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

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Abstract

In the light of China's increasing importance in the global economy, we investigate changes in the international spillovers of quarterly GDP growth rates since 1975 in a system consisting of the USA, Euro area and China. Utilizing an iterative procedure for detecting structural breaks in the VAR coefficients and covariance matrix, we find dynamics to be unchanged, but volatilities change in 1983, 1993 and 2007, with cross-country correlations markedly increasing around the time of the Great Recession. This recent period consequently shows increased international growth spillovers, measured through generalized impulse responses. Although largely isolated from the other large economies until 2007, growth in China is subsequently important for both the US and the Euro area. At the same time, the volatility of China's growth becomes more closely associated with these other large economies, especially the US in terms of net volatility spillovers.

JEL classifications: C32, E32, F43.

Keywords: International growth, structural breaks, growth spillovers, globalization

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1 Introduction

The increasing global influence of China is illustrated in Figure 1, with its share of world GDP[1] rising from a (post-1970) low of 1.6% in 1987 to 13.3% in 2014. This contrasts with overall declining shares over the period for both the US and the Euro area, the latter measured here as the so-called EU12 (that is, the twelve countries that constituted the Euro area in 2001). According to the World Bank, China has the second largest share of world GDP after the US in 2014 and overtook Japan as the world's second largest economy in 2009. China's economy is now so entwined internationally that any knocks to its system are expected to spill over to the rest of the world through trade and financial market linkages[2].

Autor, Dorn and Hanson (2016) detail the events that led to China's increased global trade and ensuing rapid growth since the 1990s. In line with the GDP pattern seen in Figure 1, China's trade expansion began in 1990s when the Government allowed the creation of less regulated Special Economic Zones that permitted foreign companies to set up factories importing inputs and exporting final outputs. China's exports growth further accelerated after it joined the World Trade Organisation in 2001, with its share of world manufacturing value added growing from 4.1% in 1991 to 24% in 2012. The benefits or otherwise of China's rapid growth to other large economies can be debated, with Acemoglu, Autor, Dorn, Hanson and Price (2016) estimating that around 2 million US jobs have been lost between 1999 and 2011 from rising Chinese import competition.

Contemporary analyses of international growth spillovers therefore need to take account of China's key role in the world economy. However, few studies to date do so, for at least two reasons. The first is widespread doubt about the quality of historical data relating to the China 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 available data and, in any case, the general pattern of China's growth is undisputed. Secondly and more importantly, econometric models need to be able to track the rise of China in the world economy, implying that conventional constant parameter specifications do not provide adequate tools for these analyses. In a vector autoregressive (VAR) framework, Cesa-Bianchi, Pesaran, Rebucci and Xu (2012) surmount this problem by employing time-varying weights derived from cross-country trade linkages to construct foreign aggregates relevant to each country. While their approach recognises China's increasing share of total trade for individual countries, the influence of (aggregate) foreign variables on each country, including China, is assumed constant over their sample period of 1979 to 2009. Consequently, this does not acknowledge China changing from essentially closed to become a key influence in the world economy. Other studies employ samples with later starting dates, presumably in the hope of avoiding issues of parameter change, such as 1988 by Arora and Vamvakidis (2011) or 1998 by Pang and Siklos (2015). The choice of such dates is, however, arbitrary.

[1] See the World Bank GDP data at: http://databank.worldbank.org/data/download/GDP.pdf and http://data.worldbank.org/indicator/NY.GDP.MKTP.CD for annual series 1959-2014.

[2] See, for example, Chris Giles in the Financial Times: http://www.ft.com/cms/s/2/30441208-b548-11e5-b147-e5e5bba42e51.html#axzz47mQFWti5.

In contrast, this paper employs formal structural break tests in a VAR model, in order to detect any changes and to date their occurrences for growth relationships across the world's major economic blocks. We focus on the US, China and the Euro area, the last of which represented by EU12[3]. As seen from Figure 1, these economies have together accounted for more than half of world GDP from the 1970s onwards. Our analysis not only examines evidence of change, but also explores its implications through impulse response functions and forecast error variance decompositions. Rather than assuming a specific causal ordering, this analysis primarily focuses on the generalized techniques of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) that allow for non-zero contemporaneous correlations. These techniques are also used by Diebold and Yilmaz (2015) in an international growth context, but those authors do not examine parameter change, which is a central feature of our study.

There is no shortage of previous empirical evidence relating to the nature of international growth or business cycle linkages and possible change over the recent so-called globalization era, including Doyle and Faust (2005), Kose, Otrok and Prasad (2012), Kalemli-Ozcan, Papaioannou and Peydro (2013) and Stock and Watson (2005). However, Kose *et al.* (2012) is the only one of these studies to include China, and even then it is one of 106 countries. China is the focus of Cesa-Bianchi *et al.* (2012), but their main interest is on the changing effects of China on Latin American economies. As already noted, although both Arora and Vamvakidis (2011) and Pang and Siklos (2015) study China in an international context, they assume constancy of relationships, the validity of which is questionable in the light of China's remarkable growth. Other recent studies, including Bagliano and Morna (2012) and Dees, Di Mauro, Pesaran and Smith (2007), also assume constancy when China is included as one of many countries in an international model. On the whole, the existing literature is of limited usefulness for analysis of the contemporary world economy, both because China is generally neglected, but also because the sample periods used for analysis typically end prior to the Great Recession. If cross-country affiliations have increased, as implicitly assumed in much of the recent general discussion covering globalization and the rise of China, then purely domestic models become less relevant for explaining economic growth even for large economies.

Although the literature on growth linkages employs a variety of econometric techniques, relatively little use has been made of formal tests for structural change at unknown dates. Having to assume neither the existence of change nor the dates at which it may have occurred is particularly attractive in a study of the emergence of China in the world economy, since it is difficult to pin down *a priori* what has changed and when.

