China's Increasing Global Influence: Changes in International Growth Linkages

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March 2018

Abstract

Changes in linkages between growth in the USA, Euro area and China are investigated utilising an iterative procedure for detecting structural breaks in VAR coefficients and disturbance covariance matrix. We find dynamics to be unchanged and, accounting for volatility changes, cross-country correlations are constant until the end of 2007. Although largely isolated from the other large economies until 2007, growth in China is subsequently strongly related to that of the US and the Euro area. The effects are illustrated using generalised impulse responses and forecast error variance decompositions. The increased international synchronisation found may be associated with the effects of the Great Recession on the US and Euro area together with China's extraordinary export growth since joining the World Trade Organisation in 2001.

JEL classifications: C32, E32, F43.

Keywords: China, international growth, structural breaks, globalization

1

1 Introduction

The economic rise of China over the last four decades is well-documented, with its share of world GDP rising from less than 2% in 1979 to almost 15% in 2016, alongside its share of world trade in the export of goods increasing from 0.8% in 1979 to 13% in 2016[1]. Indeed, China overtook the US in 2007 to become the world's largest exporter of goods. Although relatively few studies focussed on the role of China in the international economy until its rise was cemented by overtaking Japan as the world's second largest economy in 2009 (by share of world GDP), it is now attracting a great deal of attention. For example, recent studies undertaken within the IMF examine the nature and extent of international spillovers from China, including Arora and Vamvakidis (2011), Blagrave and Vesperoni (2016) and Furceri *et al.* (2017). Other authors, including Cesa-Bianchi *et al.* (2012), Dreger and Zhang (2014), Osborn and Vehbi (2015) and Pang and Siklos (2016), also examine how shocks to growth in China affect other economies, while related studies focus on the role played by China for exchange rates and inflation (for example, Granville *et al.* 2011, Metelli and Natoli, 2017). Although much of this work is motivated by the growing importance of China, empirical analyses nevertheless typically assume constancy over time.

The aim of the present paper is to inform discussion about the nature and timing of any change(s) in growth relationships across the world's major economic blocks by applying formal structural break tests to a VAR model for GDP growth in the US, China and the Euro area. Previous studies that consider time-variation in China's relationship with other economies include Fidrmuc *et al.* (2014), Furceri *et al.* (2017) and Osborn and Vehbi (2015), but the methods they employ are not designed to pinpoint the nature of change and when this occurred. However, through a structural breaks analysis, we examine evidence for change in the cross-country dynamics of growth, its volatility and the strength of contemporaneous growth linkages. Although methods such as random coefficient models and rolling regressions can be employed to capture change, we prefer to take a structural breaks perspective because it does not require *a priori* assumptions about the existence or timing of change, and hence may be particularly useful for examining the emergence of China as an economic force. The implications of the breaks we uncover are explored through impulse response functions and forecast error variance decompositions. Following Diebold and Yilmaz (2015), our principal results are not based on any assumed cross-country causal ordering for growth 'shocks', but employ the generalised techniques of Koop *et al.* (1996) and Pesaran and Shin (1998).

We employ quarterly data over 1975 to 2015, allowing us to focus on changes in international growth affiliations in the post-Bretton Woods period. Although there would be some advantages in expanding the analysis beyond the US, the Euro area and China, difficulties associated with econometric inference for multiple breaks in a system with a limited amount of data means that parsimony is required in the number of economies included. We study the Euro area as an aggregate, in order to recognise the international

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[1]Figures in this discussion employ GDP data from the World Bank and trade data from the World Trade Organisation.

importance of this economic region, with aggregate output comparable to the US. Breaks are examined within our three equation system using the iterative testing procedure of Bataa *et al.* (2013), which not only separates coefficient and covariance breaks, but also further decomposes covariance breaks into variance and correlation breaks. While the broad approach is similar to that employed by Doyle and Faust (2005), who study changes in linkages between G7 countries, ours is more flexible in that we neither specify *a priori* the number of breaks nor are coefficient and covariance breaks required to be contemporaneous. Further, we separate correlations from volatilities, which is crucial since the former measure the strength of contemporaneous linkages, whereas volatility changes may arise from purely domestic factors.

Our results imply that breaks in the contemporaneous correlations of 'shocks' are the most important feature of changing international growth affiliations. More specifically, a correlation break around 2007 evidences the growing importance of China, with substantially increased comovement across the three economies after this time. On the other hand, no changes in cross-country dynamic interactions (breaks in the VAR coefficients) are found. Due to the greater integration of China into the international economy, the effect of a one standard deviation 'shock' to its growth is associated with strong growth effects for both the US and the Euro area, whereas growth in China was largely isolated from these other economies until 2007. However, the greater integration of China also has the consequence that its growth volatility is also now more closely associated with growth shocks from these other economies. The structure of this paper is as follows. Section 2 discusses data, with Section 3 then outlining our methodology for measuring linkages; an example of the role of volatility breaks and an overview of the methodology employed for econometric inference can be found in the Appendix. Our principal results on growth linkages are presented in Section 4, while Section 5 provides some discussion and conclusions.

2   Data

Our analysis employs quarterly real GDP growth rates of the US, Euro area and China over the period 1975Q2 to 2015Q2. All data are seasonally adjusted and, except for China before 2011, obtained from the OECD database[2]. Data for China starts in 2011Q1 in that database, with growth rates for the earlier period computed using Abeysinghe and Rajaguru's (2004) estimates of real seasonally adjusted quarterly GDP for China. Abeysinghe and Rajaguru (2004) interpolate available annual data through the Chow-Lin technique that exploits information in related quarterly series (namely M1 and total external trade) and observed autocorrelation, and hence the estimated values are anticipated to be more reliable than those based on univariate interpolation. We acknowledge that there is widespread doubt about the quality of historical data relating to the Chinese economy; see, for example, the study of quarterly GDP by Franses and Mees (2013). Nevertheless, there is little that individual researchers can do beyond working with the

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[2]The OECD is one of a number of international organisations which publishes data collected by the national statistical agencies for a range of countries.

Figure 1. Quarterly GDP Growth Rates
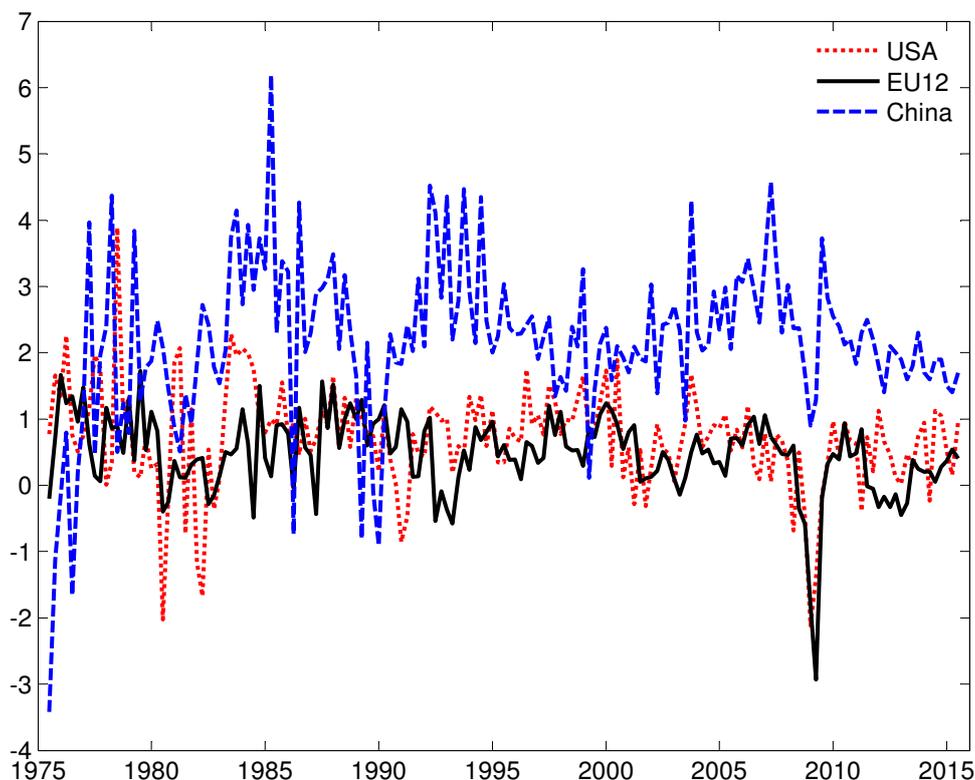
Note: Real GDP growth rate for each economy. EU12 is an aggregate of the twelve countries that were members of the Euro area in 2001. See text for data sources.

available data and, despite its limitations, we consider this data to be sufficiently reliable to show the patterns of growth in the real GDP of China.

Of course, the Euro area came into existence only in 1999 and its membership has expanded since that date. To maintain a consistent composition, our Euro area data relate to the original 'Euro 12' (denoted EU12), namely the twelve countries that comprised the Euro area at the launch of the physical notes and coins in January 2002[3]. EU12 is used in preference to an aggregate for the entire Euro area because of the changing country composition of the latter. The growth rate in each case is measured as 100 times the first difference of the log real GDP values.

