International trade fluctuations: Global versus regional factors

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Abstract. This paper examines the relative importance of global, regional, country and idiosyncratic factors as well as the determinants that underpin fluctuations in international trade flows across different regions of the world. Our analysis starts by using a Bayesian dynamic latent factor model (BDFM) to simultaneously estimate the four dynamic factors, followed by the application of Bayesian model averaging to identify the variables that explain the shares of variance. Our key findings are: (i) international factors are the most important in explaining fluctuations in international trade, suggesting that the interconnections between economies and policies/shocks at the regional and global level tend to be more important than country-level factors and (ii) regional integration, particularly when the agreement goes beyond trade in goods, is positively related to the share of the regional factor and inversely related to the importance of the global factor. Furthermore, the regional factor is more important in the case of economically large trade blocks. Overall, our analysis illustrates the usefulness of applying a BDFM model to study the co-movements of international trade series.

Résumé. Fluctuations du commerce international : facteurs mondiaux et régionaux. L'article examine l'importance relative des facteurs mondiaux, régionaux, nationaux et idiosyncratiques, ainsi que les déterminants qui sous-tendent les fluctuations des flux du commerce international entre les diverses régions du monde. Notre analyse commence en utilisant un modèle bayésien dynamique à facteurs latents pour estimer simultanément les quatre facteurs dynamiques et applique ensuite le calcul de la moyenne des modèles bayésiens pour déterminer les variables qui expliquent les parts de la variance. Nos principales constatations sont les suivantes : (i) les facteurs internationaux sont les plus importants pour expliquer les fluctuations du commerce international, ce qui suggère que les interconnections entre les économies et les politiques ou les chocs aux échelons régionaux et mondiaux tendent à être plus importantes que les facteurs à l'échelon national; (ii) l'intégration régionale, surtout lorsqu'un accord englobe d'autres aspects que le commerce de marchandises, est positivement liée à la part du facteur régional et inversement liée à l'importance du facteur mondial. En outre, le facteur régional est plus important dans le cas de groupes d'échanges commerciaux vastes sur le plan économique. De façon générale, notre analyse illustre l'utilité des modèles bayésiens dynamiques à facteurs latents dans l'étude des covariations des cycles du commerce international.

JEL classification: C11, F14, F15

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1. Introduction

THE CROSS-COUNTRY SYNCHRONIZATION of trade is well established (Antonakakis, 2012), where the great trade collapse of late 2008 is a striking example. Nevertheless, the extent to which global, regional and country factors are more (less) important in explaining the co-movement of trade is under-researched; nor do we understand what the determinants are of these patterns. This paper aims to fill both gaps. Armed with this information, policy-makers can target national, regional or global policy initiatives. For example, if the regional factor is found to be one of the most important drivers for co-movements of international trade involving a group of countries that are part of a regional trade agreement, then we may expect that policy-making efforts targeted towards deepening this arrangement could be effective in promoting trade flows. Alternatively, the dominance of the global factor may suggest that countries should focus on guarding global value chains (GVCs) from protectionist tendencies as well as demand and supply shocks.

The current paper uses a dynamic factor model (DFM)—one of the dominant tools used to examine the co-movement of data series—while our focus is to understand the co-movement of trade in more detail such that we can simultaneously estimate the dynamic global, regional, country and idiosyncratic factors for different regions of the world. Therefore, our contribution is to use these techniques to understand the relative importance of different factors driving international trade; we focus on the analysis of historical data to conduct an in-sample analysis rather than an out-of-sample forecasting exercise. Our analysis provides evidence concerning the source of the variation, at a time when there is great concern about international trade cycles.

This paper starts by using a Bayesian dynamic latent factor model (BDFM); for a broadly similar approach applied to business cycles, see Kose et al. (2008). In our case, the data set covers 153 countries and nine regions (1981−2018), where the application of the Bayesian method is particularly efficient in the case of large cross-sections of data (Kose et al., 2003). We analyze 306 international trade series (153 export and 153 import series) together before extracting the results by region. Therefore, we avoid the problems associated with analyzing each regional grouping separately and wrongly attributing a world factor as a regional factor. Then we move to re-run our analysis with a shorter time series (2000−2019) but a broader cross-section that allows us to analyze more regions; this consists of 203 countries (406 international trade series) and 12 regions. Moreover, this variation of the data set permits us to check whether similar results are found for the regions that are present in both data sets. Second, we go on to examine the influence of a range of variables that may explain the share of the regional and global factors. We focus on these two factors because our BDFM results show that they explain the majority of the share of variance. This analysis consists of applying Bayesian model averaging (BMA), where the variables include measures of the degree of economic integration, openness to trade and macroeconomic fundamentals. In conducting this analysis, we address the following questions in this paper: (i) What is the relative importance of global, regional, country and idiosyncratic factors in explaining trade? (ii) What are the differences in the importance of the four factors across different regional groupings? (iii) Which variables may explain the share of variance attributed to the regional and global factors?

Our findings suggest that there is significant heterogeneity across regions in terms of the relative importance of global, regional, country and idiosyncratic factors in explaining trade, while international factors explain the majority of the share of the variance. We find that the regional factor accounts for a larger share of the international trade variability for the European Union (EU), the euro area and North American Free Trade Agreement (NAFTA) compared with the other regions under consideration. The global factor is of particularly limited importance for NAFTA. Alternatively, the country factor dominates for the diverse group of countries under the Caribbean Community (CARICOM) umbrella. Moreover, the world factor, rather than the regional factor, accounts for a larger share of international trade variability in African and Commonwealth of Independent States Free Trade Area (CISFTA) economies. Comparing across regions suggests that differences in the extent to which the regional factor explains trade cannot simply be understood with reference to intra-regional trade flows. The depth of trade integration may be relevant. Our BMA analysis confirms that the regional factor is generally more important in the case of economically large trade blocks and in the cases where regional integration extends beyond trade in goods. More generally, our analysis illustrates the usefulness of applying a BDFM to study the co-movements of international trade data. This methodological approach allows us to understand the importance of global, regional and country specific drivers, and therefore the types of policy prescriptions (global/regional/country) that may be effectively applied. Overall, international policies and shocks are found to be the most important considerations.

The remainder of this paper is laid out as follows. The next section discusses the methodology, estimation and data and examines the factor plots. Both the BDFM and BMA empirical results are discussed in section 3. Section 4 concludes.

2. Methodology

2.1. Set-up of the model

DFMs, first proposed by Geweke (1977), are used to extract a common component of macroeconomic time series in order to assess the degree of their co-movement at the regional and international level. The present study uses a three-level BDFM model, depicted in figure 1, to extract factors associated with the co-movement of time series within the entire sample, region and countries (Otrok and Whiteman 1998; Kose et al. 2003, 2008, 2012; and Jackson et al. 2016)[1] Let N denote the total number of countries used in the analysis, M the number of time series per country and T the length of the time series. In the analysis, we consider growth rates of exports and imports, therefore $M = 2$. An observable variable is denoted by y_{it}, where $i = 1, ..., M\text{x}N$ and $t = 1, ..., T$. Within the model, there are three types of factors: Global (G) factor (common to all time series under scrutiny), regional (R) factors (common to all time series within a given region) and country (C) factors (common to both time series within one country). Accordingly, the equation for the observable variable can be written as follows:

$$y_{it} = \alpha_i + \beta_i^G F_t^G + \beta_i^R F_{mt}^R + \beta_i^C F_{nt}^C + \varepsilon_{it}, \tag{1}$$

where m denotes the region, n denotes the country and $E(\varepsilon_{it}, \varepsilon_{jt-s}) = 0$ for $i \neq j$. F_t, F_{mt}^R and F_{nt}^C denote global, regional and country factors, respectively. β_l^k are the factor loadings, and they show the degree to which the variation in y_{it} can be attributed to each factor. The unexplained part of y_{it} is given by the idiosyncratic term ε_{it}, which shows the variation explained by developments specific to a given time series in a given country and measurement error. Idiosyncratic terms can be serially correlated but are assumed to be normally distributed and cross-sectionally uncorrelated at all leads and lags (Kose et al., 2008; Jackson et al., 2016). This term follows autoregression of order p:

$$\varepsilon_{it} = \phi_{i1}\varepsilon_{it-1} + \phi_{i2}\varepsilon_{it-2} + ... + \phi_{ip}\varepsilon_{it-p} + u_{it}, \tag{2}$$

1 For more on multi-level dynamic factor models see Breitung and Eickmeier (2016), while for hierarchical dynamic factor models see Moench et al. (2013).

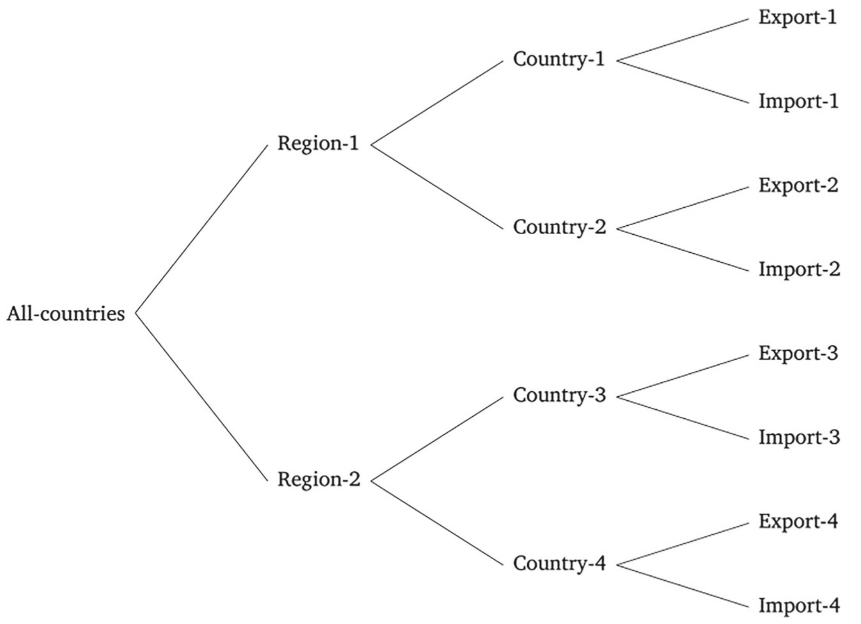

FIGURE 1 Three-level Bayesian dynamic latent factor model
NOTE: The figure presents the relationship between the data structure and the factors within the three-level BDFM.

where $u_{it} \sim N(0, \sigma_i^2)$. Similar to the idiosyncratic term, the evolution of factors is governed by the autoregression of order q. Accordingly, factor k follows $AR(q)$ process:

$$F_t^k = \Psi_{k1} F_{t-1}^k + \Psi_{k2} F_{t-2}^k + ... + \Psi_{kq} F_{t-q}^k + \nu_{kt}, \tag{3}$$

where $\nu_{kt} \sim N(0, \sigma_k^2)$. Moreover, ν_{kt} for all $k = 1, ..., G + R + C$ and ε_{it} are all mutually orthogonal.[2] In order to assess the degree of co-movement between the analyzed time series within two years, both q and p were set at 8 (quarters). We experimented with different lag structures; however, the results remain almost the same.[3] This should come as no surprise because the variance around zero of a prior on polynomial terms declines exponentially with the lag. The details of prior structure are left for subsection 2.2.