An important econometric complication is that various countries have experienced substantial changes in output volatility over the last four decades. This is best documented for the US (see Kim and Nelson, 1999, and McConnell and Perez-Quiros, 2000, Sensier and van Dijk, 2004, among others), but has also been established for other G-7 countries (van Dijk, Osborn and Sensier, 2002; Doyle and Faust, 2005), while Del Negro and Otrok (2008) refer to business cycle volatility as converging across countries. Con-

[3]EU12 is used in preference to an aggregate for the entire Euro area becuse of the changing country composition of the latter; see also the discussion of data in the next section.

sequently, results based on an explicit or implicit assumption of constant variances may not be valid. To our knowledge, Doyle and Faust (2005) is the only previous study to employ formal tests for breaks in both the comovement and volatility of international linkages.

In common with many previous international analyses, this paper examines quarterly GDP growth within a VAR framework. Our sample period of 1975 to 2015 allows us to focus on changes in international growth affiliations post-Bretton Woods period and allows us to examine the impact of changes relevant to the international economy, including globalization and the rise of China, the establishment of the Euro area and the effect of the Great Recession. Our analysis seeks to examine changes in not only the growth rate spillovers across the world's largest economies, but also in spillovers to volatility. 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 we need to be parsimonious in the number of economies included. We study the Euro area as an aggregate, in order to recognise the international importance of this economic region, with aggregate output comparable to the US.

Following Diebold and Yilmaz (2015), we employ spillover measures based on the Generalized Impulse Response and the Generalized Forecast Error Variance Decomposition techniques of Koop *et al.* (1996) and Pesaran and Shin (1998). However, some measures we employ differ from those of Diebold and Yilmaz (2015). The generalized approach, which allows non-zero contemporaneous correlations, is preferred to the use of a VAR orthogonalized through a Cholesky decomposition because the latter would require an *a priori* assumption to be made about contemporaneous causality for international growth linkages. Against the background of the relative sizes of the three economies we study and the increasing importance of China, any such assumption may be difficult to justify. Nevertheless, we illustrate the role it would play by also presenting results when VAR is orthogonalized by assuming such causality runs in the direction of the US, Euro area and finally China.

Spillover measures are applied to the system after taking account of detected structural breaks. To that end, we use the iterative testing procedure of Bataa, Osborn, Sensier and van Dijk (2013) which not only separates coefficient and covariance breaks, but also further decomposes covariance breaks into variance and correlation breaks. The latter is important, because correlations provide information about contemporaneous spillovers, which do not necessarily change when volatility changes. While the broad approach is similar to that employed by Doyle and Faust (2005), 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. Our methodology provides an alternative to the dynamic factor models that have been widely used in the international business cycle literature (e.g. Crucini, Kose and Otrok 2011, Kose *et al.* 2012). Here time invariance of factor loadings is a standard assumption but failure to properly take account of structural breaks inflates the number of factors identified or the estimated factors are no longer consistent estimators of 'true' factors (see e.g. Breitung and Eickmeier 2011, Corradi and Swanson 2014, Chen, Dolado and Gonzalo 2014).

Our results imply that correlation breaks (rather than coefficient or volatility breaks) are the most important feature of changing international growth affiliations. More specifically, a correlation break that we detect at the end of 2007, which may be associated both with the onset of the Great Recession in the following year and the rise of China, leads to substantially increased comovement across the three economies examined. Associated with these higher correlations, both growth spillovers and spillovers to volatility increase. The role of China in this most recent period is notable, with the effect of a one standard deviation shock to China's growth having greater bilateral effects on both the US and the Euro area after one or two years than a corresponding US or Euro area shock does on China. However, the greater integration of China into the international economy also has the consequence that its volatility is more closely associated with growth in these other economies than was previously the case. In contrast, our results indicate that growth in China was largely isolated from that of other countries until the end of 2007.

The structure of this paper is as follows. Section 2 discusses data, with Section 3 then outlining our methodology for measuring spillovers; an example of the role of volatility breaks for growth spillovers and an overview of the methodology employed for econometric inference can be found in the Appendix. Our principal results on growth spillovers are presented in Section 4, while Section 5 concludes.

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 as far as possible obtained from the OECD database. As noted in the Introduction, there remain doubts about the accuracy of official GDP data for China and, in any case, quarterly data are not available over a long historical period. Indeed, data for China starts in 2011Q1 in the OECD database. For the earlier period we compute growth rates using Abeysinghe and Rajaguru's (2004) estimates of real seasonally adjusted quarterly GDP for China. Abeysinghe and Rajaguru (2004) interpolate available annual data for China 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. Despite its obvious 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.[4].

[4]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 in expressed in millions of US dollars, volume estimates, fixed PPPs and in

The growth rate in each case is measured as 100 times the first difference of the log real GDP values.

As evidenced by Figure 2, there appears to be a relatively strong association between the US and EU12 growth rates, especially since the early 1990s. The rise of China is evident in it having a substantially higher than the 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. The constancy of these features is subject to test in Section 4.

Our analysis directly employs the quarterly growth rates of Figure 2. 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 Methodology

When employing the conventional tools of impulse response functions and forecast error variance decompositions for VAR analysis, it is plausible in many contexts to impose restrictions in order to deliver orthogonalized shocks. However, such restrictions can be difficult to justify for cross-country growth spillovers between the major international economies. Consequently, we allow for correlated shocks through the generalized methodology associated with Koop, Pesaran and Potter (1996), Pesaran and Shin (1998), Diebold and Yilmaz (2012, 2014, 2015), and others. However, for comparison purposes, we also provide results for the VAR orthogonalized using contemporaneous ordering restrictions, in which the US is ordered first, followed by EU12 and then China. Subsections 3.1 and 3.2 describe the spillover measures that we employ in our analysis.

As usually applied, these spillover measures implicitly assume that the VAR parameters are constant over time. However, Doyle and Faust (2005) find evidence of breaks in both the VAR coefficients and the covariance matrix for international output growth. In principle, however, such coefficient and covariance breaks need not occur with the same frequency or at the same dates. 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 globalization may affect dynamic linkages and contemporaneous correlations from the latter part of the century (Kose *et al.* 2008). Therefore, our analysis of the next section first examines whether the coefficients and covariance matrix of our international VAR change over time using the iterative structural break testing method of Bataa *et al.* (2013) that separates coefficient and covariance breaks. This methodology is outlined in Appendix 7.2.

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

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.

