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Nowcasting World Trade With a Multi-Region Factor Model

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Nowcasting World Trade With a Multi-Region Factor Model

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ABSTRACT: This paper presents a nowcasting model for global trade that allows for regional dynamics and spillovers. World trade growth is driven by common global factors but also regional trends. While existing trade nowcasting models have focused on the former, we allow for the latter using a dynamic factor model (DFM) with a multi-factor block structure. By directly modeling global trends, regional variation and spillovers, we improve on the performance of standard trade nowcasting models, particularly periods characterized by regional heterogeneity. A multi-factor regional framework may be particularly advantageous for tracking trade developments in the future given a period changing trade patterns and geo-economic fragmentation. The model also sheds light on trade spillovers and the drivers of news in global trade: Asia, in particular, has notable spillovers to the global and other regional trade cycles.

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* The views expressed in this paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

WORKING PAPERS

Nowcasting world trade with a multi-region factor model

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1 Introduction

Trade is an important part of the global economy and viewed as a leading indicator of global activity. The ability to track global trade growth reliably in real time is therefore of keen interest to policymakers. Doing so, however, presents several challenges. Global trade data are published with a lag. A variety of more timely relevant indicators exist to help forecast trade, but they are often noisy and their mapping to trade data is uncertain. More so than other global macroeconomic data, trade data are also interrelated: trade growth in one region has implications for the outlook for trade in another.

Dynamic Factor Models (DFMs) present a way to deal with these challenges. DFMs are a popular tool for nowcasting macroeconomic data because they efficiently utilize information from large and varied datasets. This is achieved by modeling the common dynamics of several series as explained by a small number of latent factors (Stock and Watson 2016). They also have the advantage of being able to handle efficiently the real-time data flow and allow for missing data at the end of samples due to asynchronous publication lags, the so-called 'jagged' or 'ragged edge' problem (Giannone et al. 2008).

As a result, the literature on nowcasting global trade has tended to focus on DFMs or related principal components analysis, including Guichard and Rusticelli 2011 and more recently Barhoumi et al. 2016 and Martínez-Martín and Rusticelli 2021. These papers model world trade as a function of a common global factor, with Guichard and Rusticelli 2011 finding that this method outperforms alternative forecasting methodologies such as bridge equations. Direct forecasts of global trade have also been found to outperform aggregated country-level forecasts (Burgert and Dees 2009), which speaks to the synchronous nature of world trade.

This paper builds on this literature in using a multi-factor DFM to nowcast global trade growth. While global factors are an important determinant of world trade growth, the forecasting performance of a DFM can be improved by allowing for regional factors and spillovers. Specifically, a multi-factor block structure can account for variation due to a global cycle, regional fluctuations and series-specific variation. As argued by Doz and Fuleky 2020, if these regional fluctuations were not properly modeled it would appear either as weak common factors or errors that are correlated within the same region. Indeed, Guichard and Rusticelli 2011 found that adding additional data, particularly regional-level data, had a diminishing effect on the forecast performance of their single global factor trade DFM. This may be not because those data have limited marginal information but because the model is incorrectly specified. Spillovers from one region to another are captured through the loading and VAR structure of the factors.

In methodology, this paper is closely related to Cascaldi-Garcia et al. 2024, who use a similar multi-region DFM for nowcasting activity in the euro area as a whole and in its largest member countries. It is also related to Kose et al. 2012 and Mumtaz and Musso 2021 who use a similar econometric framework to decompose fluctuations in economic activity and uncertainty, respectively, into global, regional and country-specific factors.

Recent literature has employed big data to construct real-time indicators of global trade. For instance, Arslanalp, Koepke, et al. 2021 utilizes AIS signals to monitor vessel activity, while Arslanalp, Choi, et al. 2025 extends this approach to nowcast global trade volumes. These methodologies offer near-live insights, particularly valuable during periods of abrupt disruption. In contrast, our framework relies on traditional high-frequency indicators which, although subject to longer reporting lags, provide broader coverage beyond maritime trade and are conceptually aligned with economic trade volumes without requiring transformation from physical measures.

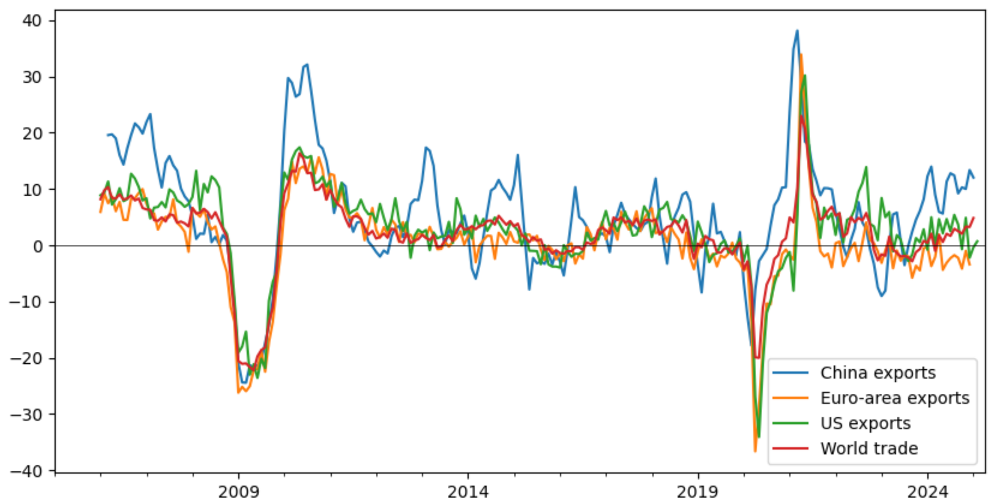
We find that the nowcasting performance of a multi-region DFM improves on that of a single global factor model, as well as other statistical benchmarks. First, we present case studies to highlight the advantages of a regional model. Our model outperforms a single-factor DFM during the Covid contraction in 2020 and recovery in world trade in 2023. This reflects its ability to identify the impact of regional trade shocks - particularly those from China - which diverge from the global trend. In contrast, it does not outperform a single-factor DFM during the Global Financial Crisis in 2008 as the slowdown was global and synchronous in nature. Second, we conduct a more systematic pseudo out-of-sample forecasting exercise over two periods: the global trade slowdown in 2017-19 and the Covid period 2020-22. The multi-factor DFM outperforms these benchmarks in both periods, with the improvement in performance greatest before the start of the quarter and absolute forecasting performance generally improving over the data cycle as data are released. Given the multi-factor and single-factor model use the same dataset, the former's relative outperformance reflects its ability to model world trade as a function of global and regional trends. A multi-factor framework such as this may be particularly advantageous for tracking trade developments if the incidence of temporary regional shocks rise relative to that that of global shocks.

The model also highlights the regional sources of fluctuations in global trade. We use a generalized forecast error variance decomposition, developed by Pesaran and Shin 1998 and Diebold and Yilmaz 2012, to analyze the spillovers between the global and regional factors in the model. The framework measures spillovers among the different factors. We find that the global and Asian factors have the largest spillovers to other factors over time. The former suggests global factors are ultimately an important driver of regional trade variation, while the latter likely speaks to the increasing integration of Asia into global value chains and global business cycle (Duval et al. 2014).

2 Data

Our main variable of interest is the index of the volume of global goods trade published by the Netherlands Bureau for Economic Policy Analysis (CPB). The indicator is monthly and captures trade data from 85 countries comprising 97% of world goods trade. As shown in Figure 1, trade flows are highly correlated across regions but not perfectly so.

Figure 1: World trade growth (y/y, percent)



Note: Three-month average used to smooth China's data.

A key advantage of a DFM is its ability to incorporate information from a large number of indicators. The data are summarized in Table 1, including their typical publication lag from the end of the month in question and their transformation to ensure stationarity. Our dataset includes 81 monthly variables and a variety of data types and geographies: 15 variables are global, 11 US-specific, 16 Asian, 9 Chinese and 30 European. The data are a mix of surveys (e.g. PMIs), hard data (e.g. industrial production) and some financial data (e.g. US effective exchange rate). While world trade is published with a lag of almost two months, other data are more timely, particularly surveys but also country-level hard data. One restriction is the dataset for the model is limited to series with a relatively long backrun, which excludes some newer series, such as IMF's PortWatch.