Alongside positive association between US and EU12 growth rates, the rise of China is evident in Figure 1, with its growth rate typically being substantially above than the

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[3]These 12 OECD member countries are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain. The series used is labelled VPVOBARSA in the OECD database, which is expressed in millions of US dollars, volume estimates, fixed PPPs and in annual levels. A single series for EU12 is not available, with our series obtained by subtracting the Denmark, Sweden and UK series from that for EU15.

others since at least the early 1980s. The Great Recession is clearly visible as a decline in growth for each country around 2008/2009, albeit with that for China remaining positive. The figure also indicates that all three economies may have experienced changes in the volatility of growth over our sample period. Although some changes in patterns may be seen in the figure, it is nevertheless important to undertake formal analysis in order to confirm (or otherwise) their nature, since they could be due to random variation rather than changes in the underlying process.

Our analysis employs the quarterly growth rates of Figure 1. Although some researchers filter GDP growth rate data in order to remove very short run fluctuations and hence concentrate on the so-called business cycle frequencies, such filtering has substantial consequences for the dynamics of the process and hence we prefer to analyse unfiltered growth rate data.

3 Measuring Growth Linkages

As already explained, our analysis is based on a VAR model for GDP growth in the US, Euro Area and China. In common with many VAR analyses, we employ the tools of impulse response functions and forecast error variance decompositions in order to examine the nature of interactions across variables (in our case, the three economies). However, our analysis is distinctive in two respects. Firstly, employing the methodology of Bataa *et al.* (2013), we examine whether changes have occurred in the parameters of the VAR; details of the procedure can be found in that paper and is outlined in Appendix 7.2. Sufficient to note here that, although Doyle and Faust (2005) find evidence of breaks in both the VAR coefficients and the covariance matrix for international output growth, such breaks need not occur with the same frequency or at the same dates, as they assume. Previous studies focusing on the univariate properties of output growth imply volatility declines might be anticipated in the early 1980s (see, for example, Sensier and van Dijk, 2004), whereas globalisation may affect dynamic linkages and contemporaneous correlations from the latter part of the century (Kose *et al.* 2008). Therefore, our analysis first examines whether the coefficients, disturbance volatilities and correlations of our VAR change over time.

The second distinctive feature of our analysis is that, when comparing effects over different sub-periods, we allow shocks across economies to be correlated by utilising the generalised methodology associated with Koop *et al.* (1996), Pesaran and Shin (1998), Diebold and Yilmaz (2015, 2014, 2012), and others. For some VAR analyses, it is plausible to impose restrictions in order to deliver orthogonalised shocks for each equation. However, such restrictions can be difficult to justify for cross-country growth spillovers between the major international economies, and hence we prefer to use generalised measures. Nevertheless, for comparison purposes, we also provide results for the VAR orthogonalised using contemporaneous ordering restrictions, in which the US is ordered first, followed by EU12 and then China. Sections 3.1 and 3.2 describe the linkage measures employed in our analysis.

Once the dates of structural breaks are identified, the measures discussed in this

section become regime-specific, in that they relate to the estimated model parameter for the specific sub-period of time. When horizons such as one or two years ahead are considered, the measures computed implicitly assume that no structural break occurs within the horizon considered. The calculation of confidence intervals, included in the results of the next section, is discussed in Appendix 7.2.

3.1 Impulse responses

Following Doyle and Faust (2005), Diebold and Yilmaz (2015), and many others, the framework for our analysis is a conventional 'reduced form' VAR system for n countries, namely

$$\mathbf{y}_t = \boldsymbol{\delta} + \sum_{k=1}^{p} \boldsymbol{\Phi}_k \mathbf{y}_{t-k} + \mathbf{u}_t \tag{1}$$

where $\mathbf{y}_t$ is a cross-country vector of growth rates and $\boldsymbol{\delta}$ is an intercept vector. The disturbance vector $\mathbf{u}_t$ has mean zero and covariance matrix $E(\mathbf{u}_t \mathbf{u}_t') = \boldsymbol{\Sigma}$, and is temporally uncorrelated. The vector moving average (VMA) representation of the VAR, which shows the temporal patterns of responses to the disturbances, can be written as

$$\mathbf{y}_t = \boldsymbol{\mu} + \sum_{k=0}^{\infty} \mathbf{A}_k \mathbf{u}_{t-k} \tag{2}$$

where $\boldsymbol{\mu} = E[\mathbf{y}_t]$ and the VMA coefficient matrices $\mathbf{A}_1, \mathbf{A}_2, ...$ are determined by $\boldsymbol{\Phi}_k$, $k = 1, ..., p$ of (1). The relatively small number of papers which examine international growth linkages in a model involving the US together with China and/or the Euro area often assume that US shocks contemporaneously affect other economies, but not *vice versa* and hence employ structural VAR (SVAR) models in which the shocks in each equation are contemporaneously (as well as temporally) mutually uncorrelated; see, for example, Bagliano and Morana (2012) or Dungey and Osborn (2014). Although we present results based on an orthogonalised VAR, the validity of cross-country contemporaneous ordering restrictions is open to debate for the large economies and time period that we study. In particular, with the growing importance of China in the world economy and rise of globalisation, we wish to explore whether and how growth linkages have changed over time without making any assumptions about contemporaneous causality or what changes and what remains constant when a VAR model is subject to structural breaks. Generalised impulse response functions (GIRFs) were proposed by Koop *et al.* (1996) in the context of non-linear models and developed further for linear VAR models by Pesaran and Shin (1998). Dees *et al.* (2007) also argue that macroeconomic shocks will generally be correlated across countries and hence employ GIRFs.

Pesaran and Shin (1998) propose the scaled GIRF, with an assumed shock[4] to the jth element of $\mathbf{y}_t$ equal to one innovation standard deviation ($\sigma_{jj}^{1/2}$) in magnitude. Employing

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[4]It is convenient to refer to the disturbances as shocks, even when these are mutually correlated in a standard VAR.

the covariance matrix definition

$$\mathbf{\Sigma} = \mathbf{DPD}, \tag{3}$$

where $\mathbf{P}$ is the matrix of correlations between the elements of $\mathbf{u}_t$ and the diagonal matrix $\mathbf{D}$ has $\sigma_{jj}^{1/2}$ as its jth element, the scaled GIRF is

$$\psi_j^g(h) = \sigma_{jj}^{-0.5} \mathbf{A}_h \mathbf{DPD} \mathbf{e}_j, \qquad h = 0, 1, ... \tag{4}$$

in which $\mathbf{e}_j$ is a selection vector with unity as the jth element and zeros otherwise. Pesaran and Shin (1998, Proposition 3.1) show that, unless $\mathbf{\Sigma}$ is diagonal, orthogonalised impulse response functions (OIRFs) obtained from an ordered SVAR and GIRFs coincide only for a given shock applied to the first variable of the VAR. Impulse responses, such as (4), are often represented in cumulated form, aggregating all responses up to and including a specific horizon h.

It is important for the interpretation of both OIRFs and GIRFs to appreciate that these are influenced by both the disturbance correlations and volatilities of the VAR, that is by both $\mathbf{P}$ and $\mathbf{D}$ of (3). Consequently, the VAR coefficients, disturbance (or shock) standard deviations and correlations all play important roles when measuring the cross-country effects of a shock to growth. In particular, a break in any of the three components will, in general, affect both OIRFs and GIRFs. The simple example in the Appendix provides an illustration of the effects of volatility change in the VAR disturbances on these measures.

3.2   Growth volatility effects

In addition to GIRFs, Pesaran and Shin (1998) define the generalised forecast error variance decomposition (GFEVD). Diebold and Yilmaz (2015, 2014, 2012) build on the GFEVD concept, applying the results to financial markets and, in Diebold and Yilmaz (2015), to the international growth context. Their latter papers (Diebold and Yilmaz 2015, 2014) refer to GFEVDs as measures of 'connectedness', but we prefer to refer to such measures in our context as growth volatility linkages. In any case, some of our definitions differ from the corresponding expressions employed by Diebold and Yilmaz (2015, 2014), as explained below.

The GFEVD is defined as the percentage of the h-step ahead forecast error variance for variable i associated with innovations in variable j. Employing the definition of (3), this can be written as[5]

$$\theta_{ij}^g(h) = 100 \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^{h-1} (\mathbf{e}_i' \mathbf{A}_\ell \mathbf{DPD} \mathbf{e}_j)^2}{\sum_{\ell=0}^{h-1} \mathbf{e}_i' \mathbf{A}_\ell \mathbf{DPDA}_\ell' \mathbf{e}_i} \qquad h = 1, 2, ... \tag{5}$$

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[5]Pesaran and Shin (1998) define the sums in their expression analogous to (5) with upper limits of h, rather than $h-1$. This reflects only the timing in which the implicit forecast is made, namely at the beginning or end of period t. The notation here is more conventional, with observations at t assumed known. Pesaran and Shin (1998) also have a typo, scaling the numerator by σ_{ii}^{-1}, rather than the correct σ_{jj}^{-1} used by Diebold and Yilmaz (2012).

which makes clear the roles of the VAR coefficients (through $\mathbf{A}_\ell$), the disturbance standard deviations and correlations ($\mathbf{D}$ and $\mathbf{P}$, respectively). Therefore, if any of these groups of VAR parameters exhibits one or more structural breaks in the period under analysis, the GFEVDs will also change. Our empirical analysis employs (5) as a measure of the h-step ahead growth volatility in country i that is associated with growth rate innovations in country j. Although Pesaran and Shin (1998) refer to the GFEVD in terms of the error variance of i 'accounted for' by variable j innovations, we prefer the terminology 'associated with'. Pesaran and Shin (1998) note that, in general, $\sum_{j=1}^n \theta_{ij}^g(h) \neq 100$ in an n-variable system, in contrast to the analogous expression for orthogonalised innovations.

