ARTICLE IN PRESS

Journal of Economic Dynamics & Control ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Journal of Economic Dynamics & Control

journal homepage: www.elsevier.com/locate/jedc

World, country, and sector factors in international business cycles

Aikaterini Karadimitropoulou [a], Miguel León-Ledesma [b,*]

[a] School of Economics, University of East Anglia, United Kingdom
[b] School of Economics, University of Kent, United Kingdom

ARTICLE INFO

Article history:
Received 10 August 2012
Received in revised form
8 May 2013
Accepted 14 August 2013

JEL classification:
E32
F44

Keywords:
Dynamic factors
Disaggregated business cycles
International co-movement

ABSTRACT

Do sector-specific factors common to all countries play an important role in explaining business cycle co-movement? We address this question by analyzing international co-movements of value added (VA) growth in a multi-sector dynamic factor model. The model contains a world factor, country-specific factors, sector-specific factors, and idiosyncratic components. We estimate the model using Bayesian methods for 30 disaggregated sectors in the G7 economies for the 1974–2004 period. Our findings show that, although there is a substantial role for sector-specific factors, fluctuations are dominated by country-factors. The world factor appears to play a minimal role because, when using aggregate data, the world factor captures both the factor common to all countries and industries and the factor common to the same industry across countries. We then examine how these factors evolved as globalization deepened over the past two decades. Our results suggest that business cycles at a disaggregate level have not become more synchronized internationally. This is mainly driven by a substantial fall in the volatility of world shocks during the globalization period, rather than a lower sensitivity of sectoral growth to world factors. Our results also reveal that world factors appear to be more important for industries with a higher level of international vertical integration.

1. Introduction

We examine the dynamics of business cycle co-movements over time across sectors and countries to provide an empirical characterization of common business cycle linkages at a disaggregate level among the G7 countries. Our analysis addresses several important questions. First, what are the main factors driving international business cycles at the sector level in different countries and what structural variables explain these factors? Second, how have these factors evolved as globalization deepened over the past two decades? Third, are changes in the importance of these factors from the pre-globalization to the globalization periods the result of structural change, changes in the volatility of these factors and their persistence, or changes in the sensitivity to common shocks? We address these questions by estimating common components for Value Added (VA) growth for 30 sectors of the G7 countries for the period covering 1974–2004. We employ a Bayesian dynamic latent factor model that contains: (i) a world factor, which is common to all industries[1]

* Corresponding author. School of Economics, Keynes College, University of Kent, Canterbury, CT2 7NP, UK. Tel.: +44 1227 823026.
E-mail addresses: A.Karadimitropoulou@uea.ac.uk (A. Karadimitropoulou), m.a.leon-ledesma@kent.ac.uk (M. León-Ledesma).

[1] We use the term "industries" to refer to disaggregated sectors, as our data include sub-sectors from agriculture and mining, manufacturing, services and construction.

0165-1889/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jedc.2013.09.002

in all countries; (ii) an industry (-specific) factor, common to the same industry across all countries; (iii) a country factor, common to all industries within the same country and, finally, (iv) an idiosyncratic component specific to each industry time series.

This allows us to extend the empirical research on business cycle co-movements in several directions. Firstly, there are relatively few papers examining the importance of industry-specific factors for international business cycles. The Bayesian approach to multiple dynamic factor models allows us to work with a large number of cross-sectional units and factors. Following Kose et al. (2012), this model enables us to capture not only the contemporaneous spillovers of shocks but also the dynamic propagation of business cycles in a flexible manner, without a priori restrictions on the direction of these spillovers or the structure of the propagation mechanism. Secondly, we make use of a detailed level of disaggregation that also includes all major sectors in the economies considered.[2] The level of disaggregation is important as more aggregated data may hide the role of industry-specific shocks, especially if industries have similar production structures as argued by Imbs (2004). Therefore, the inclusion of industry-specific factors may have important consequences for the role of other more commonly studied factors, such as the world factor. Third, our data span covers the period of globalization characterized by increased trade and financial integration. This enables us to estimate the model for two sub-samples characterizing the pre-globalization and the globalization periods and, therefore, to analyze the sources of changes in business cycle co-movement at a disaggregate level.

Our results provide a rich body of evidence about the role and evolution of common business cycles at the sectoral level. They indicate that the country factor explains the largest proportion of the variance of VA growth for most of the G7 countries,[3] while the industry-specific factor is the second most important source for the majority of the countries considered. The world factor seems to play a minimal role in accounting for variations in industrial VA growth. The introduction of sector-specific factors appears to reduce the relevance of the world factor when compared to previous studies. We cannot, however, conclude against the existence of a "world business cycle", as argued in aggregate data studies by Kose et al. (2003, 2008, 2012). When using aggregate data, the world factor appears to be capturing not only the dynamic factor common to all countries but also the dynamic factor common to the same industry across countries. If the proportion of the variance explained by world and industry factors is added up, our results would support the prominence of "international" over "country-specific" factors. We then relate these results to different sector-level trade measures from input–output tables. We find that the world factor is more important for industries that are more vertically integrated, whereas industry factors appear more relevant for industries whose final demand has a larger export component.

During the pre-globalization period (1974–1988) there is support for an international business cycle at a disaggregate level for most countries. However, during the globalization period, country factors dominate. Thus, we do not find support for the hypothesis that disaggregate business cycles have become more synchronized at the international level. We also find that a small majority of industries display business cycle divergence. This indicates that international factors have become less important than the country factor in driving cyclical fluctuations in the G7 countries. When we decompose the sources of the change in the variance of VA between these two periods, our results show little effect coming from changes in the structural composition of sectors. The main reason for the apparent lower co-movement is a reduction in the volatility of world factor shocks. This is partially compensated by an increase in the persistence of these factors. The co-movement between sectoral growth and the world factor, reflected in the world factor loadings, increased on average, although its effect is quantitatively small.

There is a large body of theoretical and empirical literature related to our study. For example, Frankel and Rose (1998) unveiled the empirical regularity that higher bilateral trade between country pairs is associated with more correlated business cycles, placing trade at the heart of international business cycles transmission. On the other hand, economic theory suggests that if trade increases specialization and if industry-specific shocks are dominant, the degree of output co-movement should fall with increased trade integration. A number of empirical studies have examined the impact of trade and financial linkages on international business cycles. For instance, Baxter and Kouparitsas (2005) argue that the most important channel explaining business cycle co-movements is international trade. Imbs (2004), however, is a proponent of the "common shock" view and argues that countries commove because their shocks are correlated. In particular, given that individual industries are subject to common shocks, two countries with similar production structures will be subject to greater business cycle co-movements.[4]

Other studies employ dynamic factor models to quantify the importance of common factors to explain business cycle synchronization. Gregory et al. (1997) decomposed aggregate output, consumption, and investment for the G7 countries into a world and a country-specific factor. They show that both factors are statistically significant and quantitatively important for the common fluctuations across macroeconomic aggregates. Kose et al. (2003) examined the common dynamic properties of output, consumption, and investment across countries, regions, and the world for the 1960–1992 period for a 60-country panel using a Bayesian approach to model dynamic factors.[5] Their results show that while the world factor accounts for a large fraction of fluctuations in most countries, the regional factor does not play an important role in

[2] Norrbin and Schlagenhauf (1996), for instance, consider 7 sub-sectors belonging to mining and industry only.

[3] Excluding the idiosyncratic factor which, as expected, dominates for most of the industries considered.

[4] Other important studies examining the impact of trade and financial linkages on the nature of business cycles are Backus et al. (1995), Clark and van Wincoop (2001), Calderon et al. (2007), Burstein et al. (2008) and di Giovanni and Levchenko (2010).

[5] For other works using a Bayesian approach to dynamic factors to quantify international business cycles co-movements see Crucini et al. (2011), Kose et al. (2008), Kose et al. (2012), and Hirata et al. (2013).

Please cite this article as: Karadimitropoulou, A., León-Ledesma, M., World, country, and sector factors in international business cycles. Journal of Economic Dynamics and Control (2013), http://dx.doi.org/10.1016/j.jedc.2013.09.002

explaining aggregate fluctuations. In a study closely related to ours, Foerster et al. (2011) analyze co-movements in industrial production for 117 US sectors using a factor model with a common factor and idiosyncratic factors. They find that most of the variability in industrial production is accounted for by the common factor. They also find that, because of a fall in the volatility of the country factor, the Great Moderation period witnessed an increase in the importance of idiosyncratic factors. Although our model contains three factors in a multi-country setting and is not directly comparable, we observe a similar pattern with a fall in the world factor volatility during the Great Moderation period.

