authors' calculations. Saudi Arabia exports (SAU_X) are non-oil exports. Asterisks next to the name of the economy indicate the significance level of the contemporaneous coefficient on SWIFT in the regression results at the 10 percent (*), 5 percent (**),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

In the Western Hemisphere, letters of credit are more relevant to forecast national trade than documentary collections. The coefficient on MT 700 messages is positive and significant in the regressions for Chile, Mexico, and Peru exports, and in the regressions for Argentina, Mexico, and Peru imports. By contrast, the coefficient on MT 400 messages is positive and significant only in the regressions for Argentina and Peru exports, and in the regression for Peru imports. The coefficients for both SWIFT messages are insignificant in the regressions for Brazil, Canada, Colombia, Mexico, and the United States (both exports and imports). Overall, these results confirm that the use of documentary collections in Western Hemisphere is limited.

Figure 10. Significance of Contemporaneous Coefficients on SWIFT Messages

(Regression Results with Full Specification as Defined in Equation 1)



Source: Authors' regression results.

In the Middle East, both letters of credit and documentary collections are relevant to forecast national trade. The coefficient on MT 700 messages is positive and significant for Israel, Pakistan, and Turkey exports, and in the regressions for Saudi Arabia, and Turkey imports. By contrast, the coefficient on MT 400 messages is positive and significant in the regression for Egypt, Saudi Arabia, and Turkey imports, and in Israel (total) and Saudi Arabia (non-oil) exports. Overall, these results indicate a mixed use of letters of credit and documentary collections in the region.

In Africa, only letters of credits are relevant to forecast Ghana imports and Nigeria exports. The coefficient on MT 700 and MT 400 messages for the other regressions, including for Kenya and South Africa, are insignificant (both exports and imports).

Overall, these results are consistent with earlier work by Antras and Foley (2015) and Niepmann and Schmidt-Eisenlohr (2017), which showed that letters of credit are used mostly by emerging economies, while advanced economies finance their trade predominantly with open accounts that are not intermediated by financial institutions. Developing economies finance their trade mostly through a cash-in-advance system.[12]

Horse Race Between Linear Regression and Machine-Learning Forecasts

This section presents a horse race between linear regression and machine-learning forecasts, and an overall assessment of these forecasts. For a detailed description of the machine-learning algorithms (MLAs), Appendix III of CHMMR presents the different forecast methodologies and the advantages and disadvantages of linear regressions vs. machine-learning algorithms.

Linear Regression Forecasts

Linear regression forecasts are built using the estimated regressions above to forecast one-step ahead and then recursively longer forecast horizons up to six-months ahead. CPB and national 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 Manufacturing 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 forecast is the one for world trade on November 30, 2020. At the time, world trade was only available up to September 2020 and was still below pre-Covid crisis levels. There was no indication that world trade would boom above pre-Covid crisis levels in the latter part of 2020 and the beginning of 2021. SWIFT data was available up to October 2020 showed a 20 percent increase in the dollar value of letters of credit and a 10 percent increase in the dollar value of documentary collections from the trough in April 2020. Brent crude oil prices had recovered from less than $10 per barrel in mid-April 2020 to about $47 per barrel at the end of November 2020, with a slight increase in the futures curve six months out to $49 per barrel. The

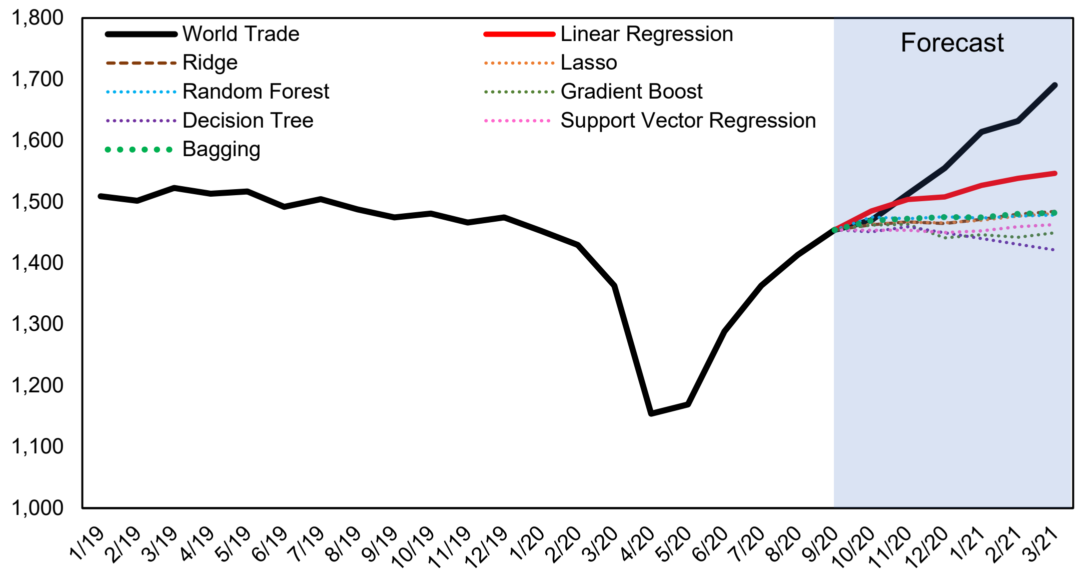
[12] See Appendix I of CHMMR for a full description of these different methods of international trade financing.

export orders subcomponent of the world manufacturing PMI was in slight expansionary territory as of October 2020.

Based on these explanatory variables, the linear regression forecast on November 30, 2020 indicated a significant rise in world trade going forward (red line in Figure 11). Other machine-learning forecasts showed instead a stabilization or another downturn in world trade (dotted lines in Figure 11). World trade turned out broadly in line with the linear regression forecast up to December 2020, while decidedly stronger than the forecast in the first quarter of 2021.

Figure 11. World Trade: Forecasts Based on Linear Regression and MLAs, November 30, 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[13]

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.

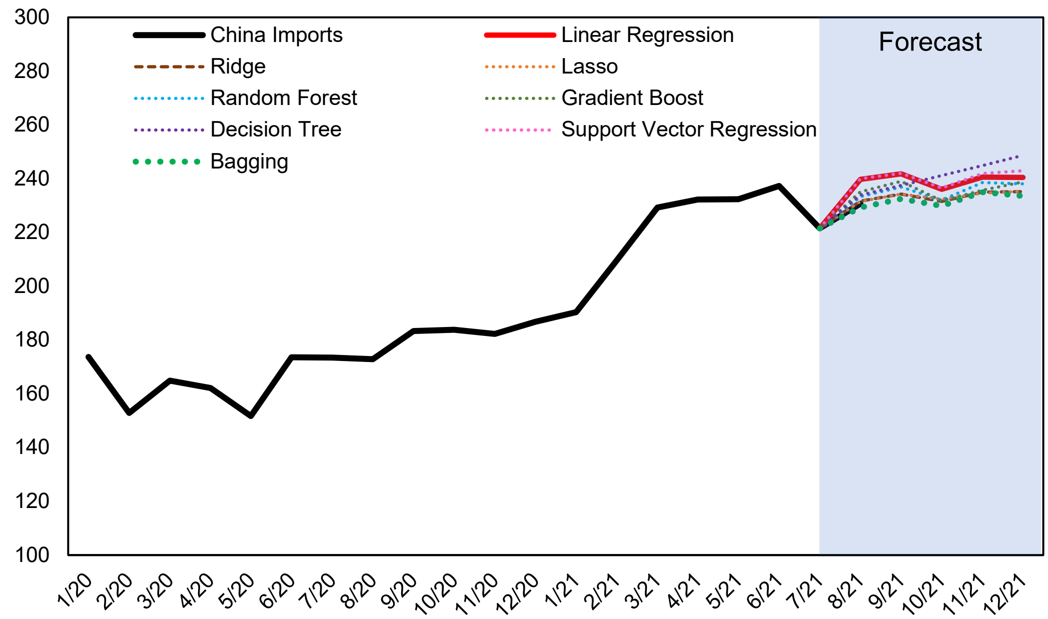
A good example of an MLA forecast superior to a linear regression one is that of China imports at the end of August 2021 (Figure 12). While the linear regression has positive and significant coefficients on MT 700 messages and the first lag of MT 400 messages, the bagging MLA forecast has proven superior to other methods in forecasting imports over the previous 12 months, suggesting a non-linear relationship between

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

merchandise imports and the dependent variables. For the August 31 forecast, the linear regression predicted an 8.3 percent rebound in imports in August, while the Bagging forecast indicated a more moderate 3.5 percent rebound. The subsequent data (published in early September) showed a 4.1 percent increase in nominal imports in August. Overall, this may indicate significant non-linearities currently at play with the China import data that cannot be captured through a linear regression.

Figure 12. China Imports: Forecasts Based on Linear Regression and MLAs, August 31, 2021

(Billions of US dollars, Seasonally Adjusted)



Sources: General Administration of Customs, China/Haver Analytics, SWIFT, Brent crude oil prices and futures, Caixin/IHS Markit/Haver Analytics, 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 August 2020 (the training set). The forecasts thus computed are then evaluated over the data between September 2020 and August 2021 (the test set), based on monthly rolling forecasts. The RMSEs are then calculated over the one-, two-, three-, four-, five-, and six-month ahead forecasts.

The best-performing one-step ahead forecasts based on the lowest RMSE for the world and the 60 economies are presented in Table 3. It is worth noting that only about one third of the best performing forecasts are linear regression or parametric (Ridge, and Lasso) MLA forecasts. Two thirds of the best performing forecasts, including for world trade, are non-linear MLAs. This is in stark contrast with CHMMR, where the ratio between best-performing forecasts was two-thirds for linear (including Ridge and Lasso) and one-third non-linear. This may be explained by the significant non-linearities introduced by the Covid-19 crisis and speaks to the usefulness of running both linear and non-linear forecasts over time.

All forecasts are also evaluated formally using the Diebold-Mariano (DM) test.[14] 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 forecasts are also shown in Table 3, together with the corresponding P-statistics and RMSEs. The results show that about one quarter of all regressions have forecasts that are statistically better than a naïve constant-growth forecast. While this is a significant improvement on the results of CHMMR, more work needs to be done to improve the quality of the forecasts, possibly by considering additional explanatory variables, including financial variables, as in the DFM model for world trade shown above.