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. Our results in the next section also include regime-specific confidence intervals for impulse responses and standard errors for spillover measures, the calculation of which is also discussed in Appendix 7.2.

3.1 Growth Spillovers

This subsection sets out the GIRF methodology for measuring cross-country spillovers for growth, focusing on the role of volatility changes, which is often overlooked.

3.1.1 Impulse responses

Following Canova and Dellas (1993), Doyle and Faust (2005), Bordo and Helbling (2011), 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

$$\mathbf{y}_t = \boldsymbol{\mu} + \sum_{k=1}^{\infty} \mathbf{A}_k \mathbf{u}_{t-k} \tag{2}$$

where $\boldsymbol{\mu} = E[\mathbf{y}_t]$ and the VMA coefficient matrices are determined by $\boldsymbol{\Phi}_k$, $k = 1, ..., p$.

The relatively small number of papers which examine international growth spillovers 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*; see, for example, Bagliano and Morana (2012) or Dungey and Osborn (2014). In other words, through the causal ordering assumption, such studies employ structural VAR (SVAR) models in which the shocks in each equation are contemporaneously (as well as temporally) mutually uncorrelated. The contemporaneous causality assumption defines a matrix $\mathbf{Q}$ which orthogonalizes the disturbances, such that $\mathbf{Q}\mathbf{Q}' = \boldsymbol{\Sigma}$. By convention, equations are ordered such that $\mathbf{Q}$ is lower triangular when ordering restrictions are employed, with $\mathbf{Q}$ then obtained as the Cholesky decomposition of $\boldsymbol{\Sigma}$. As discussed by Pesaran and Shin (1998), the vector of orthogonalized impulse response functions (IRFs) at horizon h for a shock applied to the j^{th} element of $\mathbf{y}_t$ is given by

$$\boldsymbol{\psi}_j^o(h) = \mathbf{A}_h \mathbf{Q} \mathbf{e}_j, \qquad h = 0, 1, ... \tag{3}$$

where $\mathbf{e}_j$ is a selection vector with unity as the j^{th} element and zeros otherwise. The magnitude of the shock in (3) is equivalent to one standard deviation in the SVAR system. We can further write the matrix of orthogonalized IRFs as

$$\mathbf{\Psi}^o(h) = \mathbf{A}_h\mathbf{Q}, \qquad h = 0, 1, ... \tag{4}$$

in which the elements of the j^{th} column give the vector of IRFs (3) for a unit shock to the j^{th} element of $\mathbf{y}_t$.

As discussed below, our VAR analysis not only considers possible changes in the coefficient matrices of (1), but also the disturbance variances and correlations embedded in $\mathbf{\Sigma}$. Therefore, write

$$\mathbf{\Sigma} = \mathbf{DPD} \tag{5}$$

where $\mathbf{P}$ is the matrix of correlations between the elements of $\mathbf{u}_t$. When obtaining orthogonalized IRFs, it is important to appreciate that $\mathbf{Q}$ is influenced by both the disturbance correlations and volatilities of the VAR, that is by both $\mathbf{P}$ and $\mathbf{D}$ of (5).

The approach of Rigobon (2003) provides an alternative methodology to the imposition of causal ordering restrictions for specifying an SVAR. Indeed, his methodology exploits heteroskedasticity, by effectively assuming that IRFs for shocks of given magnitudes in the SVAR remain unchanged in the presence of variance changes. In other words, the SVAR coefficient matrices remain constant when the shock volatility changes; see also Lanne and Lütkepohl (2008). However, we do not wish to impose any *a priori* assumptions about what changes and what remains constant when a VAR model is subject to structural breaks. Similarly the validity of cross-country contemporaneous ordering restrictions is open to debate for the large economies we study.

With the growing importance of China in the world economy and the increased extent of cross-country linkages through globalization, we wish to explore whether and how growth spillovers have changed over time. Therefore, as in Diebold and Yilmaz (2015), our main analysis builds on generalized impulse response functions (GIRFs). These were proposed by Koop, Pesran and Potter (1996) in the context of non-linear models and developed further for linear VAR models by Pesaran and Shin (1998); Diebold and Yilmaz (2012, 2014, 2015) have applied GIRFs to explore international volatility linkages for financial markets and economic growth. When analysing international linkages, Dees *et al.* (2007) identify shocks within the US through ordering restrictions, but argue that such shocks can be expected to be correlated across countries and hence employ GIRFs in that context.

Pesaran and Shin (1998) propose the use of the scaled GIRF, where the assumed shock[5] to the j^{th} element of $\mathbf{y}_t$ is equal to one innovation standard deviation in magnitude. More specifically, a shock is considered of magnitude $\sigma_{jj}^{1/2}$ and the scaled vector GIRF analogous to (3) is then given by

$$\psi_j^g(h) = \sigma_{jj}^{-0.5}\mathbf{A}_h\mathbf{\Sigma}\mathbf{e}_j, \qquad h = 0, 1, ... \tag{6}$$

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

Noting that appropriate division by $\sigma_{jj}^{0.5}$ in (6) is achieved in the matrix case by post-multiplication by $\mathbf{D}^{-1}$, the matrix of scaled GIRFs (6), namely the responses to shocks of one standard deviation in magnitude to the respective innovations, is

$$\mathbf{\Psi}^{g}(h) = \mathbf{A}_h \mathbf{DP}. \tag{7}$$

Pesaran and Shin (1998, Proposition 3.1) show that, unless $\mathbf{\Sigma}$ is diagonal, orthogonalized and normalized IRFs obtained from a Cholesky decomposition and GIRFs coincide only for a given shock applied to the first variable of the VAR.

The representation (7) is important for our analysis, because it shows the distinct roles of the VAR coefficients, disturbance standard deviations and disturbance correlations in GIRFs. Therefore, it is clear that a break in any of these three components will, in general, affect the GIRFs. The example in the Appendix provides a simple illustration.