Our data selection also includes monthly country and regional trade data. These are excluded from many global trade nowcast models which focus on forecasting the global aggregate. However, as Table 1 shows, they are often published earlier than the global measure and therefore can provide a timely signal about global trade growth. These data are also important for constructing the regional factors, which is discussed in the next section.

Table 1: Summary of data

Series	Frequency	Publication lag (days)	Transformation	Global	US	China	Asia	Europe
World trade	M	56	Log difference	•	•	•	•	•
Global PMI new export orders	M	1	Level	•	•	•	•	•
Global PMI manufacturing	M	1	Level	•	•	•	•	•
Global PMI stocks of purchases	M	1	Level	•	•	•	•	•
PMI electrical equipment	M	4	Level	•	•	•	•	•
World industrial production	M	56	Log difference	•	•	•	•	•
Advanced economies industrial production	M	56	Log difference	•	•	•	•	•
Global container throughput index	M	30	Log difference	•	•	•	•	•
Global Supply Chain Index	M	5	Level	•	•	•	•	•
Harper Peterson Chart Rate Index	M	0	Log difference	•	•	•	•	•
Brent oil price	M	0	Log difference	•	•	•	•	•
US nominal effective exchange rate	M	2	Log difference	•	•	•	•	•
US high-yield spread	M	0	First difference	•	•	•	•	•
MSCI World Index	M	0	Log difference	•	•	•	•	•
Trade policy uncertainty	M	1	Log difference	•	•	•	•	•
US imports	M	35	Log difference	•	•			
US exports	M	35	Log difference	•	•			
US industrial production	M	16	Log difference	•	•			
US manufacturing inventories	M	25	Log difference	•	•			
US manufacturing PMI	M	-7	Level	•	•			
US PMI new export orders	M	-7	Level	•	•			
US ISM new export orders	M	1	Level	•	•			
US goods consumption	M	26	Log difference	•	•			
US retail sales	M	16	Log difference	•	•			
US durable goods	M	25	Log difference	•	•			
US capital goods orders	M	25	Log difference	•	•			
China exports	M	56	Log difference	•		•	•	
China imports	M	56	Log difference	•		•	•	
China industrial production	M	14	Log difference	•		•	•	
China Caixin PMI new export orders	M	-1	Level	•		•	•	
China Caixin PMI manufacturing	M	-1	Level	•		•	•	
China NBS PMI new export orders	M	-1	Level	•		•	•	
China NBS PMI manufacturing	M	-1	Level	•		•	•	
China retail sales	M	17	Log difference	•		•	•	
China international aviation cargo and mail	M	18	Log difference	•		•	•	
Emerging Asia ex China exports	M	56	Log difference	•			•	
Emerging Asia ex China imports	M	56	Log difference	•			•	
Japan exports	M	17	Log difference	•			•	
Japan imports	M	17	Log difference	•			•	
Korea exports	M	15	Log difference	•			•	
Korea imports	M	15	Log difference	•			•	
Malaysia exports	M	25	Log difference	•			•	
Malaysia imports	M	25	Log difference	•			•	
Taiwan Province of China exports	M	24	Log difference	•			•	
Taiwan Province of China imports	M	24	Log difference	•			•	
ASEAN PMI new export orders	M	0	Level	•			•	
Japan PMI new export orders	M	0	Level	•			•	
Korea PMI new export orders	M	0	Level	•			•	
Japan industrial production	M	29	Log difference	•			•	
Korea industrial production	M	29	Log difference	•			•	
EM Asia ex China industrial production	M	56	Log difference	•			•	
Euro-area exports	M	78	Log difference	•				•
Euro-area imports	M	78	Log difference	•				•
Euro-area manufacturing exports	M	46	Log difference	•				•
Euro-area manufacturing imports	M	46	Log difference	•				•
Germany exports	M	55	Log difference	•				•
Germany imports	M	55	Log difference	•				•
France exports	M	77	Log difference	•				•
France imports	M	77	Log difference	•				•
Italy exports	M	77	Log difference	•				•
Italy imports	M	77	Log difference	•				•
UK imports	M	43	Log difference	•				•
UK exports	M	43	Log difference	•				•
Euro-area manufacturing PMI	M	-7	Level	•				•
Euro-area PMI new export orders	M	-7	Level	•				•
Germany manufacturing PMI	M	-7	Level	•				•
Germany PMI new export orders	M	-7	Level	•				•
Germany IFO export expectations	M	-5	Level	•				•
EU incl UK manufacturing PMI	M	1	Level	•				•
Euro-area industrial production (ex IRL)	M	47	Log difference	•				•
Germany industrial production	M	39	Log difference	•				•
France industrial production	M	40	Log difference	•				•
Italy industrial production	M	41	Log difference	•				•
UK industrial production	M	43	Log difference	•				•
Euro-area retail sales	M	36	Log difference	•				•
Germany retail sales	M	30	Log difference	•				•
France retail sales	M	57	Log difference	•				•
Italy retail sales	M	36	Log difference	•				•
UK retail sales	M	19	Log difference	•				•
Eastern Europe industrial production	M	56	Log difference	•				•
North Range container throughput index	M	30	Log difference	•				•

3 Model

The model uses a Dynamic Factor Model (DFM) framework with a multi-factor block structure to allow for regional variation and spillovers. Following Banbura, Giannone, et al. 2011, $y_t = (y_{1,t}, y_{2,t}, ..., y_{n,t})'$ denotes the vector of monthly data transformed to ensure stationarity. y_t is modeled as the factor model representation below:

$$y_t = \mu + \Lambda\, f_t + e_t \tag{1}$$

$$f_t = A_1 f_{t-1} + u_t, \qquad u_t \sim N(0, Q) \tag{2}$$

$$e_t = B e_{t-1} + v_t, \qquad v_t \sim N(0, R) \tag{3}$$

where f_t is a vector of unobserved common factors and e_t is a vector of idiosyncratic errors. μ is a vector of unconditional means. Λ denotes the factor loadings. The factors jointly evolve according to a VAR(1) process. The total number of lags is chosen via the Bayesian Information Criterion[1]. The idiosyncratic component of the monthly observed variables is assumed to follow an AR(1) process, as monthly trade data often exhibit 'payback' after a strong or weak month.

The model allows for regional variation and spillovers through the factor and VAR structure. In contrast to other trade DFMs, we model global trade as a function of a global trade cycle and regional ones. We partition f_t into six factors: two global factors and US, China, Asia and Europe factors. The choice of two world factors is determined by the inspection of a scree plot, which shows that eigenvalues of principal components of the data flatten out by the third component. In practice, the two global factors pick up an underlying trend driven largely by the surveys and month-to-month volatility driven by the hard data. This distinction between the cycles identified by the two global factors is discussed later in Section 4.1.

The loading structure is shown in equation 4, where the data are partitioned into global variables ($\mathbf{y_t^{global}}$), US variables ($\mathbf{y_t^{us}}$), China variables ($\mathbf{y_t^{china}}$), Asia variables ($\mathbf{y_t^{asia}}$), and Europe variables ($\mathbf{y_t^{eur}}$). All variables load on the two global factors and capture the global trade-business cycle. Regional data load on the regional factors, which capture the fact that activity in certain regions may deviate from this global cycle. Given China's prominence in global trade, its data load on its own factor as well as the Asia and global factors. Global variables, including world trade, load on all the factors.

[1]The Akaike Information Criterion suggests more than one lag. But the BIC, which in addition to the AIC penalizes model complexity, suggests just one. Additional lags do not significantly improve the forecasting performance and therefore we chose one lag to keep the model as simple as possible.

$$
\begin{pmatrix} \mathbf{y_t^{global}} \\ \mathbf{y_t^{us}} \\ \mathbf{y_t^{china}} \\ \mathbf{y_t^{asia}} \\ \mathbf{y_t^{eur}} \end{pmatrix} = \begin{pmatrix} \mathbf{\Lambda_{11}} & \mathbf{\Lambda_{12}} & \mathbf{\Lambda_{13}} & \mathbf{\Lambda_{14}} & \mathbf{\Lambda_{15}} & \mathbf{\Lambda_{16}} \\ \mathbf{\Lambda_{21}} & \mathbf{\Lambda_{22}} & \mathbf{\Lambda_{23}} & 0 & 0 & 0 \\ \mathbf{\Lambda_{31}} & \mathbf{\Lambda_{32}} & 0 & \mathbf{\Lambda_{34}} & \mathbf{\Lambda_{35}} & 0 \\ \mathbf{\Lambda_{41}} & \mathbf{\Lambda_{42}} & 0 & 0 & \mathbf{\Lambda_{45}} & 0 \\ \mathbf{\Lambda_{51}} & \mathbf{\Lambda_{52}} & 0 & 0 & 0 & \mathbf{\Lambda_{56}} \end{pmatrix} \begin{pmatrix} f_t^{g_1} \\ f_t^{g_2} \\ f_t^{us} \\ f_t^{china} \\ f_t^{asia} \\ f_t^{eur} \end{pmatrix} + \begin{pmatrix} \mathbf{e_t^{global}} \\ \mathbf{e_t^{us}} \\ \mathbf{e_t^{china}} \\ \mathbf{e_t^{asia}} \\ \mathbf{e_t^{eur}} \end{pmatrix} \tag{4}
$$

Regional data may affect world trade via three channels. First, news in regional trade data has a direct effect on the global factor. Second, it may affect the regional factor on which global trade also loads. Finally, the dynamics of the factors is modeled as a VAR(1) which evolves jointly. Innovations in a regional factor may therefore spillover to global and other regional trends.