Conclusions

This paper has extended CHMMR by adding SWIFT data on documentary collections to the forecast of international trade. While financing only about one percent of world trade, documentary collections have a strong informational content to forecast world trade and international trade in a selected number of economies, mostly in Asia. The SWIFT linear regression forecast performed relatively well during the trough and rebound of the Covid-19 crisis in 2020-21. This performance was broadly equivalent to an alternative DFM forecast over the same period based on 27 different variables. Unlike the previous paper, however, the Covid-19 crisis brought significant non-linearities in the relationship between international trade and its regressors, showing the usefulness of running MLA forecasts to improve on linear regression forecasts, particularly during large shocks to the world economy.

[14] Diebold and Mariano (1995).

Table 3. Diebold-Mariano Tests of One-Step Ahead Forecast[15]

Economies	Exp/Imp	Best Forecast	DM Statistic	P-Value	RMSE	Naïve RMSE
World		**Gradient Boost**	-2.7577	0.0058	0.0128	0.0251
Argentina	Imp.	Linear Regression	-0.3229	0.7468	0.0806	0.0828
	Exp.	Bagging	-1.6257	0.1040	0.1317	0.1373
Australia	Imp.	Random Forest	-0.1085	0.9136	0.0705	0.0712
	Exp.	Decision Tree	-0.9500	0.3421	0.0413	0.0432
Austria	Imp.	**Random Forest**	2.0935	0.0363	0.0478	0.0440
	Exp.	Gradient Boost	0.8050	0.4208	0.0519	0.0498
Bangladesh	Imp.	Ridge	-0.6751	0.4996	0.0666	0.0866
	Exp.	Gradient Boost	-1.4959	0.1347	0.0381	0.0538
Belgium	Imp.	**Gradient Boost**	-2.2299	0.0258	0.0391	0.0481
	Exp.	Gradient Boost	-0.2251	0.8219	0.0521	0.0526
Bulgaria	Imp.	Lasso	1.5278	0.1266	0.0678	0.0637
	Exp.	**Lasso**	-2.6112	0.0090	0.0559	0.0658
Brazil	Imp.	Gradient Boost	-1.8713	0.0613	0.1078	0.1263
	Exp.	Lasso	1.3413	0.1798	0.0995	0.0979
Canada	Imp.	Gradient Boost	-1.4060	0.1597	0.0256	0.0450
	Exp.	Bagging	-0.9197	0.3577	0.0388	0.0459
Chile	Imp.	Random Forest	-1.7757	0.0758	0.0748	0.0849
	Exp.	**Bagging**	-4.5403	0.0000	0.0656	0.0840
China	Imp.	**Bagging**	2.4942	0.0126	0.0476	0.0441
	Exp.	Gradient Boost	-1.8046	0.0711	0.0264	0.0372
Colombia	Imp.	Random Forest	-1.0774	0.2813	0.1138	0.1263
	Exp.	Random Forest	0.0689	0.9451	0.0699	0.0693
Cyprus	Imp.	Lasso	-1.5851	0.1129	0.1918	0.2208
	Exp.	Decision Tree	-0.4568	0.6478	0.2458	0.2566
Denmark	Imp.	Bagging	0.2896	0.7721	0.0401	0.0390
	Exp.	Random Forest	-1.8432	0.0653	0.0298	0.0335
Egypt	Imp.	Random Forest	-1.1730	0.2408	0.0983	0.1106
	Exp.	**Lasso**	-2.8725	0.0041	0.0773	0.1133
Estonia	Imp.	Bagging	-0.0849	0.9323	0.0588	0.0593
	Exp.	**Decision Tree**	-1.9652	0.0494	0.0830	0.0895
Finland	Imp.	**Linear Regression**	-2.5736	0.0101	0.0456	0.0607
	Exp.	Linear Regression	-1.6149	0.1063	0.0892	0.1257
France	Imp.	Gradient Boost	-0.1749	0.8612	0.0254	0.0259
	Exp.	Bagging	-0.8494	0.3956	0.0322	0.0381
Germany	Imp.	**Bagging**	-4.3229	0.0000	0.0321	0.0375
	Exp.	Gradient Boost	-0.9253	0.3548	0.0200	0.0244
Ghana	Imp.	**Linear Regression**	-2.1054	0.0353	0.0939	0.1504
	Exp.	Ridge	1.6177	0.1057	0.0676	0.0613
Greece	Imp.	Linear Regression	-0.5342	0.5932	0.0915	0.0974
	Exp.	Lasso	-1.7343	0.0829	0.0587	0.0747
Hong Kong SAR	Imp.	Ridge	0.4509	0.6520	0.0391	0.0382
	Exp.	Ridge	0.8893	0.3738	0.0638	0.0631
Hungary	Imp.	Random Forest	0.4077	0.6835	0.0483	0.0476
	Exp.	Gradient Boost	-1.1382	0.2551	0.0357	0.0545
India	Imp.	Bagging	0.5703	0.5685	0.1158	0.1136
	Exp.	Decision Tree	-0.3865	0.6991	0.0659	0.0670
Indonesia	Imp.	Support Vector Regression	-0.5673	0.5705	0.1070	0.1118
	Exp.	Ridge	-0.6821	0.4952	0.0712	0.0746
Ireland	Imp.	Support Vector Regression	1.7600	0.0784	0.1151	0.1134
	Exp.	Lasso	-1.8218	0.0685	0.0525	0.0710
Israel	Imp.	Random Forest	1.4406	0.1497	0.0768	0.0646
	Exp.	Random Forest	0.4325	0.6654	0.0876	0.0859
Italy	Imp.	Random Forest	-1.9196	0.0549	0.0342	0.0354
	Exp.	Gradient Boost	-1.1992	0.2305	0.0247	0.0346
Japan	Imp.	Ridge	0.4499	0.6528	0.0351	0.0333
	Exp.	Decision Tree	-0.8451	0.3981	0.0374	0.0399

15 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 (Cont.). Diebold-Mariano Tests of One-Step Ahead Forecast

Kenya	Imp.	Linear Regression	-0.1282	0.8980	0.0807	0.0828
	Exp.	**Lasso**	-2.8866	0.0039	0.0822	0.1114
Korea	Imp.	Random Forest	-1.5422	0.1230	0.0518	0.0557
	Exp.	Bagging	-0.8187	0.4130	0.0472	0.0495
Latvia	Imp.	Lasso	0.4031	0.6868	0.0575	0.0551
	Exp.	**Support Vector Regression**	-2.2131	0.0269	0.0522	0.0647
Lithuania	Imp.	**Ridge**	-3.2204	0.0013	0.0432	0.0584
	Exp.	Lasso	-1.4343	0.1515	0.0599	0.0654
Luxembourg	Imp.	Ridge	1.5203	0.1284	0.0702	0.0651
	Exp.	Lasso	-1.5519	0.1207	0.0583	0.0656
Malaysia	Imp.	Gradient Boost	-0.7421	0.4580	0.0581	0.0705
	Exp.	**Linear Regression**	-2.4068	0.0161	0.0758	0.1121
Malta	Imp.	Linear Regression	-0.7910	0.4289	0.1611	0.1766
	Exp.	Bagging	-1.3919	0.1639	0.1547	0.1784
Mexico	Imp.	Random Forest	-0.8150	0.4151	0.0639	0.0665
	Exp.	Random Forest	1.4873	0.1369	0.0301	0.0261
Netherlands	Imp.	**Decision Tree**	-3.5703	0.0004	0.0183	0.0303
	Exp.	**Lasso**	-3.0404	0.0024	0.0206	0.0296
New Zealand	Imp.	Support Vector Regression	-1.7918	0.0732	0.0628	0.0742
	Exp.	Bagging	-0.1517	0.8794	0.0625	0.0628
Nigeria	Imp.	**Decision Tree**	-2.2573	0.0240	0.1348	0.1683
	Exp.	Gradient Boost	-1.7540	0.0794	0.1387	0.1615
Norway	Imp.	Decision Tree	-0.9711	0.3315	0.0662	0.0671
	Exp.	Bagging	-1.9055	0.0567	0.0718	0.0784
Pakistan	Imp.	Linear Regression	-1.9384	0.0526	0.1180	0.1391
	Exp.	Linear Regression	-1.3083	0.1908	0.1770	0.2289
Peru	Imp.	Gradient Boost	-1.8541	0.0637	0.0766	0.0874
	Exp.	Gradient Boost	-1.1938	0.2326	0.0743	0.0943
Philippines	Imp.	Random Forest	-0.5607	0.5750	0.0484	0.0500
	Exp.	Random Forest	-0.0804	0.9359	0.0649	0.0652
Poland	Imp.	**Support Vector Regression**	-3.9634	0.0001	0.0499	0.0546
	Exp.	**Bagging**	-2.9460	0.0032	0.0389	0.0417
Portugal	Imp.	Ridge	-0.2695	0.7875	0.0617	0.0639
	Exp.	Bagging	-1.7448	0.0810	0.0370	0.0497
Russia	Imp.	Bagging	0.6149	0.5386	0.0415	0.0398
	Exp.	**Gradient Boost**	-5.3495	0.0000	0.1003	0.1173
Saudi Arabia	Imp.	Bagging	-1.7722	0.0764	0.0776	0.0987
	Exp.	**Support Vector Regression**	3.5672	0.0004	0.0526	0.0510
Singapore	Imp.	**Support Vector Regression**	-7.6461	0.0000	0.0419	0.0662
	Exp.	Ridge	-1.2241	0.2209	0.0508	0.0584
Slovenia	Imp.	Linear Regression	-0.9661	0.3340	0.0759	0.0855
	Exp.	Lasso	0.4633	0.6431	0.0499	0.0494
Slovakia	Imp.	Decision Tree	0.2109	0.8330	0.0551	0.0542
	Exp.	Gradient Boost	-1.5632	0.1180	0.0503	0.0594
Spain	Imp.	Random Forest	-0.8032	0.4218	0.0740	0.0800
	Exp.	Lasso	-0.4921	0.6227	0.0449	0.0471
South Africa	Imp.	**Decision Tree**	-2.1795	0.0293	0.0908	0.1050
	Exp.	**Random Forest**	3.4398	0.0006	0.0999	0.0958
Sweden	Imp.	Support Vector Regression	-0.1092	0.9130	0.0327	0.0330
	Exp.	**Ridge**	-2.2771	0.0228	0.0345	0.0437
Switzerland	Imp.	**Lasso**	-2.9749	0.0029	0.0568	0.0681
	Exp.	Random Forest	-0.8553	0.3924	0.0508	0.0610
Taiwan Prov. of China	Imp.	Lasso	-1.1853	0.2359	0.0467	0.0549
	Exp.	**Gradient Boost**	-2.0828	0.0373	0.0324	0.0379
Thailand	Imp.	**Gradient Boost**	-2.7978	0.0051	0.0557	0.0652
	Exp.	Gradient Boost	-0.9348	0.3499	0.0429	0.0493
Turkey	Imp.	Random Forest	-1.2865	0.1983	0.0910	0.1040
	Exp.	Support Vector Regression	-1.0138	0.3107	0.1110	0.1302
United Kingdom	Imp.	Support Vector Regression	-1.9970	0.0458	0.0880	0.0980
	Exp.	Linear Regression	-0.3933	0.6941	0.0848	0.0871
United States	Imp.	Lasso	-0.6328	0.5269	0.0221	0.0247
	Exp.	Bagging	-0.5016	0.6160	0.0320	0.0322
Vietnam	Imp.	Bagging	1.1919	0.2333	0.0526	0.0469
	Exp.	Random Forest	-0.1903	0.8491	0.0430	0.0438