As discussed by Otrok and Whiteman (1998) (in the context of a one factor model) and Kose et al. (2003) (extended to three factors), the model described by equations (1) to (3) suffers from rotational indeterminacy, and, consequently, it is impossible to identify the signs and scales of factors and factor loadings separately. To overcome this issue, we identify the signs by the requirement that one-factor loading is positive for each factor. Specifically, following Kose et al. (2003), the global factor is positive for the exports of the USA because this is the largest economy in the world. Country factors are identified by setting the requirement of positive factor loading for the exports of each country. Finally, regional factors are identified by requiring positive factor loading for the exports of the first

2 This assumption is required to allow for variance decomposition, see Jackson et al. (2016)

3 We experimented with p and q, set to 4, 6, 8, 10 and 12. The results are not reported for brevity but are available upon request.

country in the region, as shown in appendix tables C1 to C4.[4] Scale identification follows Sargent and Sims (1977) and Stock and Watson (1989, 1992, 1993) by assuming that each σ_k^2 is constant.

2.2. Model estimation, priors and the share of variance attributable to a factor

The model set out in equations (1) to (3) is estimated using the approach proposed by Otrok and Whiteman (1998) using the work on data augmentation by Tanner and Wong (1987).The model applies a Gibbs sampling method (Chib and Greenberg, 1996) to approximate the marginal and joint distributions by sampling from the conditional ones. Because all the conditional distributions are known (parameters given data and factors, and factors given data and parameters), a Markov chain Monto Carlo (MCMC) can be applied to generate random samples from the joint posterior distribution of the unknown parameters and the unobserved factors.[5] The Gibbs algorithm can be summarized by the following three steps:

1. Simulation of AR coefficients and the variance innovation of shocks to (2-3) conditional on a draw of factors
2. Draw of factor loadings conditional on the draw of factors
3. Simulation of factors conditional on all the above parameters

These steps are repeated 60,000 times to ensure the convergence of the chains, with the first 10,000 draws being discarded.

We conform to the standard practice of using uninformative priors (Kose et al. 2008; Crucini et al. 2011; Karadimitropoulou and Leén-Ledesma 2013; Jackson et al. 2016; Chen 2018; Karadimitropoulou 2018; Beck and Stanek 2019 and Beck 2020, 2021). The prior on all factor loadings is $N(0,1)$, while for the autoregressive parameters, the prior is $N(0,\Sigma)$, where

$$\Sigma = \begin{bmatrix} 1 & 0 & 0 & . & . & . & 0 \\ 0 & 0.5 & 0 & . & . & . & 0 \\ 0 & 0 & 0.25 & . & . & . & 0 \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ 0 & 0 & .0 & . & . & . & 0.5^{q-1} \end{bmatrix}. \tag{4}$$

In the main results, we use a maximum lag for the autoregressive components equal to eight. We tested the robustness of the results with respect to changes in the maximum lag specification by using the models with maximum lag set to 4 and 12. The results we obtained are similar to those we reported in the main text (see footnote 3). We do not present them here, for brevity; however, they are available from the authors upon request. The prior on the innovation variances in the observable equation is given by inverse gamma:

$$\sigma_i^2 \sim IG(6, 0.001), \tag{5}$$

which can be classified as diffuse. Various changes in the prior structure had a very limited impact on the results.

4 Country choice influences factor plots; however, it does not affect variance decomposition

5 The more detailed description of the estimation process is beyond the scope of this manuscript. We refer the interested reader to Otrok and Whiteman (1998) and Jackson et al. (2016)

The main questions addressed in the present paper concern the relative importance of global, regional and country factors in international trade. Therefore, the share of variance attributable to global, regional, country and idiosyncratic components were estimated. With orthogonal factors, the variance of the observable variable i can be written as follows:[6]

$$var(y_{it}) = (\beta_i^G)^2 var(F_t^G) + (\beta_i^R)^2 var(F_{mt}^R) + (\beta_i^C)^2 var(F_{nt}^C) + var(\varepsilon_{it}). \quad (6)$$

Consequently, the share of variance attributable to factor k is given by

$$VS_{it}^k = \frac{(\beta_i^k)^2 var(F_t^k)}{var(y_{it})}. \quad (7)$$

Within this setting, the variance share attributable to a given factor depends on two elements. First, the share of variance explained by factor k. Second, it depends on the responsiveness of a given time series to a given factor, measured by the (square of the) factor loading.

First, the model was calculated for the entire period in order to extract the factors. The evolution of factors is described in subsection2.5.[7] Second, the model was estimated using a 27 quarter rolling window to obtain the variance decomposition over time, as it is unreasonable to assume parameter stability over the entire analyzed period.[8] However, we should note that the drawback of using a rolling window is that you cannot pin point changes in the variance decomposition in a given quarter. The variance decompositions are presented from a regional perspective. We calculate weighted averages of the shares of the variance explained by a given factor and use individual country export and import shares in regional exports and imports as weights. Very similar results are obtained when we use GDP shares. The main conclusions also remain the same when we use simple averages.

2.3. Estimating the determinants of the share of variance explained by global and regional factors

In the BMA analysis, we examine the role of 11 determinants that can influence the share of variance explained by global and regional factors. The list of the regressors used are in table 1. We used variables EIA, CU, Common and Currency to assess whether the degree of economic integration determines the share of global and regional factors. OPEN is used to analyze the connection between the factors and the general level of openness of the economy. The remaining variables (GDP, POP, GDPpc, GOV, RegionGDP and RegionSize) were included to capture the impact of macroeconomic variables on the relative shares of international factors. Macroeconomics variables, namely GDP, POP, OPEN, GDPpc and GOV, have already been examined in the literature within the context of the variance shares explained by global and regional factors (Kose et al., 2003; Karadimitropoulou, 2018; Stoykova, 2021). The remaining variables are proposed by us to capture the impact of regional agreements on the global and regional factors share of variance.2

6 To ensure that the variance shares sum up to one, we follow Kose et al. (2003) and orthogonalized the sampled factors. We refer the interested reader to subsection 3.4 of Jackson et al. (2016).

7 For brevity not all the results are reported, but are available upon request

8 We examined the robustness of the results using 25, 29 and 31 rolling windows (which is more than the time dimension used in the seminal works of Kose et al. 2003 and Kose et al. 2012). We received fairly similar results. The results are not reported for brevity but are available upon request.

TABLE 1
Regressors used in the analysis

Abbreviation	Description
GDP	Real GDP in PPP
POP	Population
OPEN	Imports plus exports as a share of GDP
GDPpc	GDP per capita
GOV	Government spending as a share of GDP
RegionGDP	Total real GDP in PPP of the agreement the country belongs to
RegionSize	Number of countries in the agreement
EIA	Binary variable equal to 1 for countries that are members of an economic integration agreement
CU	Binary variable equal to 1 for countries that are members of a customs union
Common	Binary variable equal to 1 for countries that are members of a common market
Currency	Binary variable equal to 1 for countries that are members of a currency union

NOTES: Data on GDP, POP, OPEN, GDPpc, GOV and Region GDP come from Penn World Tables. An EIA is defined in Article V of the General Agreement Trade in Services and indicates that the agreement covers services. Information on the degree of economic integration comes from the WTO Regional Trade Agreements Database.

To assess the robustness of the variables, we applied BMA. With 11 variables it is possible to estimate $2^{11} = 2048$ models. Once estimated, each model is assigned a posterior model probability (PMP) given by Bayes' rule:

$$PMP_m = \frac{L(data|M_m) \times P(M_m)}{\sum_{m=1}^{2048} L(data|M_m) \times P(M_m)}, \tag{8}$$

where $L(data|M_m)$ is the value of the likelihood function for model m (M_m) and $P(M_m)$ is the prior probability of model m. Using the PMPs in the role of weights allows for the calculation of posterior mean and standard deviation of the coefficient β_k ($k = 1, \ldots, 11$). In order to account for potential multicollinearity between regressors, a dilution prior was used. Accordingly, a uniform model prior is supplemented with a function accounting for multicollinearity (George, 2010) to obtain prior model probabilities:

$$P(M_m) \propto |R_j|^{0.5} \left(\frac{1}{2}\right)^{11}, \tag{9}$$

where ($|R_m|$) is the determinant of the correlation matrix for all the regressors in the model j. The uniform model prior implies equal probabilities are assigned to all the models, so the ($|R_m|$) component of (9) determines the distribution of the prior probability mass. The higher the multicollinearity between the variables, the closer the value of ($|R_j|$) to 0 and the lower the prior ascribed to a given model.

The posterior mean (PM) of the coefficient β_k is given by

$$PM_k = \sum_{m=1}^{2048} \hat{\beta}_{k,m} \times PMP_m, \tag{10}$$

where $\hat{\beta}_{k,m}$ is the value of the coefficient β_k estimated for the model m and k indexes the regressor. The posterior standard deviation (PSD) is equal to

$$PSD_k = \sqrt{\sum_{m=1}^{2048} V(\beta_{k,m}|data, M_j) \times PMP_m + \sum_{m=1}^{2048} [\hat{\beta}_{k,m} - PM_k]^2 \times PMP_m}, \tag{11}$$

where $V(\beta_{k,m}|data, M_j)$ denotes the conditional variance of the parameter in the model M_m. To allow the comparison of the relative impact of different regressors, standardized coefficients were calculated and BMA statistics based on their values. SPM denotes the standardized posterior mean, while SPSD denotes a standardized posterior standard deviation (see Doppelhofer and Weeks 2009).

Assuming that each model M_m has a binary vector ascribed to it, $\rho = (\rho_1, \ldots, \rho_{11})$, where 0 signifies exclusion and 1 signifies inclusion of a variable k in the model, the posterior inclusion probability (PIP) is calculated as

$$PIP_k = \sum_{j=1}^{2048} 1(\rho_k = 1|data, M_m) \times PMP_m. \tag{12}$$

The application of BMA requires the specification of the model prior and it is common to use g prior on the parameter space. The benchmark rule (Fernández et al., 2001) dictates the choice of unit information prior (UIP) on the coefficients. However, the results went through vast robustness checks and are resilient to manipulations in both model and g prior. Kass and Raftery (1995) proposed a more detailed classification scheme with the robustness being weak, positive, strong, or decisive when the posterior inclusion probability is between 0.5 and 0.75, 0.75 and 0.95, 0.95 and 0.99, or 0.99 and 1, respectively.[9]

2.4. Data

The BDFM analysis, where we estimate the latent factors, covers a panel of quarterly exports and imports consisting of 153 countries and covering the period between the first quarter of 1981 and the second quarter of 2018. The data was retrieved from IMF Directions of Trade. The time series were logarithmized, differentiated and demeaned. Countries are grouped according to the membership of free trade agreements (FTA), customs union, economic and monetary unions they are a part of. We present our results based on two slightly different regional groupings. Initially, we consider the following nine regions: (i) NAFTA, (ii) Association of Southeast Asian Nations (ASEAN), (iii) CARICOM Single Market and Economy (CSME), (iv) Central American Integration System (SICA or CAIS), (v) Mercosur, (vi) Gulf Cooperation Council (GCC), (vii) Common Market for Eastern and Southern Africa (COMESA), (viii) the EU and (ix) the Rest of the World. Then, the euro area replaces the EU, with the difference between the two being assigned to the Rest of the World.[10] The details of the regional compositions are depicted in figure C1 as well as in tables C1 and C2. For the BMA analysis, where we estimate the determinants of the share of variance, in the cases where variables are non-binary, we use data from 2017 from Penn World Tables.[11]

9 The results presented in the main text went through various changes in g prior as well as model prior. Moreover, we explored model selection approaches based on reversible jump and birth−death MCMC algorithms. The results are robust to these changes. For brevity, we do not report them in the paper but they are available upon request.