Following Banbura and Modugno 2014, the parameters are estimated iteratively by maximum likelihood implemented using a Kalman filter and the Expectation Maximization (EM) algorithm. Preliminary estimates of Λ and f_t are first obtained by principal component analysis, which are used in the VAR to obtain estimates of A_i. In the second stage, updated expected estimates of the factors are obtained applying the Kalman smoother to the data using these preliminary parameter estimates. The procedure is iterated until the two steps converge and maximum likelihood is achieved. This procedure efficiently handles missing data by writing the likelihood as complete and filling in the missing data in the expectation step.

The advantage of a multi-region block structure is that it reduces the risk that idiosyncratic regional variation is confounded with common global shocks. We motivate the use of this structure and the presence of regional drivers with two exercises:

1. We estimate a DFM with only the two global factors. If a common global factor structure describes the data well, then the residuals for regional variables block should be no more correlated with one another than with residuals outside that region. But correlation within regions would suggest the presence of underlying regional factors.

2. Following Moench et al. 2013, we examine whether the principal components of the dataset capture region-specific as well as common global dynamics. The principal components are first regressed on the global factors from the DFM. The residuals represent variation that the principal components regard as common but not by the DFM. These residuals are then regressed on the regional factors. If the regional factors help explain the residuals, it adds support to the notion that there is regional variation in the data identified by a more agnostic principal components analysis.

Table 2 reports the correlations of the residuals from a global factor DFM. It shows that the correlation of residuals for variables within the regional blocks are generally better correlated with each other than with variables outside those blocks. This suggests that there may be some missing regional factor driving variables within these blocks not captured by a global factor.

Table 2: Correlation of residuals within and outside of regional group

Group Name	Average Within Group	Average Outside Group
USA	0.15	0.11
China	0.20	0.14
Asia	0.18	0.14
Europe	0.18	0.13

Table 3 reports the sum of R^2s of the regressions in the second exercise. The US factor explains 31% of the variation in residuals of the first and second principal components relative to the DFM global factor. The Asia, Europe and China factors explain 16%, 17% and 11%, respectively. This suggests that some of what is identified as common variation in the principal components analysis is reasonably well correlated with the regional factors identified by the DFM, particularly for the US.

Table 3: Correlation of PC-global factor residuals with regional factors

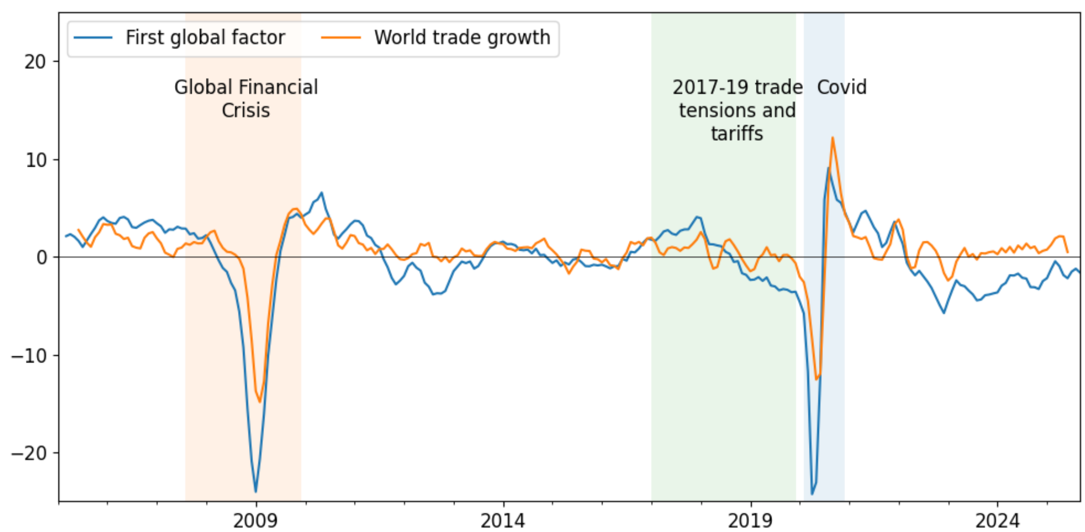
Principal Component	Regional Block	Sum of R^2
PC1, PC2	US	0.31
PC1, PC2	Asia	0.16
PC1, PC2	Europe	0.17
PC1, PC2	China	0.11

4 Results

4.1 Estimated factors

The parameters of the model are estimated on data over 2005-19. Covid is omitted from the estimation sample because the extreme volatility means that this period is likely to distort the estimated parameters and hinder the model's ability to forecast in more normal times. Figure 2 shows the estimated first global factor, plotted against global trade growth. The factors are well correlated with global trade growth, such as the sharp fall during the Global Financial Crisis or the more moderate slowdown in 2018-19 during a period of heightened trade tensions.

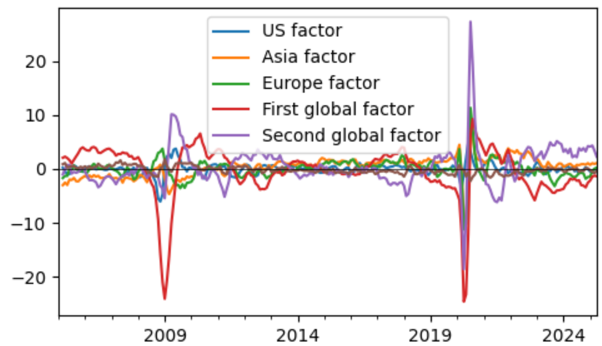
Figure 2: Global factor and world trade growth



Note: World trade growth uses the 3-month/3-month annualized growth rate to average over monthly volatility in the trade data and is shown against the comparable three-month average of factor.

Figure 3 and Table 4 show that while the global factors identify the broad trend, the regional factors identify fluctuations around that trend. Table 5 shows the explanatory power of each factor for different variables in the dataset. The first global factor is best correlated with the various surveys and PMI indicators, whereas the second global factor is better correlated with the hard data. This suggests that the first factor picks up the broad underlying trend while the second reflects the month-to-month variation in the hard data. In contrast to the other regional factors, the US factor is either uncorrelated or negatively correlated with the other factors. This suggests it may be picking up idiosyncratic US news around broad global trends. The explanatory power of the US factor in Table 5 also suggests it may be picking up the role of US and global financial conditions not captured elsewhere.

Figure 3: Global and regional factors



Note: Three-month averages.