Following Diebold and Yilmaz (2012), we make pairwise comparisons using GFEVDs. In particular, using (5), the net (percentage) growth volatility linkage from j to i at horizon h is

$$S_{ij}^V(h) = \theta_{ij}^g(h) - \theta_{ji}^g(h). \tag{6}$$

This compares the percentage of the forecast variation in each of i and j associated with shocks to the other innovation series[6]. Thus, for example, the net growth volatility linkage can be compared from US to Chinese growth, providing a measure of the extent to which the contribution of US growth innovations to forecast growth volatility for China is larger (or smaller) than China's contributions to US volatility.

A straightforward measure of the (percentage) total growth volatility for country i that is associated with shocks arising from other countries is

$$S_{i\cdot}^V(h) = 100 - \theta_{ii}^g(h). \tag{7}$$

Since the GFEVD component $\theta_{ii}^g(h)$ is the percentage of the forecast error variance for i at horizon h associated with its own shocks, $S_{i\cdot}^V(h)$ gives the percentage *not* associated with own innovations. Obviously, this measure will be strongly influenced by the extent to which u_{it} is correlated with other u_{jt} ($j \neq i$) in (1). Based on (7), the average growth volatility across all n equations that is not associated with shocks arising from other countries is

$$S_{\cdot\cdot}^V(h) = \frac{1}{n}\sum_{i=1}^n [100 - \theta_{ii}^g(h)]. \tag{8}$$

It is important to recognise that, because $\sum_{j=1}^n \theta_{ij}^g(h) \neq 100$, our definitions in (6) and (7) differ from the corresponding ones adopted by Diebold and Yilmaz (2015, 2014, 2012). For the latter they employ

$$S_{i\cdot}^{V,DY}(h) = \sum_{\substack{j=1 \\ j \neq i}}^n \widetilde{\theta}_{ij}^g(h) \tag{9}$$

as the total 'connectedness' or 'volatility spillover' to i from others, where $\widetilde{\theta}_{ij}^g(h) = \theta_{ij}^g(h)/\sum_{k=1}^n \theta_{ik}^g(h)$. Our preference is not to adopt such a normalisation, but to exclude

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[6]Note that $S_{ij}^V(1) = 0$.

all contributions associated with country i innovations through the use of (7). On the other hand, in (9) Diebold and Yilmaz (2015, 2014, 2012) effectively include own (country i) innovations to the extent they are correlated with those of other countries in the system, but normalise the total 'connectedness' (including each country with itself) to 100. Similarly, our measure of average growth volatility not associated with other countries in (8) differs from the corresponding measure used by Diebold and Yilmaz (2015, 2012), while their measure analogous to (6) also employs the normalised GFEVD measure $\widetilde{\theta}_{ij}^g(h)$.

It is arguable that the measures we employ may understate growth volatility linkages, in the sense that all variation associated with innovations in i is allocated to i and hence not treated as a cross-country linkage. In that sense, measures such as (7) and (8) provide lower bounds. On the other hand, a measure such as (9) as employed by Diebold and Yilmaz (2015, 2014, 2012), may be viewed as an upper bound. Orthogonalised counterparts to all the GFEVD spillover measures considered here can be obtained, for example replacing $\theta_{ij}^g(h)$ by $\theta_{ij}^o(h)$, where $\theta_{ij}^o(h)$ is the analogous expression to (5) based on the orthogonalised VAR. These OFEVD measures, of course, reflect the ordering assumptions employed.

4 Results

We now turn to the principal interest of this paper, namely changes in international growth linkages and China's increasing role in the world economy. Subsection 4.1 provides evidence on the structural breaks in the three-economy VAR model of (1) for the US, EU12 and China, while the implications for international growth linkages are discussed in subsections 4.2 and 4.3.

4.1 Structural breaks

Structural break testing requires the researcher to set *a priori* the maximum number of breaks that can occur in the sample period (M) and the minimum percentage (ε) of the sample within each regime identified between breaks. We specify these as $M = 5$ and $\varepsilon = 15\%$, with the aim of having sufficient observations in each detected regime for reliable inference while also being able to detect important changes during the sample period. It is important to appreciate, however, that these values apply separately when considering coefficients and the covariance matrix, since we employ the methodology of Bataa *et al.* (2013), outlined in Appendix 7.2. For our sample period, the 15% minimum regime length requires any initial break to occur after the second quarter of 1981 and any final break before the third quarter of 2009, with at least 6 years (24 quarters) between two breaks of the same (coefficient or covariance) form. The maximum of five breaks considered is fairly arbitrary, but appears reasonable in our sample covering four decades. We employ a VAR with $p = 1$, identified using the Hannan-Quinn criterion and all hypothesis tests are conducted at a 5 percent significance level.

Table 1 (panel A) shows an apparent single break in the VAR coefficients in 2009Q2

9

TABLE 1. VAR BREAK TEST RESULTS

Statistic	Value	Asymptotic critical value	Break date(s)	Bootstrap p-value
		A. VAR Coefficients		
$WDMax$	149.59*	34.13		
$Seq2/1$	22.82	32.67	2009Q2	50.58
		B. Covariance Matrix		
$WDMax$	73.83*	22.59		
$Seq2/1$	46.75*	23.23	1983Q4	0.05*
$Seq3/2$	32.83*	24.15	1993Q3	0.00*
$Seq4/3$	10.44	17.72	2007Q4	0.17*

Notes: Values reported are at convergence of the iterative procedure of Bataa *et al.* (2013). The overall test ($WDMax$) examines the null hypothesis of no break against an unknown number of breaks, to a maximum of 5 breaks. If the overall statistic is significant at 5%, sequential tests are applied starting with the null hypothesis of one break and continuing until the relevant statistic is not significant. Asymptotic critical values for the 5% significance level are reported for the respective test statistics. * indicates the statistic is significant at 5%. The estimated break dates are also reported together with percentage bootstrap p-values corresponding to the null hypothesis that an asymptotically detected break does not exist.

by the asymptotic *WDMax* test of Qu and Perron (2007), applied in the iterative co-efficient/covariance break testing procedure of Bataa *et al.* (2013). However, the finite sample bootstrap test of Bataa *et al.* (2013) finds the single break identified by the asymptotic procedure to be insignificant, with a p-value over 50 percent. Thus we conclude there is no statistically significant change in the VAR coefficients. This initial result is itself notable in the light of the changes in the international economy over the period that we study, and implies that any changes apply within the covariance matrix of the shocks rather than the temporal dynamics. The modelling implication is that all subsequent analysis is based on a VAR with time-invariant coefficients.

Panel A of Table 3 presents the estimated VAR coefficients and their significance. These indicate statistically significant growth persistence (positive own lag coefficient) in all three economies. Further, there is evidence of positive Granger causality in growth from the US to EU12, with the reverse (EU12 to the US) coefficient also positive and close to significance at the 5 percent level[7]. The relative isolation of China from direct dynamic effects originating in the other major economies is seen in the lagged VAR coefficients relating to China (as either the dependent or explanatory variable) being both numerically small and statistically insignificant. In contrast to the constant VAR coefficients, panel B of Table 1 shows three breaks in the VAR covariance matrix, with

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[7]Although the results presented in this paper do not impose any restrictions on the VAR coefficients, they remain qualitatively unaffected overall when Granger causality is imposed. These results are available from the authors on request.

TABLE 2. SOURCES OF COVARIANCE MATRIX BREAKS

	Jointly	Individually		
		US	EU12	China
		A. Volatility		
1983Q4	0.57*	0.00*	34.58	46.32
1993Q3	0.00*	66.38	0.00*	0.00*
2007Q4	1.89*	7.52	0.44*	17.21
		B. Correlation and zero correlation test		
1983Q4	8.85	10.80	11.87	46.02
1993Q3	85.93			
2007Q4	0.46*	3.89**	0.23**	0.30**
[No break model]		[0.45**]	[1.13**]	[11.94]

Notes: The column labelled "Jointly" shows the significance (percentage bootstrap p-values) of joint tests for the diagonal elements of the covariance matrix (Panel A) and off-diagonal elements of the correlation matrix (Panel B) for the null hypothesis of no change at the indicated covariance matrix break date inferred from Table. Results in the columns "Individually" in Panel A report percentage bootstrap p-values corresponding to the null hypothesis that a significant system-wide volatility break does not emanate from the specified country. Individual country tests in Panel B report the bootstrap p-values for the joint hypothesis test that all contemporaneous correlations relating to that country are 0 in a regime defined by significant correlation breaks. As only the 2007Q4 correlation break is significant at 5%, the first set of p-values refer to the sub-period to 2007Q4, with the second set relating to 2008Q1 to 2015Q2.