Source: Authors' forecasts and calculations.

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Appendix I. 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 economy or the whole world (Table 1). The explanatory variables are lags of the dependent variables, the corresponding SWIFT MT 700 or MT 400 messages, 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.

Dataset and estimation

The dataset spans the period November 2010 to June 2021. 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:

$$\hat{\boldsymbol{x}}_{\boldsymbol{t}} = \boldsymbol{f}(\boldsymbol{x}_{\boldsymbol{t-1}}, \dots, \boldsymbol{x}_{\boldsymbol{t-4}}, \boldsymbol{Y}_{\boldsymbol{t}}, \dots, \boldsymbol{Y}_{\boldsymbol{t-4}})$$

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:

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

Table I.1. Data Description, Sources and Transformation

Variable	Data description and source	Transformation
MG_t	Total monthly merchandise imports (or exports) of a given economy 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 economy.	$x_t = \log(MG_t) - \log(MG_{t-1})$
$SWIFT4_t$	Corresponding USD amount of total monthly SWIFT MT 400 messages, seasonally adjusted. Source: SWIFT.	$y_t^1 = \log(SWIFT4_t) - \log(SWIFT4_{t-1})$
$SWIFT7_t$	Corresponding USD amount of total monthly SWIFT MT 700 messages, seasonally adjusted. Source: SWIFT.	$y_t^2 = \log(SWIFT7_t) - \log(SWIFT7_{t-1})$
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.	$y_t^3 = \log(POIL_t) - \log(POIL_{t-1})$
PMI_t	New export orders subcomponent of manufacturing PMI. Centered around zero instead of fifty. Available for the world and for 45 out of 60 economies in the sample. Where not available, this explanatory variable is dropped. Sources: Markit, JP Morgan, Haver.	$y_t^4 = PMI_t - 50$

Source: Authors' description and calculations.

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:

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

where

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

Recursively, the three-month ahead forecast is given by

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

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.

Appendix II. A Dynamic Factor Model of World Trade

The Dynamic Factor Model (DFM) is a widely used statistical method to estimate and forecast macroeconomic variables. DFMs estimate a limited number of factors from a large dataset that capture the major forces shaping the dynamics of the main macroeconomic variable. The estimated factors can then be combined to monitor and forecast key macroeconomic variables, such as real GDP, inflation, and international trade (see Giannone et al. (2005)) and Uhlig (2004)).

DFMs use a large dataset for two reasons. First, models with more limited time series may miss important information about the economy, thus leading to an erroneous forecast of the main macroeconomic variables, which is usually the case when one relies on a simple vector auto regressive (VAR) analysis with limited time series. The well-known "price puzzle" in monetary policy is a vivid example of this problem (see Bernanke and Blinder (1992), Christiano, Eichenbaum and Evans (1994) and Sims (1992)). Sims brings the example of inflation and policy rates in Europe and US during the oil price shock of 1970s. As both inflation and interest rates were high during this period, the impulse responses of the VAR suggested that high interest rates cause high inflation, which is in contrast with economic theory. A deeper analysis with more macroeconomic variables helped to understand the correct interplay of economic forces. In particular, the identification of supply shocks with commodity prices and exchange rate movements during the 1970s helped to produce intuitive impulse responses and solve the "price puzzle."

Second, the amount of the impulse responses will be constrained with the limited number of input time series (see Canova (1995)). For example, to understand the future path of economic activity, the forecast of real GDP may not be enough. Additional variables, like private demand, capacity utilization, real estate prices, real wages, and labor costs, may also be needed for policy makers to have a full picture of the state of the economy, a more accurate forecast of future economic activity, and a more inclusive policy response (see Bernanke et al (2005)). Standard econometric models, such as VAR systems, cannot be used to analyze large datasets as the estimated parameters and impulse responses tend to be biased and unreliable due to a loss of degrees of freedom and overfitting. DFMs, on the other hand, reduce the informational content from a large dataset to a few common factors. These series are then used to produce robust forecasts for the main macroeconomic variables.

Structure of the DFM model

Let $X_t' = (X_{1,t}, \dots X_{N,t})$ denote a vector of stationary variables, where $t = 1, \dots, T$ is the time dimension and N is the number of variables. The X_t' vector can be represented as a linear combination of unobserved p common factors $F_t' = (F_{1,t}, \dots F_{P,t})$ and a series of white-noise disturbances ξ_t. The X_t' vector can then be written as:

$$X_t' = \Lambda^f F_t' + \xi_t \quad (1)$$

where Λ^f is a $N \times P$ matrix of factor loadings and ξ_t is *a* $N \times 1$ vector of white-noise disturbances. The number of factors is assumed to be relatively small, compared with the size of the full dataset. Equation (2) suggests that a few major forces in the economy, proxied by the estimated common factors F_{it}' $(i = 1, \dots, P)$, define the dynamics of any macroeconomic variable present in the database X_t'. The conceptual common shocks for the economy summarized in these factors can be interpreted as economic activity, financial conditions, inflationary pressures, global trade momentum, etc. The joint dynamics of these common factors, in its turn is defined by a VAR process.

$$F_t' = A_1(F_{t-1}') + \cdots + A_l(F_{t-l}') + \vartheta_t \quad (2)$$

where $A_1 \dots A_l$ in the above equation are the coefficient matrices of the lagged factors and the ϑ_t is a vector of mean zero common shocks with a diagonal covariance matrix Θ. As the factors F_t' are unobservable, equation (2) cannot be estimated directly. A two-step principal component estimation procedure is therefore used for estimating equations (1) and (2). In the first step, factors are estimated using the first p principal components of the dataset X_t' using equation 1. In the second step, the estimated principal components ($\widehat{F_t'}$) are used to estimate equation (2) with standard VAR techniques (see Banbura and Modugno (2014), Doz et al (2005) and Stock and Watson (2002a)).

Estimating a DFM for CPB Global Trade

In building a DFM model to forecast global trade activity, it is important to find variables that are timely, updated frequently (monthly or higher frequency) and correlated with global trade in value, as measured by the CPB (see Stratford 2013). For example, the World Trade Organization uses a set of high frequency indicators as described above, to construct Goods Trade Barometer, which is a leading indicator for the world merchandise trade[16]. The dataset used in this paper includes 28 global macroeconomic variables carefully chosen to meet the above criteria. The selected series have a monthly or higher frequency, cover various aspects of the global economy, and are strongly correlated with global trade, with absolute value of correlation ranging from 15 to 76 percent (Table II.1).

The dataset includes the new export orders subcomponent of JP Morgan's Global Purchasing Managers Index (PMI), the services and manufacturing employment PMI subcomponents, the output prices, stock of purchases and backlogs of works PMI subcomponents in the manufacturing sector, Sentix global sentiment index, availability of cargo and seats provided by international air transport association (IATA), Tracking Index for Global Economic Recovery (TIGER), the Baltic Exchange Dry index, and the RWI Container Throughput index.[17] The database also includes a list of important global financial indicators, such as J.P. Morgan's sovereign and corporate bond indices in emerging markets, U.S. BB corporate bond spread over government bonds, global policy related and long-term interest rates, global money supply (M3), Morgan Stanley's global stock market price index and the stock market index of the largest containerized cargo shipping companies[18]. To capture the movements in the value of global trade, we also use global consumer and producer price

[16] Details on the methodology of the trade outlook indicator are available in WTO (2020).

[17] The RWI/ISL (Institute of Shipping Economics and Logistics) Container Throughput Index uses the fact that international trade is primarily handled by ships and containers, which means the container throughput in ports is an important indicator of global trade. Currently, the database consists of 82 international ports covering more than 60% of world container handling. These ports are continuously monitored by the ISL as part of their market analysis.

[18] The index is a weighted average of share prices of eight major publicly listed containerized shipping companies. The weights are given by the average market capitalization over the previous 30 calendar days. The eight companies are (2010-2016 average market cap weight in parentheses): A.P. Moller-Maersk Group (59 percent), China COSCO Shipping (16 percent), Mitsui OSK Lines (8 percent), Orient Overseas International Ltd (6 percent), Hyundai Merchant Marine (4 percent), Evergreen Marine (3 percent), Yang Ming Marine Transport Corporation (2 percent), and Wan Hai Lines (2 percent). All data are collected through Bloomberg.