Table 4: Correlation between factors

	Global1	Global2	US	Asia	Europe	China
Global1	1.00	0.32	-0.01	0.41	0.48	-0.10
Global2	0.32	1.00	0.04	0.54	0.54	-0.21
US	-0.01	0.04	1.00	-0.11	-0.19	0.19
Asia	0.41	0.54	-0.11	1.00	0.77	-0.10
Europe	0.48	0.54	-0.19	0.77	1.00	-0.27
China	-0.10	-0.21	0.19	-0.10	-0.27	1.00

Table 5: Explanatory power of factors: top ten variables

Global1	R^2	Global2	R^2
Global PMI new export orders	0.72	France industrial production	0.53
Global PMI manufacturing	0.68	Advanced economies industrial production	0.52
Euro-area manufacturing PMI	0.68	Euro-area industrial production (ex IRL)	0.52
Advanced economies industrial production	0.66	UK industrial production	0.52
EU incl UK manufacturing PMI	0.66	Italy exports	0.49
Euro-area PMI new export orders	0.64	Germany exports	0.46
World trade	0.62	Euro-area exports	0.45
World industrial production	0.61	Germany industrial production	0.43
Germany manufacturing PMI	0.60	Euro-area manufacturing exports	0.43
Germany PMI new export orders	0.60	EM Asia ex China industrial production	0.43

US	R^2	Asia	R^2	Europe	R^2	China	R^2
US high-yield spread	0.56	Advanced economies industrial production	0.48	Euro-area industrial production (ex IRL)	0.56	China exports	0.33
MSCI World Index	0.36	EM Asia ex China industrial production	0.38	UK industrial production	0.55	China imports	0.19
Brent oil price	0.30	China industrial production	0.23	France industrial production	0.52	Global container throughput index	0.16
US nominal effective exchange rate	0.29	World industrial production	0.22	Germany exports	0.50	World trade	0.15
US PMI new export orders	0.09	China retail sales	0.19	Italy exports	0.49	China industrial production	0.10
US retail sales	0.08	China NBS PMI manufacturing	0.16	UK retail sales	0.47	Global Supply Chain Index	0.08
Global PMI stocks of purchases	0.07	World trade	0.16	Advanced economies industrial production	0.47	China international aviation cargo and mail	0.05
US manufacturing PMI	0.05	ASEAN PMI new export orders	0.12	Euro-area manufacturing exports	0.47	US high-yield spread	0.04
US goods consumption	0.04	Emerging Asia ex China exports	0.12	Euro-area exports	0.46	China retail sales	0.03
US exports	0.04	Malaysia exports	0.10	Germany industrial production	0.44	Global PMI stocks of purchases	0.03

4.2 Spillovers

The interrelation between the factors can be shown through a generalized forecast error variance decomposition (GFEVD). The use of the GFEVDs and generalized impulse responses was popularized by Pesaran and Shin 1998 and Diebold and Yilmaz 2012, and applied by the latter to a measure of financial market volatility spillovers. In the absence of an identification scheme, the generalized approach is reduced form but accounts for the correlation of shocks using the observed distribution of errors. It therefore shows the share of the variation accounted for by the residuals for each of the variables (here, our factors). But the absence of an identification scheme means that the innovations are correlated and so lack a structural interpretation[2].

The VAR(1) equation for the factor dynamics in the DFM, $f_t = A_1 f_{t-1} + u_t$, can be re-expressed

[2]As such, the sum of the contributions to the variance of the forecast error does not necessarily equal one.

in its moving average representation as:

$$f_t = \sum_{j=0}^{\infty} \Psi_j u_{t-j} \tag{5}$$

where $\Psi_i = A_1 \Psi_{i-1}$, with Ψ_0 an $N \times N$ identity matrix with $\Psi_i = 0$ for $i < 0$.

$$u \sim N(0, Q) \tag{6}$$

The variance shares for the H-step ahead error variances forecasting f_j are then given by:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h Q e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h Q \Psi_h' e_i)} \tag{7}$$

where Q is the variance matrix for the vector u, σ_{jj} is the variance of the error term for the jth equation. e_i is a selection vector, with a one on the ith element and zeros otherwise.

Given the sum of the elements in each row of the variance decomposition is not equal to one, each entry is normalized by its row sum:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)} \tag{8}$$

Finally, the generalized VAR framework also allows us to examine the direction of spillovers between factors. We can calculate spillovers received by region i from all other regions j as:

$$S_{i\leftarrow}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{N} 100 \tag{9}$$

Spillovers transmitted by region i to all other regions j is defined as:

$$S_{i\rightarrow}^g(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^g(H)}{N} 100 \tag{10}$$

The resulting decomposition is shown in Figure 4. In the short run, most of the forecast error variance in each region is due to news in its own factor. Over time, the first global factor drives more the variation. This is consistent with the first global factor picking up the underlying trend but the other factors identifying idiosyncratic news or month-to-month volatility. The Asian factor has the largest and most persistent spillovers to the errors of the other factors, particularly to Europe but it is also the largest contributor to news in the global factor. This is consistent with the integral role that Asian exporters play in global trade. Utilizing different model specifications and samples tell a broadly similar story, with only modest variation in the relative contributions of different factors, as seen in the Appendix (Figure A.1).

Figure 4: Generalized forecast error variance decomposition
(share of variance, percent)

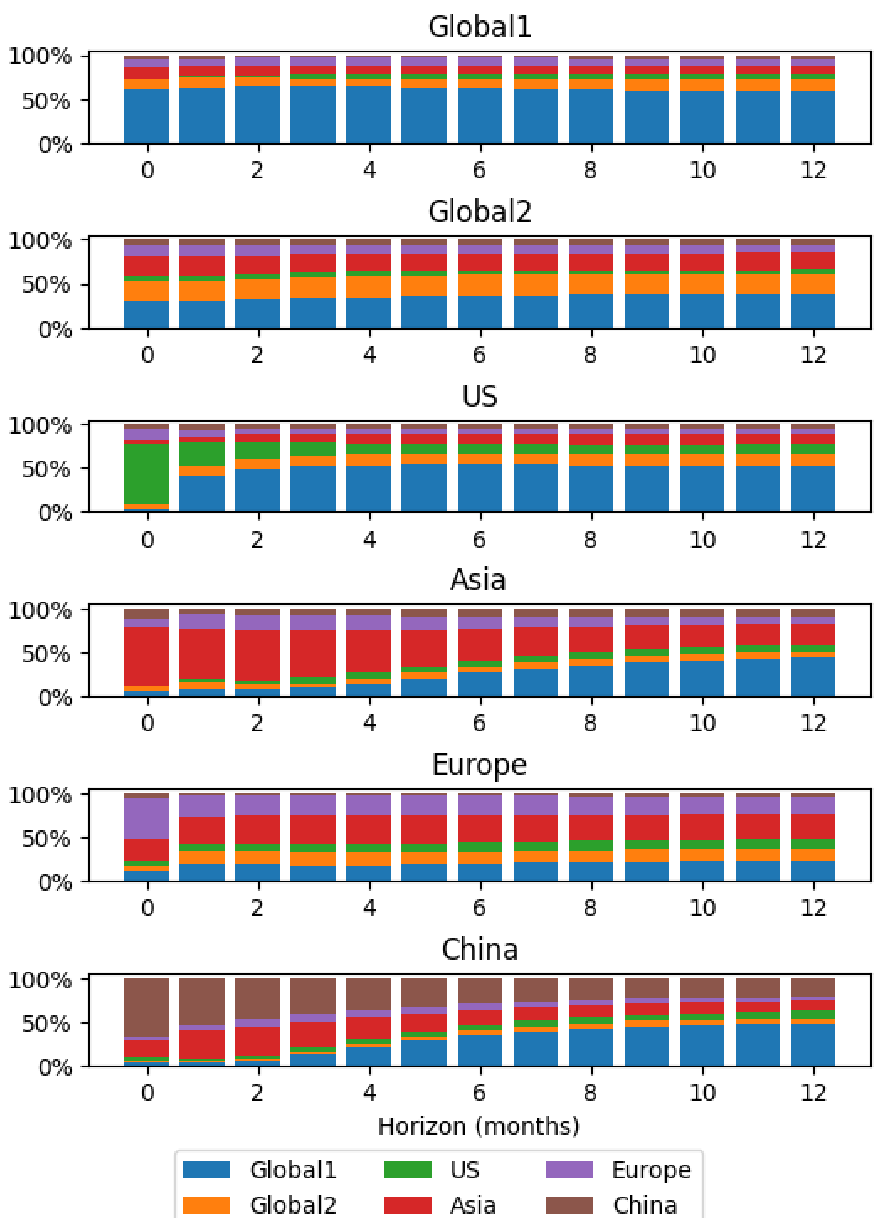


Table 6 is the volatility spillover table, showing the contribution to the forecast error variance three months ahead of factor i from innovations in factor j. The last column, "directional from others", shows the total impact of spillovers on factor i from other factors, while “directional to others” shows the total contribution of factor i to the forecast error variance of the other factors. The diagonal entries represent the share of error variance from each region receives from its own errors. Net spillovers are calculated by subtracting the ‘from’ contribution from the ‘to’ contribution. Finally, the total spillover index is calculated as the total “directional from others” effects over the total forecast error variance in the table.