The theoretical literature on international business cycles has emphasized the role of common country-level shocks and trade linkages in explaining business cycles co-movement. However, since Long and Plosser (1983), disaggregate business cycle models have highlighted the potential role of sectors and firms in the transmission of shocks.[6] This line of thought has been recently revisited by Gabaix (2011) and Acemoglu et al. (2012). In Gabaix (2011), a mechanism linking sectors or firms to aggregate fluctuations arises because the size distribution is fat-tailed (the 'granularity' hypothesis) and hence idiosyncratic shocks do not average out. Acemoglu et al. (2012) emphasize input-output 'linkages' as in Foerster et al. (2011). There, idiosyncratic shocks to one sector can have aggregate effects if it has strong input-output links with other sectors. Di Giovanni and Levchenko (2010), for instance, test the hypothesis that input–output trade links are important to explain international co-movement at the disaggregate level and find that vertical linkages (i.e. sectors that use each other as intermediates) increase aggregate co-movement. This motivates our quantitative question about whether sector-specific factors play an important role in shaping international business cycles. Relatively few papers have considered this question at the international level. Exceptions are Costello (1993), and Norrbin and Schlagenhauf (1996).[7] Norrbin and Schlagenhauf (1996) is perhaps the closest to our approach. They develop a model at an industry level by allowing a propagation of output changes between industries and across countries. They use data for nine industrialized countries disaggregated into seven sectors belonging to industry and mining. Using a dynamic factor state-space approach, they decompose industrial output fluctuations into a nation-specific, an industry-specific, a common, and an idiosyncratic component. Their analysis shows that the industry-specific shock explains only a small part of the variance of the forecast error, which is mostly explained by nation-specific shocks.

The rest of the paper is organized as follows. Next section presents the econometric methodology. Section 3 provides a description of the data. Section 4 presents and discusses the empirical results. Section 5 presents the results for the sample split and, finally, Section 6 concludes.

2. Empirical methodology

The specification and estimation method used draws from Kose et al. (2003), which we adapt to our factor structure. This approach extends the single dynamic factor model of Otrok and Whiteman (1998) to a multi-factor setting.[8]

As mentioned in the introduction, our model contains (i) a world factor, which is a factor common to all countries and industries in the system; (ii) an industry factor, which is common to the same industry across countries; (iii) a country factor, common to all industries within the same country, and (iv) an idiosyncratic component. We observe one variable (VA growth) for 30 industries for the G7 countries plus the aggregate industrial VA growth for each of the economies from 1974 to 2004. As discussed below, the aggregate is only used for identification purposes. An autoregressive process for each of the factors and idiosyncratic components is used to capture the dynamic relationships in the model. For simplicity and parsimony the factors and the idiosyncratic term are restricted to follow an AR(3) process, following Kose et al. (2003). Given that our data are annually distributed, this lag length should capture most spillovers (lagged or contemporaneous) across industries and countries.

Consider a panel of industrial VA growth rate series, $Y_{i,j,t}$, where the subscript i indexes the industry, with $i=1,\ldots,I$, j indexes the country, with $j=1,\ldots,J$, and $t=1,\ldots,T$ indexes time, so that $Y_{i,j,t}$ is the growth rate of VA for industry i in country j at time t. We assume that $Y_{i,j,t}$ can be described by the following dynamic factor model:

$$Y_{i,j,t}=\beta^{w}_{i,j}F^{w}_{t}+\beta^{s}_{i,j}F^{s}_{i,t}+\beta^{c}_{i,j}F^{c}_{j,t}+\varepsilon_{i,j,t}, \tag{1}$$

where F^w represents the world factor, F^s denotes the industry-specific factor, and F^c corresponds to the country-specific factor. Coefficients β^w, β^s, and β^c are the factor loadings on the world, industry-, and country-specific factors, respectively. Finally, $\varepsilon_{i,j,t}$ is the error term and is assumed to be uncorrelated cross-sectionally at all leads and lags, but can be serially correlated. The error term, $\varepsilon_{i,j,t}$, follows an autoregressive process of order p (3 in our case):

$$\varepsilon_{i,j,t}=\textstyle\sum_{l=1}^{p}\varphi_{i,j,l}\varepsilon_{i,j,t-l}+e_{i,j,t} \tag{2}$$

where $e_{i,j,t}$ are distributed as $N(0,\sigma^2_{i,j})$. The three unobserved factors F^w, F^s, and F^c are also assumed to follow an AR(3) process:

$$F^{w}_{t}=\textstyle\sum_{l=1}^{p}\varphi^{w}_{l}F^{w}_{t-l}+\nu^{w}_{t} \tag{3}$$

[6] As shown by Foerster et al. (2011), these models can have an approximate dynamic factor representation like the one used in this paper.

[7] Long and Plosser (1987), Norrbin and Schlagenhauf (1988, 1990), Stockman (1988) and Pesaran et al. (1993) also apply factor methods to disaggregate data but in a closed economy setting.

[8] We refer the reader to Kose et al. (2003) and Otrok and Whiteman (1998) for more details.

Please cite this article as: Karadimitropoulou, A., León-Ledesma, M., World, country, and sector factors in international business cycles. Journal of Economic Dynamics and Control (2013), http://dx.doi.org/10.1016/j.jedc.2013.09.002

$$F^s_{i,t} = \sum_{l=1}^{p} \varphi^s_{i,l} F^s_{i,t-l} + \nu^s_{i,t} \tag{4}$$

$$F^c_{j,t} = \sum_{l=1}^{p} \varphi^c_{j,l} F^c_{j,t-l} + \nu^c_{j,t} \tag{5}$$

where ν^w_t, $\nu^s_{i,t}$, $\nu^c_{j,t} \sim N(0, \sigma^2_w)$, $N(0, \sigma^2_{i,s})$, and $N(0, \sigma^2_{j,c})$ respectively. Finally, the innovations, $e_{i,j,t}$ and ν^w_t, $\nu^s_{i,t}$, $\nu^c_{j,t}$, are mutually orthogonal across all equations in the system.

The model set out by Eqs. (1)–(5) suffers from rotational indeterminacy and there are two related identification problems. The signs and the scales of the factors and their loadings are not separately identified. To overcome the identification issue of the signs, we require one of the factor loadings to be positive for each of the factors. In particular, the factor loading for the world factor is required to be positive for the aggregate industrial VA growth rate series of the first country in the dataset; the industry factors are restricted to load positively for all industries of the first country in the dataset; and, finally, the factor loadings for the country factors have to be positive for the aggregate variable of each country. Scales can be identified by assuming that each σ^2_w, $\sigma^2_{i,s}$ and $\sigma^2_{j,c}$ are constant.[9]

We make use of the Bayesian approach with Gibbs sampling to estimate the model described by Eqs. (1)–(5). Gibbs sampling is a Markov Chain Monte Carlo (MCMC) method for approximating joint and marginal distributions by sampling from conditional distributions.[10] Using a MCMC procedure, we can generate random samples for the unknown parameters and the unobserved factors from the joint posterior distribution. This is feasible in this study as the full set of conditional distributions is known. That is, parameters given data and factors, and factors given data and parameters. More precisely, in our case, the algorithm can be summarized by the following steps:

1. Conditional on a draw for F^w, F^s, and F^c, we simulate the AR coefficients and the variance of the shocks to Eqs. (2)–(5).
2. Conditional on a draw of F^w, F^s, and F^c, we draw the factor loadings β^w, β^s, and β^c.
3. Simulate F^w, F^s, and F^c conditional on all other parameters above.

The sample produced is the realization of one step of the Markov-Chain. This process is then repeated generating at each step drawings for the regression parameters and the factors.

Our methodology does not allow us to identify the structural shocks driving these factors. Nevertheless, based on economic theory, a number of possible interpretations of these factors can be suggested. More precisely, the world factor could be capturing global demand and supply shocks (including policy shocks) or sector specific shocks that are transmitted through international inter-sectoral linkages becoming global as in Acemoglu et al. (2012). The country factors could be capturing country-specific macro-shocks affecting all sectors or sectoral shocks that are transmitted through national input–output linkages as in Foerster et al. (2011). The sectoral factors could be capturing industry-specific demand and cost shocks or sectoral shocks that are transmitted through international intra-sectoral linkages.

There are alternative approaches to estimating dynamic factor models such as the EM algorithm combined with hill climbing techniques. However, in our case, these methods are not feasible given the dimension of our dataset (7 countries ($J=7$), 30 industries ($I=30$)), 210 VA growth rate series ($IJ=210$), and 38 factors ($K=38$). An effective estimation procedure to extract factors is the approximate factor model of Stock and Watson (1989) and Forni and Reichlin (1998). However, as argued by Kose et al. (2012), those models cannot be used when we aim to categorize some factors as belonging to a specific country by imposing zero restrictions on some factor loadings. In other words, given that in our study a country factor is identified by restricting the industrial output growth rate series of all industries in all countries, except the one we are interested on, to have zero factor loadings on the country under examination, this type of approach is not suitable. The Bayesian approach exploiting Gibbs sampling techniques overcomes both issues.