Table II.1. List of Variables Used in DFM Model

Variable	Source	Time Span	Correlation with CPB World Trade
CPB World Trade in Value	CPB Netherlands Bureau for Economic Policy Analysis	2010M10 2020M10	1.0
Industrial Production Volume Index	Haver Analytics	2010M10 2020M10	0.76
Employment Index	Haver Analytics	2010M10 2020M09	0.73
Car Production Volume	Haver Analytics	2010M10 2020M11	0.69
Primary Commodity Prices	IMF Commodity Data Portal	2010M10 2020M12	0.65
Available Passenger Capacity	International Air Transportation Association	2010M10 2020M12	0.63
Advanced Economies' Retail Sales in Value	Haver Analytics	2010M10 2020M11	0.60
Producer Price Index	Haver Analytics	2010M10 2020M11	0.52
Consumer Price Index	Haver Analytics	2010M10 2020M11	0.50
PMI: Manufacturing New Export Orders	IHS Markit	2010M10 2020M12	0.46
TIGER Confidence Index	Brookings Institute	2010M10 2020M08	0.39
Available Cargo Capacity	International Air Transportation Association	2010M10 2020M12	0.38
PMI: Manufacturing Output Prices	IHS Markit	2010M10 2020M12	0.36
PMI: Manufacturing Employment	IHS Markit	2010M10 2020M12	0.34
PMI: Services Employment	IHS Markit	2010M10 2020M12	0.32
PMI: Manufacturing Backlogs of Work	IHS Markit	2010M10 2020M12	0.30
PMI: Manufacturing Stocks of Purchases	IHS Markit	2010M10 2020M12	0.29
Container Throughput Index	Institute of Shipping Economics and Logistics	2010M10 2020M12	0.29
Largest Containerized Shipping Companies' Price	Bloomberg	2010M10 2020M12	0.25
Policy Related Interest Rate	Haver Analytics	2010M10 2020M12	0.24
Sentix Overall Economic Index	Sentix	2010M10 2020M12	0.24
Morgan Stanley's Stock Price Index	Bloomberg	2010M10 2020M12	0.16
Baltic Exchange Dry Index	Baltic Exchange/ Haver Analytics	2010M10 2020M12	0.15
U.S. BB corporate bond spread over government securities	Bloomberg	2010M10 2020M12	-0.31
Broad Money Index	Haver Analytics	2010M10 2020M12	-0.36
J.P. Morgan Sovereign Emerging Market Bond Index	Bloomberg	2010M10 2020M12	-0.40
J.P. Morgan Corporate Emerging Market Bond Index	Bloomberg	2010M10 2020M12	-0.44
Unemployment Rate	Haver Analytics	2010M10 2020M10	-0.63

Source: Authors' calculations.

indices and the IMF's primary commodities price index. Finally, we use several hard indicators to increase the precision and reliability of global trade forecasts, these include global industrial production[19], number of employed people globally, the global unemployment rate, volume of retail sales in advanced economies and the volume of global car production.[20]

For robust estimation of the DFM model, the dataset is also transformed to apply seasonal adjustment, balancing and stationarity. Seasonal adjustment (X12) is applied to all variables, excluding CPB world trade, to account for seasonality, and the variables are then transformed in logarithmic differences. In the final step, the database is balanced, so that all the series in the dataset start and end at the same exact date. The "Jagged edge" of the panel is used however during the forecasting stage, so that all the available information in real time is utilized (see the next section for more detailed discussion). To make the estimation result fully comparable with other methods used in this paper, we use a balanced panel spanning from October 2010 to October 2020.

Estimation of the DFM on CPB World Trade

The DFM estimation on CPB world trade requires two steps as described above. As a first step, the principal component analysis is applied to the adjusted dataset to estimate the unobserved factors. In the second step of the estimation, the common factors are modeled as a VAR process.

The hyper parameters of the DFM, the number of unobservable factors and lag length of the underlying VAR (p and l described in the previous section) are provided exogenously. The rest of the parameters of the system are estimated endogenously using maximum likelihood.

Our final choice for the number of the factors is 6 and the lag length of the underlying VAR is 4[21], based on out of sample forecasting performance analysis. We produce 8 periods ahead out of sample forecasts[22] and calculate the associated RMSEs, for different combinations of hyper parameters, the pair of hyper parameters which implies the minimum RMSE over the forecast horizon is chosen for the final DFM estimation.

The forecast evaluation is composed of 13 cycles starting with the dataset available at the end of December 2019 and ending with the dataset available as of the end of December 2020. We use a balanced panel to estimate the system in each forecasting cycle, as a result, the last 2 months of the original dataset are dropped each time, as many indicators including the world trade are released with two months lag. For example, the balanced panel ends in October 2019, when we use the dataset available as of December 2019.

When the DFM is estimated, we use conditional forecasting approach to produce 2 months of newscast and 6 months ahead forecasts. This approach allows us to use all the available information in real time and produce more precise forecasts, as the information set is widened with the so-called "Jagged edge" of the panel (see Banbura and Modugno (2014), Banbura et al (2014), Matheson 2011 and Jarocinski 2010). The data release

[19] The global Industrial production, employment, unemployment rate , global CPI, policy related interest rate and the broad money indices are generally used by the IMF staff, the source for the individual country series is the national statistical service of respective country.

[20] The volume of the global car production is constructed as the sum of the car production in the USA, Canada, UK, Germany, Spain, Italy, and Japan. The primary source for the country data is the Haver Analytics.

[21] The estimated underlying VAR meets all the stability criteria, as all the eigenvalues of the coefficient matrix lay within the unit circle.

[22] The first 2 periods of the projections are nowcasts due to missing world trade data in real time.

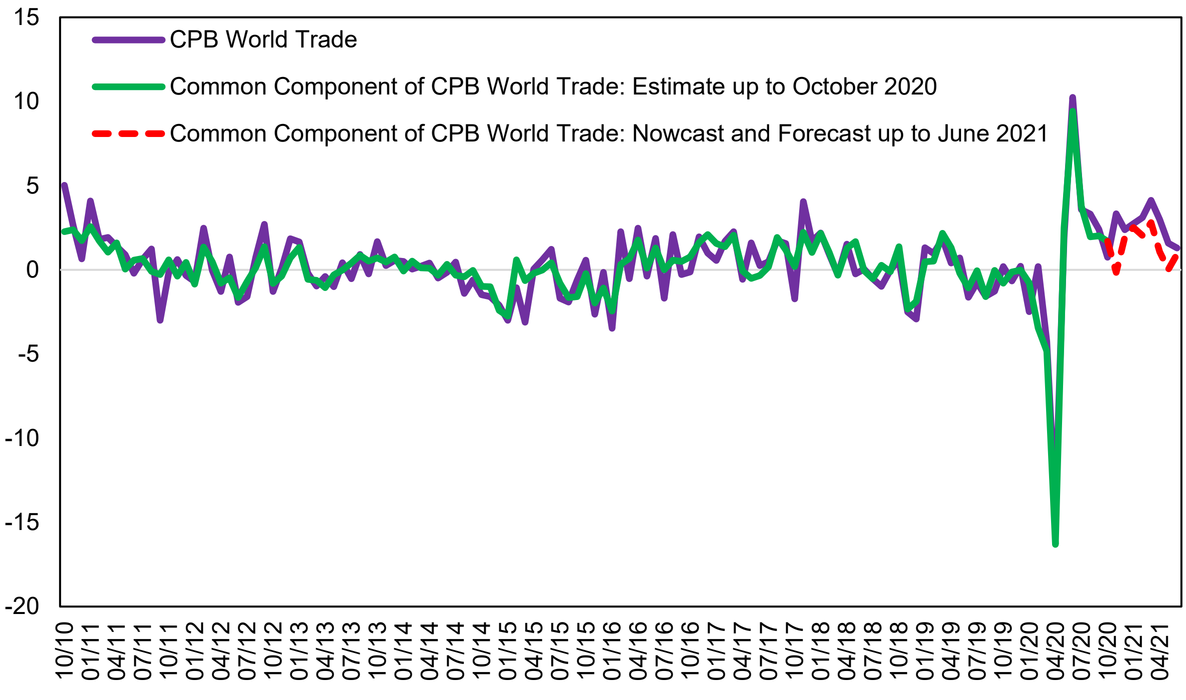
calendar available as of December 2020 is used to construct a quasi-real time historical database for each forecasting cycle, starting from December 2019.

Once the system is estimated, the growth rate of the CBP trade can be represented as the sum of the weighted average of estimated common factors and idiosyncratic shocks (Equation 3). The weights of the common factors in equation (3), are estimated with the algorithm described above.

$$dlog\left(CPB_{Trade_t}\right) = 0.8 * f_t^1 + 0.3 * f_t^2 - 0.2 * f_t^3 + \\ +0.3 * f_t^4 + 0.1 * f_t^5 + 0.1 * f_t^6 + \vartheta_t \quad (3)$$

The weighted sum of the estimated common factors denotes the common component of the world trade and can be interpreted as the world trade growth momentum. The common component plays a key role for nowcasting and forecasting the global trade. As Figure II.1 shows, the estimated common component commoves strongly with the headline world trade series over the estimation sample. A multivariate regression analysis suggests that the common component explains 86 percent of the global trade and thus can serve as a reliable indicator for forecasting the global trade in the near term. The nowcast and forecast up to June 2021 confirm the good fit out-of-sample of the forecast with the actual data.

Figure II.1. CPB World Trade and the Common Component Estimated With the DFM
(Month-on-month growth rates; seasonally adjusted)



Sources: CPB and authors' calculations and forecasts.

Appendix III. Selected Linear Regression Results[23]

Table III.1. Regression Results for Bangladesh Imports

Variables		Diagnostics	
Constant	0.0119 (0.006)**	Observations	123
Imports (-1)	-0.7829 (0.093)***	R^2	0.65
Imports (-2)	-0.4466 (0.101)***	Adjusted R^2	0.59
Imports (-3)	-0.4094 (0.096)***	F-Statistic	17.35
Imports (-4)	-0.2007 (0.101)**	Prob. (F-Statistic)	5.13e-24
SWIFT4	0.0319 (0.018)*	Log-likelihood	172.6
SWIFT4 (-1)	0.0375 (0.018)**	Durbin-Watson	1.922
SWIFT4 (-2)	0.0348 (0.016)**		
SWIFT4 (-3)	0.0442 (0.019)**		
SWIFT4 (-4)	0.0373 (0.014)**		
SWIFT7	0.168 (0.052)***		
SWIFT7 (-1)	0.1093 (0.073)		
SWIFT7 (-2)	0.148 (0.066)**		
SWIFT7 (-3)	0.1224 (0.071)*		
SWIFT7 (-4)	0.0355 (0.063)		
BRENT	0.2376 (0.054)***		
BRENT (-1)	0.4172 (0.094)***		
BRENT (-2)	0.0775 (0.063)		
BRENT (-3)	0.1208 (0.061)*		
BRENT (-4)	0.0308 (0.059)		

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.