The two largest contributors to the forecast error variance in other factors are the first global and Asian factors. This points to the overall importance of the global trade cycle and Asia’s influential role in global trade. By contrast, the US factor is a small generator of forecast error variance but significant recipient. At first sight, this might be surprising given the importance of the US for global activity. As discussed above, however, this most likely reflects the fact that the US factor is picking up short-term idiosyncratic variation in the US data. The underlying trend in US trade may be closely related to the global trade cycle. Finally, the value of total spillover index is 73%, which is high and is not surprising given the interrelated nature of trade. This indicates that the majority of the forecast error variance is driven by innovations to other factors rather than a factor’s own innovations.

Table 6: Volatility spillover table

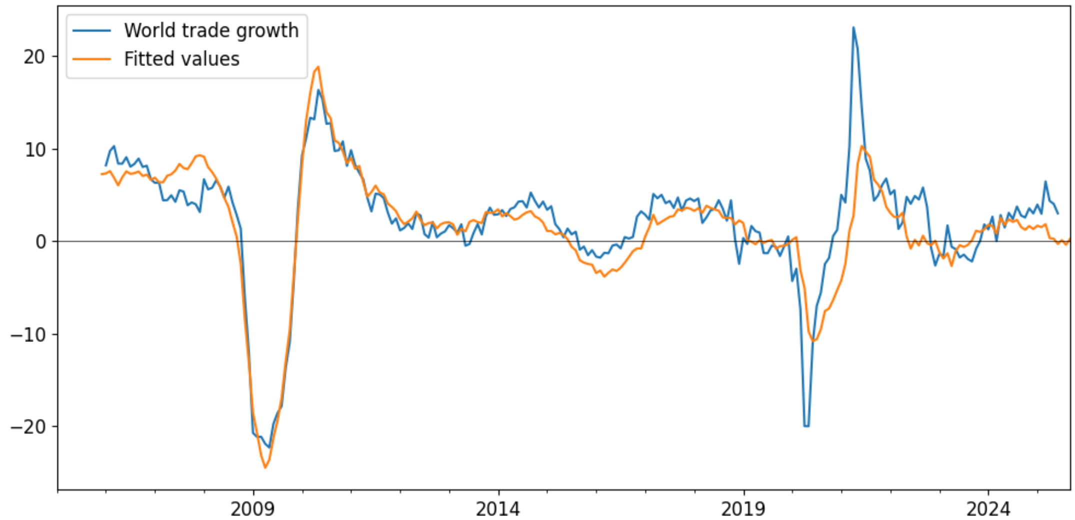
	Global1	Global2	US	Asia	Europe	China	Directional FROM others
Global1	57.0	13.1	5.6	11.8	8.1	4.5	43.0
Global2	36.6	23.4	4.6	19.3	8.9	7.3	76.6
US	51.6	12.4	11.1	12.6	7.1	5.2	88.9
Asia	43.1	6.8	7.6	24.4	8.5	9.5	75.6
Europe	23.5	13.3	10.1	28.6	20.6	3.8	79.4
China	48.4	6.2	7.2	11.7	4.0	22.4	77.6
Directional TO others	203.2	51.9	35.1	84.0	36.6	30.3	Total spillover index:
Directional including own	260.2	75.2	46.2	108.4	57.2	52.8	73.5

4.3 Forecast accuracy

We next consider the forecast accuracy of the model systematically using a set of pseudo out-of-sample exercises. Figure 5 shows that the fitted values of the model track the underlying trends in global trade growth relatively well, although month-to-month the data are relatively noisy. However, given the model is designed primarily to nowcast global trade we are most interested in its ability to forecast out of sample. Indeed, given the higher number of factors than standard trade DFMs one might be concerned that in-sample fit reflects a degree of overfitting.

A pseudo out-of-sample forecast exercise is used to evaluate the model’s nowcasting performance. Monthly trade is volatile and, outside of sudden turning points, policymakers are typically inter-

Figure 5: Fitted values of global trade growth (y/y, percent)



ested in the underlying trend. We therefore evaluate the monthly model's forecast for quarterly trade growth. Quarterly growth rates are calculated from the monthly forecasts using the Mariano and Murasawa 2003 approximation: $y_t^{3m/3m} = (y_t^{m/m} + 2y_{t-1}^{m/m} + 3y_{t-2}^{m/m} + 2y_{t-3}^{m/m} + y_{t-4}^{m/m})/3$. The dataset is restricted to reflect the available unbalanced dataset at different points relative to the end of the nowcasted quarter, using the standard publication lag for each data series. The model is re-estimated each month using this pseudo real-time dataset up to the end of 2019. After this point, the model's parameters are no longer updated and we use the model estimated over the full pre-Covid sample of 2005-19.

The nowcasts are evaluated using the root mean square forecast errors (RMSFE) and mean absolute error (MAE) and benchmarked against alternative models. This includes standard time-series benchmarks such as an AR(1) and a random walk. The model is also compared against a more standard DFM estimated with one factor which loads on all variables, similar in spirit to Guichard and Rusticelli 2011, to investigate the additional forecast accuracy offered by a multi-regional approach. As with the main models, the benchmark forecasts are also iterated using a pseudo real-time data set and refitted each month up to the start of Covid.

We assess the out-of-sample forecasting performance of the model in two different samples, chosen because they provide sufficient variation in the data from trend growth rates to provide a useful test of the model's forecasting performance:

1. **2017-19:** A slowdown in global trade reflecting heightened trade tensions, reduced policy support in some economies and a slowdown in the auto sector (IMF 2019).

2. **2020-22:** The peak of Covid disruption which resulted in a sharp drop in global trade flows and economic activity. It also saw divergence in regional trade trends as exports fell less and recovered more strongly in China and Asia relative to Advanced Economies.

The DFM outperforms the benchmark models, including a single-factor DFM, at most horizons. Figure 6 shows the RMSFE of the models at different horizons from the end of the nowcasted quarter for the 2017-19 and 2020-22 samples. For instance, Week 0 shows the forecast performance using data available up to the end of the quarter while Week -12 uses only data available up to the start of the quarter. Table 7 compares the RMSFE and MAE of the main model relative to that of the benchmarks with less than one indicating the main model is more accurate than the benchmarks(i.e. $\mathrm{RMSFE}_{\mathrm{DFM}}/\mathrm{RMSFE}_{benchmark}$). The improvement in forecast performance is greatest before the start of the nowcasted quarter (i.e. weeks -20 to -12). For instance, Table 7 shows that at the RMSFE of the DFM is 40% lower than that of a single-factor model in week -12 of pre-Covid sample and 20% lower than an AR(1), a meaningful improvement in forecast performance. In the Covid period, the equivalent improvement in forecast performance is similar. The relative improvement in forecast performance is similar for MAE. Given the model is assessed quarterly, the sample sizes are relatively small: twelve quarters in each sub-period. Nonetheless, the Diebold-Mariano tests in Table 7 indicate the DFM out-performance relative to the single-factor model is statistically significant at most horizons in the pre-Covid period. [3]

The relative forecasting performance narrows as we get closer to the end of the quarter as more data are released. This reflects the fact that we have more information about the quarter. But there is also a mechanical effect: by the end of the quarter (week 0) we have five out of the six monthly data points for quarterly growth. Therefore the forecast performance of all the model's converge as the prediction of the final month is relatively unimportant for calculating quarterly growth rates, carrying a weight of just 11%

Additional variations on the model, including different factor structure, lag orders, and estimation windows, yield qualitatively similar out-of-sample performance, reinforcing the robustness of the baseline results. However, the baseline multi-factor model does not outperform single-global factor specifications during periods in which a global trade cycle dominates, such as 2014–2016. These results are shown in the Appendix (Figure A.2).

[3] The Diebold-Mariano tests use the Harvey et al. 1997 adjustment for small samples.