10 The results remain almost the same if the difference is left outside the model.

11 The results presented here involve the last examined time period in the rolling window. However, we repeated the calculations using the past data and the results were qualitatively similar. They are available upon request.

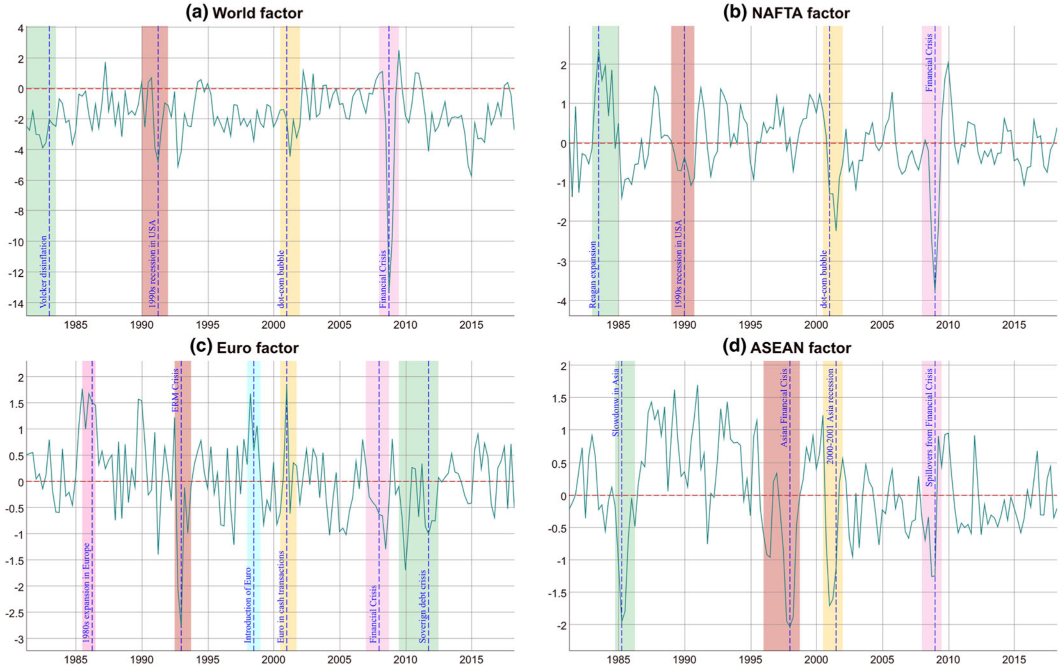

FIGURE 2 Factor plots
NOTES: Dashed line represents main event of the period. Shaded area represents the approximate length of the event.

2.5. Factor plots

We will now consider the potential economic interpretations for the three different unobserved dynamic factors that explain the co-movements of the international trade series under consideration. First, the global factor may be the implementation of multilateral (WTO) policies, escalation of trade disputes and the impact of international shocks (e.g., global financial crisis). Second, regional factors may include the implementation or disintegration of regional trade agreements (RTAs), or similar, and the impact of regional shocks (e.g., Asian financial crisis). Finally, in terms of the country factor, there are of course country specific trade policies (e.g., post-Brexit UK Global Tariff) as well as the impact of shocks that remain confined to a particular country (e.g., negative weather shock leading to food export ban in a small exporting country).

Figure 2 provides four illustrative factor plots, which include the world factor and three regional factors. There are two aspects to these graphs; first the general size (in percent) of each factor and, second, the peaks and troughs of the cycles. In the case of the regional factors, the variation in size between regions may be attributed to differences such as the degree of economic integration, while the world factor may be affected by global integration, e.g., multilateralism. Since the 1990s, trade economists have enthusiastically debated the link between regional and multilateral integration (Baldwin, 1993, 1997, 2004, 2006). However, the literature provides little evidence on the relative importance of world and regional factors. As explained earlier, this is the focus of the contribution of this paper.

The peaks and troughs are driven by other changes/shocks, where examples are highlighted on the plots. Volcker disinflation (Goodfriend and King, 2005) can be seen as a global phenomenon (Bayoumi and Vitek, 2013). In Europe, the 1980s was a period of expansion

(Eichengreen, 2008). Also during the 1980s, ASEAN economies were heavily dependent on industrialized countries, particularly the USA. Therefore, the slower growth in these industrialized countries triggered a slowdown in Asia (Rieger, 1986). This weakening of industrialized economies contributed to the 1990s recession in North America as well as in many other industrialized countries (Walsh, 1993). In Europe, we highlight the ERM crisis (Bryon, 1993; Aykens, 2002; Eichengreen and Naef, 2022). Moreover, we also refer to the 1997 Asian crisis (Krugman, 2008; Stiglitz, 2002). The ASEAN economies continued to rely on industrialized countries. Therefore, the weakening of the US economy, further exacerbated by the 2001 terrorist attacks as well as higher oil prices and the decline of ASEAN equities, led to the 2000−2001 Asian recession (Sharma, 2018). Furthermore, we also identify spillovers from the financial crisis to Asia (Hwang et al., 2013). Finally, the main events for NAFTA and world factors are similar. This would suggest that macroeconomic events underpinning the world factor are actually the same as for NAFTA, ergo the United States.

3. Empirical results

3.1. Latent factor estimation results

For the presentation of the results, the groupings that remain consistent, i.e., all apart from EU, the euro area and Rest of the World, are reported only once and based on version 1 of the groupings (table C1). The other results, based on version 2 of the groupings (table C2), are very similar to those presented here and are available upon request. The algorithm described in the previous section generates a variance decomposition (equation (6)), whereby we have one graph per region as shown in figure 3, which allows us to visualize the mean percentage share of the variance attributable to each factor (calculation based on equation (7)). Two alternative presentations of the compositions are depicted in figures C2 and C3. In figure C2, we combine the global and regional factor and label these as the international factors; further, we combine the country and idiosyncratic factors and label these as the national factors. Moreover, we conducted further robustness checks by examining the data using a dynamic factor model with time-varying parameters.4

Starting with the NAFTA grouping, the regional factor dominates as we expect given that this is a well-established trade arrangement, starting with the US−Canada FTA, which dates back more than 30 years. Intra-regional trade flows between Canada, Mexico and the USA are consistently high—50% in 2017 (World Trade Organization, 2019). However, this fact alone, does not explain the importance of the regional factor when comparing with the results for the EU or the euro area, where 64% of EU-28 trade is between member states (World Trade Organization 2019) and the regional factor is often less important. Therefore, our results indicate that other regional factors, apart from the level of intra-RTA trade, drive the co-movement of the international trade series. The three members have large economies heavily reliant on each other; therefore, shocks or policy measures undertaken in one country can easily impact the trade of other countries in the block. Moreover, the results for NAFTA suggest greater stability in the percentage share of the variance attributable to each factor compared with the other reported groupings. For NAFTA, the global factor is the least important out of all the regions in terms of its explanation of the share of variance.

Across the EU and euro area results, there are a great deal of similarities. We also note that the importance of the global factor increases sharply towards the first half of the 1980s and then gradually declines, before levelling off in recent years. The rise in the share of the global factor is largely at the expense of the regional factor, and vice versa. The increasing

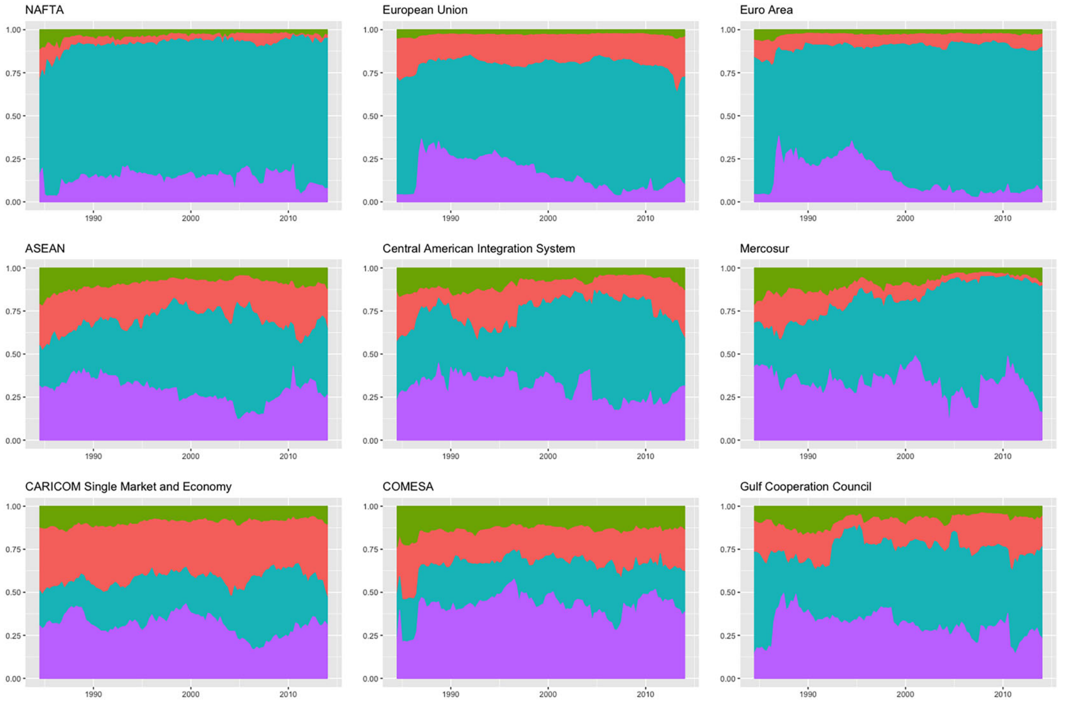

FIGURE 3 Estimates of the share of variance attributable to global, regional, country and idiosyncratic components

NOTES: Green (top): Idiosyncratic factor. Orange/red (second from top): Country factor. Blue (third from top): Regional factor. Purple (bottom): Global factor.

importance of the regional factor for EU states, whether part of the euro area or not, is in line with the deepening and widening integration process that dominated the 1990s and early 2000s. Our findings indicate that regional policies are important because there is a distinct regional factor that explains the co-movement of international trade series within Europe. As expected, the EU results suggest a bigger role for the country factor compared with the euro area.

The ASEAN grouping involves considerably less intra-RTA trade, 24% in 2017 (World Trade Organization 2019), and our results show a more restricted share of the variance attributed to the regional factor, compared with NAFTA or the EU/euro area. There was a gradual decline of the share of variance of the world factor during the 1990s and 2000s, covering the period leading up to and following the 1997 Asian financial crisis. Towards the end of the 2000s, the share for the world factor peaks.