To describe our results, we employ variance decompositions measuring the relative contributions of the different factors to the variance of VA fluctuations for each individual industry. Using previous notations, the variance of $Y_{i,j,t}$, with orthogonal factors is given by:

$$var(Y_{i,j,t}) = (\beta^w_{i,j})^2 var(F^w_t) + (\beta^s_{i,j})^2 var(F^s_{i,t}) + (\beta^c_{i,j})^2 var(F^c_{j,t}) + var(\varepsilon_{i,j,t}). \tag{6}$$

Then, we can decompose the variance of each industrial VA growth rate series, $Y_{i,j,t}$, into the fraction due to each of the three factors. In particular, the fraction of fluctuations due to factor $f = w, s, c$ is computed as:

$$\frac{(\beta^f_{i,j})^2 var(F^f)}{var(Y_{i,j,t})}. \tag{7}$$

We obtain measures of Eqs. (6) and (7) at each step of the Markov-Chain.

Given the number of industries in our sample, we condense the results for expositional ease in two different ways: first, we aggregate $var(Y_{i,j,t})$ into an aggregate forecast error over industries and, second, over countries.[11] We thus obtain the relative importance of the factors from both a country and an industry perspective. In particular, we build a $(J \times I)$ matrix of

[9] We also estimated the model without the aggregate series, using either the first or the last industrial series of each country for the identification of the signs. The results, available upon request, remained quantitatively unchanged.

[10] For more technical details on Gibbs sampling, see Chib and Greenberg (1996) and Geweke (1996).

[11] The aggregate VA series is ignored for aggregation purposes, so that industry weights sum up to one.

VA weights W_J. The variance matrix is then reduced to J country variance decompositions by multiplying (6) times W_J'. To aggregate by industry, we construct a $(I \times J)$ country-weights matrix using real VA data in US dollars. The variance matrix is reduced to I industry variance decompositions by multiplying (6) times W_I'.

3. Data

Our data come from the 2009 release of the EU Klems Growth and Productivity Accounts[12] which covers 32 industries up to 2007 for a variety of OECD countries. The EU Klems database has two main advantages. First, it covers not only manufacturing, but also services, construction, and agriculture. Second, it has been carefully harmonized improving on data quality.[13]

We select our data based on availability. We make use of 30 industries for each of the G7 countries up to 2004. Data were missing for the remaining two industries, namely Extra-territorial organizations and Bodies, and Private households with employed persons.[14] Not all countries' datasets spanned the period up to 2007, so our sample stops at 2004. Our data cover all of the economy, including Agriculture, Hunting, Forestry and Fishing; Mining and Quarrying; Total Manufacturing; Electricity, Gas and Water Supply; Construction; Wholesale and Retail Trade; Hotels and Restaurants; Transport and Storage and Communication; Financial Intermediation; Real Estate, Renting and Business Activities; Public Administration and Defense; Education; Health and Social Work; Other Community, Social and Personal Services. All these sectors have the same level of disaggregation. Whenever data were available, sectors were further disaggregated. Appendix provides the list of the sectors. Each series was log first-differenced and demeaned. For the models estimated for the pre-globalization and the globalization periods, $T=15$ and $T=16$ respectively. The sample split point for the pre-globalization and globalization periods was moved up to 2 years either side of that breakpoint and the results remained very similar.

As previously mentioned, both the idiosyncratic term and the factors follow an AR(3) process. The prior on all the factor loadings is $N(0,1)$, while the one for the autoregressive polynomial parameters is $N(0,\Sigma)$, where $\Sigma = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.25 \end{bmatrix}$. We experimented with either tighter or looser priors for both the factors and the autoregressive parameters, but the results remained very similar. The prior on the innovation variances in the observable equations is Inverted Gamma (6, 0.001), which is quite diffuse, as in Kose et al. (2003).

Finally, following Kose et al. (2012), since we are not sampling from the posterior itself as the elements of the Markov chain are converging to drawings from the posterior, it is important to monitor the convergence of the chain. Apart from starting the chain from different initial values, as mentioned above, we also used chains of different lengths ranging from 5000 to 21,000. The results were essentially the same for any chosen chain length. The analysis presented in the next section is based on 21,000 Gibbs sampling replications, from which the first 1000 are discarded as burn-in. Therefore, the results are from the remaining 20,000 iterations.

4. Results

4.1. Factors and variance decompositions

Fig. 1 plots the world factor (solid line) and the 33 and 66 percent quantile bands (dotted lines). The tightness of the bands shows that the factor is estimated quite precisely. The factor reflects the volatile world economic environment during the 1970s and 1980s followed by the Great Moderation period. Several of the peaks and troughs seem to be in line with US NBER reference dates. Table 1 shows that the standard deviation of the world factor fell from 1.845% in the 1974–1988 period to 0.672% in the 1989–2004 period. Changes in the standard deviation are significantly smaller for the country and industry factors.[15]

Fig. 2 presents a comparison of the international (world plus industry) and country factors with the aggregate VA growth for each country. The scales of the factors and VA growth are made comparable by multiplying the world, industry, and country factors by the estimated factor loadings (median of the MCMC chain). For most countries, both the international and country factors appear to co-move strongly with aggregate growth. This correlation, in the case of international factors, is highest for the US. For Japan, however, this correlation is very weak, highlighting how Japanese business cycles appear to be country-specific. Tables 2 and 3 present the correlations between aggregate VA growth and the world factor (Table 2) and the country factor (Table 3). All countries display a high correlation with their respective country factors, but this is more pronounced for Japan and some European countries such as Italy. The US is more correlated with the world factor most likely because it is the largest economy in the sample. Note, however, that estimation does not consider the relative size of countries and hence this result is not obtained by construction. We also present bilateral correlations between country factors in Table 4 to analyze the possible presence of a "regional" factor for European countries which is not large enough to

[12] See O'Mahony and Timmer (2009) and the web link at: http://www.euklems.net/

[13] For an analysis on the advantages of the EU Klems dataset, see Koszerek et al. (2007).

[14] For a correspondence between the industry numbers, EU Klems codes, and the actual industry names, see Appendix.

[15] Industry factor plots are available upon request.

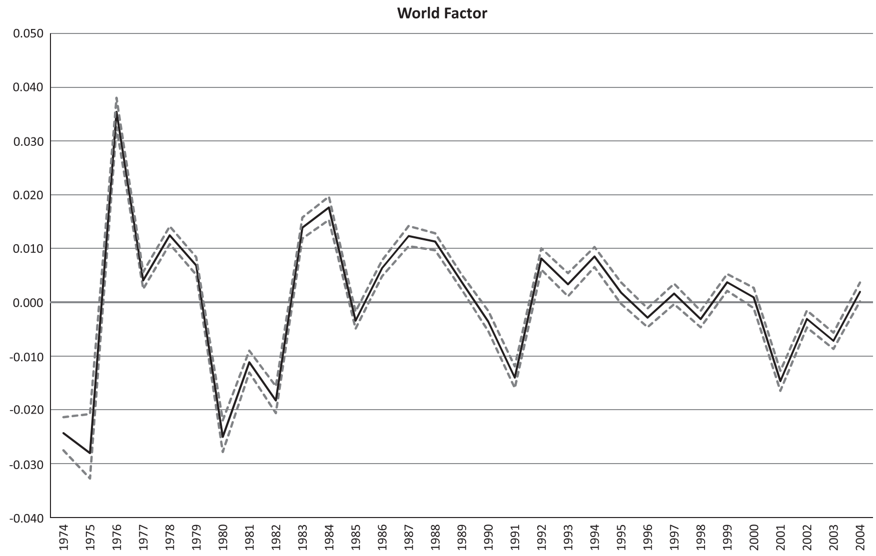

Fig. 1. World factor.

Table 1
Standard deviation (in %) of the world, country and industry factors.

StDev	WF	CF	IF
1974–1988	1.844931	1.303318	2.51436
1989–2004	0.672128	1.108657	2.446483

Note: WF is the world factor, CF is the country factor, and IF is the industry factor.

be captured by the world factor. Although the French, Italian and German country factors display large correlations, the UK country factor is negatively correlated with Germany and Italy, and is uncorrelated with the French country factor. We also observe a high correlation between Japanese and German and Italian country factors. It is thus difficult to conclude in favor of a "European" factor.[16]

Table 5 presents the country-level aggregation of the variance of VA growth explained by each factor. It presents the median (50%) and 33% and 66% posterior quantiles. As expected, because of the high level of disaggregation, idiosyncratic components dominate and are responsible for about 55% of the variation of industrial VA growth. That is, most of the variability of VA at the industry level is due to shocks that affect specific industries differently in different countries. These can be interpreted as industry-specific shocks that are not transmitted either nationally or internationally. Of the other three, the country factor explains the largest fraction of the fluctuations in industrial VA growth for all countries except France and the US. For France, it is the industry factor that marginally dominates, whereas for the US it is the world factor. We conclude that, apart from idiosyncratic shocks, for the majority of the countries, country-specific factors drive the largest share of industrial VA growth. However, reflecting the evidence in Fig. 2 and Tables 2 and 3, the percentage accounted for by the country factor in the US is the lowest. This contrasts with the results in Foerster et al. (2011) who find a strong common factor for US industrial production series. It has to be noted, however, that, apart from different levels of aggregation and different output measures, Foerster et al. (2011) work with a single common factor in the context of a closed economy. This is a relevant result, as it appears that industry factors are better identified using international data. Estimation of industry factors in the context of a closed economy model may be undermining the role of industries, especially considering the increase in vertical trade integration in the last decades (see Section 4.2 below).