Figure 6: Pseudo out-of-sample forecast performance

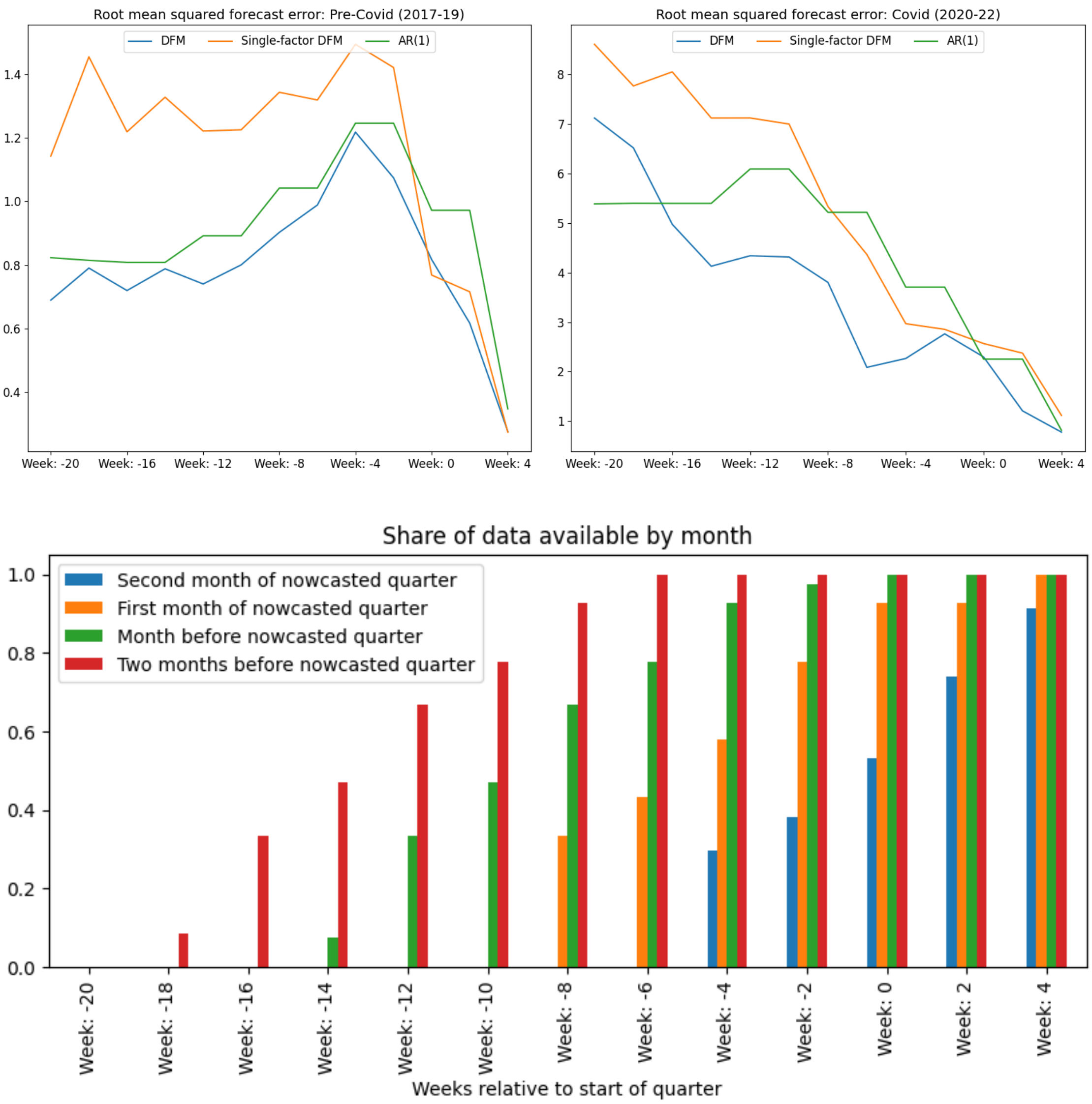


Table 7: Pseudo out-of-sample forecast accuracy

		Pre-Covid					Covid				
		Week: -20	Week: -16	Week: -12	Week: -8	Week: -4	Week: -20	Week: -16	Week: -12	Week: -8	Week: -4
Relative RMSFE	**vs Single-factor DFM**	0.604	0.591	0.607	0.672	0.820	0.827	0.618	0.609	0.713	0.765
	vs AR(1)	0.838	0.891	0.831	0.864	0.982	1.322	0.922	0.713	0.729	0.613
	vs Random walk	0.185	0.235	0.249	0.259	0.436	1.155	0.524	0.284	0.683	0.549
Relative MAE	**vs Single-factor DFM**	0.586	0.569	0.652	0.733	0.933	0.870	0.767	0.635	0.654	0.750
	vs AR(1)	0.828	0.895	0.907	0.941	1.046	1.283	1.020	0.757	0.700	0.662
	vs Random walk	0.174	0.224	0.254	0.275	0.479	0.872	0.516	0.400	0.543	0.524
Diebold-Mariano (p-values)	**vs Single-factor DFM**	0.062*	0.045*	0.067*	0.095*	0.174	0.16	0.147	0.142	0.142	0.088*
	vs AR(1)	0.226	0.338	0.188	0.176	0.449	0.837	0.363	0.086*	0.161	0.087*
	vs RW	0.005*	0.002*	0.001*	0.019*	0.011*	0.691	0.036*	0.158	0.157	0.002*

4.4 Case studies

We next use three case studies to illustrate that a multi-factor framework is best suited to situations in which there are strong regional dynamics affecting global trade rather than a common global driver. We focus on world trade over a year in three episodes: 2020, 2023 and 2008. These are chosen to illustrate a range of episodes in which regional factors are more and less important. We focus on world trade growth over a year as trade data can be volatile, and tracking the forecast over a longer horizon makes it easier to understand how evolution of data affects the nowcasts of the model.

The evolution of world and some regions' trade growth during these three episodes is shown in Figure 7. In the first two cases, there were notable regional divergences in trade growth and the multi-factor model performs well relative to a single-factor model. In the latter case, however, the slowdown in world trade was more synchronous across regions and the multi-region DFM does not outperform a single-factor model. These case studies therefore highlight the benefits of a more flexible regional model structure.

Figure 7: World trade in the three case studies

(a) Case study I: 2020 (Level: 2019 = 100) | **(b)** Case study II: Trade in 2023 (y/y, percent) | **(c)** Case study III: Trade in 2008 (y/y, percent)

4.4.1 Case study I: 2020 and the Covid shock

The first case study tracks how the model's forecast for world trade growth for 2020 evolves over the course of that year and compares it to the prediction from a single-factor DFM. We begin by restricting the dataset to the end 2019 and use the models to forecast annual trade growth in 2020. We then recalculate the 2020 forecast using one additional month of data until the end of the year. The first chart in Figure 8a shows how the forecasts for world trade evolve growth during 2020 as more data is released. The last value is the actual outturn for 2020. The second and third charts show the contribution of data news by region to the cumulative revision in trade growth forecast for the two models relative to its initial forecast at the end of 2019. The world trade data bars show the contribution of surprises in world trade growth data. This captures both the difference in actual and predicted trade that month, but also any changes to projected world trade for the rest of the year on the basis of that data.

The example of 2020 and Covid is an instructive one not just because there was such a large shock to trade but because trade - particularly in China - recovered rapidly in the second half of the year. Several features of the forecast comparison are worth noting. First, the contribution of cumulative world trade data surprises are smaller in the multi-factor model than the single-factor DFM, indicating that the former does a better job predicting world trade growth in each month conditional on knowing the other data points. Even knowing regional trade data for that month, the single-factor model makes large errors.

Second, the contribution of data surprises from each region also helps highlight why the multi-factor DFM model performs better. It picks up that world trade was likely to contract sharply in 2020 earlier than the single-factor model. Examining Figure 8a helps us understand why. China's trade contracted sharply in the first three months of the year given its economy was affected by the pandemic earlier, but trade elsewhere was relatively resilient. The single-factor model attached a relatively low weight to these developments because the deterioration in the data was concentrated in a few variables and so more likely to be noise rather than a deterioration in the global trade cycle. In contrast, the multi-factor identifies that there has been a China shock - the weak China data has a much larger effect on the global trade forecast than in the single-factor model.