estimated dates of 1983Q4, 1993Q3 and 2007Q4, and all are highly significant according to both the asymptotic (*WDMax* and sequential) and the bootstrap tests. Using a sample ending in 2002, Doyle and Faust (2005) identify breaks at similar dates to ours, namely in 1981Q1 and 1992Q2, in their VAR for GDP growth for the G-7 countries. However, the methodology available to Doyle and Faust (2005) considers only coincident breaks across coefficients, variances and correlations, whereas our finding of unchanged coefficients implies that relevant breaks in our VAR are confined to the disturbance covariance matrix. The focus of much of our empirical analysis is, therefore, the nature of changes in the volatilities and cross-country correlations of growth in these major economies and how such changes impact on spillovers between them. When considering cross-market relationships, the finance literature has long recognised the importance of distinguishing between changes in volatility and changes in correlations, since the former may be due to specific market influences whereas the latter measure the strength of interlinkages; for example, see Longin and Solnik (1995). The same considerations apply in our analysis of cross-country growth linkages, and hence it is important to control for volatility changes so that these do not contaminate an examination of correlations. Table 2 therefore decomposes changes in the covariance matrix of our international growth VAR, with volatility considered in panel A and correlations in panel B. A joint bootstrap test that volatility in the three economies is unchanged at each covariance break date is rejected at significance levels of 2 percent or less. Further investigation by considering each country individually indicates that the 1983 volatility break emanates from only the US, which is a manifestation in our data of the so-called Great Moderation (McConnell and Perez-Quiros, 2000, Sensier and van Dijk, 2004, and Stock and Watson, 2005), whereas the 1993 break is associated with highly significant volatility reductions for China and the EU12, but the US is unaffected (see the volatility estimates in Panel B of Table 3[8], which are computed with restrictions imposed based on the individual volatility test results of panel A of Table 2 using a 5% significance level). The EU12 volatility reduction around this time has been found in other studies (see, for example, Perez *et al.* 2006) and can be associated with the move towards greater European integration signalled by the Maastricht Treaty bringing lower growth volatility for the EU12 economy. Interpretation of the volatility decline for China at this date is more difficult, partly because of the lower reliability of China GDP data, particularly in the earlier part of the sample. Finally, the significant change in volatility in 2007Q4 is associated particularly with a substantial increase for EU12, although Table 2 also indicates some evidence (with a *p*-value of 7.5%) of a change also for the US. This break for the Euro area and (possibly) the US may be associated with the onset of the Great Recession in 2008, with EU12 volatility more than doubling after this break. No break is detected in China at this time.

Employing the standard deviation estimates of Table 3, panel B of Table 2 investigates the nature of correlation changes at the covariance break dates. In contrast to the significance of volatility changes at all three dates, correlations alter (according to 5% significance) only at the end of 2007 and hence we recognise only two regimes for the

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[8]Without the imposition of restrictions, standard deviations over the four covariance regimes are 1.16, 0.48, 0.51 and 0.65 for the US, 0.52, 0.61, 0.27 and 0.58 for EU12 and 1.25, 1.45, 0.79 and 0.49 for China.

TABLE 3. VAR COEFFICIENT AND COVARIANCE MATRIX ESTIMATES

	US	Equation EU12	China
	Panel A. Coefficients		
US coefficient	0.31*	0.18*	-0.04
	(0.2)	(1.8)	(68.9)
EU12 coefficient	0.20	0.42*	-0.01
	(5.5)	(0.0)	(95.9)
China coefficient	0.05	-0.04	0.35*
	(38.1)	(29.0)	(0.2)
	B. Standard Deviations		
1975Q3-1983Q4	1.16	0.57	1.38
1984Q1-1993Q3	0.54	0.57	1.38
1993Q4-2007Q4	0.54	0.27	0.71
2008Q1-2015Q2	0.54	0.58	0.71
[No break model]	[0.71]	[0.49]	[1.07]
	C. Correlations		
		US	EU12
1975Q3-2007Q4	EU12	0	
2008Q1-2015Q2		0.413	
[No break model]		[0.241]	
1975Q3-2007Q4	China	0	0
2008Q1-2015Q2		0.416	0.614
[No break model]		[0]	[0]

Notes: Panel A relates to VAR coefficients. Columns represent equations. The first value in each cell reports the estimated coefficient, the value in parentheses is the bootstrap p-value (expressed as a percentage) for the null hypothesis that the coefficient is 0. * indicates significant at 5%. Relevant sub-sample residual standard deviations are reported in panel B. Relevant sub-sample contemporaneous residual correlations are in panel C. For panels B and C we also report relevant estimates ignoring the breaks.

matrix **P**. Indeed, until the end of 2007, the contemporaneous correlations are small[9] and a bootstrap test that the residual correlations for each economy with the other two are jointly zero is not rejected (panel B, Table 2). In other words, prior to the end of 2007, none of the three major economies exhibited statistically significant contemporaneous (within quarter) growth linkages with the other two and the correlations are consequently imposed at zero in panel C of Table 3. Thereafter, the zero correlation null hypothesis is clearly rejected; the resulting correlations of the US with both the EU12 and China are about 0.4, with that between EU12 and China higher at 0.6.

The period from the end of 2007 has therefore seen a very substantial change in international growth linkages, from a situation of effectively no contemporaneous association to one of strong and positive cross-economy effects. Our dating of this change is supported by the finding of Fidrmuc *et al.* (2014) of increased synchronisation of short-term GDP growth between China and individual G7 countries from 2006. Whereas the US and particularly the Euro area have seen relatively weak growth since the onset of the Great Recession, the first decade of the 21st century was notable for China's entry into the World Trade Organisation (December 2001) and the increasing role it has subsequently played in world trade (see the discussion in Section 5). Bearing in mind the small dynamic spillovers to and from China revealed by the VAR coefficients, the period since 2007 is therefore not only one in which China has important interactions with the other two major economies, but the cross-country effects of growth 'surprises' are seen quickly, namely within a quarter.

For reference, Tables 2 and 3 also provide relevant results for a VAR which ignores covariance breaks. A key consequence of such an analysis is that China would appear to be contemporaneously uncorrelated with the other major economies, with the zero correlation test *p*-value of nearly 12% in panel B of Table 2 for the no break model. Therefore, in contrast to the strong positive contemporaneous correlations estimated for the period from 2008 in Table 3 (panel C) when covariance breaks are recognised, correlations for China with both the US and EU12 are imposed at zero in the no breaks model. Further, the US-EU12 correlations in the no breaks model are moderate at 0.24. To the extent that our results from 2008 reflect on-going cross-country growth linkages, use of a constant parameter VAR analysis would be seriously misleading.

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[9]Over 1975Q3-2007Q4 these are estimated as 0.162 for US-EU12, 0.081 for US-China and -0.054 for EU12-China.

Figure 2. Response to a US shock
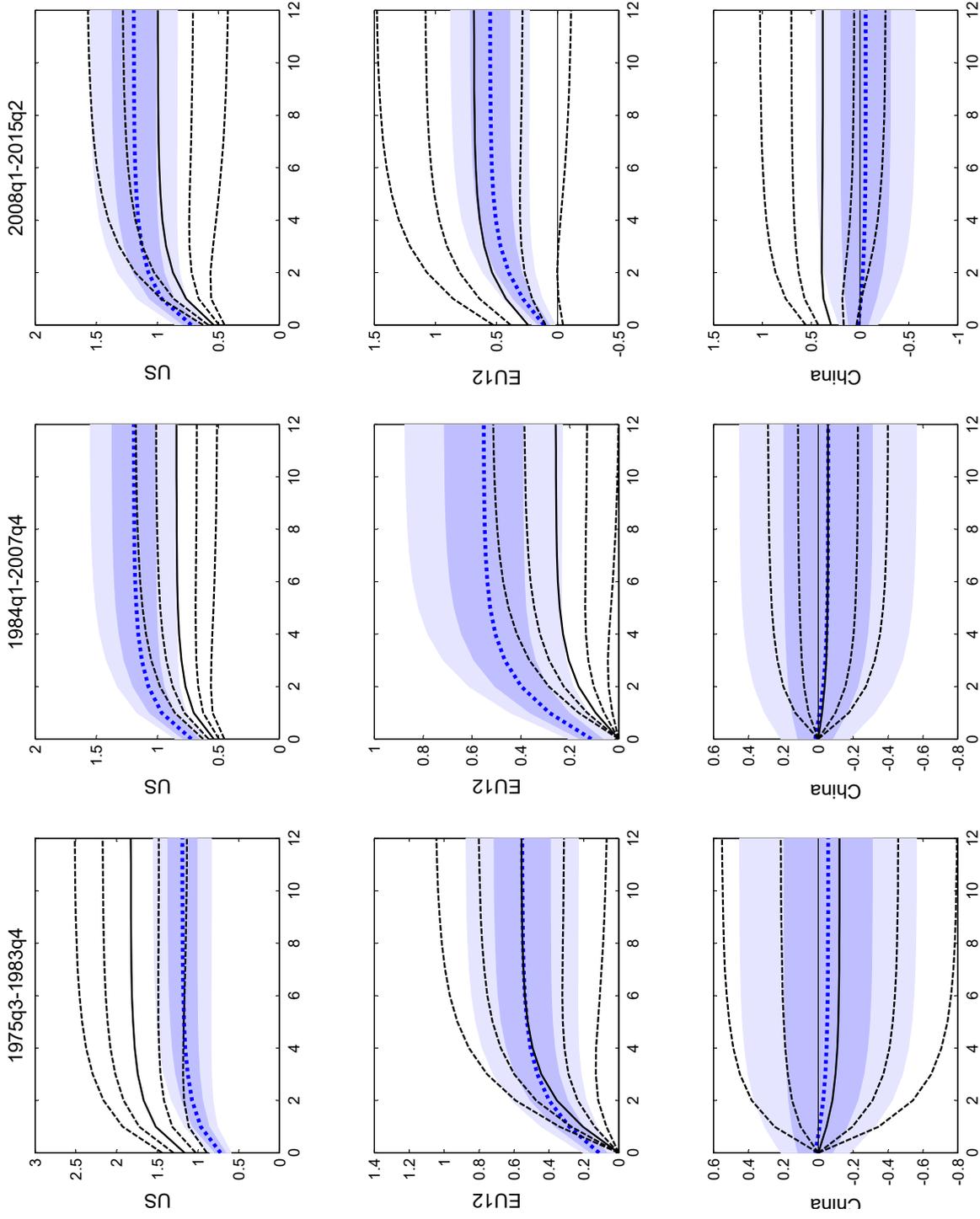
Notes: Cumulated impulse responses (GIRFs) to a one standard deviation US shock are shown to three years (horizontal axis). Rows indicate the variables that respond to the shock. Closely dotted blue lines with shaded confidence intervals assume parameter constancy (the no breaks model). A response in solid black line with dotted and dashed confidence intervals is specific to the regime specified in the column heading. For each plot a one and two standard error confidence interval is obtained using a bootstrap procedure explained in the Appendix.