3.1.2 Growth spillovers

A natural GIRF-based measure of the growth spillover of a one standard deviation shock applied to country j on country i at horizon h is the total response to h, namely from (6) and (7)

$$R_{ij}^{g1}(h) = \sum_{\ell=0}^{h} \mathbf{e}_i' \mathbf{A}_\ell \mathbf{DP} \mathbf{e}_j, \qquad h = 0, 1, ... \tag{8}$$

While the growth spillover as given by (8) is widely used for impulse response analyses, it is also of interest to consider a net measure which compares the strength of bi-directional spillovers. Based on shocks of one standard deviation magnitude in the originating country, we define net growth spillovers from country i to country j as

$$S_{ij}^{gsd}(h) = \sum_{\ell=0}^{h} \mathbf{e}_i' \mathbf{A}_\ell \mathbf{DP} \mathbf{e}_j - \sum_{\ell=0}^{h} \mathbf{e}_j' \mathbf{A}_\ell \mathbf{DP} \mathbf{e}_i, \qquad h = 0, 1, ... \tag{9}$$

Although the consequences of shocks of different magnitudes are compared in (9), we prefer to use this rather than a shock of common magnitude because a one standard deviation shock is of realistic magnitude for each country in relation to its contemporary experience.

In an analogous way, growth spillovers and bilateral net growth spillovers can be computed using orthogonalized impulse responses. In this latter case, of course, both such measures may be strongly influenced by the contemporaneous causality assumption embedded in the orthogonalization. Similarly, an imposition of Granger non-causality, say restricting the lagged VAR coefficients from country i in the equation of country j to be zero, will also influence these growth spillover measures, whether a conventional VAR system or an orthogonalized system is employed.

3.2 Spillovers to Volatility

Although not employed in their analysis, Pesaran and Shin (1998) define the generalized forecast error variance decomposition (GFEVD), in addition to GIRFs. Diebold and Yilmaz (2012, 2014, 2015) build on the GFEVD concept, applying the results to financial markets and, in Diebold and Yilmaz (2015), to the international growth context. However, our definition of the total spillover to volatility differs from that employed by Diebold and Yilmaz (2015).

The GFEVD is defined as percentage of the h-step ahead forecast error variance for variable i associated with innovations in variable j, namely[6]

$$\theta_{ij}^{g}(h) = 100\frac{\sigma_{jj}^{-1}\sum_{\ell=0}^{h-1}(\mathbf{e}_i'\mathbf{A}_\ell\boldsymbol{\Sigma}\mathbf{e}_j)^2}{\sum_{\ell=0}^{h-1}\mathbf{e}_i'\mathbf{A}_\ell\boldsymbol{\Sigma}\mathbf{A}_\ell'\mathbf{e}_i} \qquad h = 1, 2, ... \tag{10}$$

Although Pesaran and Shin (1998) refer to (10) in terms of the error variance of i 'accounted for' by variable j innovations, this seems to imply a causality that the generalized approach is designed to avoid. Therefore, we prefer the terminology 'associated with'. Our empirical analysis employs (10) as a measure of the spillover to growth volatility, namely from the growth rate innovation in country j to the h-step ahead volatility in country i. Using the covariance decomposition of (5), (10) can also be written as

$$\theta_{ij}^{g}(h) = 100\frac{\sum_{\ell=0}^{h-1}(\mathbf{e}_i'\mathbf{A}_\ell\mathbf{DPD}\mathbf{e}_j)^2}{\sum_{\ell=0}^{h-1}\mathbf{e}_i'\mathbf{A}_\ell\mathbf{DPD}\mathbf{A}_\ell'\mathbf{e}_i} \qquad h = 1, 2, ... \tag{11}$$

thereby clarifying 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, then the GFEVDs will also change.

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 situation for orthogonalized innovations. Because the GFEVD innovations are correlated, the 'common component' in any non-zero correlation effectively enters the sum $\sum_{j=1}^{n}\theta_{ij}^{g}(h)$ twice. The usual orthogonalized forecast error variance decomposition (FEVD), employed by (for example) Diebold and Yilmaz (2009), is

$$\theta_{ij}^{o}(h) = 100\frac{\sum_{\ell=0}^{h-1}(\mathbf{e}_i'\mathbf{A}_\ell\mathbf{Q}\mathbf{e}_j)^2}{\sum_{\ell=0}^{h-1}\mathbf{e}_i'\mathbf{A}_\ell\boldsymbol{\Sigma}\mathbf{A}_\ell'\mathbf{e}_i} \qquad h = 1, 2, ... \tag{12}$$

Here orthogonalization ensures $\sum_{j=1}^{n}\theta_{ij}^{o}(h) = 100$ for all i.

Following Diebold and Yilmaz (2012), we make pairwise comparisons using GFEVDs. In particular, using (10), the net (percentage) GFEVD spillover from j to i at horizon

[6]Pesaran and Shin (1998) define the sums in (10) with an upper limit 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, so that observations at t are 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).

h is

$$S_{ij}^{V}(h) = \theta_{ij}^{g}(h) - \theta_{ji}^{g}(h). \tag{13}$$

This compares the percentage of the forecast variation in each of i and j associated with shocks to the other innovation series[7]. Thus, for example, the net spillover to volatility can be compared between US and China 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 spillover to growth volatility in i from shocks in all other countries is

$$S_{i.}^{V}(h) = 100 - \theta_{ii}^{g}(h). \tag{14}$$

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, $S_{i.}^{V}(h)$ 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 (14), the average spillover to volatility across all n equations is

$$S_{..}^{V}(h) = \frac{1}{n}\sum_{i=1}^{n}[100 - \theta_{ii}^{g}(h)]. \tag{15}$$

It is important to recognize that, because $\sum_{j=1}^{n} \theta_{ij}^{g}(h) \neq 100$, our definition in (14) differs from that of Diebold and Yilmaz (2012, 2014, 2015), who employ

$$S_{i.}^{V,DY}(h) = \sum_{\substack{j=1 \\ j \neq i}}^{n} \theta_{ij}^{g}(h) \tag{16}$$

as the total spillover to i. Our preference is to exclude all contributions associated with country i innovations through the use of (14), whereas in (16) Diebold and Yilmaz (2012, 2014, 2015) effectively include own (country i) innovations to the extent they are correlated with those of other countries in the system. Similarly, our measure of average volatility spillover in (15) differs from the corresponding measure used by Diebold and Yilmaz (2012, equation (3)).