In the remaining regions, a number of interesting features emerge. First, the increasing importance of the regional factor at the expense of the country factor in the Mercosur region, which is in line with the development of the trading block. Second, CARICOM tends to have the largest share of variance attributable to the country factor, where this may be due to the fact that the countries within this group are very heterogeneous in terms of population, GDP per capita, development, geography and sectors of productive capacity (Yersh, 2022). For example, in 2018, Haiti is shown to have a GDP per capita of $868.30, while Barbados is reported as $17,949.30 (The World Bank, 2023). Third, SICA is particularly interesting

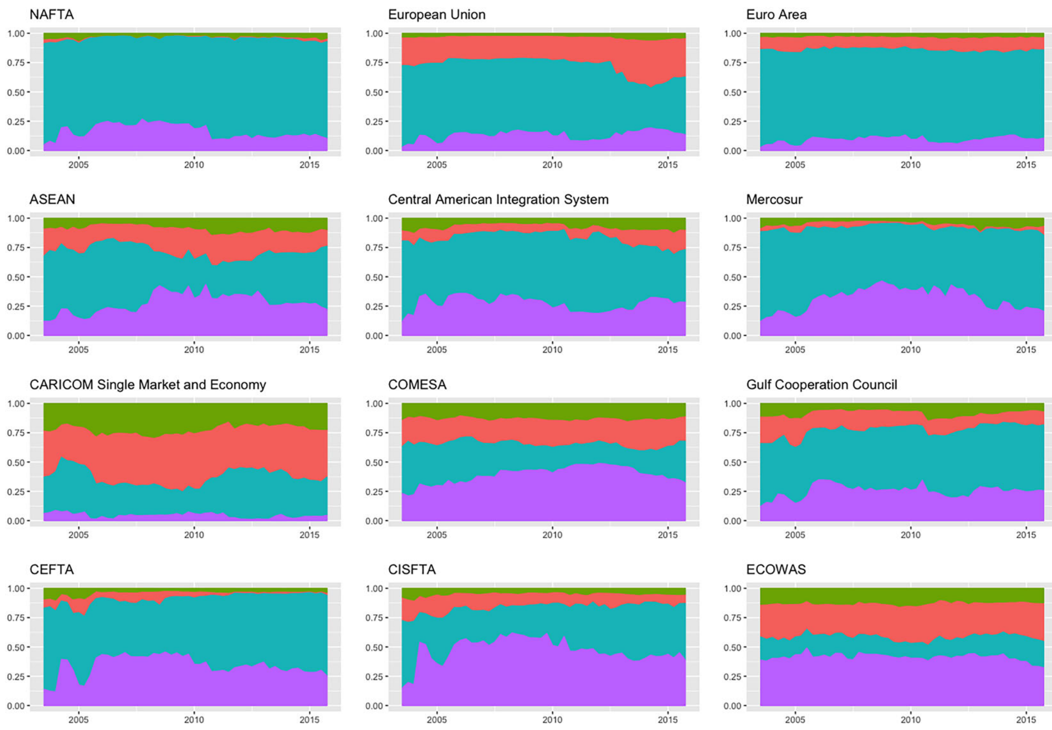

FIGURE 4 Estimates of the share of variance attributable to global, regional, country and idiosyncratic components – Alternative panel (2000–2019)
NOTES: Green (top): Idiosyncratic factor. Orange/red (second from top): Country factor. Blue (third from top): Regional factor. Purple (bottom): Global factor.

because there is a long history of regional integration, although nonlinear in its development.[12] Therefore, this may explain the importance of the regional factor as well as the variance over time. Fourth, the GCC also shares a long history dating back to the 1980s, where they were targeting the introduction of a single currency by 2010, although this has not happened to date (Sturm and Siegfried, 2005). Therefore, not unlike SICA, this is a long-standing arrangement but slow to deliver on the process of deeper integration. The GCC economies are particularly exposed to fluctuations in the oil market, and therefore, regional and global factors are very important for this grouping (Akoum et al., 2012). Last, figure C2 shows that, with the exception of CARICOM, international factors account for a much greater share of the variance compared with national factors. Therefore, our results suggest that international policy making and shocks are very important in explaining the co-movement of trade series.

12 The Central American Federation was formed in 1824. Part of the motivation for the subsequent attempts at deeper integration were a desire to take advantage of economies of scale by drawing together the relatively small individual economies into the Central American Common Market. However, the success of the 1960s did not last into the 1970s and 1980s. Nevertheless, during the 1990s, the global trend towards regional integration acted as an impetus to create SICA. Despite the historical context for SICA, this recent integration process has not been particularly stable; for example, the dispute between Nicaragua and Honduras over seaways and two islands towards the end of the 1990s, which led to escalating tariffs.

To examine further regional groupings, we consider a second panel of imports and exports with a different country coverage and time period (figure 4). In this panel, we have 203 countries, covering the period between the first quarter of 2000 and the first quarter of 2019. In this case, we have 12 regions: NAFTA, ASEAN, CSME, SICA, Mercosur, GCC, COMESA, Central European Free Trade Agreement (CEFTA), CISFTA, ECOWAS, the EU and the Rest of the World. Once again, we also introduce the additional variation of the euro area replacing the EU, with the difference between the two being assigned to the Rest of the World. The details of the regional composition are depicted in figure C4 as well as in tables C3 and C4. In terms of the presentation of the results, the groupings that remain consistent, i.e., all apart from EU, the euro area and the Rest of the World, are reported only once and based on version 3 of the groupings (table C3). The other results, based on version 4 of the groupings (table C4), are very similar to those presented here and are available upon request. Two alternative presentations of the compositions are depicted in figures C5 and C6. In figure C5, we combine the global and regional factors and label these as the international factors; further, we combine the country and idiosyncratic factors and label these as the national factors.

Once more, the evidence suggests that the regional factor is most important in the case of NAFTA. The country factor remains more important for the EU compared with the euro area. This new panel permits us to discuss the ECOWAS group, where we find the variance attributable to the regional factor is generally the smallest out of all the groups. Similar to Mercosur, ECOWAS has many elements of the integration framework mirrored on the EU. The revised ECOWAS Treaty (1993, based on the founding treaty signed in 1975) set out the intention to introduce an economic and monetary union within five years of the creation of the customs union. However, delays around adopting the common external tariff (and thereby creating the customs union) temporarily curtailed aspirations. Furthermore, intra-RTA trade remains very low, 10% in 2017 (World Trade Organization 2019). This is also an issue for the COMESA block, which has only 8% of trade between members of the agreement. Part of the explanation can be found in the colonial heritage of members of both blocks, where there was a historical tendency to trade outside the region (Bah et al., 2018). More generally, the evidence suggests that the world factor, rather than the regional factor, accounts for a larger share of international trade variability in African and CISFTA economies. Finally, figure C5 confirms the importance of international policy making and shocks in explaining the co-movement of trade series.

We performed a further robustness check by using a Bayesian dynamic latent factor model with time-varying factor loadings and stochastic volatility in both the latent factors and idiosyncratic components as developed by Del Negro and Otrok (2008).[13] The description of this alternative approach is in appendix B. The results we obtained for the variance share attributable to the world factor in the two-level model can be compared with the variance share attributable to the sum of the global and regional factors from the three-level model. The results presented in figures C7 and C8 demonstrate the similarity of the results.

3.2. Determinants of share of variance

In the BDFM analysis, we have focused on interpreting the findings by region. However, it is also interesting to try and identify broader patterns by examining across regions. Therefore, the BMA approach identifies the variables that explain the share of variance accounted

13 We tried to estimate the three-level Bayesian dynamic factor model with time-varying factor loadings and stochastic volatility; however, we were not able to attain convergence.

TABLE 2
Determinants of share of variance

Main panel

Dependent variable: Share of variance attributable to the global factor

	PIP	PM	PSD	SPM	SPSD	P(+)
Common*	0.736	−0.118	0.084	−0.306	0.218	0.000
GDPpc*	0.513	0.000	0.000	−0.131	0.151	0.000
EIA	0.451	−0.048	0.061	−0.141	0.182	0.000
CU	0.216	0.014	0.034	0.032	0.078	1.000
GDP	0.214	0.000	0.000	−0.033	0.083	0.000
RegionSize	0.151	0.000	0.001	−0.015	0.054	0.000
RegionGDP	0.122	0.000	0.000	−0.009	0.044	0.017
OPEN	0.121	−0.004	0.021	−0.011	0.053	0.147
POP	0.118	0.000	0.000	−0.009	0.048	0.082
GOV	0.110	0.008	0.079	0.004	0.040	0.696
Currency	0.086	−0.004	0.026	−0.009	0.057	0.220

Dependent variable: Share of variance attributable to the regional factor

	PIP	PM	PSD	SPM	SPSD	P(+)
GDPpc*	0.922	0.000	0.000	0.336	0.148	1.000
EIA*	0.629	0.099	0.090	0.188	0.171	1.000
Common	0.376	0.068	0.102	0.112	0.170	1.000
GDP	0.181	0.000	0.000	0.026	0.075	1.000
POP	0.156	0.000	0.000	0.018	0.060	0.989
GOV	0.142	−0.042	0.166	−0.014	0.054	0.002
CU	0.125	−0.007	0.031	−0.010	0.046	0.021
RegionGDP	0.116	0.000	0.000	0.007	0.041	1.000
OPEN	0.111	−0.006	0.033	−0.010	0.053	0.093
RegionSize	0.097	0.000	0.001	0.001	0.033	0.732
Currency	0.089	−0.004	0.038	−0.006	0.053	0.143

Alternative panel

Dependent variable: Share of variance attributable to the global factor

	PIP	PM	PSD	SPM	SPSD	P(+)
EIA*	1.000	−0.175	0.029	−0.577	0.096	0.000
GOV*	0.623	−0.185	0.173	−0.118	0.110	0.000
GDPpc	0.244	0.000	0.000	−0.038	0.080	0.000
OPEN	0.148	−0.006	0.017	−0.019	0.058	0.000
RegionSize	0.134	0.000	0.001	0.015	0.050	0.999
CU	0.089	0.001	0.010	0.004	0.027	0.980
GDP	0.082	0.000	0.000	−0.002	0.025	0.131
POP	0.081	0.000	0.000	0.001	0.024	0.490
Currency	0.076	0.002	0.014	0.006	0.034	0.975
Common	0.068	0.003	0.015	0.008	0.045	0.990
RegionGDP	0.055	0.000	0.000	0.005	0.035	0.953

Dependent variable: Share of variance attributable to the regional factor

	PIP	PM	PSD	SPM	SPSD	P(+)
RegionSize*	1.000	−0.017	0.003	−0.686	0.115	0.000
RegionGDP*	0.985	0.000	0.000	0.828	0.156	1.000
GOV	0.228	0.060	0.139	0.029	0.066	1.000
OPEN	0.224	−0.013	0.029	−0.032	0.073	0.000
CU	0.096	−0.005	0.025	−0.011	0.051	0.000
POP	0.084	0.000	0.000	−0.004	0.029	0.017
GDP	0.069	0.000	0.000	−0.003	0.027	0.032
GDPpc	0.065	0.000	0.000	−0.004	0.029	0.066
EIA	0.064	−0.002	0.014	−0.006	0.035	0.007
Currency	0.045	0.002	0.015	0.003	0.029	1.000
Common	0.023	0.008	0.061	0.017	0.132	0.998

NOTES: All estimations use a Bayesian model averaging procedure applied to 2017 data. PIP = posterior inclusion probability. PM = posterior mean. PSD = posterior standard deviation. SPM = standardized posterior mean SPSD = standardized posterior standard deviation. P(+) = posterior probability of the coefficient having a positive sign. * denotes that the variable has a PIP value above 0.5 and we can consider it a robust determinant.

for by global and regional factors. If the variable has a posterior inclusion probability (PIP) above 0.5, we can start considering it to be robust, i.e., counterpart of statistically significant in standard regression analysis. P(+) is the posterior probability of the coefficient having a positive sign, where 1 suggests that the coefficient is always positive and 0 suggests that the coefficient is always negative. We continue to use two panels with different country and time period coverage, as discussed in the earlier sections (table 2).