4.2 Impulse responses

As noted in Section 3, impulse responses change with any break in the parameters of a VAR model. Based on the identified breaks of subsection 4.1, Figures 2 to 4 show growth cumulated GIRFs and OIRFs for a one standard deviation shock applied to each of the three economies. Since the disturbance covariance matrices are diagonal for all sub-periods until 2007Q4 (Table 3), GIRFs and OIRFs coincide until that date. With VAR coefficients constant over time, the estimated impulse responses in each of Figures 2 to 4 until 2007Q4 differ only due to the magnitude of the one standard deviation shock applied. Reflecting these size effects, note that the vertical scale sometimes changes.

The volatility results in Table 2 imply a single regime from 1984 to 2007 (the period of the Great Moderation) for US shocks, and over 1975Q3 to 1993Q3 for each of EU12 and China shocks. These volatility restrictions are imposed in the results presented, with the sub-periods identified in the headings of the figures reflecting the volatility regimes relevant to the economy of the originating shock. For example, in Figure 2, a US shock is of magnitude 1.16 percent in the sub-period to 1983Q4, but declines to 0.54 from 1984Q1 onwards. Although no volatility break is detected (using 5% significance) for the US at the Great Recession (2007Q4), the correlation break at this date (see Tables 2 and 3) leads to a new sub-period applying for impulse responses resulting from a US shock. The OIRFs we consider impose a contemporaneous causal ordering of the US, followed by EU12 and then China. Therefore, the GIRFs and OIRFs are identical for the US (the first variable in the ordered VAR) also in the final sub-period and are consequently not shown separately in Figure 2.

For each graph, one and two standard error confidence intervals are included around the estimated responses, with these obtained as discussed in the Appendix subsection 7.2. For reference, each graph also includes corresponding information obtained from a VAR in which constant parameters are assumed (the no breaks model), with that estimated response shown as a blue dotted line and the corresponding confidence intervals by blue shading.

Consider, first, GIRFs for US shocks in Figure 2. As already noted, the magnitudes of the shocks differ over the 1975-1983 and 1984-2007 regimes. Although our model does not find a change in the magnitude of the US shock in 2007Q4 or a change in the VAR coefficients, the width of the confidence intervals for the own US responses substantially increase, due to contemporaneous international linkages now associated with the US. It is also notable that although the point estimates of these own responses from a model with no breaks are reasonably close to those for the 2008Q1-2015Q2 sub-period, the no breaks model implies much tighter confidence intervals. In other words, the no breaks model fails to capture the uncertainty of the most recent period for the US.

Figure 3. Response to a EU12 shock
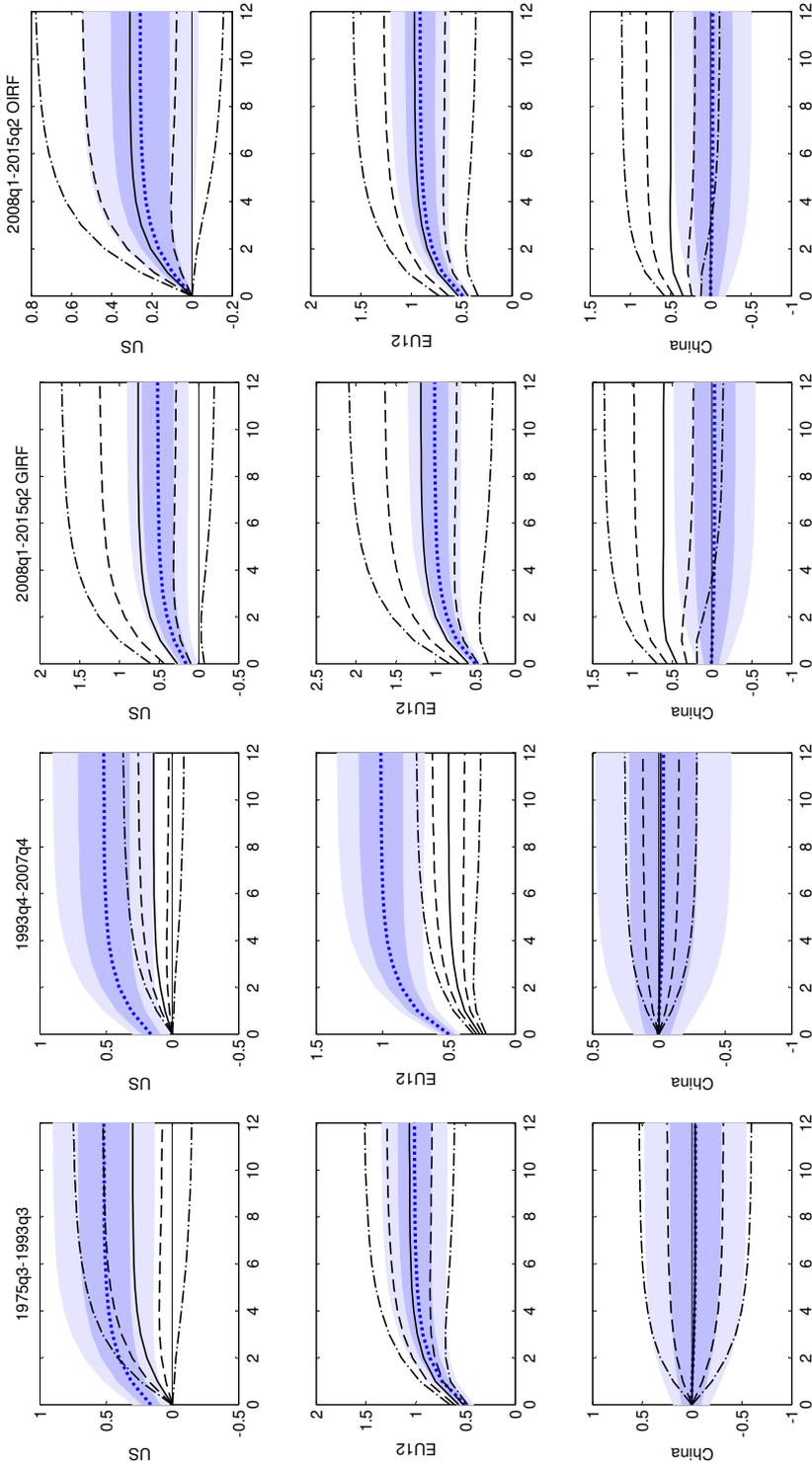
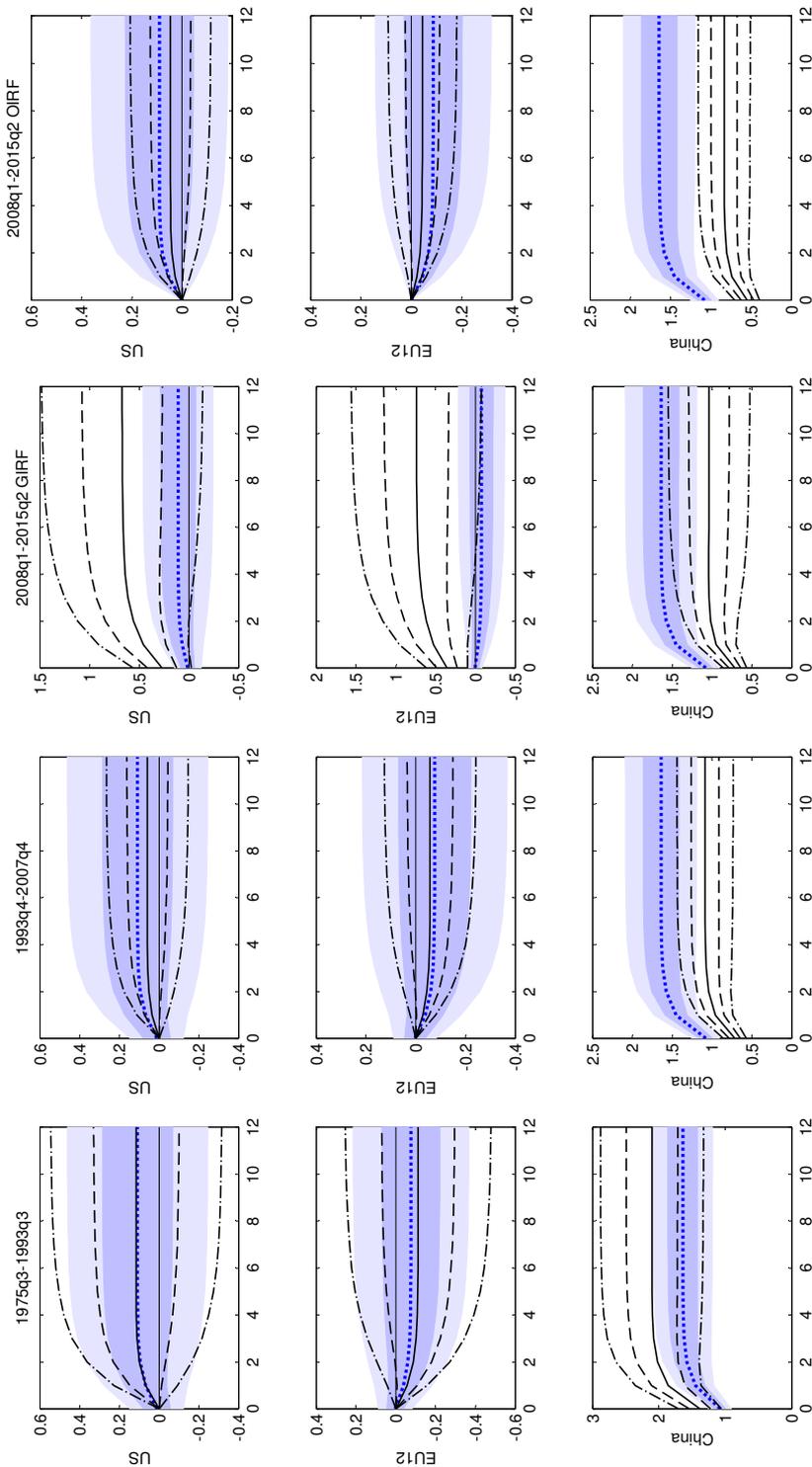Notes: See Notes to Figure 2, except that the shock is applied to EU12.