[23] The full set of regression results are available from the authors.

Table III.2. Regression Results for China Exports

Variables		Diagnostics	
Constant	0.016 (0.006)**	Observations	124
Exports (-1)	-0.6201 (0.084)***	R^2	0.57
Exports (-2)	-0.5953 (0.157)***	Adjusted R^2	0.46
Exports (-3)	-0.1803 (0.096)*	F-Statistic	5.115
Exports (-4)	-0.1071 (0.085)	Prob. (F-Statistic)	3.14e-9
SWIFT4	0.3183 (0.113)***	Log-likelihood	154.64
SWIFT4 (-1)	0.1784 (0.104)*	Durbin-Watson	2.085
SWIFT4 (-2)	0.3683 (0.099)***		
SWIFT4 (-3)	0.0795 (0.1)		
SWIFT4 (-4)	0.2253 (0.097)**		
SWIFT7	0.0017 (0.112)		
SWIFT7 (-1)	0.2024 (0.149)		
SWIFT7 (-2)	0.099 (0.108)		
SWIFT7 (-3)	0.2117 (0.106)**		
SWIFT7 (-4)	-0.1241 (0.123)		
PMI	0.0162 (0.01)		
PMI (-1)	-0.0101 (0.006)*		
PMI (-2)	-0.005 (0.004)		
PMI (-3)	-0.0002 (0.003)		
PMI (-4)	0.0024 (0.002)		
BRENT	-0.037 (0.08)		
BRENT (-1)	-0.2203 (0.132)*		
BRENT (-2)	0.0114 (0.067)		
BRENT (-3)	-0.0803 (0.08)		
BRENT (-4)	-0.1109 (0.056)**		

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.

Table III.3. Regression Results for China Imports

Variables		Diagnostics	
Constant	0.0117 (0.004)***	Observations	124
Imports (-1)	-0.63 (0.084)***	R^2	0.55
Imports (-2)	-0.446 (0.099)***	Adjusted R^2	0.44
Imports (-3)	-0.0861 (0.103)	F-Statistic	11.11
Imports (-4)	-0.0849 (0.077)	Prob. (F-Statistic)	1.05e-18
SWIFT4	-0.0533 (0.034)	Log-likelihood	217.55
SWIFT4 (-1)	-0.1141 (0.056)**	Durbin-Watson	2.035
SWIFT4 (-2)	-0.0166 (0.041)		
SWIFT4 (-3)	0.094 (0.063)		
SWIFT4 (-4)	-0.0029 (0.046)		
SWIFT7	0.1351 (0.056)**		
SWIFT7 (-1)	0.0597 (0.069)		
SWIFT7 (-2)	0.1245 (0.081)		
SWIFT7 (-3)	0.2485 (0.076)***		
SWIFT7 (-4)	0.1294 (0.062)**		
PMI	0.0058 (0.002)***		
PMI (-1)	0.003287 (0.002)		
PMI (-2)	-0.0066 (0.002)***		
PMI (-3)	0.0012 (0.002)		
PMI (-4)	0.0029 (0.002)		
BRENT	0.0776 (0.048)		
BRENT (-1)	0.0743 (0.054)		
BRENT (-2)	0.0829 (0.053)		
BRENT (-3)	0.0536 (0.036)		
BRENT (-4)	-0.0085 (0.039)		

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.

Table III.4. Regression Results for Egypt Imports

Variables		Diagnostics	
Constant	0.018 (0.009)*	Observations	119
Imports (-1)	-0.5434 (0.089)***	R^2	0.51
Imports (-2)	-0.0062 (0.091)	Adjusted R^2	0.38
Imports (-3)	-0.0816 (0.095)	F-Statistic	7.344
Imports (-4)	-0.1416 (0.086)	Prob. (F-Statistic)	6.53e-13
SWIFT4	0.1979 (0.054)***	Log-likelihood	143.64
SWIFT4 (-1)	0.1566 (0.054)***	Durbin-Watson	2.039
SWIFT4 (-2)	0.0544 (0.064)		
SWIFT4 (-3)	0.0563 (0.049)		
SWIFT4 (-4)	0.0375 (0.044)		
SWIFT7	0.0491 (0.035)		
SWIFT7 (-1)	0.035 (0.044)		
SWIFT7 (-2)	0.0411 (0.052)		
SWIFT7 (-3)	0.0588 (0.036)		
SWIFT7 (-4)	-0.0443 (0.033)		
PMI	0.0034 (0.002)		
PMI (-1)	0.0028 (0.002)		
PMI (-2)	-0.0013 (0.002)		
PMI (-3)	0.0012 (0.002)		
PMI (-4)	0.0008 (0.001)		
BRENT	-0.0409 (0.086)		
BRENT (-1)	0.1188 (0.093)		
BRENT (-2)	-0.0531 (0.062)		
BRENT (-3)	-0.0514 (0.055)		
BRENT (-4)	0.0165 (0.064)		

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.

Table III.5. Regression Results for Estonia Exports

Variables		Diagnostics	
Constant	0.0066 (0.005)	Observations	123
Exports (-1)	-0.6424 (0.112)***	R^2	0.45
Exports (-2)	-0.3866 (0.116)***	Adjusted R^2	0.34
Exports (-3)	-0.0426 (0.116)	F-Statistic	9.471
Exports (-4)	0.0146 (0.086)	Prob. (F-Statistic)	3.68e-15
SWIFT4	0.0127 (0.007)*	Log-likelihood	188.15
SWIFT4 (-1)	0.015 (0.008)*	Durbin-Watson	2.049
SWIFT4 (-2)	0.0085 (0.009)		
SWIFT4 (-3)	-0.0019 (0.009)		
SWIFT4 (-4)	-0.0062 (0.008)		
SWIFT7	0.02 (0.011)*		
SWIFT7 (-1)	0.0046 (0.016)		
SWIFT7 (-2)	-0.004 (0.015)		
SWIFT7 (-3)	-0.0055 (0.015)		
SWIFT7 (-4)	-0.0043 (0.014)		
BRENT	0.0678 (0.045)		
BRENT (-1)	0.2849 (0.04)***		
BRENT (-2)	0.0671 (0.046)		
BRENT (-3)	0.0345 (0.06)		
BRENT (-4)	0.0554 (0.056)		

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.

Table III.6. Regression Results for France Exports

Variables		Diagnostics	
Constant	0.0034 (0.003)	Observations	123
Exports (-1)	-0.4354 (0.094)***	R^2	0.70
Exports (-2)	-0.3051 (0.09)***	Adjusted R^2	0.62
Exports (-3)	0.0781 (0.085)	F-Statistic	6.182
Exports (-4)	0.0885 (0.085)	Prob. (F-Statistic)	3.64e-11
SWIFT4	0.0511 (0.023)**	Log-likelihood	251.85
SWIFT4 (-1)	0.1212 (0.033)***	Durbin-Watson	2.025
SWIFT4 (-2)	0.1169 (0.037)***		
SWIFT4 (-3)	0.1362 (0.033)***		
SWIFT4 (-4)	0.0348 (0.027)		
SWIFT7	0.0681 (0.035)*		
SWIFT7 (-1)	0.0572 (0.034)*		
SWIFT7 (-2)	0.0498 (0.034)		
SWIFT7 (-3)	-0.0044 (0.032)		
SWIFT7 (-4)	-0.0094 (0.029)		
PMI	0.007 (0.002)***		
PMI (-1)	0.0006 (0.002)		
PMI (-2)	-0.0036 (0.002)**		
PMI (-3)	-0.0032 (0.002)*		
PMI (-4)	-0.0005 (0.001)		
BRENT	0.145 (0.034)***		
BRENT (-1)	0.0228 (0.045)		
BRENT (-2)	0.0623 (0.042)		
BRENT (-3)	-0.0456 (0.035)		
BRENT (-4)	-0.029 (0.037)		

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.

Table III.7. Regression Results for Hong Kong SAR Imports

Variables		Diagnostics	
Constant	0.0016 (0.004)	Observations	78
Imports (-1)	-0.4513 (0.121)***	R^2	0.47
Imports (-2)	-0.1423 (0.107)	Adjusted R^2	0.23
Imports (-3)	-0.0167 (0.132)	F-Statistic	7.654
Imports (-4)	-0.064 (0.118)	Prob. (F-Statistic)	4.22e-10
SWIFT4	0.0798 (0.026)***	Log-likelihood	174.72
SWIFT4 (-1)	0.0252 (0.031)	Durbin-Watson	2.082
SWIFT4 (-2)	0.0483 (0.028)*		
SWIFT4 (-3)	0.0543 (0.029)*		
SWIFT4 (-4)	0.0542 (0.035)		
SWIFT7	0.1027 (0.048)**		
SWIFT7 (-1)	0.0293 (0.053)		
SWIFT7 (-2)	-0.0209 (0.062)		
SWIFT7 (-3)	0.0289 (0.069)		
SWIFT7 (-4)	-0.0229 (0.057)		
PMI	-0.0011 (0.001)		
PMI (-1)	0.0006 (0.001)		
PMI (-2)	-0.0008 (0.001)		
PMI (-3)	0.0024 (0.001)**		
PMI (-4)	-0.0017 (0.001)**		
BRENT	0.0478 (0.034)		
BRENT (-1)	0.0051 (0.028)		
BRENT (-2)	0.0471 (0.024)*		
BRENT (-3)	-0.0351 (0.026)		
BRENT (-4)	0.0541 (0.025)**		

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.