It is arguable that the measures we employ may understate spillovers to growth volatility, in the sense that all variation associated with innovations in i is allocated to i, and hence not treated as spillovers. In that sense, measures such as (14) and (15) provide lower bounds to volatility spillovers. On the other hand, a measure such as (16) as employed by Diebold and Yilmaz (2012, 2014, 2015), provides an upper bound. Orthogonalized counterparts to all the GFEVD spillover measures considered here can be obtained, for example replacing $\theta_{ij}^{g}(h)$ by $\theta_{ij}^{o}(h)$ as defined in (12). Such orthogonalized measures, of course, reflect the ordering assumptions employed.

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

4 Results

We now turn to the principal interest of this paper, namely changes in international growth spillovers and China's increasing influence 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 of the model in terms of growth spillovers and spillovers to volatility, are discussed in subsections 4.2 and 4.3, respectively.

4.1 Structural Breaks

The structural break test methodology we employ 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 as 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. 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. Therefore, this specification allows us to identify potential breaks associated with the Great Recession. 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 uncovered in 2009Q2 by the asymptotic *WDMax* test of Qu and Perron (2007), applied in the iterative coefficient/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 at 2009Q2 to be statistically 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. The modelling implication is that all subsequent analysis is based on a VAR with time-invariant coefficients.

However, dynamics as reflected in the VAR coefficients are only part of the analysis. In contrast to the coefficients, the procedure identifies three significant breaks in the covariance matrix. As can be seen from panel B of Table 1, the asymptotic *WDMax* and sequential tests for the covariance matrix (applied within the final iteration) point to the existence of three such breaks, dated as 1983Q4, 1993Q3 and 2007Q4, and all are highly significant according to the bootstrap tests. Using a sample ending in 2002, Doyle and Faust (2005) identify breaks in 1981Q1 and 1992Q2 in their VAR for GDP growth for the G-7 countries, which are similar dates to those of our covariance breaks. However, the methodology available to Doyle and Faust (2005) considers only coincident breaks across coefficients, variances and correlations, whereas our finding of unchanged coefficients from 1975 to 2015 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 changes in the volatilities and cross-country correlations of growth in these major economies and how such changes impact on spillovers between them.

Table 2 presents the estimated VAR coefficients (panel A) and information about changes in the covariance matrix (panel B) of the international growth VAR. The former 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. 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. If Granger causality is imposed, China therefore has no dynamic interactions with the other two economies and, further, the US is unaffected by past EU12 growth. However, this last restriction is very marginal in relation to the 5% level.

The remainder of Table 1 provides analyses the covariance breaks, with panel C showing that all three are identified as volatility breaks, but only the 2007Q4 one is associated with significant changes in the correlation matrix **P.** These findings, together with the corresponding estimated values in panels B and C of Table 2, imply that the 1983Q4 covariance break is not only a pure volatility break, but also that the change within our VAR is effectively confined to the US, where volatility (measured by the VAR standard deviation) declines by nearly 60 percent. This is a manifestation in our data of the so-called Great Moderation in the US (see e.g. McConnell and Perez-Quiros, 2000, Sensier and van Dijk, 2004 and Stock and Watson, 2005). The residual standard deviations (Table 2, panel B) also indicate that the 1993 break is associated with volatility reductions for China and the EU12 (but not the US). Indeed, after a turbulent period in European exhange rate markets, the Maastricht Treaty agreeing the conditions for the establishment of the euro currency came into force on 1 November 1993. Our results imply that the subsequent move towards greater European integration (see, for example, Perez, Osborn and Artis 2006) brought 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.

In contrast to the two earlier covariance breaks, the break at the end of 2007 is significant according to bootstrap tests for both variances and correlations (Table 1). Although dated here a little before the collapse of Lehman Brothers in September 2008, this break may be associated with the beginning of the Great Recession, while volatility increases in the US, it more than doubles for the EU12 (Table 2, Panel B). For China, however, volatility continues to decline. Nevertheless, arguably the most important change at this time is the increased contemporaneous correlations seen in Panel C of Table 2. For the period to the end of 2007, the contemporaneous correlations are small and, indeed, the correlations for each country in relation to the other two are jointly insignificant. 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. Thereafter, the correlations of the US with both the EU12 and China are about 0.4, with that between EU12 and China higher at 0.6. Perhaps surprisingly, the zero correlation test finds the US not to be significantly contemporaneously jointly linked with the other economies at 5 percent in this later period, but the relatively small number of observations implies the test will have low power. Nevertheless, tests for both EU12 and China are highly significant.

Although the discussion above associates the 2007Q4 covariance break with the onset of the Great Recession, China's emergence into the international economy is largely a distinct phenomenon. Nevertheless, the importance of China in the global context has been underlined by the relatively weak growth seen in the US and particularly in Euro area economies since 2008. Bearing in mind the small dynamic spillovers to and from China, the period since the Great Recession is therefore not only one in which China is seen to have important interactions with the other two major economies, but the cross-country effects of growth 'surprises' are seen quickly, namely largely within a quarter. Therefore, the 2007 break relates not only to the Great Recession, but also the emergence of China in the international economy.

For reference, Table 2 also provides information about the volatilities and correlations implied by the VAR for an analysis ignoring covariance breaks. Chinese current growth volatility in that case would be estimated as twice that implied by the model with breaks (that is, from 2008). It is clear from Panel C, in particular, that the correlations primarily reflect the period until 2007 and consequently evidence only low contemporaneous links. 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.

4.2 Impulse Responses

As explained in Section 3, GIRFs change with any break in the parameters of a VAR model, even if the break applies only to volatility and a shock of constant magnitude is considered. Based on the identified breaks of subsection 4.1, and with unrestricted VAR coefficients (that is, without the imposition of Granger causality), panel (a) of Figures 3 to 5 shows growth spillovers in the form of cumulated GIRFs for a one standard deviation shock applied to each of the three countries. When comparing the GIRFs for the effect of a particular shock over time, note that the vertical scale sometimes changes. For each graph, one and two standard deviation confidence intervals are included around each estimated response, 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, with that estimated response shown as a blue dotted line and the corresponding confidence intervals by blue shading. Panel (b) of each figure provides corresponding information based on orthogonalized IRFs, which recognize the same structural breaks, but impose a contemporaneous causal ordering of the US, followed by EU12 and then China.