Responses by the EU12 and China to US shocks, also, of course, shift with the Great Moderation due to the relative sizes of US shocks. Notice also that in both the period before the Great Moderation and since 2007Q4, a one standard deviation US shock leads to a GIRF point estimate for the EU12 growth response of approximately 0.6 percent after about a year. For China, the point estimate response to a US shock is positive only from 2008, from when it is also significant according to the one standard error band. Since the size of the US shock does not change in the latest period, it is now more "potent" due to contemporaneous international linkages. Although the changed role played by China in the world economy is illustrated by it responding to US shocks only from 2008, the GIRFs show US shocks to have positive, and typically highly significant, effects on EU12 growth over the entire sample period.

Historical interactions between growth in the US and the Euro area are emphasized by Figure 3, which shows EU12 shocks to have effects on the US which are significant according to the one standard error bands. Of course, the 1993 volatility reduction for EU12 leads to responses declining in magnitude and the confidence intervals narrowing. The figure includes, for the most recent period, both GIRFs and OIRFs. According to the former, effects of EU12 on the US are largest in the most recent sub-period, due to both increased EU12 volatility and increased US/EU12 correlation (Table 3). However, use of the orthogonalised VAR in the final column diminishes the EU12 role for the US since 2008 relative to the use of GIRFs due to the causality assumed.

Except for the period between 1993 and 2007 when growth volatility in EU12 was relatively low, the GIRF point estimates of the own effects of EU12 shocks are relatively constant over time, albeit with wider confidence bands in the post-2007 period. Until the end of 2007, these shocks have inconsequential effects on China, but the substantial correlation of the most recent period leads to positive and significant (according to the one standard error bands) responses after that date, whether measured by GIRFs or OIRFs.

Of particular interest for our analysis, Figure 4 presents impulse responses for China shocks. Throughout the period to 2007, the linkages of China shocks with the other two economies are small in magnitude (indeed, negative for EU12) and not significant according to the one standard error bands; with a diagonal covariance matrix, these effects come only through the VAR coefficients (Panel A of Table 3). With increased contemporaneous correlations from 2008, the GIRFs show strong responses of both other economies to China shocks, with those for EU12 being significant at two standard errors for short lags. With China ordered last in the orthogonalised VAR, the OIRFs in Figure 4 contrast with the GIRFs for the international spillovers from China shocks for 2008 onwards. In particular, with no contemporaneous effects allowed to flow from China to these other economies, OIRFs show effectively no spillovers from growth in China. We consider such a finding to be implausible and hence concentrate on GIRFs.

Figure 4. Response to a Chinese shock

Notes: See Notes to Figure 2, except that the shock is applied to China.

Therefore, one key result from the GIRFs of Figure 4 is that China shocks are important for growth in both the US and the Euro area since 2008. This result is driven by the strong positive correlations between the China disturbances and those of the US and EU12 over this period (Panel C of Table 3). Although impulse responses are shown for a model which does not recognise structural breaks, it should be noted that this model has zero correlations for China shocks with those of the US and EU12 and hence the GIRFs for this model find effectively no responses of the other economies to China shocks. This again emphasizes the importance of recognising the possibility of changes in international relationships over our sample period, with breaks in the contemporary correlations of growth shocks being particularly important.

4.3 Growth volatility

Turning to growth volatility resulting from cross-country shocks, Table 4 provides forecast error variance decompositions in the form of both GFEVDs and (post-2007) OFEVDs. Results for horizons $h = 1$ and $h = 4$ are shown, with longer horizons being similar to the latter.

The results indicate that, as measured through the GFEVD, growth volatility in all three economies and across all covariance regimes is primarily associated with own shocks. This applies especially for China, where at least 99% of the growth forecast error variance at both horizons considered is associated with own shocks. Although a little lower, the corresponding figures are 90% or more for the US. The lowest percentage applies in EU12, where own shocks are associated with around 85% of volatility at a one year horizon over 1975-1983 and during the European integration phase of 1994-2007. As discussed in subsection 3.2, the use of GFEVDs implies that decompositions do not sum to 100% across shocks unless the covariance matrix is diagonal, which is the case in our model until the end of 2007. However, the positive correlations from 2008 mean that the sums of GFEVDs across shocks for each of the three economies substantially exceed this value in the final sub-period.

Although 1983Q4 represents a pure volatility break according to our test results of Table 2, the results in Table 4 indicate that this brings about a marked change in US/EU12 volatility linkages. In particular, whereas US shocks are associated with about 15% of EU12 growth forecast error volatility at $h = 4$ in the earlier sub-period, the decline in US volatility during the Great Moderation causes this to drop to only 3% over the decade from 1984, before subsequently increasing again. Until 2008, however, volatility in China is effectively isolated from these other major economies. Not surprisingly in the light of the international shock correlations after 2007, GFEVDs show shocks in each of the other countries to be important (and generally statistically significant) for growth volatility in all three economies in the final sub-period. On the other hand, the use of OFEVDs leads to weaker effects to China from both the EU12 and its own shocks in this recent period.

The final column block, labelled From Others, shows the total volatility not associated with own innovations, as defined by (7). As discussed in section 3.2, the GFEVD measure we present here excludes all effects associated with own shocks. In 1975-1983

and 1994-2007, the converse of the lower volatility percentage accounted for by own shocks in EU12 is that international growth volatility linkages to this economy from others are larger (and often more statistically significant) than for other economies and other sub-periods. However, the strong post-2007 shock correlations lead to values that are relatively small for all three economies in this period, and these are all less than one standard error in magnitude.

Bidirectional comparisons obtained using (6) are also shown in Table 4. The GFEVD results indicate that net volatility linkages from the US to EU12 are positive until the end of 2007, with the exception of the sub-period following the Great Moderation (1984-1993). Over the remaining two sub-periods US shocks are estimated to account for substantially more EU12 forecast error volatility than the EU12 does for the US, underlining the international role played by the US. Although negative, the net US-EU12 GFEVD values are very small post-2007, again reflecting the strong shock correlation during this time. Perhaps surprisingly, the GFEVD estimates indicate that the US has a negative net growth volatility linkage to China (that is, the net value is in the direction of China to the US) over all sub-periods, but the values are relatively small and typically less than one standard error in magnitude. This last comment applies also when net GFEVD volatility spillovers between EU12 and China are considered. Orthogonalisation increases net growth volatility linkages post-2008.

Of course, if a constant parameter model is employed, the changes over time discussed above that arise as a result of both volatility and correlation breaks cannot be detected. Nevertheless, the general patterns can be seen of international effects on growth volatility being most marked for EU12, with positive net volatility bilateral linkages from the US to EU12, but net linkages with China being small.

An interesting comparison between the two (generalised versus orthogonalised) FEVD approaches is provided by the average of the percentage volatility from others, as defined in (8) and shown in the bottom horizontal block of Table 4. The averages obtained from the GFEVD are relatively small (6% or less) and have not increased in the recent period, suggesting that international growth volatility linkages have remained rather muted throughout our sample period. In contrast, causal ordering due to orthogonalisation suggests a huge increase in growth volatility due to shocks originating in other economies in the period after 2007Q4, being over 20% for EU12 and around 40% for China.

Once again, however, we consider these orthogonalised results to be a consequence of the imposition of ordering restrictions that do not reflect current macroeconomic relationships. Indeed, increased contemporaneous correlation but low net growth volatility linkages (as indicated by FEVDs post-2007) are consistent with increased synchronisation of growth across these major economies.