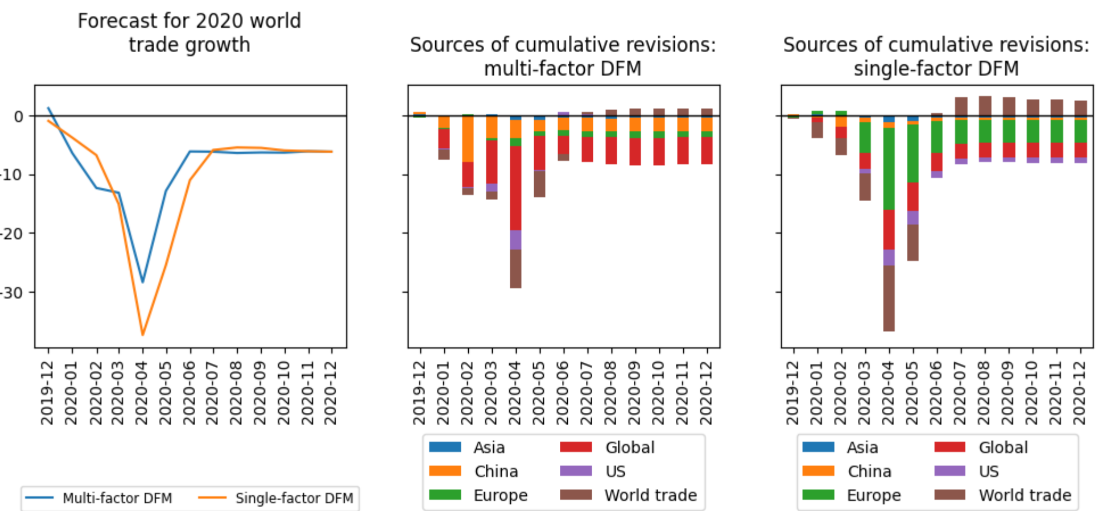
Finally, the regional factors also help capture the fact that world trade recovered unexpectedly quickly in the second half of the year. The multi-factor model is better able to capture the fact that China's trade already started to recover by spring 2020 in contrast to the deteriorating signal from data elsewhere in the world. The single-factor model, however, overweights the importance of European data which usually comove strongly with a global trade cycle but not in this instance.

4.4.2 Case study II: 2023 and post-Covid trade divergence

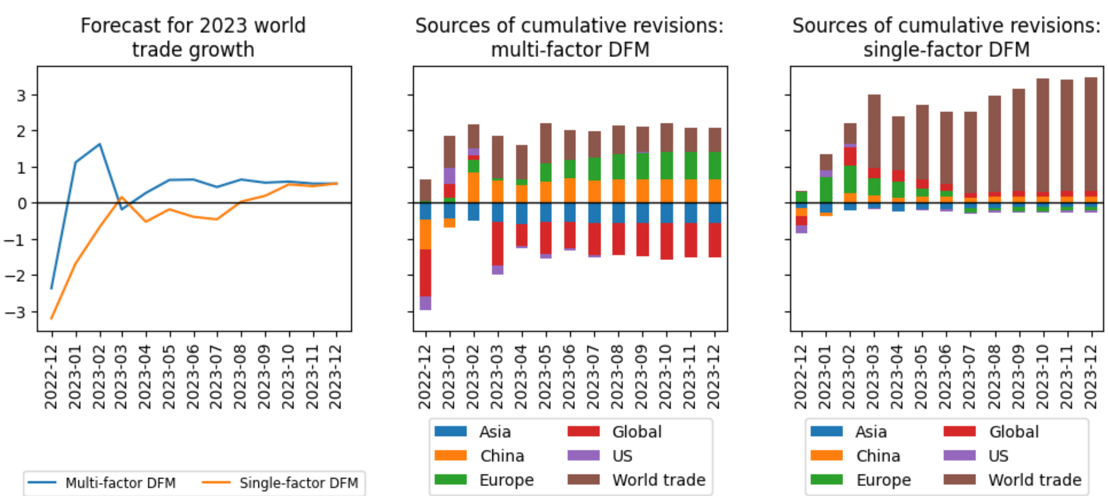
The second case studies considers another episode of trade divergence when the multi-factor structure of the model performs well. In 2023, trade recovered strongly in China but remained weak across most advanced economies (Figure 7b). By late 2022, global trade started to show signs of recovering from the pandemic and severe supply shocks. But that recovery was uneven. Trade growth remained weak among Advanced Economies but picked up strongly in China. That divergence persisted throughout 2023. Such dynamics present a challenge for a model trying to identify a global trade cycle but are more easily accommodated within a multi-region model structure.

Figure 8: World trade growth forecasts

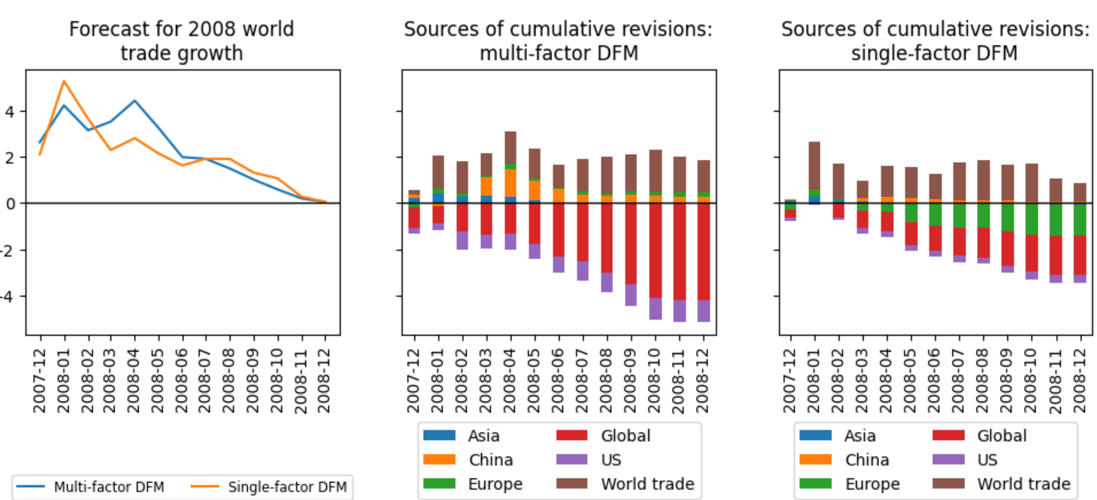
(a) Case study I: 2020



(b) Case study II: 2023



(c) Case study III: 2008



By the start of 2023, the multi-factor model correctly identifies that China's trade data were outperforming expectations and therefore revised up its forecast for world trade growth in 2023 by 3 percentage points (Figure 8b). Global and Advanced Economy indicators continued to underperform, however. As such, the single-factor model expected trade growth to remain weak. As such, Figure 8b shows that the single-factor model picked up the recovery in trade much later than the multi-factor model, continuing to forecast a contraction in global trade until August when in fact world trade growth was overall positive in 2023.

4.4.3 Case study III: 2008 and a global trade slowdown

Finally, we consider an example where a multi-factor model offers little advantage over a single-factor model: a synchronized downturn in global trade Figure 7c. As shown in Figure 8c, both models overpredicted the strength of global trade at the start of 2008. As the Global Financial Crisis took hold and the data deteriorated dramatically, both models marked down their forecasts for world trade growth in 2008 by around 4 percentage points. In fact, the single-factor model picked up the deterioration slightly earlier than the multi-factor model. The drivers of those revisions reveal that the deterioration was driven by weaker-than-expected global data as well as worse data in the US (Figure 8c). Crucially, therefore the slowdown was global in nature and a multi-factor structure that accounted for regional variation from a global cycle adds little additional forecasting power.

5 Conclusion

This paper develops a multi-region dynamic factor model to nowcast global trade growth, providing a more granular view of the forces shaping global trade. By summarizing a large dataset into common global factors and distinct regional factors, our analysis yields several key insights into the dynamics of world trade.

First, the nature of economic shocks matters for nowcasting global trade. The model distinguishes between synchronized global events, such as the 2008 financial crisis, when a single-factor model performs well, and periods characterized by regional heterogeneity, such as around Covid, where our multi-factor framework provides superior near-term forecasts. The outperformance of our multi-factor model during periods of regional divergence highlights the limitations of relying solely on global factors. This adaptability is particularly valuable at a time of changing trade patterns or rising geo-economic fragmentation.

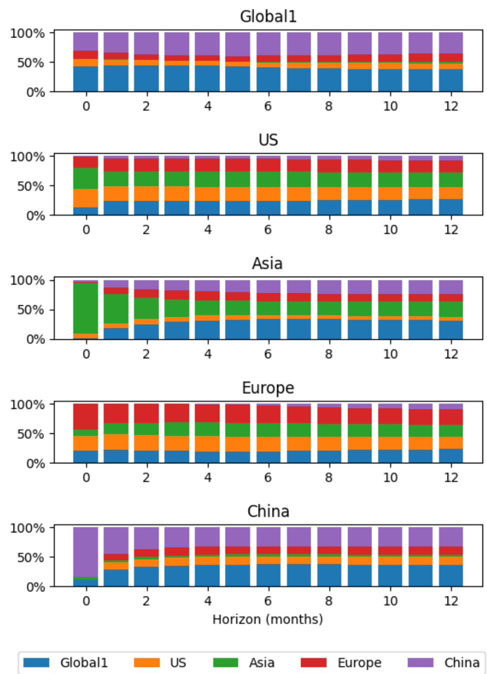
Second, our model shows that regional factors - particularly those for Asia - are a significant source of spillovers to other regions and to the global outlook. This finding is consistent with the increasing integration of Asia into global value chains and its importance as a driver of global economic activity.