Consider, first, GIRFs for US shocks in panel (a) of Figure 3. The pattern and significance of own US responses are relatively unchanged over time, except that volatility changes causes the magnitude of the immediate response ($h = 0$) to shift and the width of the confidence bands also reflect this shift. Effects on the EU12, however, do alter. Notice, in particular, that in both the period before the Great Moderation and that since the Great Recession, a one standard deviation US shock leads to a GIRF for EU12 growth of approximately 0.7 percent after approximately a year. Given the size of a US shock measured by its standard deviation in the latest period is almost a half of that prior to the Great Moderation (Table 2), the current shock appears to be more "potent". Moreover, the immediate response in the latest period (at 0.24 percent) is more than twice that in the initial period (0.09 percent). This increased contemporaneous correlation is the key factor in this faster response. Although more subtle, the volatility changes of 1983 and 1993 also play a role in the GIRF patterns. For example, US shocks have similar effects on EU12 growth after one or two years over 1984-1993 and 1993-2007, but the impact response in the earlier sub-period is more than twice that in the later one. Nevertheless, the GIRFs show US shocks to have positive, and typically highly significant effects on EU12 growth over the entire sample period.

In contrast to that just discussed, US shocks have relatively small effects on China, with these approaching statistical significance according to the one standard deviation confidence bands only in the period since the Great Recession. Therefore, despite the increased correlation in this period, GIRFs imply US shocks have a relatively modest impact on China even after 2008, with this contrasting to the stronger and significant effects of these shocks on EU12. As discussed by Pesaran and Shin (1998), since the US is ordered first in the orthogonalized VAR, the corresponding GIRFs and orthogonalized IRFs, the latter in panel (b) of Figure 3, are identical where US shocks are considered.

Turning to EU12 shocks (Figure 4), GIRFs show effects on the US to be positive and typically significant even according to the two standard error bands in panel (a). Nevertheless, once again volatility (as well as correlation) breaks cause changes in the patterns of responses. For example, although the immediate effect of a one standard deviation EU12 shock on the US is around 0.08 percent throughout 1984 to 2007, after one year ($h = 4$), the cumulated GIRF effect on the US is 0.40 percent during the Great Moderation period of 1984 to 1993, but only 0.25 percent from 1994 to 2007. Effects are largest in the most recent sub-period, due to both increased volatility and increased US/EU12 correlation (Table 2). Orthogonalized IRFs in panel (b) imply, of course, that the EU12 plays a smaller role for the US than the GIRFs, with this especially so since 2008.

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) effects after that date.

Figure 5 then provides GIRFs for China shocks. Although the estimated coefficient for China in the US equation and the contemporaneous US/China correlation are relatively small, both are positive and the GIRFs for the effect of a China shock on the US in panel (a) are close to the one standard error band through the period to 2007. This provides an interesting contrast to the effect of a US shock on China in Figure 3, panel (a), with the difference due particularly to the negative (albeit numerically small) VAR coefficient of US in the equation for China growth. With increased contemporaneous correlations from 2008, the significance is enhanced of China shocks for the US, being borderline significant at two standard deviations at short lags. It is also seen that China shocks are estimated to have negative GIRF effects on EU12 until the end of 2007, sometimes approaching (one standard error) significance, but positive and much more statistically significant from 2008. Despite the different historical relationships of the US to the EU12 and China, GIRFs show that US shocks are estimated to have quantitatively very similar effects on these two major economies. It is clear in Panel (b) that the causality assumption embedded in the orthogonalization adopted is crucial, with China effects on both the US and EU12 remaining small and statistically insignificant in this case. According to the VAR coefficients (panel A of Table 2), the dynamics of China's growth are largely self-generated, with both the GIRFs and orthogonalized IRFs quickly stabilizing for the own effects of shocks in Figure 5.

To emphasize one key result, the GIRFs of Figure 5 show China shocks to be important for growth in both the US and the Euro area since 2008. The primary reason for this is the positive correlations existing between the China disturbances and those of the US and EU12 from 2008Q1, equal to 0.34 and 0.59 respectively (see Panel C of Table 2).

In order to compare the strengths of bilateral spillovers in terms of impulse responses, Table 3 shows the net growth spillovers for one standard deviation shock, defined in (8) for GIRFs (panel A) and employing an analogous definition when orthogonalized impulse responses are employed (panel b). In common with the impulse response functions shown in Figures 3 to 5, the results of Table 3 are for unrestricted VAR coefficients, while Appendix Table A.2 provides corresponding results when Granger causality is imposed using a 5% significance threshold. In all cases, bootstrap standard errors are provided as a measure of the significance of the estimated bilateral spillovers.

The GIRF net growth spillovers in panel A are generally insignificant at conventional levels. Nevertheless, it is, perhaps, surprising that the contemporaneous net spillover from the US to EU12 in the initial regime (1975 to 1983) is negative and close to significance using a two standard error band, implying that a one standard deviation EU12 shock has a larger effect on the US than *vice versa*. The reason for this can be seen in the US shock standard deviation being more than twice that for EU12 in this period (Table 2); see also the example of Section 3.1. However, it may be noted that the imposition of Granger causality changes the estimated net spillover patterns, with net spillovers from the US to EU12 typically significant for a VAR with unrestricted coefficients (Appendix Table A.1). Net GIRF spillovers to China from either the US or EU12 to China are generally small in relation to their standard errors over all subperiods in Table 3. However, the increased role of China for the US is indicated by the negative US to China spillover (that is, a net spillover from China to the US) since

2008 in panel A. Although not significant at a conventional two standard errors, the net spillovers at horizons of four and eight quarters exceed one bootstrap standard error. Similarly, a net spillover from China to EU12 equal of approximately one bootstrap standard error also applies from 2008. The use of orthogonalized impulse responses, of course, strengthens the estimated net effects from the US to EU12, while both the US and EU12 then have stronger estimated net effects on China in the most recent regime from 2008. Imposing both contemporaneous ordering and Granger causality implies that the US has a positive and significant (at two standard errors) effect on China from 2008 in panel B of Appendix Table A.1, but we consider this to be a consequence of the assumptions imposed, particularly causality with China ordered last, rather than economic reality.