TABLE 4. FORECAST ERROR VARIANCE DECOMPOSITION AND VOLATILITY EFFECTS

Regimes	US shock		EU12 shock		Chinese shock		FROM OTHERS	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
US								
75q3-83q4	98.86 (1.88)	98.24 (2.86)	0.84 (1.40)	1.39 (2.32)	0.30 (1.17)	0.37 (1.58)	1.14 (1.88)	1.76 (2.86)
84q1-93q3	93.96 (6.84)	90.91 (9.36)	4.45 (5.43)	7.18 (8.17)	1.59 (4.52)	1.91 (5.77)	6.04 (6.84)	9.09 (9.36)
93q4-07q4	98.51 (2.06)	97.73 (3.21)	1.04 (1.59)	1.73 (2.70)	0.44 (1.25)	0.55 (1.75)	1.49 (2.06)	2.27 (3.21)
08q1-15q4 GFEVD	96.92 (3.91)	95.31 (5.65)	23.65 (15.93)	26.31 (16.71)	21.47 (13.47)	22.78 (13.70)	3.08 (3.91)	4.69 (5.65)
08q1-15q4 OFEVD	96.92 (3.91)	95.31 (5.65)	2.94 (3.76)	4.52 (5.51)	0.14 (0.56)	0.17 (0.73)	3.08 (3.91)	4.69 (5.65)
[No breaks GFEVD]	[97.98 (2.10)]	[96.88 (2.99)]	[8.07 (4.70)]	[9.58 (5.32)]	[0.55 (1.90)]	[0.67 (2.25)]	[2.02 (2.10)]	[3.12 (2.99)]
[No breaks OFEVD]	[97.98 (2.10)]	[96.88 (2.99)]	[1.56 (1.73)]	[2.56 (2.58)]	[0.46 (1.15)]	[0.56 (1.57)]	[2.02 (2.10)]	[3.12 (2.99)]
EU12								
75q3-83q4	9.89 (6.53)	15.27 (9.20)	89.36 (6.79)	83.81 (9.45)	0.75 (1.48)	0.92 (2.20)	10.64 (6.79)	16.19 (9.45)
84q1-93q3	1.92 (1.54)	3.12 (2.49)	97.26 (2.36)	95.83 (3.64)	0.82 (1.59)	1.05 (2.41)	2.74 (2.36)	4.17 (3.64)
93q4-07q4	8.06 (5.42)	12.58 (7.94)	91.03 (5.69)	86.30 (8.21)	0.91 (1.44)	1.13 (2.11)	8.97 (5.69)	13.70 (8.21)
08q1-15q4 GFEVD	23.26 (15.72)	26.14 (16.20)	97.60 (2.70)	96.16 (4.06)	36.84 (15.34)	36.52 (15.23)	2.40 (2.70)	3.84 (4.06)
08q1-15q4 OFEVD	23.26 (15.72)	26.14 (16.20)	76.63 (15.67)	73.71 (16.12)	0.12 (0.32)	0.15 (0.45)	23.37 (15.67)	26.29 (16.12)
[No breaks GFEVD]	[13.07 (6.05)]	[16.96 (7.22)]	[94.71 (3.27)]	[91.88 (4.63)]	[0.52 (1.69)]	[0.64 (2.14)]	[5.29 (3.27)]	[8.12 (4.63)]
[No breaks OFEVD]	[13.07 (6.05)]	[16.96 (7.22)]	[86.33 (6.09)]	[82.30 (7.29)]	[0.60 (1.17)]	[0.74 (1.69)]	[13.67 (6.09)]	[17.70 (7.29)]
China								
75q3-83q4	0.11 (1.63)	0.17 (2.09)	0.00 (0.66)	0.01 (1.04)	99.89 (1.90)	99.82 (2.50)	0.11 (1.90)	0.18 (2.50)
84q1-93q3	0.02 (0.35)	0.03 (0.44)	0.00 (0.70)	0.01 (1.10)	99.98 (0.85)	99.96 (1.26)	0.02 (0.85)	0.04 (1.26)
93q4-07q4	0.07 (1.35)	0.12 (1.76)	0.00 (0.62)	0.01 (1.00)	99.93 (1.58)	99.88 (2.11)	0.07 (1.58)	0.12 (2.11)
08q1-15q4 GFEVD	16.62 (12.98)	16.47 (13.11)	37.31 (15.69)	37.15 (15.79)	99.88 (2.26)	99.79 (3.38)	0.12 (2.26)	0.21 (3.38)
08q1-15q4 OFEVD	16.62 (12.98)	16.47 (13.11)	23.65 (12.50)	23.61 (12.58)	59.73 (15.16)	59.92 (15.21)	40.27 (15.16)	40.08 (15.21)
[No breaks GFEVD]	[0.07 (1.51)]	[0.11 (1.74)]	[0.01 (1.23)]	[0.02 (1.50)]	[99.93 (1.01)]	[99.87 (1.58)]	[0.07 (1.01)]	[0.13 (1.58)]
[No breaks OFEVD]	[0.07 (1.51)]	[0.11 (1.74)]	[0.00 (1.29)]	[0.01 (1.50)]	[99.93 (1.96)]	[99.88 (2.29)]	[0.07 (1.96)]	[0.12 (2.29)]

AVERAGE

Regimes	Net US to EU12		Net US to China		Net EU12 to China		AVERAGE	
	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
75q3-83q4	9.05 (6.93)	13.89 (10.06)	-0.19 (2.00)	-0.20 (2.65)	-0.75 (1.66)	-0.91 (2.49)	3.96 (2.32)	6.04 (3.16)
84q1-93q3	-2.52 (5.85)	-4.06 (9.02)	-1.57 (4.54)	-1.88 (5.81)	-0.82 (1.76)	-1.04 (2.69)	2.93 (2.32)	4.43 (3.15)
93q4-07q4	7.01 (5.88)	10.85 (8.94)	-0.37 (1.85)	-0.43 (2.52)	-0.91 (1.58)	-1.12 (2.37)	3.51 (1.99)	5.37 (2.79)
08q1-15q4 GFEVD	-0.40 (6.24)	-0.17 (9.06)	-4.85 (4.20)	-6.31 (5.54)	0.47 (3.62)	0.62 (5.16)	1.87 (1.64)	2.91 (2.35)
08q1-15q4 OFEVD	20.32 (16.91)	21.62 (18.31)	16.48 (13.12)	16.31 (13.30)	23.54 (12.53)	23.46 (12.63)	22.24 (8.85)	23.68 (8.91)
[No breaks GFEVD]	[5.01 (4.76)]	[7.38 (6.73)]	[-0.48 (1.67)]	[-0.56 (2.24)]	[-0.51 (1.56)]	[-0.61 (2.27)]	[2.46 (1.23)]	[3.79 (1.73)]
[No breaks OFEVD]	[11.51 (6.55)]	[14.40 (8.12)]	[-0.39 (1.88)]	[-0.45 (2.31)]	[-0.60 (1.74)]	[-0.74 (2.28)]	[5.26 (2.15)]	[6.98 (2.57)]

Notes: Values are shown at horizons $h = 1, 4$. The ij^{th} FEVD is the percentage of forecast error variance of series i associated with shocks to series j, with standard errors shown in parentheses. Quantities estimated over the whole sample without allowing for structural breaks are shown in square brackets. Net bilateral growth volatility linkages are defined as the difference (to minus from), while Average values are defined in (14) in the text. Except for the regime from 2008Q1, generalized and orthogonalized values are equal.

5 Discussion and Conclusions

Although it is beyond the scope of the present paper to analyse in detail the reasons why China has become such a force in the world economy, some comments are nevertheless in order. Many recent studies, including Autor *et al.* (2016), Caporale *et al.* (2015) and Yao (2014), point to China's remarkable growth since the 1970s being led by exports. After increasing quickly from then until 2008, Yao (2014) also notes that China's share of world exports has subsequently been in line with its share of world GDP, which is compatible with our finding of a new regime of China's integration in the world economy from 2008. Caporale, Sova and Sova (2015) study the changing composition of China's trade, documenting a shift from labour-intensive to capital- and technology-intensive exports over two decades to 2012; see also Autor *et al.* (2016). The key to China's increased trade in the current century is its accession to the World Trade Organisation at the end of 2001 (Autor *et al.*, 2016, Yao, 2014). In particular, China's exports of goods rose dramatically after it joined the WTO, and (as noted in the Introduction) it's share overtook the US in 2007. This suggests our finding of greater integration for China with the US and Euro area from 2008 is associated with its role as a major trading nation.

The results of this study are in line with these analyses and emphasise the key role played by China in the world economy over the last decade or so. Using a VAR model to capture GDP growth interactions across the US, Euro area and China, our principal finding is the substantial increase in the contemporaneous correlations of cross-country disturbances at the end of 2007. Using wavelet analysis, Fidrmuc *et al.* (2014) also detect increased synchronisation of GDP growth in China with major economies from around this date. Since China's growth was effectively isolated from influences from these other major economies until 2007, this most recent sub-period is very different from earlier ones in terms of the synchronicity of international growth. Consequently, cross-country shock responses to and from China are not only more marked, but these occur more quickly then previously, with the China-Euro area growth relationship being particularly strong. Volatility linkages have also become important since 2008, with China's volatility more strongly associated with growth shocks in the other economies. Interestingly, however, net growth volatility linkages in this period are in the direction of China to the US, underlining its increased role for even the largest economy in the world.