Table III.8. Regression Results for Indonesia Exports

Variables		Diagnostics	
Constant	-0.0033 (0.004)	Observations	120
Exports (-1)	-0.6186 (0.09)***	R^2	0.60
Exports (-2)	-0.1061 (0.115)	Adjusted R^2	0.50
Exports (-3)	0.0782 (0.113)	F-Statistic	11.5
Exports (-4)	0.1335 (0.099)	Prob. (F-Statistic)	8.38e-19
SWIFT4	0.0968 (0.046)**	Log-likelihood	206.09
SWIFT4 (-1)	-0.037 (0.055)	Durbin-Watson	1.998
SWIFT4 (-2)	-0.077 (0.051)		
SWIFT4 (-3)	0.0163 (0.059)		
SWIFT4 (-4)	-0.1235 (0.047)**		
SWIFT7	0.2016 (0.047)***		
SWIFT7 (-1)	0.1359 (0.062)**		
SWIFT7 (-2)	0.0781 (0.061)		
SWIFT7 (-3)	-0.0446 (0.042)		
SWIFT7 (-4)	0.0084 (0.053)		
PMI	0.0021 (0.001)		
PMI (-1)	0.0007 (0.002)		
PMI (-2)	-0.0032 (0.002)**		
PMI (-3)	0.0005 (0.002)		
PMI (-4)	-0.0007 (0.001)		
BRENT	-0.0101 (0.049)		
BRENT (-1)	0.0825 (0.042)*		
BRENT (-2)	-0.0004 (0.045)		
BRENT (-3)	0.0197 (0.048)		
BRENT (-4)	0.0557 (0.049)		

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.

Table III.9. Regression Results for India Imports

Variables		Diagnostics	
Constant	0.0066 (0.005)	Observations	124
Imports (-1)	-0.4941 (0.075)***	R^2	0.61
Imports (-2)	-0.2052 (0.096)**	Adjusted R^2	0.52
Imports (-3)	-0.1885 (0.112)*	F-Statistic	12.94
Imports (-4)	0.0077 (0.065)	Prob. (F-Statistic)	5.71e-21
SWIFT4	0.0337 (0.03)	Log-likelihood	176.03
SWIFT4 (-1)	0.0222 (0.037)	Durbin-Watson	2.014
SWIFT4 (-2)	-0.0263 (0.043)		
SWIFT4 (-3)	-0.0381 (0.036)		
SWIFT4 (-4)	-0.0042 (0.026)		
SWIFT7	0.1007 (0.046)**		
SWIFT7 (-1)	0.1164 (0.059)*		
SWIFT7 (-2)	0.1316 (0.064)**		
SWIFT7 (-3)	0.149 (0.068)**		
SWIFT7 (-4)	0.0468 (0.062)		
PMI	0.0071 (0.002)***		
PMI (-1)	-0.0083 (0.003)***		
PMI (-2)	0.0045 (0.002)*		
PMI (-3)	-0.0034 (0.003)		
PMI (-4)	0.0001 (0.002)		
BRENT	0.2489 (0.071)***		
BRENT (-1)	0.135 (0.086)		
BRENT (-2)	0.3447 (0.079)***		
BRENT (-3)	-0.0102 (0.085)		
BRENT (-4)	0.073 (0.074)		

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.

Table III.10. Regression Results for Israel Imports

Variables		Diagnostics	
Constant	0.0037 (0.007)	Observations	124
Exports (-1)	-0.9432 (0.072)***	R^2	0.58
Exports (-2)	-0.7053 (0.081)***	Adjusted R^2	0.48
Exports (-3)	-0.4139 (0.087)***	F-Statistic	15.04
Exports (-4)	-0.2371 (0.07)***	Prob. (F-Statistic)	2.68e-23
SWIFT4	0.1044 (0.048)**	Log-likelihood	145.74
SWIFT4 (-1)	-0.0294 (0.065)	Durbin-Watson	2.084
SWIFT4 (-2)	-0.0819 (0.058)		
SWIFT4 (-3)	-0.042 (0.071)		
SWIFT4 (-4)	0.0122 (0.066)		
SWIFT7	0.0771 (0.032)**		
SWIFT7 (-1)	0.0711 (0.03)**		
SWIFT7 (-2)	0.0528 (0.034)		
SWIFT7 (-3)	0.0403 (0.033)		
SWIFT7 (-4)	0.0345 (0.03)		
PMI	0.0012 (0.001)		
PMI (-1)	0.0021 (0.002)		
PMI (-2)	-0.0022 (0.001)		
PMI (-3)	0.0019 (0.001)		
PMI (-4)	-0.0013 (0.001)		
BRENT	0.0868 (0.048)*		
BRENT (-1)	0.098 (0.058)*		
BRENT (-2)	0.0866 (0.063)		
BRENT (-3)	0.0241 (0.059)		
BRENT (-4)	0.0629 (0.066)		

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.

Table III.11. Regression Results for Japan Imports

Variables		Diagnostics	
Constant	0.001 (0.003)	Observations	124
Imports (-1)	-0.4007 (0.112)***	R^2	0.37
Imports (-2)	-0.172 (0.107)	Adjusted R^2	0.22
Imports (-3)	0.0121 (0.111)	F-Statistic	4.936
Imports (-4)	-0.0392 (0.104)	Prob. (F-Statistic)	7.01e-9
SWIFT4	-0.0415 (0.03)	Log-likelihood	243.65
SWIFT4 (-1)	-0.0572 (0.052)	Durbin-Watson	2.072
SWIFT4 (-2)	0.0072 (0.057)		
SWIFT4 (-3)	-0.0137 (0.046)		
SWIFT4 (-4)	0.0394 (0.03)		
SWIFT7	0.0765 (0.035)**		
SWIFT7 (-1)	0.0593 (0.052)		
SWIFT7 (-2)	0.0896 (0.05)*		
SWIFT7 (-3)	-0.0422 (0.052)		
SWIFT7 (-4)	0.0265 (0.049)		
PMI	0.0012 (0.002)		
PMI (-1)	-0.0048 (0.002)**		
PMI (-2)	0.0018 (0.002)		
PMI (-3)	0.0031 (0.002)		
PMI (-4)	-0.0012 (0.002)		
BRENT	-0.0045 (0.037)		
BRENT (-1)	0.0662 (0.04)		
BRENT (-2)	0.0881 (0.031)***		
BRENT (-3)	0.0708 (0.03)**		
BRENT (-4)	0.0924 (0.04)**		

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.

Table III.12. Regression Results for Korea Imports

Variables		Diagnostics	
Constant	0.0082 (0.003)***	Observations	124
Imports (-1)	-0.7003 (0.077)***	R^2	0.63
Imports (-2)	-0.5061 (0.103)***	Adjusted R^2	0.54
Imports (-3)	-0.0363 (0.096)	F-Statistic	26.44
Imports (-4)	-0.1465 (0.086)*	Prob. (F-Statistic)	7.06e-33
SWIFT4	0.048 (0.022)**	Log-likelihood	265.35
SWIFT4 (-1)	0.035 (0.028)	Durbin-Watson	2.108
SWIFT4 (-2)	0.0799 (0.028)***		
SWIFT4 (-3)	0.058 (0.027)**		
SWIFT4 (-4)	0.0413 (0.023)*		
SWIFT7	0.1861 (0.057)***		
SWIFT7 (-1)	0.2492 (0.057)***		
SWIFT7 (-2)	0.0111 (0.06)		
SWIFT7 (-3)	0.1355 (0.068)**		
SWIFT7 (-4)	0.0979 (0.053)*		
PMI	-0.0006 (0.002)		
PMI (-1)	-0.001 (0.002)		
PMI (-2)	-0.0032 (0.002)		
PMI (-3)	0.0042 (0.002)**		
PMI (-4)	0.0004 (0.001)		
BRENT	0.0243 (0.025)		
BRENT (-1)	0.1283 (0.029)***		
BRENT (-2)	0.1227 (0.026)***		
BRENT (-3)	0.101 (0.033)***		
BRENT (-4)	0.058 (0.035)		

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.

Table III.13. Regression Results for Lithuania Exports

Variables		Diagnostics	
Constant	0.0072 (0.004)	Observations	123
Exports (-1)	-0.5994 (0.094)***	R^2	0.45
Exports (-2)	-0.2021 (0.103)*	Adjusted R^2	0.34
Exports (-3)	0.0192 (0.103)	F-Statistic	6.506
Exports (-4)	0.0434 (0.073)	Prob. (F-Statistic)	9.63e-11
SWIFT4	0.0065 (0.003)**	Log-likelihood	203.79
SWIFT4 (-1)	0.0021 (0.003)	Durbin-Watson	1.978
SWIFT4 (-2)	0.0018 (0.003)		
SWIFT4 (-3)	-0.0024 (0.003)		
SWIFT4 (-4)	-0.0036 (0.003)		
SWIFT7	0.0275 (0.013)**		
SWIFT7 (-1)	0.0215 (0.011)*		
SWIFT7 (-2)	0.0076 (0.012)		
SWIFT7 (-3)	-0.0076 (0.011)		
SWIFT7 (-4)	-0.0089 (0.008)		
BRENT	0.1047 (0.047)**		
BRENT (-1)	0.1863 (0.039)***		
BRENT (-2)	0.0711 (0.047)		
BRENT (-3)	-0.0049 (0.044)		
BRENT (-4)	0.0163 (0.042)		

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.

Table III.14. Regression Results for Mexico Exports

Variables		Diagnostics	
Constant	0.0066 (0.004)*	Observations	119
Exports (-1)	-0.1078 (0.087)	R^2	0.76
Exports (-2)	-0.2163 (0.148)	Adjusted R^2	0.70
Exports (-3)	-0.07 (0.076)	F-Statistic	6.837
Exports (-4)	-0.0586 (0.108)	Prob. (F-Statistic)	4.35e-12
SWIFT4	0.0122 (0.007)	Log-likelihood	228.39
SWIFT4 (-1)	-0.0098 (0.01)	Durbin-Watson	1.84
SWIFT4 (-2)	-0.0017 (0.011)		
SWIFT4 (-3)	0.0062 (0.01)		
SWIFT4 (-4)	0.0021 (0.007)		
SWIFT7	0.029 (0.009)***		
SWIFT7 (-1)	0.0358 (0.014)**		
SWIFT7 (-2)	0.0093 (0.016)		
SWIFT7 (-3)	-0.0183 (0.013)		
SWIFT7 (-4)	-0.0283 (0.011)**		
PMI	0.0077 (0.003)***		
PMI (-1)	0.0009 (0.003)		
PMI (-2)	-0.0117 (0.003)***		
PMI (-3)	0.0046 (0.002)*		
PMI (-4)	-0.0025 (0.002)		
BRENT	0.0398 (0.039)		
BRENT (-1)	0.2548 (0.056)***		
BRENT (-2)	-0.0388 (0.043)		
BRENT (-3)	-0.0058 (0.044)		
BRENT (-4)	0.0639 (0.049)		

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.