We find evidence that the share of the global factor is negatively related to deeper forms of trade arrangements, such as a common market and an EIA involving services. The common market dummy and integration agreement dummy have a PIP of 0.736 and 1, respectively, in the main and alternative panel. The standardized posterior mean shows that these variables have the strongest impact among all the regressors considered. On the other hand, the share of the regional factor is positively correlated with deeper trade arrangements including services (EIA) because the PIP on the regressors amounts to 0.629 and the posterior probability of a positive sign of a coefficient is 1.

Furthermore, we identify a negative relationship between the share of the global factor and GDP per capita indicating that more developed countries are generally characterized by stronger connections with countries in their regional agreements. The PIP on this variable in the main panel is equal to 0.513, while the standardized posterior mean indicates that this regressor has the second strongest impact on the variance share of the regional factor in the main panel. Similarly, government spending as a share of GDP is associated with a lower share of the global factor. This indicates that higher government involvement in the economy comes at the expense of integration with the rest of the world.

The most interesting conclusion comes from the alternative panel for the regional factor. On the one hand, the share of the regional factor is positively related to the GDP of the regional economic agreement. On the other hand, there is a negative relationship between the share of the regional factor and the number of countries in the agreement. The PIP on these variables is 1 and 0.985, and from the SPM, we can conclude that their influence is considerably stronger than other regressors. On the basis of this result, we can summarize that the regional factor is strongest in the regions with a small number of big countries, e.g., NAFTA.

These findings support the notion that regional integration plays a role in determining the relative importance of regional and world factors in driving international trade. More specifically, a trade-off occurs when there are deeper forms of economic integration beyond trade in goods, such as an EIA that includes services. Furthermore, the economic size of a region will tend to increase the importance of the regional factor, while the global factor will increase in importance for poorer countries. As we would expect, these patterns were identified in our discussion of our BDFM results.

4. Conclusions

This paper uses a BDFM model to explore the synchronization of international trade flows and dissect their co-movements. This method was chosen for two reasons: (i) DFMs have become one of the dominant tools to examine the co-movement of data series and (ii) BDFMs are particularly well suited to analyzing panels with large cross-sections. While DFMs have been deployed for forecasting purposes, international trade series have not been examined using a three-level BDFM model. Therefore, this paper provides an important contribution to the literature by introducing a novel application of DFMs within an international trade context; first, we develop an understanding of the relative importance of global, regional, country and idiosyncratic factors in explaining the co-movements of trade; second, we examine the patterns for different regions. Additionally, we use a BMA approach to identify variables that explain the share of variance attributed to regional and global factors, which allows us to confirm general patterns across regions.

Our findings suggest that the co-movement in trade series due to global, regional and country factors are heterogeneous across regional groups. However, we can identify some broad patterns, such as the greater importance of the regional factor and lesser importance of the global factor, in the case of trade agreements involving services. The regional factor also tends to be responsible for a larger share of variance in the case of economically larger blocks of countries. Overall, international factors explain the majority of the share of variance across most regions. However, as an exception, CARICOM member states should be aware of the particular importance of country specific policies in driving trade. Overall, the results provide evidence that can help policy-makers concerned with managing and responding to international trade cycles.

This paper extends the empirical research using DFMs beyond the study of macroeconomic business cycles and predicting international trade cycles. The international trade and international macroeconomic literature still remains very divided and tends to use different methodological approaches. This paper is part of an emerging literature bridging the gap between the two areas, by seeking out ways in which methodological approaches can be used beyond the strand of literature where they have become established.

Appendix A: Detailed methdology

The model described in equation (1) can be rewritten as

$$y_{rc,it} = \alpha_{rc,i} + \beta^{G}_{rc,i} F^{G}_{t} + \beta^{R}_{rc,i} F^{R}_{r,t} + \beta^{C}_{rc,i} F^{C}_{ct} + \varepsilon_{rc,it} \tag{A1}$$

with three sets of indices: $i = 1, 2, ..., N$ denotes the number of the time series (observable variables), while $r = 1, 2, ..., R$ indicates the region and $c = 1, 2, ..., C$ denotes a country. The system can be written as

$$\begin{bmatrix} y_{11,t} \\ \vdots \\ y_{R1,t} \\ y_{12,t} \\ \vdots \\ y_{R2,t} \\ \vdots \\ y_{1C,t} \\ \vdots \\ y_{RC,t} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & b^{G}_{11} & b^{R}_{11} & 0 & \dots & 0 & b^{C}_{11} & 0 & \dots & 0 \\ \alpha_{21} & b^{G}_{21} & 0 & b^{R}_{21} & \dots & 0 & b^{C}_{21} & 0 & \dots & 0 \\ \vdots & \vdots & & & \ddots & \vdots & \vdots & \vdots & & \vdots \\ \alpha_{R1} & b^{G}_{R1} & 0 & 0 & \dots & b^{R}_{R1} & b^{C}_{R1} & 0 & \dots & 0 \\ \alpha_{12} & b^{G}_{12} & b^{R}_{21} & 0 & \dots & 0 & 0 & b^{C}_{12} & \dots & 0 \\ \alpha_{22} & b^{G}_{22} & 0 & b^{R}_{22} & \dots & 0 & 0 & b^{C}_{22} & \dots & 0 \\ \vdots & \vdots & & & \ddots & \vdots & \vdots & \vdots & & \vdots \\ \alpha_{R2} & b^{G}_{R2} & 0 & 0 & \dots & b^{R}_{R2} & 0 & b^{C}_{R2} & \dots & 0 \\ \vdots & \vdots & & & \ddots & \vdots & \vdots & \vdots & & \vdots \\ \alpha_{1C} & b^{G}_{1C} & b^{R}_{1C} & 0 & \dots & 0 & 0 & 0 & \dots & b^{C}_{1C} \\ \alpha_{2C} & b^{G}_{2C} & 0 & b^{R}_{2C} & \dots & 0 & 0 & 0 & \dots & b^{C}_{2C} \\ \vdots & \vdots & & & \ddots & \vdots & \vdots & \vdots & & \vdots \\ \alpha_{RC} & b^{G}_{RC} & 0 & 0 & \dots & b^{R}_{RC} & 0 & 0 & \dots & b^{C}_{RC} \end{bmatrix} * \begin{bmatrix} 1 \\ F^{G}_{t} \\ \vdots \\ F^{R}_{1,t} \\ \vdots \\ F^{R}_{R,t} \\ \vdots \\ F^{C}_{1,t} \\ \vdots \\ F^{C}_{C,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{11,t} \\ \vdots \\ \varepsilon_{R1,t} \\ \varepsilon_{12,t} \\ \vdots \\ \varepsilon_{R2,t} \\ \vdots \\ \varepsilon_{1C,t} \\ \vdots \\ \varepsilon_{RC,t} \end{bmatrix} \tag{A2}$$

or, more compactly, in matrix form,

$$Y_t = \beta F_t + \varepsilon_t. \tag{A3}$$

The factors are given by

$$F_t^k = \Psi_{k1} F_{t-1}^k + \Psi_{k2} F_{t-2}^k + \dots + \Psi_{kq} F_{t-q}^k + \nu_{kt} \tag{A4}$$

or, in the matrix form,

$$F_t = \Psi(L) F_{t-1} + \nu_t, \tag{A5}$$

where $\nu_{kt} \sim N(0, \sigma_k^2), k = 1, \dots, 1 + R + C$ indices factors and order of the autoregression is given by q. Finally, the idiosyncratic term is given by

$$\varepsilon_{it} = \phi_{i1} \varepsilon_{it-1} + \phi_{i2} \varepsilon_{it-2} + \dots + \phi_{ip} \varepsilon_{it-p} + u_{it}, \tag{A6}$$

which, in the matrix from, can be written as

$$\varepsilon_t = \Phi(L) \varepsilon_{t-1} + u_t, \tag{A7}$$

where $u_{it} \sim N(0, \sigma_i^2)$ and the order of autoregression is given by p.

The model described in equations (A3), (A5) and (A7) is characterized by the joint distribution of data, parameters and latent factors given by Del Negro (2013):

$$\begin{aligned} p\big(Y_{1:T}, F_{0:T}, \{\theta_i\}_{i=1}^N, \theta_k\big) &= \Pi_{t=p+1}^T \big[\Pi_{i=1}^N p(y_{i,t} | Y_{i,t-p:t-1}, F_{t-p:t}, \theta_i) p(F_t | F_{t-q:t-1}, \theta_0)\big] \\ &\quad * \big[\Pi_{i=1}^N p(Y_{i,1:p} | F_{0:p}, \theta_0)\big] p(F_{0:p} | \theta_0) [\Pi_{i=1}^N p(\theta_i)\big] p(\theta_0), \end{aligned} \tag{A8}$$

where $\theta_i = [\beta_i, \Phi_i, \sigma_i^2]$, $\theta_k = \big[\Psi, \{\sigma_k^2\}_{k=1}^{1+R+C}\big]$. Conditional on the factors, equation (A3) is a linear Gaussian regression with AR(p) errors, and the conditional posterior density takes the form

$$\begin{aligned} p(\theta_i | F_{0:T}, \theta_k, Y_{1:T}) \propto p(\theta_i) \Pi_{t=p+1}^T \big[\Pi_{i=1}^N p(y_{i,t} | Y_{i,t-p:t-1}, F_{t-p:t}, \theta_i)\big] \\ * \, p(Y_{i,t-p:t-1} | F_{t-p:t}, \theta_i). \end{aligned} \tag{A9}$$

The conditional posterior density of the parameters in the equations of motion (A5) is given by

$$p\big(\theta_k | F_{0:T}, \{\theta_i\}_{i=1}^N, Y_{1:T}\big) \propto \Pi_{t=p+1}^T p\big(f_t | F_{t-q:t-1}, \theta_k\big) p(\theta_k) p(F_{0:p} | \theta_k). \tag{A10}$$

The model described in equations (A3), (A5) and (A7) is estimated using the approach proposed by Otrok and Whiteman (1998) using the work on data augmentation by Tanner and Wong (1987). It applies a Gibbs sampling method (Chib and Greenberg, 1996) to approximate the marginal and joint distributions by sampling from the conditional ones. Because all the conditional distributions are known (parameters given data and factors, and factors given data and parameters), a Markov chain Monto Carlo (MCMC) can be applied to generate random samples from the joint posterior distribution of the unknown parameters and the unobserved factors. The algorithm can be summarized as follows:

For $s = 1, 2, \dots, S$

1. Draw θ_k^s conditional on $F_{0:T}^{(s-1)}, \{\theta_i^{(s-1)}\}_{i=1}^N, Y_{1:T}$ from (22).
2. Draw θ_i^s conditional on $F_{0:T}^{(s-1)}, \theta_k^{(s)}, Y_{1:T}$ from (21). This could be done independently for each $i = 1, 2, \dots, N$.
3. Draw $F_{0:T}^{(s)}$ conditional on $\theta_k^{(s)}$, $\{\theta_i^{(s)}\}_{i=1}^N, Y_{1:T}$ from (20).