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7 Appendix

This Appendix first illustrates how structural breaks affect both GIRFs and conventional IRFs based on an assumed contemporaneous causal ordering. Following this, the methodology we employ for structural break inference is outlined, more details of which can be found in Bataa, *et al.* (2013).

7.1 Example: Structural Breaks and Impulse Responses

An example will illustrate some features of impulse response measures in the context of structural change, focusing particularly on volatility breaks. Consider a two-variable first-order VAR process with

$$\mathbf{\Phi} = \begin{bmatrix} 0.8 & -0.4 \\ 0.1 & 0.6 \end{bmatrix}, \ \mathbf{D}_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \ \mathbf{P} = \begin{bmatrix} 1 & 0.6 \\ 0.6 & 1 \end{bmatrix} \tag{10}$$

These parameter values yield GIRFs for $h = 0, 1$ as

$$\mathbf{\Psi}_0^g(0) = \mathbf{D}_0 \mathbf{P} = \begin{bmatrix} 1 & 0.6 \\ 0.6 & 1 \end{bmatrix}, \quad \mathbf{\Psi}_0^g(1) = \mathbf{\Phi} \mathbf{D}_0 \mathbf{P} = \begin{bmatrix} 0.56 & 0.08 \\ 0.46 & 0.66 \end{bmatrix}.$$

Now consider a volatility change, such that $\sigma_{11}^{1/2} = 2$, but all other parameters remain unchanged. Denoting the new volatility matrix as $\mathbf{D}_1$, the GIRFs for $h = 0, 1$ are given by

$$\mathbf{\Psi}_1^g(0) = \mathbf{D}_1 \mathbf{P} = \begin{bmatrix} 2 & 1.2 \\ 0.6 & 1 \end{bmatrix}, \quad \mathbf{\Psi}_1^g(1) = \mathbf{\Phi} \mathbf{D}_1 \mathbf{P} = \begin{bmatrix} 1.36 & 0.56 \\ 0.56 & 0.72 \end{bmatrix}.$$

Comparing, in particular, $\mathbf{\Psi}_0^g(1)$ and $\mathbf{\Psi}_1^g(1)$, the volatility change has a substantial effect on the nature of the responses. In particular, although the magnitude of the u_{2t} shock is unchanged at 1, the contemporaneous response of y_{1t} to a u_{2t} shock is 1.2 after the change (scaled by 2 compared to the baseline, due to the volatility of u_{1t} being doubled), whereas the response of $y_{1,t+1}$ is 7 times the baseline value. The volatility change is pervasive for GIRFs, in the sense that a simple normalization to unit shocks for both u_{1t} and u_{2t}, achieved by dividing the first column of $\mathbf{\Psi}_1^g(h)$ by 2, does not remove its effects.

It should, however, be noted that a common volatility change which applies to all variables in the system has a simple scaling effect on the GIRFs. Hence, in the above example, if the standard deviations of both u_{1t} and u_{2t} double after a volatility break, then all GIRFs $\mathbf{\Psi}_1^g(h)$, $h = 0, 1, 2, \ldots$ also double.

For orthogonalized IRFs, and again considering one standard deviation shocks, the matrices of orthogonalized IRFs at horizons $h = 0, 1$ for the baseline parameters are (rounded to two decimal places)

$$\mathbf{\Psi}_0^o(0) = \mathbf{Q}_0 = \begin{bmatrix} 1 & 0 \\ 0.6 & 0.8 \end{bmatrix}, \quad \mathbf{\Psi}_0^o(1) = \mathbf{\Phi}_1 \mathbf{Q}_0 = \begin{bmatrix} 0.56 & -0.32 \\ 0.46 & 0.48 \end{bmatrix}.$$

After the volatility change in which $\sigma_{11}^{1/2}$ (alone) doubles,

$$\boldsymbol{\Psi}_1^o(0) = \mathbf{Q}_1 = \begin{bmatrix} 2 & 0 \\ 0.6 & 0.8 \end{bmatrix}, \quad \boldsymbol{\Psi}_1^o(1) = \boldsymbol{\Phi}_1 \mathbf{Q}_1 = \begin{bmatrix} 1.36 & -0.32 \\ 0.56 & 0.48 \end{bmatrix}.$$

Clearly, shocks to the first equation have different effects after the volatility change, although those of the second equation are unaffected when only σ_{11} changes. As for GIRFs, if the volatility shift is common (in the sense of all diagonal elements of $\mathbf{D}$ being scaled by the same factor), then the effect is simply to scale the IRFs by this factor.

In each case, and as discussed by Pesaran and Shin (1998), the IRFs relating to first equation shocks are identical for GIRFs as for the corresponding orthogonalized IRFs. It is noteworthy that, whereas imposition of an ordering assumption causes the orthogonalized IRFs for the final equation to be constant in the presence of volatility change, all GIRFs are affected.

7.2   Econometric Inference

As noted in the text, our analysis employs the structural break inference procedure of Bataa *et al.* (2013) that allows breaks to occur at different dates for the VAR coefficients ($\boldsymbol{\delta}$ and $\boldsymbol{\Phi}_k$) and the covariance matrix $\boldsymbol{\Sigma}$ in (1). This procedure relies on the Qu and Perron (2007) test, and the details can be found in those studies. For completeness, however, we provide a brief summary.

Prior to structural break testing, the VAR order p of (1) is selected using the Hannan-Quinn criterion over the entire sample period. The procedure then iteratively checks the stability of the VAR coefficients and the variance covariance matrix against the possibility of $m \leq M$ breaks in each, where m is unknown and the maximum number of breaks M is pre-specified alongside with the minimum fraction ε of the sample in each regime.

Break detection initially examines the VAR coefficients using heteroskedasticity robust tests, subsequently testing for covariance and coefficient breaks iteratively. In these iterations, the latest coefficient break dates are employed when testing for covariance breaks, while a feasible generalized least squares (GLS) procedure based on the covariance breaks detected is employed when testing for coefficient changes. Convergence[10] is defined in terms of the break dates in both the coefficients and the variance-covariance matrix, with the maximum number of iterations set to 40.

Turning to the identified covariance breaks, the identity $\boldsymbol{\Sigma} = \mathbf{DPD}$ implies that a detected covariance break can originate from a change in volatility or correlations, or both. Since these have different implications in terms of the nature of international business cycle linkages, identifying volatility or correlation as the source of a covariance break is of crucial importance to our analysis. Indeed, correlation changes are a key focus of interest for measuring the strength of international business cycles. Essentially, volatility

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[10]The procedure can occasionally converge to a cycle of two or more sets of break dates, rather than a unique set. In such a case, the break dates are selected using the modified BIC criterion proposed by Hall, Osborn and Sakkas (2013) for structural break inference.

is captured by squared residuals, with finite sample inference used to examine constancy of $\mathbf{D}^2$ over the specified covariance regimes, with a general to specific procedure used to eliminate any insignificant volatility breaks. Conditional on significant volatility breaks, the VAR residuals are standardized and breaks in the correlation matrix $\mathbf{P}$ are examined by applying finite sample bootstrap inference to the statistic of Jennrich (1970). The test is applied initially to each break date identified for $\mathbf{\Sigma}$. If not all breaks in $\mathbf{P}$ are significant (at five percent), the least significant is dropped and the procedure repeated until all remaining correlation breaks are significant. Note that these tests are applied to the system, so that all standard deviations or correlations are allowed to change at identified break dates.

Contemporaneous correlations provide an important measure of international business cycle linkages and hence it is relevant to test whether a specific country is contemporaneously influenced by output shocks originating in other countries. Since correlation breaks may result in these changing from zero to nonzero (or vice versa), these tests are conducted for each regime for the correlation matrix $\mathbf{P}$ as identified by the correlation break dates. The test employed is the instantaneous causality test of Lutkepohl (2005).

The initial analysis of dynamic and covariance breaks in the VAR system of (1) employs the asymptotic critical values provided by Qu and Perron (2007). However, conditional on these dates, all breaks (for both the VAR coefficients and the covariance matrix) are confirmed by a finite sample bootstrap analysis. In particular, if any individual break yields an empirical *p-value* for the system test that is greater than 5 percent, then the maximum number of breaks is reduced appropriately and the asymptotic analysis of Qu and Perron (2007) is re-applied. Although this finite sample analysis is conditional on the break dates identified at a given stage, nevertheless building it into the iterative procedure that identifies (separate) breaks in $\boldsymbol{\delta}$, $\mathbf{\Phi}_k$ and $\mathbf{\Sigma}$ provides some assurance that the asymptotic procedure does not lead to spurious break; see Bataa *et al.* (2013) for details.

Confidence intervals and standard errors for IRFs, FEVDs and linkage measures are bootstrapped and allow for breaks in the VAR coefficients, volatility and correlation, conditioning on the dates of breaks estimated from the system analysis. For this purpose, we first standardize the VAR residuals with respect to their standard deviations in each volatility regime and then i.i.d re-sample the vector of standardized residuals within each correlation regime[11]. The sampled residuals are then re-scaled by the (regime-dependent) standard deviations and used to generate artificial data series using the recursive-design bootstrap (Goncalves and Kilian, 2004).

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[11]Note that re-sampling the vector, rather than individual elements, maintains the cross-equation correlations.