Importantly, industry factors are the second most important drivers of sectoral output growth except for the US and the UK. They explain an economically significant fraction of around 12%. It is noteworthy that the world factor seems to play a smaller role ($<9\%$) in four out of seven countries although it remains a relatively important factor for the US and the UK. The introduction of sector-specific factors appears to reduce the relevance of the world factor when compared to previous studies such as Kose et al. (2003, 2008, 2012). Nevertheless, we cannot conclude that a "world business cycle", as argued by these authors, is no longer supported when using disaggregated data. If the proportion of the variance explained by world and industry factors is added up, our results would support the prominence of "international" over "country-specific" factors.

[16] Recently, Hirata et al. (2013) also show that regional factors play a major role in explaining business cycles co-movement, especially in regions where financial and trade linkages grew after the mid-1980's.

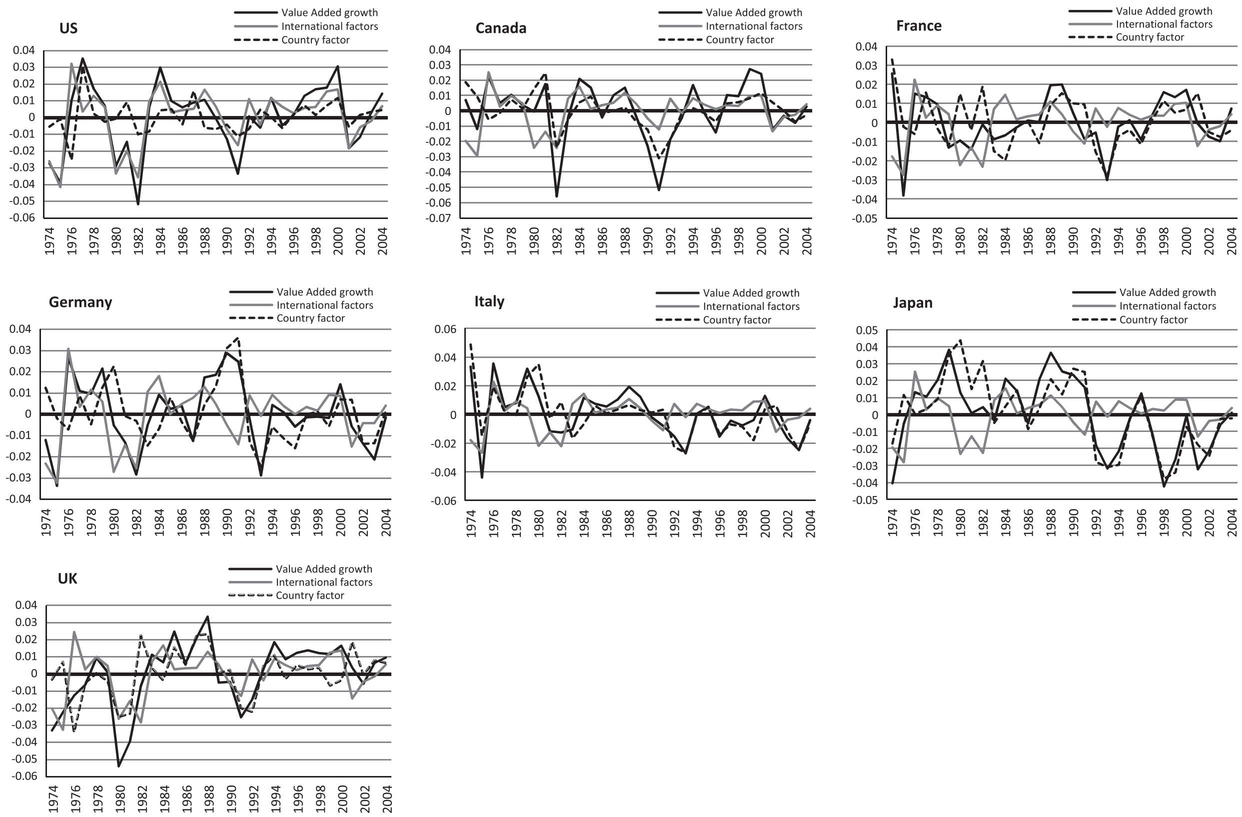

Fig. 2. Country factors.

Table 2
Correlation between world factor and the aggregate VA growth.

	WF–CA	WF–GER	WF–FR	WF–IT	WF–JP	WF–UK	WF–US
Correlation	0.4705	0.5029	0.2881	0.3881	0.2934	0.5410	0.7368

Note: CA is Canada; GER is Germany; FR is France; IT is Italy; JP is Japan; UK is the United Kingdom; and US is the United States.

Table 3
Correlation between country factor and aggregate VA growth.

	CF–CA	CF–GER	CF–FR	CF–IT	CF–JP	CF–UK	CF–US
Correlation	0.75346	0.55126	0.59282	0.78630	0.82977	0.66648	0.46920

Note: see Table 2.

Table 4
Correlations between country factors (1974–2004).

Correlation	CA	GER	FR	IT	JP	UK	US
CA	1						
GER	−0.0574	1					
FR	0.0967	0.6613	1				
IT	0.2655	0.5761	0.5939	1			
JP	−0.1423	0.5355	0.1850	0.4455	1		
UK	−0.0357	−0.2011	0.0470	−0.1724	−0.0623	1	
US	0.3898	−0.0994	−0.0593	−0.2354	−0.1362	0.2021	1

Table 5
Variance decomposition by country.

	World			Industry			Country			Idiosyncratic		
	33%	50%	66%	33%	50%	66%	33%	50%	66%	33%	50%	66%
Canada	8.84	10.55	12.15	10.02	12.98	16.68	21.18	23.24	25.42	48.38	52.02	55.35
Germany	6.71	7.89	9.17	7.97	11.31	15.44	16.46	18.39	20.43	56.70	61.02	64.85
France	2.15	2.85	3.67	11.79	16.14	21.43	13.37	15.41	17.58	58.60	63.92	68.53
Italy	7.02	8.47	10.07	7.35	10.55	14.46	22.40	24.30	26.22	51.22	55.32	58.94
Japan	4.67	5.83	7.24	7.57	10.52	14.11	22.51	24.36	26.30	53.90	57.78	61.30
UK	13.35	15.25	16.94	9.66	12.79	16.47	15.67	17.79	20.21	49.32	53.12	56.61
US	14.21	15.95	17.56	7.41	11.08	15.71	9.73	11.75	14.11	54.60	59.68	64.02

A potential reason for the reduced importance of the world factor in our model is that, in studies using aggregate variables such as GDP, factors that are industry-specific but common to all countries would then be captured by the world factor as they contribute to aggregate co-movement. We analyze this hypothesis running the model using only the country aggregates, i.e. 7 VA growth series. In this model we only have a world factor and an idiosyncratic component which is interpreted as a country-specific factor.[17] Table 6 presents the resulting variance decomposition for this model. Indeed, when using only aggregate data, the importance of the world factor increases substantially for all countries and is comparable to that found in previous studies.

Table 7 presents the weighted variance decomposition by industry. For expositional ease, we only present the median of the posterior quantiles. The idiosyncratic factor varies substantially between industries, but it appears to dominate more in primary activities and services. International factors appear more important for manufacturing sectors. Industry factors are found to be very important for about 1/4 of the sectors such as agriculture, petroleum, metal products, textiles and chemicals. The world factor is important for most manufacturing sectors as well as construction and transport. Finally, the country factor explains a larger variance proportion for several of the sectors within services. The results point out that VA growth in sectors that are more tradable is explained to a larger extent by international factors. This, however, deserves further analysis. In the next sub-section we relate the importance of international factors to trade variables emphasized by the theoretical literature.