Table III.15. Regression Results for Nigeria Exports

Variables		Diagnostics	
Constant	-0.0119 (0.009)	Observations	84
Exports (-1)	-0.4791 (0.12)***	R^2	0.73
Exports (-2)	-0.3241 (0.103)***	Adjusted R^2	0.61
Exports (-3)	-0.0795 (0.112)	F-Statistic	33.93
Exports (-4)	-0.1593 (0.1)	Prob. (F-Statistic)	3.86e-26
SWIFT4	-0.001 (0.008)	Log-likelihood	100.75
SWIFT4 (-1)	0.0055 (0.011)	Durbin-Watson	1.899
SWIFT4 (-2)	0.0207 (0.011)*		
SWIFT4 (-3)	0.0067 (0.009)		
SWIFT4 (-4)	-0.0141 (0.008)*		
SWIFT7	0.1053 (0.038)***		
SWIFT7 (-1)	0.1963 (0.064)***		
SWIFT7 (-2)	0.1384 (0.061)**		
SWIFT7 (-3)	0.0628 (0.055)		
SWIFT7 (-4)	-0.0283 (0.049)		
PMI	0.0047 (0.002)**		
PMI (-1)	-0.0006 (0.005)		
PMI (-2)	0.0042 (0.004)		
PMI (-3)	-0.009 (0.003)***		
PMI (-4)	0.0042 (0.002)*		
BRENT	0.7029 (0.083)***		
BRENT (-1)	0.1561 (0.141)		
BRENT (-2)	0.1202 (0.101)		
BRENT (-3)	-0.0442 (0.089)		
BRENT (-4)	0.1106 (0.11)		

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.

Table III.16. Regression Results for Pakistan Imports

Variables		Diagnostics	
Constant	0.0006 (0.007)	Observations	124
Imports (-1)	-0.8052 (0.107)***	R^2	0.56
Imports (-2)	-0.596 (0.157)***	Adjusted R^2	0.48
Imports (-3)	-0.3676 (0.138)***	F-Statistic	10.37
Imports (-4)	-0.1258 (0.117)	Prob. (F-Statistic)	1.97e-16
SWIFT4	-0.165 (0.134)	Log-likelihood	131.43
SWIFT4 (-1)	-0.2764 (0.147)*	Durbin-Watson	2.04
SWIFT4 (-2)	-0.2443 (0.139)*		
SWIFT4 (-3)	-0.1882 (0.152)		
SWIFT4 (-4)	-0.1793 (0.148)		
SWIFT7	0.3022 (0.087)***		
SWIFT7 (-1)	0.5523 (0.143)***		
SWIFT7 (-2)	0.4842 (0.127)***		
SWIFT7 (-3)	0.3456 (0.114)***		
SWIFT7 (-4)	0.2519 (0.094)***		
BRENT	0.1484 (0.11)		
BRENT (-1)	0.1361 (0.074)*		
BRENT (-2)	0.0242 (0.091)		
BRENT (-3)	-0.203 (0.094)**		
BRENT (-4)	0.0389 (0.074)		

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.

Table III.17. Regression Results for Peru Exports

Variables		Diagnostics	
Constant	0.0095 (0.006)*	Observations	123
Exports (-1)	-0.4773 (0.08)***	R^2	0.57
Exports (-2)	-0.3134 (0.096)***	Adjusted R^2	0.49
Exports (-3)	-0.3496 (0.106)***	F-Statistic	10.85
Exports (-4)	-0.1443 (0.086)*	Prob. (F-Statistic)	5.68e-17
SWIFT4	0.0531 (0.026)**	Log-likelihood	174.53
SWIFT4 (-1)	0.0081 (0.031)	Durbin-Watson	2.031
SWIFT4 (-2)	0.0169 (0.035)		
SWIFT4 (-3)	-0.0626 (0.028)**		
SWIFT4 (-4)	-0.0647 (0.025)**		
SWIFT7	0.0541 (0.02)***		
SWIFT7 (-1)	0.0955 (0.023)***		
SWIFT7 (-2)	0.0418 (0.026)		
SWIFT7 (-3)	0.054 (0.025)**		
SWIFT7 (-4)	0.0271 (0.023)		
BRENT	0.25 (0.062)***		
BRENT (-1)	0.2799 (0.069)***		
BRENT (-2)	0.1731 (0.061)***		
BRENT (-3)	-0.0069 (0.064)		
BRENT (-4)	0.1795 (0.059)***		

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.

Table III.18. Regression Results for Peru Imports

Variables		Diagnostics	
Constant	0.0116 (0.004)***	Observations	123
Imports (-1)	-0.697 (0.09)***	R^2	0.59
Imports (-2)	-0.4899 (0.094)***	Adjusted R^2	0.51
Imports (-3)	-0.0604 (0.095)	F-Statistic	9.794
Imports (-4)	-0.0956 (0.084)	Prob. (F-Statistic)	1.34e-15
SWIFT4	0.0685 (0.013)***	Log-likelihood	211.95
SWIFT4 (-1)	0.0956 (0.021)***	Durbin-Watson	1.98
SWIFT4 (-2)	0.0538 (0.025)**		
SWIFT4 (-3)	0.0574 (0.025)**		
SWIFT4 (-4)	0.0297 (0.022)		
SWIFT7	0.0631 (0.025)**		
SWIFT7 (-1)	0.038 (0.028)		
SWIFT7 (-2)	0.0374 (0.029)		
SWIFT7 (-3)	0.0835 (0.026)***		
SWIFT7 (-4)	0.0596 (0.021)***		
BRENT	0.1692 (0.043)***		
BRENT (-1)	0.2113 (0.037)***		
BRENT (-2)	0.1916 (0.051)***		
BRENT (-3)	-0.022 (0.043)		
BRENT (-4)	0.098 (0.05)*		

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.

Table III.19. Regression Results for Russia Imports

Variables		Diagnostics	
Constant	-0.0001 (0.004)	Observations	123
Imports (-1)	-0.4007 (0.083)***	R^2	0.49
Imports (-2)	-0.0497 (0.094)	Adjusted R^2	0.36
Imports (-3)	0.2609 (0.086)***	F-Statistic	9.241
Imports (-4)	-0.0329 (0.086)	Prob. (F-Statistic)	4.61e-16
SWIFT4	0.012 (0.007)*	Log-likelihood	220.91
SWIFT4 (-1)	0.0259 (0.008)***	Durbin-Watson	2.073
SWIFT4 (-2)	0.0087 (0.006)		
SWIFT4 (-3)	0.0064 (0.007)		
SWIFT4 (-4)	0.0091 (0.005)*		
SWIFT7	0.0619 (0.016)***		
SWIFT7 (-1)	0.0383 (0.023)		
SWIFT7 (-2)	0.049 (0.025)*		
SWIFT7 (-3)	0.054 (0.018)***		
SWIFT7 (-4)	0.0073 (0.017)		
PMI	0.0001 (0.001)		
PMI (-1)	0.0014 (0.002)		
PMI (-2)	-0.0026 (0.001)*		
PMI (-3)	0.0015 (0.002)		
PMI (-4)	-0.0014 (0.002)		
BRENT	0.1657 (0.053)***		
BRENT (-1)	0.0543 (0.043)		
BRENT (-2)	0.0573 (0.045)		
BRENT (-3)	-0.0374 (0.05)		
BRENT (-4)	0.0856 (0.035)**		

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.

Table III.20. Regression Results for Saudi Arabia Imports

Variables		Diagnostics	
Constant	0.0035 (0.007)	Observations	123
Imports (-1)	-0.7204 (0.093)***	R^2	0.52
Imports (-2)	-0.2307 (0.116)*	Adjusted R^2	0.41
Imports (-3)	-0.0424 (0.112)	F-Statistic	8.044
Imports (-4)	0.0808 (0.097)	Prob. (F-Statistic)	2.88e-14
SWIFT4	0.0633 (0.036)*	Log-likelihood	180.2
SWIFT4 (-1)	0.0188 (0.037)	Durbin-Watson	2.044
SWIFT4 (-2)	0.0278 (0.036)		
SWIFT4 (-3)	-0.0234 (0.04)		
SWIFT4 (-4)	-0.0043 (0.035)		
SWIFT7	0.1454 (0.064)**		
SWIFT7 (-1)	0.1559 (0.06)**		
SWIFT7 (-2)	0.1621 (0.057)***		
SWIFT7 (-3)	0.1113 (0.054)**		
SWIFT7 (-4)	0.0445 (0.047)		
PMI	3.584e (-5)**		
PMI (-1)	-4.498e (-5)***		
PMI (-2)	0.0004 (0.003)		
PMI (-3)	0.0001 (0.003)		
PMI (-4)	6.758e (-5)**		
BRENT	0.0435 (0.039)		
BRENT (-1)	0.1526 (0.044)***		
BRENT (-2)	-0.1863 (0.045)***		
BRENT (-3)	0.0845 (0.058)		
BRENT (-4)	0.0349 (0.053)		

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.

Table III.21. Regression Results for Singapore Exports

Variables		Diagnostics	
Constant	0.0026 (0.003)	Observations	124
Exports (-1)	-0.6465 (0.102)***	R^2	0.65
Exports (-2)	-0.5457 (0.095)***	Adjusted R^2	0.59
Exports (-3)	-0.0843 (0.105)	F-Statistic	24.81
Exports (-4)	-0.1991 (0.103)*	Prob. (F-Statistic)	3.00e-30
SWIFT4	0.1667 (0.037)***	Log-likelihood	253.7
SWIFT4 (-1)	0.0314 (0.044)	Durbin-Watson	1.988
SWIFT4 (-2)	0.0188 (0.049)		
SWIFT4 (-3)	0.0017 (0.046)		
SWIFT4 (-4)	0.0565 (0.044)		
SWIFT7	0.0058 (0.033)		
SWIFT7 (-1)	0.0619 (0.039)		
SWIFT7 (-2)	-0.0556 (0.044)		
SWIFT7 (-3)	0.0169 (0.049)		
SWIFT7 (-4)	-0.0104 (0.035)		
BRENT	0.0654 (0.026)**		
BRENT (-1)	0.2157 (0.026)***		
BRENT (-2)	0.0819 (0.035)**		
BRENT (-3)	0.0984 (0.031)***		
BRENT (-4)	0.0133 (0.037)		

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.