These steps are repeated 60,000 times to ensure the convergence of the chains, with the first 10,000 draws being discarded. For a more detailed exposition, see Otrok and Whiteman (1998) and Del Negro (2013).

Appendix B: Bayesian dynamic latent factor model with time-varying factor loadings and stochastic volatility

We examine the robustness of the obtained results using an alternative approach proposed by Del Negro and Otrok (2008). The authors developed a Bayesian dynamic latent factor model with time-varying factor loadings and stochastic volatility in both the latent factors and idiosyncratic components. This approach provides an alternative method to that of rolling windows (applied in the main text) as a way of dealing with the issue of parameter instability. However, this greater flexibility comes at a cost, and the model combines global and regional factors together, in the form of the world factor. Below, we provide detailed description of the approach.

Let N denote the total number of countries used in the analysis, M the number of time series per country and T the length of the time series (growth rates of exports and imports). An observable variable is denoted by y_{it}, where $i = 1, ..., M\text{x}N$ and $t = 1, ..., T$. Within the model, there are two types of factors: a world (W) factor (common to all time series under scrutiny) and a country (C) factor (common to both time series within one country). Accordingly, the observable equation can be written as follows:

$$y_{it} = \alpha_i + \beta_{it}^W F_t^W + \beta_{it}^C F_{nt}^C + \varepsilon_{it}, \tag{B1}$$

where n denotes the country, and $E(\varepsilon_{it}, \varepsilon_{jt-s}) = 0$ for $i \neq j$. β_{it}^k are the factor loadings. The unexplained part of y_{it} is given by the idiosyncratic term ε_{it}, which shows the variation explained by developments specific to a given time series in a given country and measurement error. Idiosyncratic terms can be serially correlated but are assumed to be normally distributed and cross-sectionally uncorrelated at all leads and lags. The evolution of factor loadings is given by random walk:

$$\beta_{it}^k = \beta_{it-1}^k + \sigma_{\eta_i}\eta_{it}, \tag{B2}$$

where $\eta_{it} \sim N(0, 1)$ is independent across i, σ_{η_i} is the standard deviation of η_{it}, and $k = 1, ..., 1 + C$. The idiosyncratic term follows autoregression of order p:

$$\varepsilon_{it} = \phi_{i1}\varepsilon_{it-1} + \phi_{i2}\varepsilon_{it-2} + ... + \phi_{i\rho}\varepsilon_{it-\rho} + e^{h_{it}}\sigma_i u_{it}, \tag{B3}$$

where $u_{it} \sim N(0, 1)$ and σ_i^2 denotes standard deviation of u_{it}. Similar to the idiosyncratic term, the evolution of factors is governed by the autoregression of order q. Accordingly, factor k follows AR(q) process:

$$F_t^k = \Psi_{k1}F_{t-1}^k + \Psi_{k2}F_{t-2}^k + ... + \Psi_{kq}F_{t-q}^k + e^{h_{kt}}\sigma_k\nu_{kt}, \tag{B4}$$

where $\nu_{kt} \sim N(0, 1)$ and σ_k denotes standard deviation of ν_{kt}. Moreover, ν_{kt} for all $k = 1, ..., 1 + C$ and ε_{it} are all mutually orthogonal. The terms $e^{h_{it}}$ and $e^{h_{kt}}$ represent the stochastic volatility components, and h_{it} (and similarly h_{kt}) follows a random walk:

$$h_{it} = h_{it-1} + \sigma_{\zeta_i}\zeta_{it}. \tag{B5}$$

In order to assess the degree of co-movement between the analyzed time series within two years, both q and p were set at 8 (quarters). Because factor loadings and innovation variance cannot be identified separately, we apply a standard normalization assumption and set innovation variance equal to one. The scale of h_{it} is identified by restricting $h_{i0} = 0$.

The prior on standard deviations of innovations in the equations for factor loadings (σ_{η_i}) and stochastic volatilities (σ_{ζ_i}) reflects the assumption that loadings and volatilities evolve over time. Therefore, the prior distribution for σ_{η_i} is given by inverse gamma $IG(\omega_{\eta_i}, s_{\eta_i}^2)$:

$$p(\sigma_{\eta_i}|\omega_{\eta_i}, s_{\eta_i}^2) = \frac{2}{\Gamma(\omega_{\eta_i}/2)}\left(\frac{\omega_{\eta_i}}{2}s_{\eta_i}^2\right)^{\frac{\omega_{\eta_i}}{2}}(\sigma_{\eta_i}^2)^{-\frac{\omega_{\eta_i}}{2}-\frac{1}{2}}\exp\left\{-\frac{\omega_{\eta_i}}{2}\frac{s_{\eta_i}^2}{\sigma_{\eta_i}^2}\right\}, \tag{B6}$$

where $\sigma^2_{\eta_i} = \frac{1}{\omega_{\eta_i}} \Sigma_{t=1}^{\omega_{\eta_i}} (\beta^k_{it} - \beta^k_{it-1})^2$. In a similar fashion, the prior on (σ_{ζ_i}) is given by inverse gamma $IG(\omega_{\zeta_i}, s^2_{\zeta_i})$. In the results presented here, $\omega_{\eta_i} = 0.1T$, $s^2_{\eta_i} = 0.01$, $\omega_{\zeta_i} = T$ and $s^2_{\zeta_i} = 0.0625$ were chosen following the advice of Del Negro and Otrok (2008).

The prior for σ_i is inverse gamma $IG(\omega_i, s^2_i)$ with $\omega_i = 0.5T$ and $s^2_i = 1$. The prior on the α_i term is normal $N(\overline{\alpha_i}, A_i^{-1})$ where $\overline{\alpha_i} = 2$ and $A_i^{-1} = 1$. Similarly, the prior distribution of the initial conditions on factor loading βio is normal $N(\overline{\beta_i}, B_i^{-1})$ with $\overline{\beta_i} = 0$ and $B_i^{-1} = 0.1$. The coefficients on factors $(\Psi_{kq} \quad q = 1, 2, ..., 8)$ as well as the idiosyncratic component $(\phi_{ip} \quad p = 1, 2, ..., 8)$ also have normal priors given by $N(\overline{\Psi_i}, V_{1i}^{-1}) I_{\Psi_i}$, where $\overline{\Psi_i} = \{0, 0, ..., 0\}'$ and $N(\overline{\phi_i}, V_{2i}^{-1}) I_{\phi_i}$, where $\overline{\phi_i} = \{0, 0, ..., 0\}'$, respectively, while I_{Ψ_i} and I_{ϕ_i} denote an indicator function that places zero mass on the region of the parameter space characterized by non-stationarity. The idea of centring the priors on autoregressive coefficients on zero is adapted from Kose et al. (2003) and described in detail in subsection 2.2. The precision matrix V_{1i}^{-1} has $1/0.75^q$ as its diagonal elements, while V_{2i}^{-1} has $2/0.75^p$ as its diagonal elements, with $p = q = 8$.

The model set out in equations (B1) to (B5) is estimated using the approach proposed by Del Negro and Otrok (2008), which builds on the work of Otrok and Whiteman (1998), and Kose et al. (2003, 2008), which uses the work on data augmentation by Tanner and Wong (1987). It applies a Gibbs sampling method (Chib and Greenberg, 1996), to approximate the marginal and joint distributions by sampling from the conditional ones. The description of the estimation process is beyond the scope of this appendix but the interested reader is referred to Del Negro and Otrok (2008) for a detailed exposition.

The main questions addressed using this approach with time-varying factor loadings concern the relative importance of world and country factors in international trade. The variance decompositions are presented from a regional perspective. We calculate weighted averages of the shares of the variance explained by a given factor. We use individual countries export and import shares in regional exports and imports as weights. Very similar results are obtained when we use GDP shares.

Appendix C: Additional figures and tables

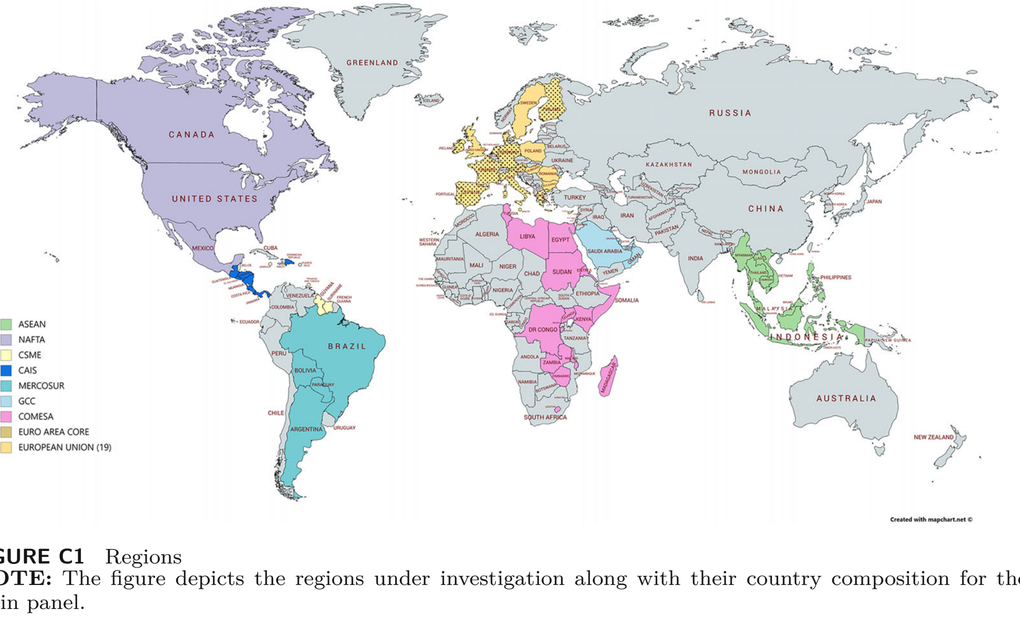

FIGURE C1 Regions
NOTE: The figure depicts the regions under investigation along with their country composition for the main panel.