4.3 Spillovers to Volatility

Turning to volatility spillovers, Table 4 provides forecast error variance decompositions for the (unrestricted coefficient) VAR of Table 2 in the form of both GFEVDs and orthogonalized FEVDs in panels A and B respectively; corresponding results with Granger causality restrictions imposed are shown in Appendix Table A.2. Results for horizons $h = 1$ and $h = 4$ are shown, with longer horizons (not shown) being similar to the latter.

The results of panel A indicate that, as measured through the GFEVD, growth volatility in all three countries 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, 90% or more of such volatility for the US is associated with own shocks. The lowest percentage applies in EU12, where own shocks are associated with 83%-87% of volatility at a one year horizon over 1975-1983 and during the European integration phase of 1994-2007. Note again that, as discussed in subsection 3.2, the use of GFEVDs implies that decompositions do not sum to 100% across shocks. In particular, the positive correlations of the post-Great Recession period means that the sums can substantially exceed this value.

Although 1983Q4 represents a pure volatility break according to our structural break test results (Table 1), the GFEVD results of Table 4 Panel A indicate that this brings about a marked change in US/EU12 volatility spillovers. In particular, whereas US shocks are associated with almost a quarter 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 7% over the decade from 1984, before subsequently increasing again. Not surprisingly in the light of the increased international shock correlations after 2007, GFEVDs show shocks in each of the other countries to be important (and generally statistically significant at two standard deviations) for volatility in all three countries in the final sub-period. Until 2007, however, volatility in China is largely isolated from these other major economies.

The final column block of panel A, labelled From Others, shows total volatility not associated with own innovations, as defined by (14). 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 volatility spillovers to this economy are larger (and more statistically significant) than for other economies and other sub-periods. However, the strong post-2007 correlations lead to relatively small "pure" spillover effects over the final sub-period for all three countries, and these are all less than one standard deviation in magnitude.

Bidirectional comparisons obtained using (13) are also shown in Table 4. The GFEVD results indicate that net spillovers are generally positive from the US to EU12, with the exception of the sub-period following the Great Moderation (1984-1993). However, the values are very small post-2007, again reflecting the strong shock correlation during this time. 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. Surprisingly, the estimates indicate that the US has a negative net spillover growth volatility to China (that is, the net spillover is in the direction of China to the US) over all sub-periods, but the values are relatively small and always less than one standard deviation in magnitude. Similar comments apply also when net volatility spillovers between EU12 and China are considered.

Of course, if a constant parameter model is employed, the GFEVD changes 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 spillovers to growth volatility being most marked in EU12 and least in China, with positive net volatility bilateral spillovers from the US to EU12 but net volatility spillovers with China being small.

For comparison, panel B of Table 4 shows a corresponding volatility analysis conducted using an orthogonalized VAR. Since the estimated cross-country correlations are relatively small until 2007, the results are broadly similar to those based on GFEVDs for the three initial sub-periods. However, with the strong post-GFC shock correlations, EU12 and China shocks here play a much smaller role for the US, and similarly China shocks play a smaller role for EU12, than for the GFEVDs in panel A. An interesting comparison between the two approaches is provided by the averages of the spillovers from others, as defined in (15) and shown in the bottom horizontal block of each panel. The average GFEVD volatility spillover from others evidences is relatively small at 6% or less, with no increase in the post-GFC period, suggesting that the volatility spillovers associated with idiosyncratic shocks have remained rather muted during our sample period. In contrast, causal ordering due to orthogonalization suggests a huge increase in volatility spillovers from others, to an average of over 20% from 2008 and with spillovers to China around 40%.

Once again, however, we consider these orthogonalized 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 volatility dynamic spillovers (as indicated by FEVDs in panel A) are consistent with increased synchronization of growth across these major economies.

5 Conclusions

Over recent decades, China has become a key player in the international economy. However, studies of macroeconomic linkages frequently ignore China and concentrate on the G-7 countries. As the second largest economy in the world, and according to the World Trade Organisation the world's top exporting country since 2009[8], it is a very serious omission when international macroeconomic models ignore the role of China. However, models that employ constant parameter specifications in relation to China need to be careful that these adequately capture the implications of change arising from its spectacular growth since the mid-1990s.

The present paper employs a VAR model to capture the quarterly growth interactions between the world's three largest economic blocks, the US, the Euro area (represented by EU12) and China from 1975Q2 to 2015Q1. The issue of change is confronted directly through the application of formal structural break tests that separately consider dynamics (the VAR coefficients) from volatility and interrelationships represented by the covariance matrix. Although no change is detected in dynamics, three breaks are detected in volatility, which can be associated with the beginning of the Great Moderation (1983Q4), the move towards increased European integration (1993Q3) and the onset of the Great Recession (2007Q4). However, only the last of these has seen a change in the contemporaneous correlations of the VAR disturbances. Although China was largely disjoint from these other economies until 2007, it has subsequently been closely associated with both, especially with the Euro area.

To avoid placing undue weight on *a priori* assumptions about the direction of contemporaneous cross-country causality of growth, our analysis of the implications of shocks relies primarily on the concepts of generalized impulse responses and generalized forecast error variance decompositions, originally proposed by Koop *et al.* (1996) and Pesaran and Shin (1998), and recently applied in a cross-country growth context by Diebold and Yilmaz (2015). However, our measures differ in some respects from the latter. In summary, and due primarily to the increased cross-country correlations that apply from 2008, spillovers between these countries are higher in the most recent period than seen over the previous three decades.

Of particular interest is the increased influence of shocks in China on both the US and the Euro area in this latest regime. One measure of this is given by what we call net growth spillovers, which show the net bilateral effects of a one standard deviation shock contemporaneously applying in both economies. The net effects between the US and EU12 are small and statistically insignificant from 1984 onwards, so that the effects of a US shock on EU12 is effectively equal to that of an EU12 shock on the US. However, at horizons of one and two years in the most recent period from 2008, China shocks are estimated to have larger effects on each of the US and EU12 than *vice versa.* Although statistical significance is difficult to achieve over a relatively short time interval, the net effects for China on the US exceed one standard error, while those on EU12 are close to this threshold.