4.2. Trade and international factors

As discussed in the introduction, input-output linkages have been highlighted as important mechanisms for the global transmission of sectoral shocks since Long and Plosser (1983) and, more recently, Acemoglu et al. (2012) and Foerster et al. (2011). At the international level, shocks can also be transmitted through world input–output linkages. The results in di Giovanni and Levchenko (2010) highlight the role of vertical integration in accounting for sectoral co-movement at the international level. Although at an exploratory level, here we analyze whether the importance of international factors is related to trade variables that measure international linkages and trade openness.

We make use of the OECD Input–Output (IO) tables for the seven countries in our sample. The tables are the mid-1990 release, which correspond to 1995 except for Canada (1993/94). This is the first IO table available that was harmonized by OECD. There is a close correspondence between IO table and our sector classification. However, some sectors were lost when building correspondences as we had to aggregate some of our sectors in the retail sector. We have 28 sectors for all countries except for Canada where we have 27.

We used several measures of trade linkages and openness. Some of them were highly correlated and we only use the following four to report our regression results[18]:

1. $\mathbf{M_{ii}}$: intermediate imports of sector i of products from sector i as a share of total production of sector i.
2. **XY**: total exports for final demand of sector i as a share of VA in sector i.
3. **IMR**: intermediate imports ratio, representing total imports of sector i of intermediate inputs from all other sectors as a share of total intermediate purchases of sector i.
4. **MCX**: import content of exports. This variable measures the intermediate import content (direct and indirect) required to

[17] Note that, keeping the structure of the data as in the original model and dropping the industry factor, the variation in industry data that was previously captured by the industry factor would naturally go to the idiosyncratic component. The "world" factor would still be the factor that is common to all industries in all countries and hence it would still capture the same common variation, pushing the industry variation into the idiosyncratic component.

[18] We used a wide range of variables and specifications of the regressions. For brevity, we only report some of them. It has to be noted, however, that the variables that appeared robust in the reported specifications remained so in the ones we do not report.

Table 6
Variance decomposition by country based on a one factor model.

	World			Idiosyncratic		
	33%	50%	66%	33%	50%	66%
Canada	25.17	29.87	34.92	65.08	70.13	74.83
Germany	45.69	51.40	56.91	43.09	48.60	54.31
France	33.52	38.08	42.48	57.52	61.92	66.48
Italy	42.95	48.53	53.93	46.07	51.47	57.05
Japan	13.17	16.79	20.69	79.31	83.21	86.83
UK	13.81	17.90	22.80	77.20	82.10	86.19
US	40.67	46.37	52.58	47.42	53.63	59.33

Table 7
Variance decomposition by industry (median).

	World	Industry	Country	Idiosyncratic
Industry 1	0.61	14.04	1.84	82.12
Industry 2	5.70	7.32	2.60	83.31
Industry 3	11.83	7.44	9.01	70.01
Industry 4	9.34	12.15	29.94	47.09
Industry 5	8.40	6.75	9.09	74.27
Industry 6	28.18	15.52	25.28	30.37
Industry 7	6.34	16.01	2.13	74.70
Industry 8	38.39	16.47	7.56	37.29
Industry 9	34.78	8.66	24.41	31.90
Industry 10	34.87	14.48	23.54	26.51
Industry 11	28.31	14.59	27.27	29.29
Industry 12	14.38	26.62	33.49	24.52
Industry 13	13.77	23.96	21.66	39.41
Industry 14	19.77	9.73	12.15	57.37
Industry 15	27.23	9.30	26.58	36.18
Industry 16	6.81	10.91	11.58	68.89
Industry 17	24.90	4.33	18.54	50.06
Industry 18	8.05	10.87	35.28	43.35
Industry 19	7.49	4.87	20.03	66.17
Industry 20	2.39	7.54	47.11	40.91
Industry 21	9.18	10.96	18.24	60.62
Industry 22	26.98	9.19	16.46	46.25
Industry 23	2.29	10.24	6.79	78.97
Industry 24	4.51	13.77	4.82	75.01
Industry 25	3.37	9.22	8.12	77.90
Industry 26	13.97	16.56	19.11	49.19
Industry 27	2.53	10.09	25.59	60.42
Industry 28	6.76	13.52	10.67	66.94
Industry 29	7.51	10.24	3.92	76.42
Industry 30	10.73	15.58	17.52	54.41

produce a unit of exports. The vector of import content of exports for all sectors is calculated as:

$$\mathrm{MCX} = \mathrm{u}\mathrm{A}_{\mathrm{M}}(\mathrm{I}-\mathrm{A}_{\mathrm{D}})^{-1}$$

where u is a $(1 \times \mathrm{I})$ vector of ones, A_{M} is the (IxI) matrix of direct import coefficients, A_{D} is the domestic direct input coefficient matrix, and I is the identity matrix. $(\mathrm{I}-\mathrm{A}_{\mathrm{D}})^{-1}$ is the Leontief matrix of indirect coefficients. This yields the import content of a unit of output produced by sector. Assuming that the import content of the domestic output is the same for domestic final use and for exports, this gives us the import content per unit exported by sector.

The first variable is a simple measure of trade intensity in intermediate inputs with the same sector in the rest of the world. Sectors that display stronger international intra-sectoral links could display stronger industry effects as shocks are transmitted through international trade within the same sector. **XY** is a basic index of openness at the sectoral level that measures exposure to international demand and competition. **IMR** and **MCX** are measures of vertical integration. The first one follows Feenstra and Hanson (1996) and represents the relative use of intermediates from foreign sectors as a share of total intermediates, measuring the extent to which a sector uses the output produced by other sectors abroad. **MCX** is a more refined measure based on Hummels et al. (2001) that calculates vertical integration in terms of the direct and indirect reliance of a sector on imported intermediate goods per unit exported. These measures have been widely used in the trade literature as indicators of outsourcing. We would expect that, for sectors that outsource parts of the production process to

Table 8
Regressions of variance decompositions on trade indicators.

	World factor			
	1	2	3	4
IMR	−0.007	–	0.012	–
M_{ii}	0.382	–	0.381	–
XY	−0.015	–	−0.018	–
MCX	0.262***	0.297**	0.303**	0.350*
Country effects	No	No	Yes	Yes
R^2	0.38	0.43	0.54	0.53
	Industry factor			
IMR	0.030	–	0.024	–
M_{ii}	−0.220	–	−0.221	–
XY	0.056*	0.055*	0.055*	0.053*
MCX	−0.115	−0.139***	−0.100	−0.131**
Country effects	No	No	Yes	Yes
R^2	0.53	0.53	0.55	0.55
Obs	195	195	195	195

Notes: Significant at the *99%, **95% and ***90%, based on heteroscedasticity consistent standard errors. IMR: intermediate import ratio. M_{ii}: intermediate import coefficient, imports of sector *i* from sector *i*. XY: exports of final goods for final demand over sector value added. MCX: import content of exports.

other sectors in the world, world factors would become more relevant as shocks to one sector are transmitted through input–output linkages to *all* other sectors in the world.

We regress the median of the posterior quantiles of the variance proportions explained by the world and the industry factors (international factors) on these variables for every sector. Table 8 presents selected results for each factor with specifications including and excluding country effects. The explanatory power of the trade variables for the industry cross-section is very satisfactory, with R-squared values ranging from 0.38 and 0.55. Neither $\mathbf{M_{ii}}$ nor **IMR** show up as significant in any of the regressions. The other two variables, however, appear to be strongly correlated with the importance of international factors. As expected, the coefficient on **MCX** is positive and highly significant for the world factor. This is consistent with the results in di Giovanni and Levchenko (2010) and the "linkages" view of international co-movement (Acemoglu et al., 2012). **MCX** is negatively correlated with the industry factor in some specifications, but this just reflects the fact that an increase in the proportion explained by the world factor reduces the proportion explained by other factors. The industry factor, however, is positively correlated with **XY**, whereas it is not correlated with $\mathbf{M_{ii}}$. A sector in one country tends to co-move more closely with the same sector in other countries if it is more intensive in final use exports. It is then likely that sector-specific international demand shocks are more important determinants of industry factors. An alternative explanation is that open sectors that compete more closely use similar (best practice) technologies that increase their correlation in the face of cost shocks.

5. Globalization and the dynamics of international business cycles

Given the importance of trade variables highlighted in the previous section, we now address a second key question: how did the importance of world, industry and country factors evolve as globalization deepened over the past two decades? We focus here on changes in the "explained" part of the variance, i.e. the part not accounted for by idiosyncratic components, in order to obtain comparable magnitudes of the relative importance of each factor. We split the sample in two periods: the pre-globalization (1974–1988) and globalization (1989–2004) periods. Admittedly, the sample split point is arbitrary. However, it is driven by the need to preserve a sufficiently long time-series components either side. As mentioned earlier, we moved the window 2 years either side, and the results remained qualitatively similar. Care, however, should be applied when attributing the results to trade and financial integration exclusively.