Finally, our findings have important implications for policymakers and analysts. The ability to identify the geographic origins of shocks to global trade in real-time offers a significant advantage for economic surveillance. Moving beyond a simple global aggregate, this approach offers a more timely and richer narrative of ongoing trade dynamics.

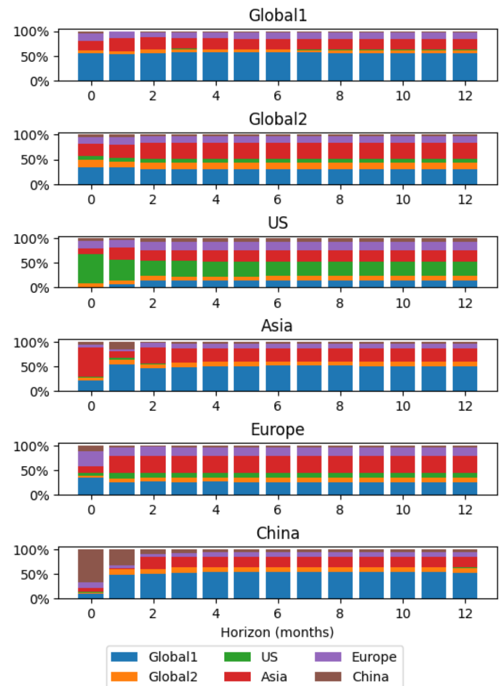
Appendix

Figure A.1: GFEVD with Different Model Specifications

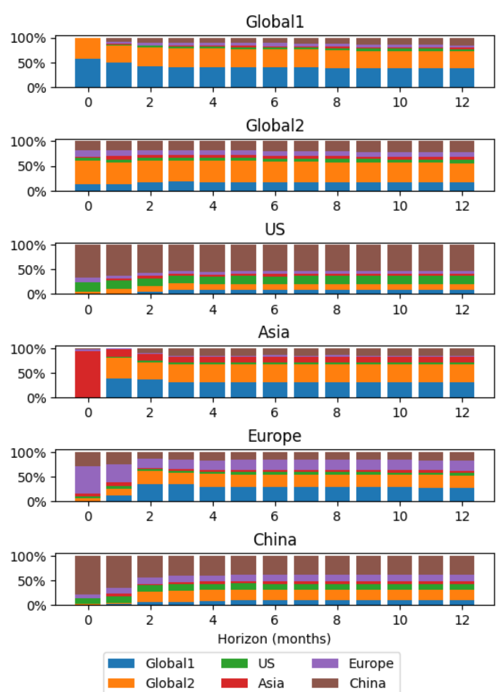
(a) Multi-factor DFM with a single global factor



(b) Multi-factor DFM with VAR(2)



(c) Estimated on full sample (2005–2024)



(d) Estimated on full sample (2005–2024) excluding COVID (2020-21)

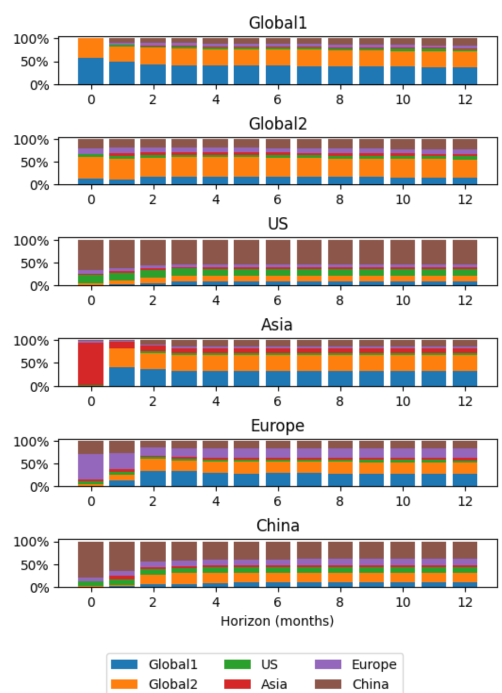
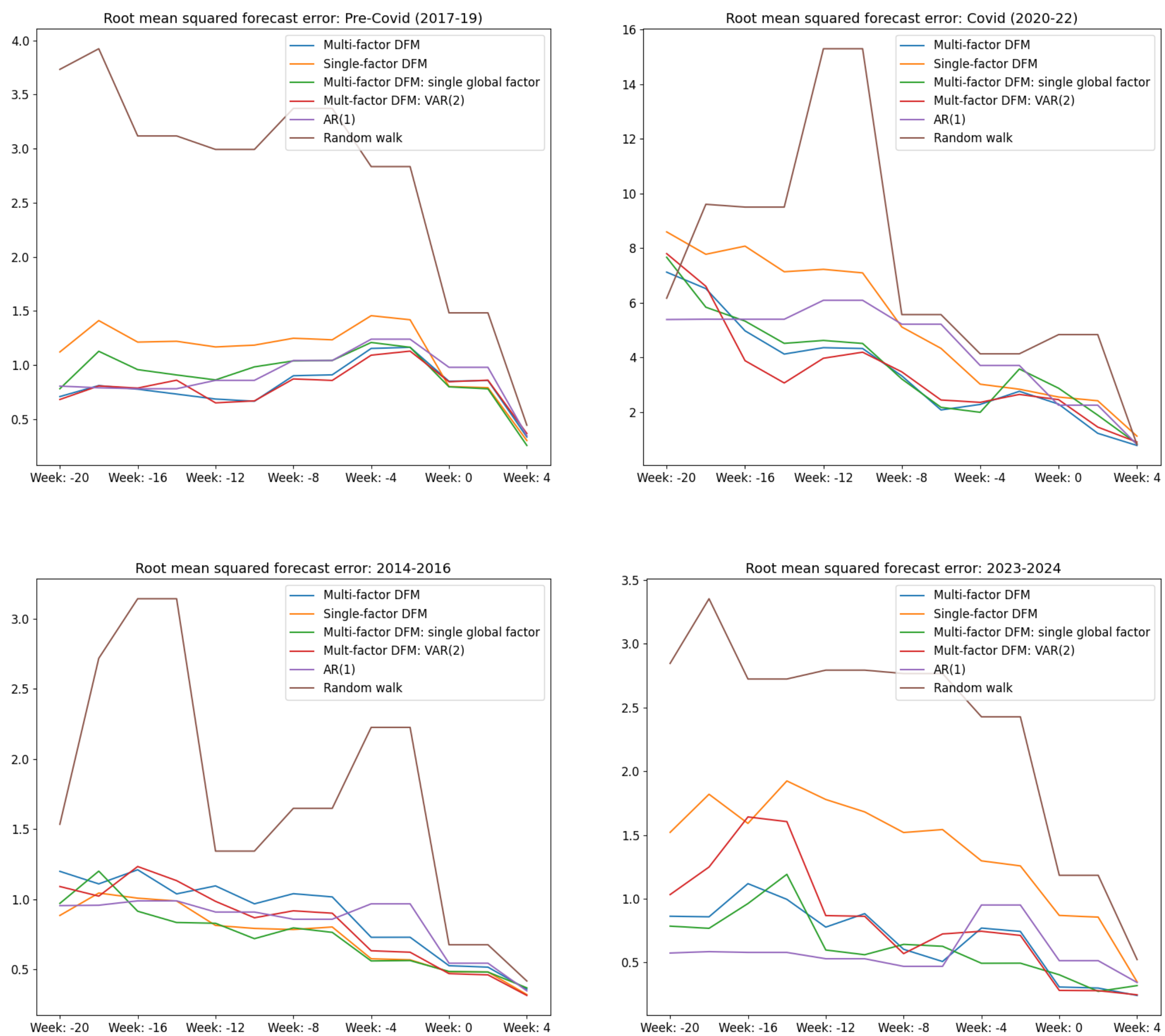


Figure A.2: Pseudo out-of-sample forecast performance for different model specifications and time periods



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