TABLE C1
Regions – Main panel, version 1

Region	Countries
NAFTA (3)	The USA, Canada, Mexico
ASEAN (10)	Thailand, Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Vietnam
CSME (10)	Barbados, Belize, Dominica, Grenada, Guyana, St. Kitts and Nevis, St. Lucia, St. Vincent and Grenadines, Suriname, Trinidad and Tobago
GCC (6)	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates
SICA (7)	Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Nicaragua, Panama
Mercosur (4)	Brazil, Argentina, Paraguay, Uruguay
COMESA (17)	Burundi, Comoros, Democratic Republic of Congo, Egypt, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Libya, Rwanda, Seychelles, Sudan, Tunisia, Uganda, Zambia, Zimbabwe
EU (19)	Germany, Austria, Bulgaria, Cyprus, Denmark, Finland, France, Greece, Hungary, Ireland, Italy, Malta, Netherlands, Poland, Portugal, Romania, Spain, Sweden, the UK
Rest of the World, version 1 (76)	Afghanistan, Albania, Algeria, Angola, Australia, Bahamas, Bangladesh, Benin, Bermuda, Bolivia, Burkina Faso, Cabo Verde, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Cuba, Djibouti, Ecuador, Equatorial Guinea, Faroe Islands, Fiji, Gabon, Gambia, Ghana, Greenland, Guinea, Guinea-Bissau, Haiti, Hong Kong, Iceland, India, Iran, Iraq, Israel, Ivory Coast, Japan, Jordan, Lebanon, Liberia, Macao, Maldives, Mali, Mauritania, Mongolia, Morocco, Mozambique, Nepal, Netherlands Antilles, New Caledonia, New Zealand, Niger, Nigeria, Norway, Pakistan, Papua New Guinea, Peru, Republic of Congo, Samoa, Sao Tome Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Korea, Sri Lanka, Switzerland, Syria, Tanzania, Togo, Tonga, Turkey, Vanuatu, Venezuela

NOTE: The table lists the countries designated to each region.

TABLE C2
Regions – Main panel, version 2

Region	Countries
NAFTA (3)	The USA, Canada, Mexico
ASEAN (10)	Thailand, Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Vietnam
CSME (10)	Barbados, Belize, Dominica, Grenada, Guyana, St. Kitts and Nevis, St. Lucia, St. Vincent and Grenadines, Suriname, Trinidad and Tobago
GCC (6)	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates
SICA (7)	Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Nicaragua, Panama
Mercosur (4)	Brazil, Argentina, Paraguay, Uruguay
COMESA (17)	Burundi, Comoros, Democratic Republic of Congo, Egypt, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Libya, Rwanda, Seychelles, Sudan, Tunisia, Uganda, Zambia, Zimbabwe
Euro area (10)	Germany, Austria, Finland, France, Greece, Ireland, Italy, Netherlands, Portugal, Spain
Rest of the World, version 2 (85)	Afghanistan, Albania, Algeria, Angola, Australia, Bahamas, Bangladesh, Benin, Bermuda, Bolivia, Bulgaria, Burkina Faso, Cabo Verde, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Cuba, Cyprus, Denmark, Djibouti, Ecuador, Equatorial Guinea, Faroe Islands, Fiji, Gabon, Gambia, Ghana, Greenland, Guinea, Guinea-Bissau, Haiti, Hungary, Hong Kong, Iceland, India, Iran, Iraq, Israel, Ivory Coast, Japan, Jordan, Lebanon, Liberia, Macao, Maldives, Mali, Malta, Mauritania, Mongolia, Morocco, Mozambique, Nepal, Netherlands Antilles, New Caledonia, New Zealand, Niger, Nigeria, Norway, Pakistan, Papua New Guinea, Peru, Poland, Republic of Congo, Romania, Samoa, Sao Tome Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Korea, Sri Lanka, Sweden, Switzerland, Syria, Tanzania, Togo, Tonga, Turkey, the UK, Vanuatu, Venezuela

NOTE: The table lists the countries designated to each region.

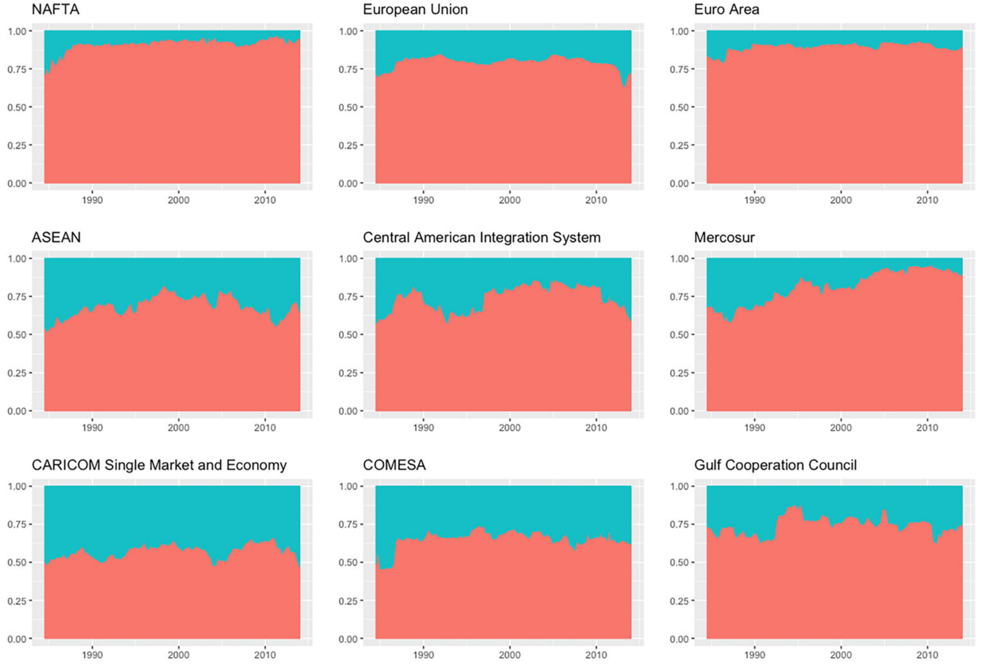

FIGURE C2 Estimates of the share of variance attributable to international and national components, main panel (1981–2018)

NOTES: Red/pink (bottom): International factors (global and regional). Blue/turquoise (top): National factors (country and idiosyncratic).

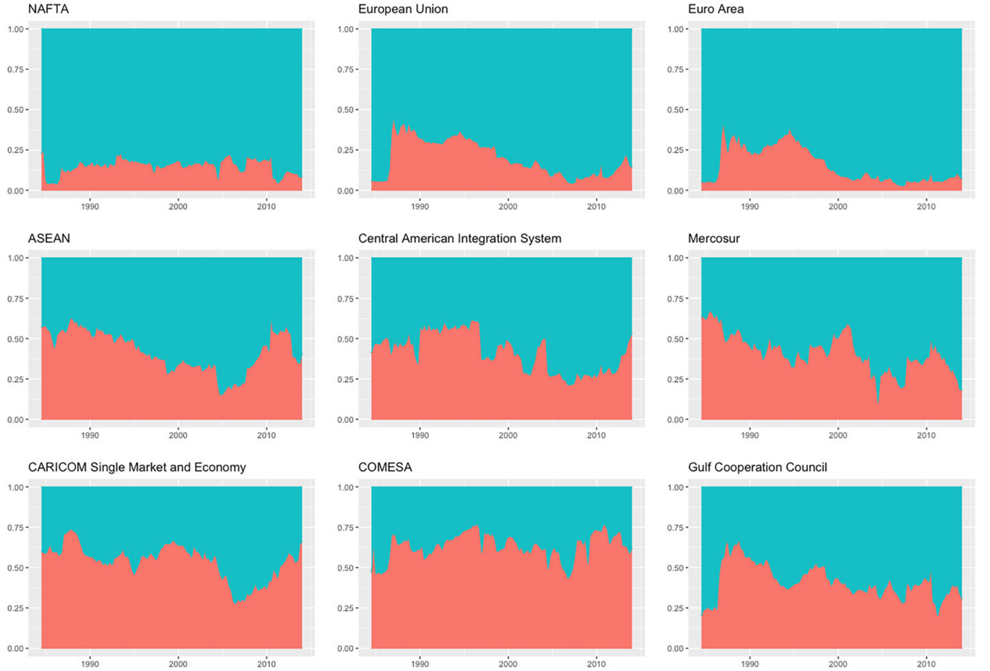

FIGURE C3 Estimates of the share of variance attributable to global and regional components, main panel (1981–2018)

NOTES: Red/pink (bottom): Global factors. Blue/turquoise (top): Regional factors.

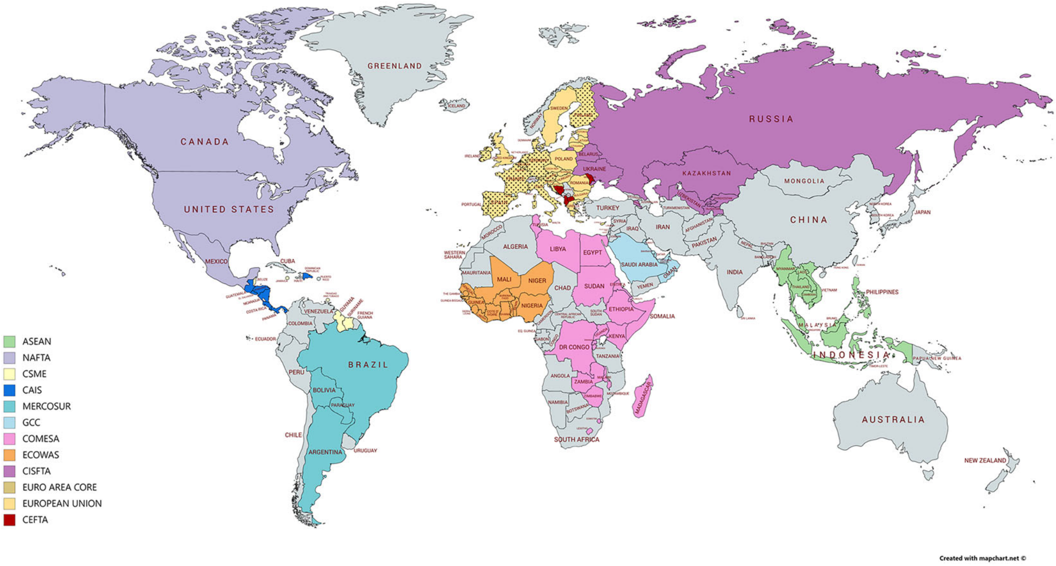

FIGURE C4 Regions – Alternative panel
NOTE: The figure depicts the regions under investigation along with their country composition for the alternative panel.