Table 9 presents the country-level aggregation of the variance decomposition (for the explained part) for each period and the difference between them. We also present the "international factor" as the sum of world and industry factors. In the 1974–1988 period, the international factor supports the existence of an international business cycle for all countries except the UK. The largest part of the volatility of G7 countries' industrial VA growth can be attributed to international factors. For the 1989–2004 period we can see that, for most of the G7 economies, the country factor plays a much larger role. These results are in accordance with Kose et al. (2012) who found that the relative importance of the global factor fell during the globalization period. France is the only country for which the industry-specific factor dominates. The world factor is only the third most important factor. International factors play now a much smaller role than in the previous sample. This is driven by a fall in the relevance of the world factor for Germany, France, Italy and Japan, and a fall in the relevance of the industry factor mainly for Canada and the US.[19]

[19] Results of the change in the proportion of the variance by industry are available on request.

Table 9
Change in the contribution of each factor in the explained part of the variance decomposition by country (median).

	World			Industry			International			Country		
	1974–1988	1989–2004	Diff	1974–1988	1989–2004	Diff	1974–1988	1989–2004	Diff	1974–1988	1989–2004	Diff
Canada	10.56	16.72	6.15	44.52	19.88	−24.64	55.08	36.59	−18.49	44.92	63.41	18.49
Germany	24.43	21.44	−2.99	29.34	23.75	−5.58	53.76	45.19	−8.57	46.24	54.81	8.57
France	40.83	31.58	−9.25	22.13	41.31	19.18	62.96	72.89	9.93	37.04	27.11	−9.93
Italy	40.75	20.17	−20.57	21.09	36.40	15.30	61.84	56.57	−5.27	38.16	43.43	5.27
Japan	26.86	14.49	−12.37	27.45	21.50	−5.95	54.31	36.00	−18.31	45.69	64.00	18.31
UK	14.51	15.80	1.29	23.82	28.24	4.42	38.33	44.04	5.71	61.67	55.96	−5.71
US	10.45	23.11	12.66	40.82	24.78	−16.04	51.27	47.89	−3.38	48.73	52.11	3.38

The fall in the relevance of international factors stands in stark contrast with increases in world trade and vertical specialization during this period. Combined with the previous evidence, one would expect an increase in the importance of international factors. It is important, thus, to take a deeper look into the driving forces behind these changes. Note that these results simply present country-level aggregates of the variance of sectoral growth explained by variations in the three factors. According to Eq. (6) and the country-level aggregation procedure used, there could be three sources of changes in the variance decomposition. First, changes in the structural composition of sectors that would affect the weighting matrices hence changing the resulting country-level aggregations. Second, changes in the factor loadings that reflect the co-variation between factors and VA growth. Third, changes in the variance of the three factors between sub-periods. The latter, according to Eqs. (3)–(5) can be further split into changes in the persistence of the factors, and changes in the variance of the factors' innovations, v_t. Trade would only drive co-movement and hence the sensitivity to global shocks reflected in the world factor loadings. Recall that Table 1 reported a significant fall in the variance of the world factor. This fall, which is not observed in the other factors, could then reduce the relative contribution of the world factor but would be un-related to globalization in a direct way in our model. In the next two subsections we construct counterfactuals to analyze the relevance of these sources for the change in the variance decompositions starting with the role of structural change.

5.1. *The role of structural change*

We now address whether country-level changes in the variance decompositions are driven by changes in the importance of factors within industries or by changes in the structural composition of these economies. To answer this question we decompose changes in the variance decomposition at the country level into "within effects", "structural change effects", and an "interaction effect". The within effect, which measures changes at the industry-level, shows the contribution of time t variance decomposition changes accounted by each factor holding VA shares at their $t-1$ values. The structural change effect is the contribution of changes in industrial VA shares between $t-1$ and t, holding the variance decompositions accounted by each factor at their $t-1$ values. Finally, the interaction effect displays the contribution arising from the co-movement between changes in the industry-level variance decompositions and structural changes. We carry out this analysis for all three factors as well as for the international factor.

Fig. 3 shows the contribution of each of these effects by factor for each country. For the case of the US, for instance, the within effect is very large and contributes positively for all factors. That is, for all factors, changes in the variance decomposition for industries dominate the effect of changes in the structural composition of the economy. The interaction term contributes negatively for the world and the country factors and positively for industry and international factors. When positive, this effect shows that, on average, sectors whose variance decomposition has gained (lost) importance have also gained (lost) shares. When negative, it implies that sectors whose variance decomposition has gained (lost) importance have lost (gained) shares. Finally, the structural effect is not very important for the US. Very similar patterns arise for the rest of the countries. The only exception is the UK, for which not only the interaction term accounts for the largest proportion, but also the structural effect plays an important role. Overall, however, structural change plays a minor role in explaining the change in the proportion of the variance explained by different factors.

5.2. *The role of changes in volatility, persistence, and factor loadings*

We now look at whether changes in the variance of the series from the pre-globalization to the globalization period can be explained by changes in the volatility of the factors' innovations, changes in the persistence of the factors, or changes in the factor loadings. Given the small role of the structural change effect found in the previous section, and also for simplicity, we assume constant sectoral weights at $t-1$ for the aggregation. Eq. (6) implies that the difference in the variance of the series between the two sub-samples can be expressed as:

$$\begin{aligned}\Delta var(Y_{i,j,t}) = {} & [(\beta_{i,j}^{w2})^2 var(F_t^{w2}) + (\beta_{i,j}^{s2})^2 var(F_{i,t}^{s2}) + (\beta_{i,j}^{c2})^2 var(F_{j,t}^{c2})] - [(\beta_{i,j}^{w1})^2 var(F_t^{w1}) \\ & + (\beta_{i,j}^{s1})^2 var(F_{i,t}^{s1}) + (\beta_{i,j}^{c1})^2 var(F_{j,t}^{c1})] + var(\varepsilon_{i,j,t}^2) - var(\varepsilon_{i,j,t}^1)\end{aligned} \quad (8)$$

Please cite this article as: Karadimitropoulou, A., León-Ledesma, M., World, country, and sector factors in international business cycles. Journal of Economic Dynamics and Control (2013), http://dx.doi.org/10.1016/j.jedc.2013.09.002

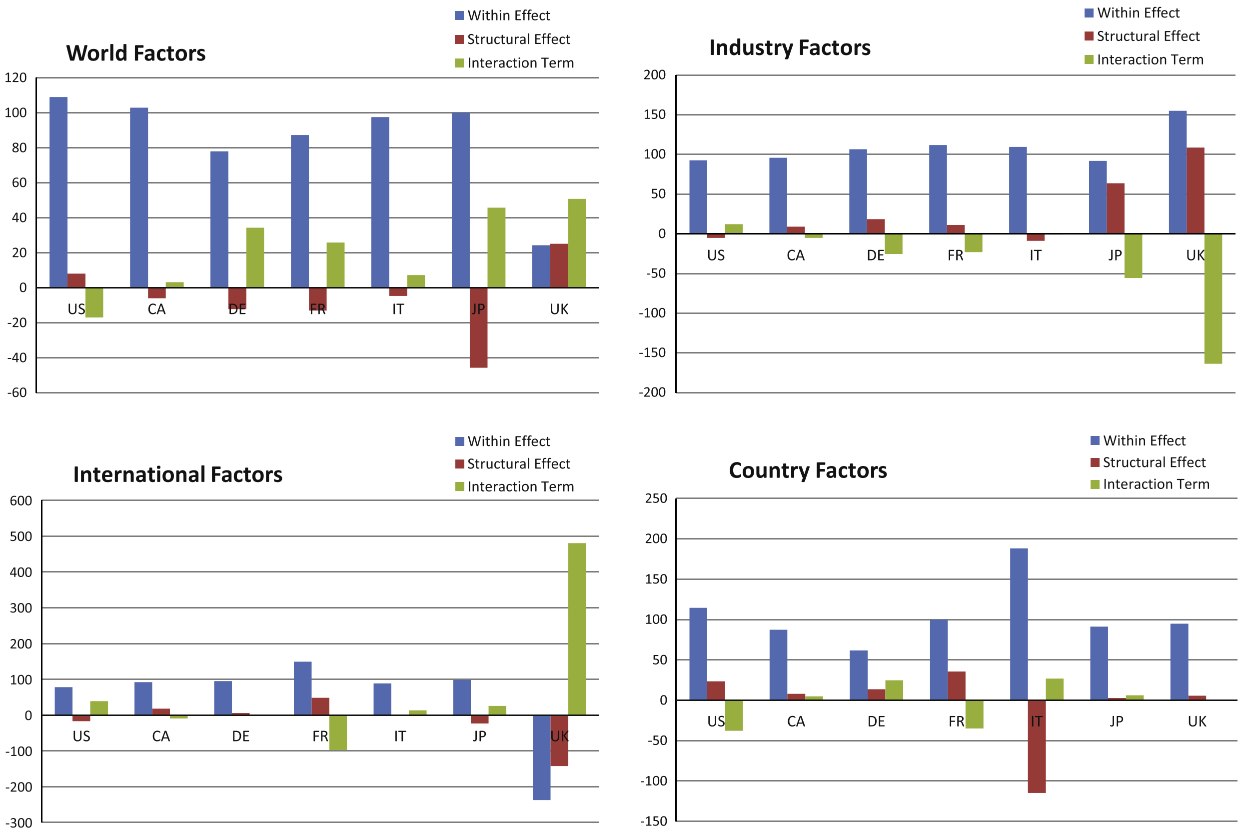

Fig. 3. Variance decomposition changes explained by within effects, structural effects and the interaction term