Table III.22. Regression Results for Slovenia Imports

Variables		Diagnostics	
Constant	0.0096 (0.005)*	Observations	81
Imports (-1)	-0.5619 (0.115)***	R^2	0.65
Imports (-2)	-0.4655 (0.13)***	Adjusted R^2	0.49
Imports (-3)	-0.182 (0.124)	F-Statistic	16.73
Imports (-4)	-0.3593 (0.093)***	Prob. (F-Statistic)	1.21e-17
SWIFT4	0.0134 (0.018)	Log-likelihood	139.84
SWIFT4 (-1)	-0.0233 (0.024)	Durbin-Watson	2.03
SWIFT4 (-2)	0.0241 (0.024)		
SWIFT4 (-3)	0.0181 (0.02)		
SWIFT4 (-4)	0.0116 (0.023)		
SWIFT7	0.0483 (0.026)*		
SWIFT7 (-1)	0.0867 (0.034)**		
SWIFT7 (-2)	0.0594 (0.035)*		
SWIFT7 (-3)	0.0453 (0.032)		
SWIFT7 (-4)	-0.0286 (0.023)		
PMI	0.0009 (0)*		
PMI (-1)	3.278e (-5)*		
PMI (-2)	0.0009 (0.001)		
PMI (-3)	-0.0005 (0)		
PMI (-4)	0.0004 (0)		
BRENT	0.1692 (0.039)***		
BRENT (-1)	0.1618 (0.049)***		
BRENT (-2)	0.0562 (0.053)		
BRENT (-3)	0.0119 (0.045)		
BRENT (-4)	0.0739 (0.066)		

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.

Table III.23. Regression Results for Spain Exports

Variables		Diagnostics	
Constant	0.0027 (0.002)	Observations	123
Exports (-1)	-0.2315 (0.087)***	R^2	0.73
Exports (-2)	0.061 (0.094)	Adjusted R^2	0.67
Exports (-3)	-0.065 (0.089)	F-Statistic	22.95
Exports (-4)	-0.0626 (0.078)	Prob. (F-Statistic)	3.49e-30
SWIFT4	0.063 (0.021)***	Log-likelihood	277.44
SWIFT4 (-1)	0.0312 (0.025)	Durbin-Watson	1.974
SWIFT4 (-2)	-0.0338 (0.031)		
SWIFT4 (-3)	-0.0254 (0.029)		
SWIFT4 (-4)	-0.0377 (0.024)		
SWIFT7	0.0357 (0.025)		
SWIFT7 (-1)	0.032 (0.02)		
SWIFT7 (-2)	0.0114 (0.025)		
SWIFT7 (-3)	0.0564 (0.022)**		
SWIFT7 (-4)	-0.0189 (0.019)		
PMI	0.0062 (0.001)***		
PMI (-1)	-0.0036 (0.001)***		
PMI (-2)	-0.0015 (0.001)		
PMI (-3)	-0.0003 (0.001)		
PMI (-4)	-0.0006 (0.001)		
BRENT	0.1587 (0.028)***		
BRENT (-1)	0.0507 (0.033)		
BRENT (-2)	-0.0241 (0.036)		
BRENT (-3)	0.0149 (0.03)		
BRENT (-4)	0.0506 (0.031)		

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.

Table III.24. Regression Results for Sweden Exports

Variables		Diagnostics	
Constant	-0.0032 (0.003)	Observations	123
Exports (-1)	-0.6464 (0.116)***	R^2	0.62
Exports (-2)	-0.2401 (0.1)**	Adjusted R^2	0.53
Exports (-3)	-0.0404 (0.087)	F-Statistic	20.22
Exports (-4)	-0.0816 (0.087)	Prob. (F-Statistic)	5.24e-28
SWIFT4	0.0273 (0.016)*	Log-likelihood	268.75
SWIFT4 (-1)	-0.0032 (0.019)	Durbin-Watson	1.98
SWIFT4 (-2)	0.0049 (0.023)		
SWIFT4 (-3)	0.0092 (0.022)		
SWIFT4 (-4)	-0.0199 (0.018)		
SWIFT7	0.0429 (0.016)**		
SWIFT7 (-1)	0.059 (0.019)***		
SWIFT7 (-2)	0.0685 (0.02)***		
SWIFT7 (-3)	0.0493 (0.021)**		
SWIFT7 (-4)	0.0523 (0.017)***		
PMI	0.0027 (0.001)***		
PMI (-1)	0.001 (0.001)		
PMI (-2)	0.0007 (0.001)		
PMI (-3)	-0.0017 (0.001)		
PMI (-4)	-0.0011 (0.001)		
BRENT	0.1305 (0.025)***		
BRENT (-1)	0.1159 (0.038)***		
BRENT (-2)	-0.0219 (0.025)		
BRENT (-3)	-0.0133 (0.026)		
BRENT (-4)	-0.0084 (0.028)		

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.

Table III.25. Regression Results for Thailand Imports

Variables		Diagnostics	
Constant	0.0005326 (0.006)	Observations	64
Imports (-1)	-0.8961 (0.119)***	R^2	0.76
Imports (-2)	-0.3976 (0.139)***	Adjusted R^2	0.61
Imports (-3)	0.2525 (0.137)*	F-Statistic	20.6
Imports (-4)	0.1997 (0.112)*	Prob. (F-Statistic)	2.17e-15
SWIFT4	0.1226 (0.031)***	Log-likelihood	115.45
SWIFT4 (-1)	-0.0021 (0.028)	Durbin-Watson	2.128
SWIFT4 (-2)	-0.0516 (0.028)*		
SWIFT4 (-3)	0.0236 (0.027)		
SWIFT4 (-4)	0.0294 (0.03)		
SWIFT7	0.0818 (0.076)		
SWIFT7 (-1)	0.1922 (0.105)*		
SWIFT7 (-2)	0.0612 (0.103)		
SWIFT7 (-3)	-0.0737 (0.098)		
SWIFT7 (-4)	0.0451 (0.069)		
PMI	0.0013 (0.002)		
PMI (-1)	-0.0034 (0.002)		
PMI (-2)	-0.0016 (0.002)		
PMI (-3)	0.0004 (0.002)		
PMI (-4)	0.0013 (0.002)		
BRENT	-0.0385 (0.047)		
BRENT (-1)	0.2048 (0.061)***		
BRENT (-2)	0.1311 (0.104)		
BRENT (-3)	0.2053 (0.056)***		
BRENT (-4)	0.1671 (0.065)**		

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.

Table III.26. Regression Results for Turkey Imports

Variables		Diagnostics	
Constant	0.0025 (0.005)	Observations	124
Imports (-1)	-0.7605 (0.122)***	R^2	0.63
Imports (-2)	-0.2131 (0.118)*	Adjusted R^2	0.54
Imports (-3)	0.1064 (0.113)	F-Statistic	11.51
Imports (-4)	0.0477 (0.133)	Prob. (F-Statistic)	3.18e-19
SWIFT4	0.1138 (0.056)**	Log-likelihood	187.02
SWIFT4 (-1)	0.0264 (0.053)	Durbin-Watson	2.005
SWIFT4 (-2)	0.0071 (0.076)		
SWIFT4 (-3)	0.0286 (0.07)		
SWIFT4 (-4)	0.0127 (0.058)		
SWIFT7	0.1937 (0.055)***		
SWIFT7 (-1)	0.0383 (0.067)		
SWIFT7 (-2)	0.0269 (0.06)		
SWIFT7 (-3)	0.075 (0.072)		
SWIFT7 (-4)	0.0095 (0.062)		
PMI	0.006 (0.002)***		
PMI (-1)	0.0037 (0.003)		
PMI (-2)	-0.0027 (0.002)		
PMI (-3)	-0.0019 (0.003)		
PMI (-4)	-0.0039 (0.002)*		
BRENT	0.1167 (0.046)**		
BRENT (-1)	0.0749 (0.058)		
BRENT (-2)	-0.0268 (0.057)		
BRENT (-3)	-0.0333 (0.075)		
BRENT (-4)	-0.0422 (0.075)		

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.

Table III.27. Regression Results for Vietnam Imports

Variables		Diagnostics	
Constant	0.0241 (0.006)***	Observations	121
Imports (-1)	-0.8751 (0.099)***	R^2	0.70
Imports (-2)	-0.5682 (0.115)***	Adjusted R^2	0.63
Imports (-3)	-0.3755 (0.089)***	F-Statistic	13.42
Imports (-4)	-0.1961 (0.065)***	Prob. (F-Statistic)	3.65e-21
SWIFT4	0.1191 (0.051)**	Log-likelihood	183.14
SWIFT4 (-1)	0.0045 (0.052)	Durbin-Watson	2.061
SWIFT4 (-2)	-0.0401 (0.048)		
SWIFT4 (-3)	0.1415 (0.049)***		
SWIFT4 (-4)	0.0578 (0.041)		
SWIFT7	0.3617 (0.081)***		
SWIFT7 (-1)	0.1847 (0.08)**		
SWIFT7 (-2)	-0.0191 (0.066)		
SWIFT7 (-3)	0.0282 (0.073)		
SWIFT7 (-4)	0.1726 (0.059)***		
PMI	0.003 (0.002)		
PMI (-1)	0.002 (0.002)		
PMI (-2)	-0.0024 (0.002)		
PMI (-3)	0.00008045 (0.002)		
PMI (-4)	-0.0027 (0.002)		
BRENT	-0.1633 (0.053)***		
BRENT (-1)	-0.0047 (0.063)		
BRENT (-2)	0.1378 (0.065)**		
BRENT (-3)	0.0364 (0.067)		
BRENT (-4)	-0.0152 (0.055)		

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.

PUBLICATIONS

Another Piece of the Puzzle: Adding SWIFT Data on Documentary Collections
Working Paper No. **WP/21/293**