TABLE C3
Regions – Alternative panel, version 3

Region	Countries
NAFTA (3)	The USA, Canada, Mexico
ASEAN (10)	Thailand, Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Vietnam
CSME (12)	Antigua and Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and Grenadines, Suriname, Trinidad and Tobago
GCC (6)	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates
SICA (7)	Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Nicaragua, Panama
Mercosur (4)	Brazil, Argentina, Paraguay, Uruguay
COMESA (21)	Burundi, Comoros, Democratic Republic of Congo, Djibouti, Egypt, Eritrea, Eswatini, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Somalia, Sudan, Tunisia, Uganda, Zambia, Zimbabwe
CEFTA (4)	Albania, Bosnia and Herzegovina, Moldova, North Macedonia
CISFTA (8)	Russia, Armenia, Belarus, Kazakhstan, Kyrgyz Republic, Tajikistan, Ukraine, Uzbekistan
ECOWAS (15)	Benin, Burkina Faso, Cabo Verde, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo
EU (28)	Germany, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, the UK

TABLE C3
(Continued)

Region	Countries
Rest of the World, version 3 (85)	Afghanistan, Algeria, American Samoa, Angola, Anguilla, Aruba, Australia, Azerbaijan, Bahamas, Bangladesh, Bermuda, Bhutan, Bolivia, Botswana, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Cuba, Ecuador, Equatorial Guinea, Falkland Islands, Faroe Islands, Fiji, French Polynesia, Gabon, Georgia, Gibraltar, Greenland, Guam, Haiti, Hong Kong, Iceland, India, Iran, Iraq, Israel, Japan, Jordan, Kiribati, Lebanon, Lesotho, Macao, Maldives, Marshall Islands, Mauritania, Micronesia, Mongolia, Montserrat, Morocco, Mozambique, Namibia, Nauru, Nepal, Netherlands Antilles, New Caledonia, New Zealand, North Korea, Norway, Pakistan, Palau, Papua New Guinea, Pera, Republic of Congo, Sao Tome and Principe, Samoa, San Marino, Solomon Islands, South Africa, South Korea, Sri Lanka, Switzerland, Syria, Tanzania, Tonga, Turkey, Turkmenistan, Tuvalu, Vanuatu, Vatican, Venezuela, West Bank and Gaza, Yemen

NOTE: The table lists the countries designated to each region.

TABLE C4
Regions – Alternative panel, version 4

Region	Countries
NAFTA (3)	The USA, Canada, Mexico
ASEAN (10)	Thailand, Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Vietnam
CSME (12)	Antigua and Barbuda, Barbados, Belize, Dominica, Grenada, Guyana, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and Grenadines, Suriname, Trinidad and Tobago
GCC (6)	Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates
SICA (7)	Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Nicaragua, Panama
Mercosur (4)	Brazil, Argentina, Paraguay, Uruguay
COMESA (21)	Burundi, Comoros, Democratic Republic of Congo, Djibouti, Egypt, Eritrea, Eswatini, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Somalia, Sudan, Tunisia, Uganda, Zambia, Zimbabwe
CEFTA (4)	Albania, Bosnia and Herzegovina, Moldova, North Macedonia
CISFTA (8)	Russia, Armenia, Belarus, Kazakhstan, Kyrgyz Republic, Tajikistan, Ukraine, Uzbekistan
ECOWAS (15)	Benin, Burkina Faso, Cabo Verde, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo
Euro area (11)	Germany, Austria, Belgium, Finland, France, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain
Rest of the World, version 4 (102)	Afghanistan, Algeria, American Samoa, Angola, Anguilla, Aruba, Australia, Azerbaijan, Bahamas, Bangladesh, Bermuda, Bhutan, Bolivia, Botswana, Bulgaria, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Croatia, Cuba, Cyprus, Czechia, Denmark, Ecuador, Equatorial Guinea, Estonia, Falkland Islands, Faroe Islands, Fiji, French Polynesia, Gabon, Georgia, Gibraltar, Greece, Greenland, Guam, Haiti, Hong Kong, Hungary, Iceland, India, Iran, Iraq, Israel, Japan, Jordan, Kiribati, Latvia, Lebanon, Lesotho, Lithuania, Macao, Maldives, Malta, Marshall Islands, Mauritania, Micronesia, Mongolia, Montserrat, Morocco, Mozambique, Nambia, Nauru, Nepal, Netherlands Antilles, New Caledonia, New Zealand, North Korea, Norway, Pakistan, Palau, Papua New Guinea, Pera, Poland, Republic of Congo, Romania, Sao Tome and Principe, Samoa, San Marino, Slovakia, Slovenia, Solomon Islands, South Africa, South Korea, Sri Lanka, Sweden, Switzerland, Syria, Tanzania, Tonga, Turkey, Turkmenistan, Tuvalu, the UK, Vanuatu, Vatican, Venezuela, West Bank and Gaza, Yemen

NOTE: The table lists the countries designated to each region.

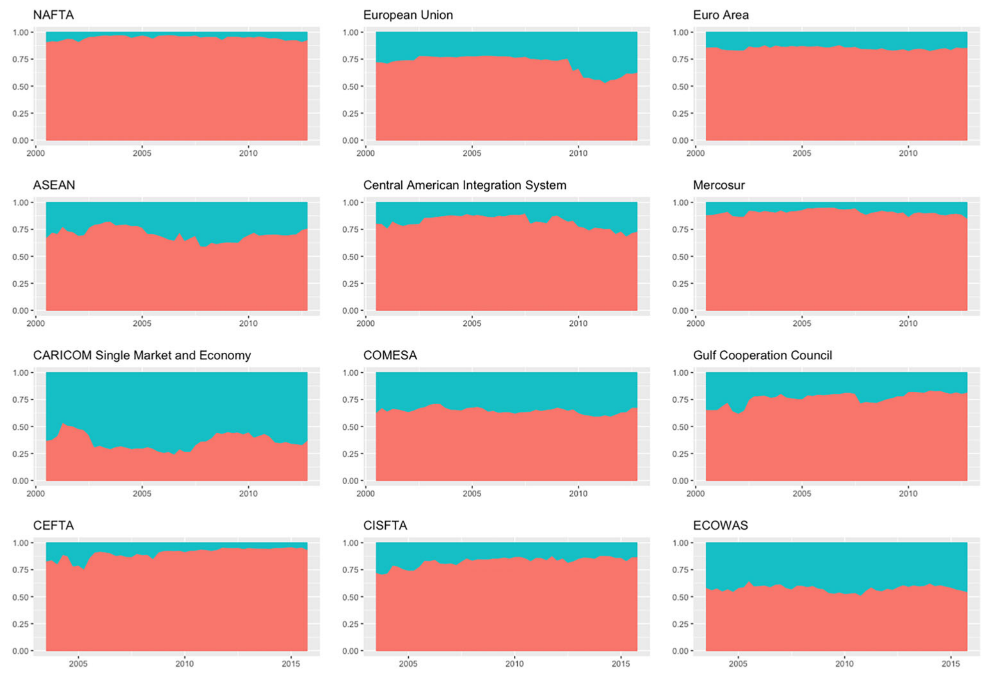

FIGURE C5 Estimates of the share of variance attributable to international and national components, alternative panel (2000–2019)

NOTE: Red/pink (bottom): International factors (global and regional). Blue/turquoise (top): National factors (country and idiosyncratic).

FIGURE C6 Estimates of the share of variance attributable to global and regional components, alternative panel (2000–2019)

NOTES: Red/pink (bottom): Global factors. Blue/turquoise (top): Regional factors.

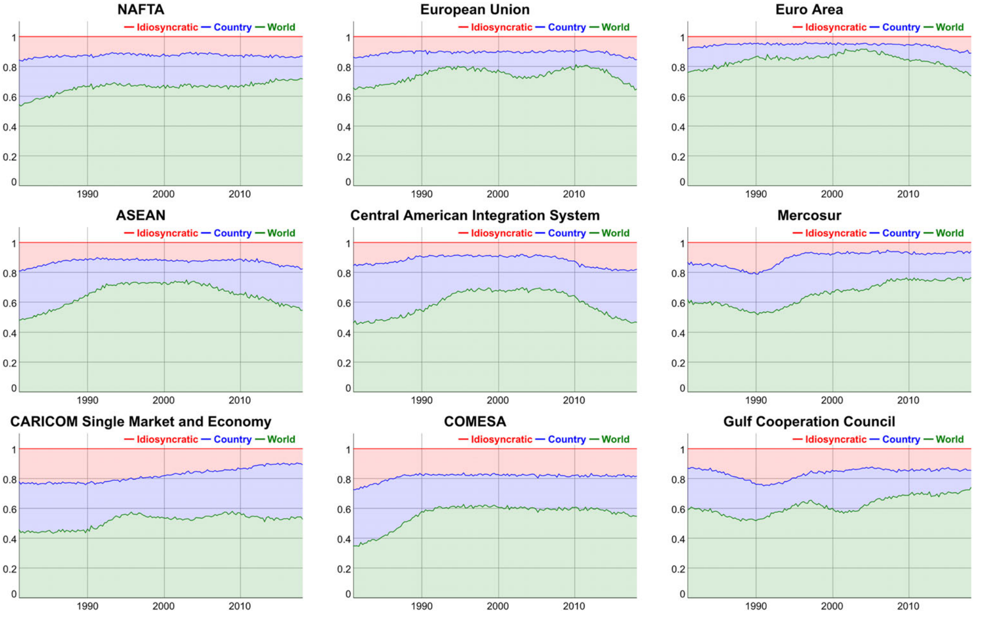

FIGURE C7 Variance decomposition obtained using the approach with time-varying parameters, main panel (1981–2018)

NOTE: The figure depicts the relative shares of the factors driving exports and imports in the main panel for a DFM with two factors, time-varying factor loadings and stochastic volatility. Idiosyncratic - top, county - middle and world - bottom.

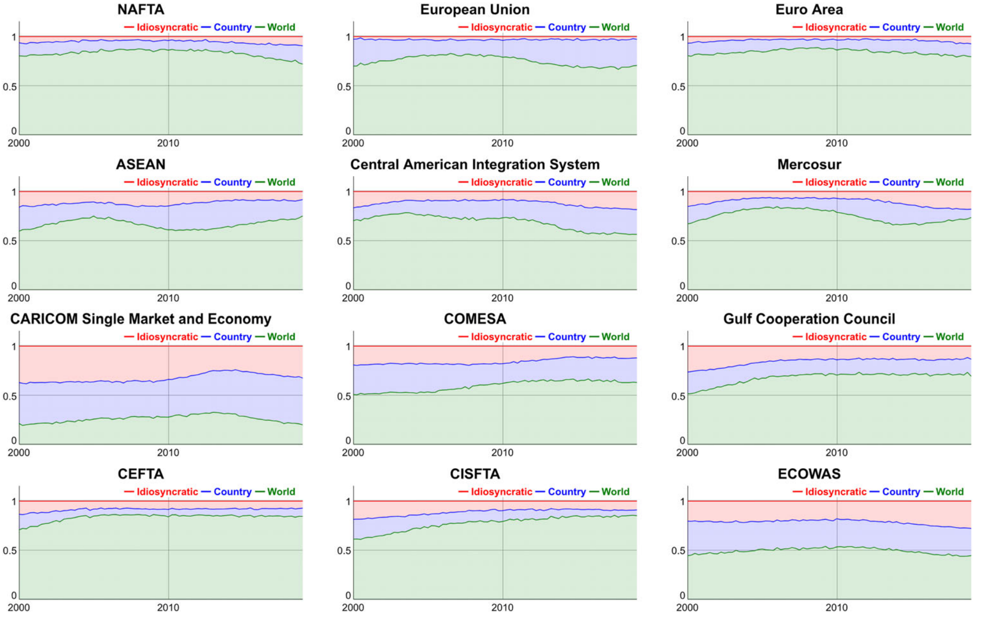

FIGURE C8 Variance decomposition obtained using the approach with time-varying parameters, alternative panel (2000–2019)

NOTE: The figure depicts the relative shares of the factors driving exports and imports in the main panel for a DFM with two factors, time-varying factor loadings and stochastic volatility. Idiosyncratic - top, county - middle and world - bottom.

Supporting information

The data and code that support the findings of this study are available in the Canadian Journal of Economics Dataverse at https://doi.org/10.5683/SP3/JITXLH.

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