where Δ is the difference operator and superscripts 1 and 2 represent the first and second sub-samples respectively. We then add and subtract $(\beta^{w2}_{i,j})^2 var(F^{w1}_t)$, $(\beta^{s2}_{i,j})^2 var(F^{s1}_{i,t})$, and $(\beta^{c2}_{i,j})^2 var(F^{c1}_{j,t})$ to obtain:

$$\Delta var(Y_{i,j,t}) = (\beta^{w2}_{i,j})^2 \Delta var(F^w_t) + (\beta^{s2}_{i,j})^2 \Delta var(F^s_{i,t}) + (\beta^{c2}_{i,j})^2 \Delta \mathrm{var}(F^c_{j,t}) + var(F^{w1}_t)\Delta(\beta^w_{i,j})^2 + var(F^{s1}_{i,t})\Delta(\beta^s_{i,j})^2 + var(F^{c1}_{j,t})\Delta(\beta^c_{i,j})^2 + \Delta var(\varepsilon_{i,j,t}). \tag{9}$$

The first three terms in (9) capture changes in the variance due to changes in the volatility of the factors, whereas the following three terms capture the effect of changes in factor loadings. As mentioned above, changes in the variance of factors can be attributed to changes in the volatility of the factor innovations or changes in the persistence of the factor. Since we have an AR(3) process the variance of any factor F can be expressed as:

$$var(F) = (\sigma)^2\{1-[(\varphi_1)^2+(\varphi_2)^2+(\varphi_3)^2+\varphi_2(\varphi_1)^2+\varphi_3(\varphi_1)^3+2\varphi_3\varphi_2\varphi_1]\}^{-1} \tag{10}$$

where σ is the variance of the error term v_t, and φ_1, φ_2 and φ_3 are the AR coefficients governing persistence in Eqs. (3)–(5). Denoting:

$$\Phi = \{1-[(\varphi_1)^2+(\varphi_2)^2+(\varphi_3)^2+\varphi_2(\varphi_1)^2+\varphi_3(\varphi_1)^3+2\varphi_3\varphi_2\varphi_1]\}^{-1}$$

we can define $var(F) = \sigma^2\Phi$.

Using these expressions, adding and subtracting $\Phi^{w2}(\sigma^{w1})^2$, $\Phi^{s2}(\sigma^{s1})^2$, and $\Phi^{c2}(\sigma^{c1})^2$, and rearranging, we obtain:

$$\begin{aligned}\Delta var(Y_{i,j,t}) = {} & \{(\beta^{w2}_{i,j})^2\Phi^{w2}\Delta(\sigma^w)^2 + (\beta^{s2}_{i,j})^2\Phi^{s2}\Delta(\sigma^s)^2) + (\beta^{c2}_{i,j})^2\Phi^{c2}\Delta(\sigma^c)^2\} + \{(\beta^{w2}_{i,j})^2(\sigma^{w1})^2\Delta\Phi^{w2} \\ & + (\beta^{s2}_{i,j})^2(\sigma^{s1})^2\Delta\Phi^{s2} + (\beta^{c2}_{i,j})^2(\sigma^{c1})^2\Delta\Phi^{c2}\} + \{(\sigma^{w1})^2\Phi^{w1}\Delta(\beta^w_{i,j})^2 + (\sigma^{s1})^2\Phi^{s1}\Delta(\beta^s_{i,j})^2 \\ & + (\sigma^{c1})^2\Phi^{c1}\Delta(\beta^c_{i,j})^2\} + \Delta var(\varepsilon_{i,j,t})\end{aligned} \tag{11}$$

Eq. (11) consists of four parts capturing the possible sources of changes in the variance of the series. The first term captures the contribution of changes in the variance of the innovations to the three factors; the second term captures the contribution of changes in the persistence of factors; the third term captures the contribution of changes in factor loadings; finally, the last term captures the contribution of changes in the volatility of the idiosyncratic shock. In other words, the first three terms capture changes in the explained part the variance, and the fourth captures the "unexplained" part.

Table 10
Percentage contribution to the total change in the variance of the series.

	Variance of factor shock	Persistence of factor	Factor loadings
Canada			
World	−442.38	365.53	80.46
Industry	−12.88	4.17	−19.07
Country	−42.05	1.39	50.62
Germany			
World	−43.31	35.79	9.70
Industry	−0.97	2.48	0.88
Country	1.14	−0.90	0.12
France			
World	−940.23	776.89	62.19
Industry	−69.94	39.85	108.91
Country	−102.07	−6.26	23.02
Italy			
World	−127.91	105.69	−17.08
Industry	−8.25	2.99	2.57
Country	−16.86	−0.31	−1.32
Japan			
World	−60.32	49.84	−10.99
Industry	−1.51	−1.83	−13.81
Country	−17.98	4.30	10.64
UK			
World	−105.43	87.11	9.39
Industry	−3.63	1.02	−3.21
Country	2.57	−24.48	−22.90
US			
World	−61.41	50.74	5.59
Industry	−5.36	2.95	−19.23
Country	−30.93	−3.88	5.92

Table 10 presents, by country and for each of the factors, the percentage contribution of these factors adding up to the explained part of the change in the variance.[20] For all countries, the world factor seems to be driving most of the change in the volatility. Most importantly, the variance of the world factor shock falls very significantly. Country factor volatility also falls for most countries although it is more important for Canada, France and the US. The fall in the variance of sector shocks is less pronounced. The substantial fall in the innovation variance of the world factor is consistent with the widely reported Great Moderation. Note that, in our case, this decrease in volatility occurs primarily at the international level, indicating a lesser role for country-specific macroeconomic policies. At the same time, we observe a large increase in the persistence of the world factor which is hardly relevant for the other two factors. Finally, the contribution of the world factor loadings is positive in most cases. Country loadings also increase in several cases, whereas for industry loadings we observe a mixed picture.

The picture that arises from this decomposition is that the observed de-coupling in disaggregated business cycles found during the globalization period is mostly driven by the fall in the variance of the world shock that reduces the relative contribution of international factors. This is partly, but not completely, compensated by an increase in the persistence with which these shocks propagate in the world economy. Co-variation between VA growth rates and the world factor, as reflected by factor loadings, actually increased during this period. These results thus reconcile the apparent paradox of a decrease in co-movement during a period of increased trade and vertical integration. Our results in this respect are similar to the findings by Foerster et al. (2011) for the US economy. They also find that, during the Great Moderation, common factors were less important due to the reduction in the variance of aggregate shocks in the US. Although we also observe a reduction in the variance of the country shock for the US, it is of a smaller magnitude than that of global factors.

6. Conclusions

We provide a comprehensive examination of the importance of industry-specific factors for international business cycle co-movement in VA growth at a disaggregate level. We estimate a dynamic latent factor model using a Bayesian approach considering world, country-, industry-specific and idiosyncratic factors on a dataset of 30 sectors for the G7 countries during the 1974–2004 period.

Our results provide a rich body of evidence about the role and evolution of common business cycles at the disaggregate level. First, idiosyncratic shocks specific to each industry dominate business cycles at a disaggregate level. Second, of the

[20] Note that this does not match exactly the total change at the country level because we have assumed constant sectoral weights at $t-1$.

Please cite this article as: Karadimitropoulou, A., León-Ledesma, M., World, country, and sector factors in international business cycles. Journal of Economic Dynamics and Control (2013), http://dx.doi.org/10.1016/j.jedc.2013.09.002

explained part of business cycles, the country factor explains the largest proportion of the variance while the industry-specific factor is the second most important source for the majority of the sectors and countries considered. Third, on average, the world factor seems to play a minimal role in accounting for co-movements in industrial VA growth. The introduction of sector-specific factors appears to reduce the relevance of the world factor when compared to previous studies. We cannot, however, conclude against the existence of a "world business cycle" found in previous studies. Our results indicate that a good part of business cycle co-movement across countries may be driven by common sector-specific factors. When using aggregate data, the world factor captures not only the dynamic factor common to all countries but also the dynamic factor common to the same industry across countries. Our results support the prominence of "international" over "country-specific" factors. We also find that world factors are more important for sectors that make intensive use of other sectors' intermediate imports to produce exports, a measure of vertical integration. This is consistent with recent theories emphasizing the role of input–output linkages for the transmission of business cycles. Sector-specific factors, however, are more important in sectors with a large share of exports for final demand.

During the pre-globalization period (1974–1988) we find support for an international business cycle at a disaggregate level for most countries. However, during the globalization period (1989–2004), we find support for the prominence of international factors only for two countries. For the rest of the countries there is evidence of business cycle de-coupling. We do not find robust support for the hypothesis that disaggregate business cycles have become more synchronized at the international level. This evidence, however, is the result of a combination of effects. On the one hand, the volatility of world shocks experienced a dramatic reduction during the Great Moderation period which reduced its relative importance *vis a vis* other factors. This drove most of the apparent de-coupling in our sample. This reduction was only partially compensated by an increase in the persistence of the transmission of world shocks. At the same time, the strength of the co-variation of sectoral outputs with the world shock increased, albeit only moderately. We also found little evidence that changes in the structural composition of output by sectors had an important role to play.

Acknowledgments

This work was supported by the Economic and Social Research Council [Grant number ES/H00288X/1]. We are thankful to Chris Otrok for invaluable guidance on some of the codes used to compute our results, to Alex Klein, Keisuke Otsu, Georgios Papadopoulos, and two anonymous referees for useful comments, and to Daniella Tsar for excellent research assistance.

Appendix. List of industries

Industry number	EU Klems code	Industry
1	AtB	Agriculture, Hunting, Forestry and Fishing
2	C	Mining and Quarrying
3	15t16	Food Products, Beverages and Tobacco
4	17t19	Textiles, Textile Products, Leather and Footwear
5	20	Wood and Products of Wood and Cork
6	21t22	Pulp, Paper, Paper Products, Printing and Publishing
7	23	Coke, Refined Petroleum Products and Nuclear Fuel
8	24	Chemicals and Chemical Products
9	25	Rubber and Plastics Products
10	26	Other Non-metallic Mineral Products
11	27t28	Basic Metals and Fabricated Metal Products
12	29	Machinery, NEC
13	30t33	Electrical and Optical Equipment
14	34t35	Transport Equipment
15	36t37	Manufacturing NEC; Recycling
16	E	Electricity, Gas and Water Supply
17	F	Construction
18	50	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
19	51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
20	52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
21	H	Hotels and Restaurants
22	60t63	Transport and Storage
23	64	Post and Telecommunications
24	J	Financial Intermediation
25	70	Real Estate Activities
26	71t74	Renting of m&eq and Other Business Activities
27	L	Public Admin and Defense; Compulsory Social Security
28	M	Education
29	N	Health and Social Work
30	O	Other Community, Social and Personal Services

Please cite this article as: Karadimitropoulou, A., León-Ledesma, M., World, country, and sector factors in international business cycles. Journal of Economic Dynamics and Control (2013), http://dx.doi.org/10.1016/j.jedc.2013.09.002

References

Acemoglu, D., Carvalho, V.M., Ozdaglar, A., Tahbaz-Salehi, A., 2012. The network origins of aggregate fluctuations. Econometrica 80, 1977–2016.

Backus, D.K., Kehoe, P.S., Kydland, F.E., 1995. International business cycles: theory and evidence. In: Cooley, T.F. (Ed.), Frontiers of Business Cycle Research, Princeton University Press, Princeton, NJ, pp. 331–357.

Baxter, M., Kouparitsas, M.A., 2005. Determinants of business cycle comovement: a robust analysis. Journal of Monetary Economics 52, 113–157.

Burstein, A., Kurz, C., Tesar, L., 2008. Trade, production sharing, and the international transmission of business cycles. Journal of Monetary Economics 55, 775–795.

Calderon, C., Chong, A., Stein, E., 2007. Trade intensity and business cycle synchronization: are developing countries any different? Journal of International Economics 71, 2–21.

Chib, S., Greenberg, E., 1996. Markov Chain Monte Carlo simulation methods in econometrics. Econometric Theory 12 (3), 409–431.

Clark, T., van Wincoop, E., 2001. Borders and business cycles. Journal of International Economics 55, 59–85.

Costello, D.M., 1993. A cross-country, cross-industry comparison of productivity growth. Journal of Political Economy 101, 207–222.

Crucini, M.J., Kose, A., Otrok, C., 2011. What are the driving forces of international business cycles. Review of Economic Dynamics 14, 156–175.

Di Giovanni, J., Levchenko, A.A., 2010. Putting the parts together: trade, vertical linkages, and business cycle comovement. American Economic Journal: Macroeconomics 2, 95–124.

Feenstra, R.C., Hanson, G.H., 1996. Globalization, outsourcing, and wage inequality. American Economic Review Papers and Proceedings 86, 240–245.

Foerster, A.T., Sarte, P.G., Watson, M.W., 2011. Sectoral vs. aggregate shocks: a structural factor analysis of industrial production. Journal of Political Economy 119, 1–38.

Forni, M., Reichlin, L., 1998. Let's get real: a factor analytical approach to disaggregated business cycle dynamics. Review of Economic Studies 65, 453–473.

Frankel, J.A., Rose, A.K., 1998. The endogeneity of the optimum currency area criteria. The Economic Journal 108, 1009–1025.

Gabaix, X., 2011. The granular origins of aggregate fluctuations. Econometrica 79, 733–772.

Geweke, J., 1996. Monte Carlo simulation and numerical integration. In: Amman, K.M., Rust, J. (Eds.), Handbook of Computational Economics, vol. 1. , North-Holland, Amsterdam, pp. 731–800.

Gregory, A.W., Head, A.C., Raynauld, J., 1997. Measuring world business cycles. International Economic Review 38, 677–702.

Hirata, H., Kose., M.A., Otrok, C., 2013. Regionalization vs. Globalization. IMF Working Paper, WP/13/19.

Hummels, D., Ishii, J., Yi, K., 2001. The nature and growth of vertical specialization in world trade. Journal of International Economics 54, 75–96.

Imbs, J., 2004. Trade, finance, specialization, and synchronization. The Review of Economics and Statistics 86, 723–734.

Kose, M.A., Otrok, C., Whiteman, C.H., 2003. International business cycles: world, region, and country-specific factors. American Economic Review 93, 1216–1239.

Kose, M.A., Otrok, C., Whiteman, C.H., 2008. Understanding the evolution of world business cycles. Journal of International Economics 75, 110–130.

Kose, M.A., Otrok, C., Prasad, E.S., 2012. Global business cycles: convergence or decoupling. International Economic Review 53, 511–538.

Koszerek, D., Havik, K., Mc Morrow, K., Röger W., Schönborn, F., 2007. An Overview of the EU KLEMS Growth and Productivity Accounts. Economic Commission, European Economy, Economic Papers No. 290.

Long, J.B., Plosser, C.I., 1983. Real business cycles. Journal of Political Economy 91, 39–69.

Long, J.B., Plosser, C.I., 1987. Sectoral vs. aggregate shocks in the business cycle. American Economic Review 77, 333–336.

Norrbin, N.C., Schlagenhauf, D.E., 1988. An inquiry into the sources of macroeconomic fluctuations. Journal of Monetary Economics 22, 255–271.

Norrbin, N.C., Schlagenhauf, D.E., 1990. Sources of output fluctuations in the united states during the inter-war and post-war years. Journal of Economic Dynamics and Control 14, 523–551.

Norrbin, N.C., Schlagenhauf, D.E., 1996. The role of International Factors in the Business Cycles: a multi-country study. Journal of International Economics 40, 85–104.

O′Mahony, M., Timmer, M.P., 2009. Output, input, and productivity measures at the industry level: the EU KLEMS database. The Economic Journal 119, 374–403.

Otrok, C., Whiteman, C.H., 1998. Bayesian leading indicators: measuring and predicting economic conditions in Iowa. International Economic Review 39, 997–1014.

Pesaran, M.H., Pierse, R.G., Lee, K.C., 1993. Persistence, cointegration, and aggregation: a disaggregated analysis of output fluctuations in the US economy. Journal of Econometrics 56, 57–88.

Stock, J.H., Watson, M.W., 1989. New indexes of coincident and leading economic indicators. In: Blanchard, O.J., Fischer, S. (Eds.), NBER Macroeconomics Annual, MIT Press, Cambridge, MA, pp. 351–394.

Stockman, A., 1988. Sectoral and aggregate national disturbances to industrial output in seven European countries. Journal of Monetary Economics 21, 387–409.

Please cite this article as: Karadimitropoulou, A., León-Ledesma, M., World, country, and sector factors in international business cycles. Journal of Economic Dynamics and Control (2013), http://dx.doi.org/10.1016/j.jedc.2013.09.002