[8]See *World Trade Statistics*, 2015, p.25.

In terms of volatility, as measured through GFEVDs, the Euro area is more susceptible to importing volatility from the other two economies than is the US or China. In terms of net volatility spillovers (measuring the difference between the respective bilateral GFEVD effects for each economy), US spillovers to EU12 are important in the initial period to 1983 and subsequently from late 1993 to the end of 2007. There is, however, some evidence that net volatility spillovers apply from the US to China over the period since the Great Recession, indicating that (at least in terms of volatility) China itself may have become more affected by external economic events in the recent period which has been marked not only by a turbulent environment, but also by the continued rising importance of China in the world economy.

This paper set out to examine the nature of any changes in growth spillovers across the three major economies of the world, focusing particularly on the implications of the rise in China as a key player in the international economy. In summary, our results point to growth in China being important for the Euro area and especially the US in the post-Great Recession period, while at the same time the volatility of China growth is now more strongly influenced by that of the other major economies. Although many recent studies of international growth and globalization ignore the role of China, we believe its role is crucial for such analyses.

6 References

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TABLE 1. VAR BREAK TEST RESULTS

Statistic	Value	Asymptotic critical value	Break date(s)	Bootstrap p-value
		Panel A. VAR Coefficients		
$WDMax$	149.59*	34.13		
$Seq2/1$	22.82	32.67	2009Q2	50.58
		Panel 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
		Panel C. Volatility		
			1983Q4	0.88
			1993Q3	0.00
			2007Q4	1.88
		Panel D. Correlations		
			1983Q4	12.48
			1993Q3	60.58
			2007Q4	0.62

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 next to 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. Panels C and D report respectively the significance of structural break tests for the diagonal elements of the covariance matrix of the VAR and for the off-diagonal elements of the correlation matrix, showing bootstrap p-values (expressed as percentages) for the test of no change over adjacent covariance matrix sub-samples inferred from Panel B, with the result placed against the estimated date of the break.

TABLE 2. VAR ESTIMATES

	Equation		
	US	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)
Panel B. Volatilities (Standard Deviations)			
1975Q3-1983Q4	1.17	0.52	1.25
1984Q1-1993Q3	0.48	0.63	1.45
1993Q4-2007Q4	0.50	0.27	0.79
2008Q1-2015Q2	0.67	0.58	0.50
No break model	0.73	0.50	1.07
Panel C. Correlations			
1975Q3-2007Q4			
EU12	0.142		
China	0.071	-0.060	
Zero correlation test p-value	17.8	19.6	51.9
2008Q1-2015Q2			
EU12	0.412		
China	0.339	0.585	
Zero correlation test p-value	6.6	0.3	0.5
No break model			
EU12	0.221		
China	0.145	0.086	
Zero correlation test p-value	0.6	1.6	14.9

Notes: Panel A assess the significance of VAR coefficients. Columns represent equations. The first value in each cell reports the estimated coefficient, the value in parentheses are bootstrap p-values (expressed as percentages) for the null hypothesis that the coefficient is 0. * indicates significant at 5%. Sub-sample residual standard deviations are reported in panel B and sub-sample contemporaneous residual correlations in panel C. The latter panel also reports the bootstrap p-value for a test of the joint hypothesis test that all contemporaneous correlations relating to that country are 0. For both panels B and C we report relevant quantities ignoring the breaks. Results in panels B and C are obtained from a VAR in which the restrictions implied by the results of persistence and dynamic interaction (Granger causality) tests (at 5% significance) are imposed.

TABLE 3. NET GROWTH SPILLOVERS

	US to EU12			US to China			EU12 to China		
Regime	$h = 0$	$h = 4$	$h = 8$	$h = 0$	$h = 4$	$h = 8$	$h = 0$	$h = 4$	$h = 8$
Panel A. GIRF spillovers									
75Q3-83Q4	-0.11 (0.06)	0.11 (0.22)	0.14 (0.25)	0.01 (0.03)	-0.19 (0.33)	-0.21 (0.38)	-0.05 (0.06)	-0.05 (0.26)	-0.05 (0.31)
84Q1-93Q3	0.02 (0.02)	-0.02 (0.18)	-0.03 (0.21)	0.07 (0.09)	-0.04 (0.25)	-0.04 (0.28)	-0.06 (0.07)	-0.01 (0.30)	-0.02 (0.35)
93Q4-07Q4	-0.04 (0.02)	0.04 (0.10)	0.05 (0.12)	0.02 (0.03)	-0.07 (0.17)	-0.08 (0.19)	-0.04 (0.04)	-0.02 (0.15)	-0.03 (0.18)
08Q1-15Q2	-0.03 (0.06)	-0.02 (0.17)	-0.01 (0.20)	-0.07 (0.08)	-0.39 (0.27)	-0.42 (0.33)	-0.06 (0.07)	-0.32 (0.32)	-0.36 (0.39)
[No break model]	[-0.05 (0.03)]	[0.02 (0.14)]	[0.03 (0.16)]	[0.01 (0.03)]	[-0.16 (0.22)]	[-0.16 (0.25)]	[0.00 (0.05)]	[0.05 (0.22)]	[0.04 (0.25)]
Panel B. Orthogonalized IRF spillovers, unrestricted VAR coefficients									
75Q3-83Q4	0.09 (0.05)	0.41 (0.25)	0.44 (0.29)	0.09 (0.12)	-0.07 (0.38)	-0.09 (0.42)	-0.10 (0.10)	-0.08 (0.28)	-0.09 (0.32)
84Q1-93Q3	0.10 (0.05)	0.10 (0.21)	0.10 (0.24)	0.11 (0.13)	-0.00 (0.28)	-0.01 (0.31)	-0.12 (0.12)	-0.10 (0.33)	-0.10 (0.37)
93Q4-07Q4	0.04 (0.02)	0.17 (0.12)	0.18 (0.14)	0.06 (0.07)	-0.02 (0.19)	-0.03 (0.21)	-0.07 (0.06)	-0.05 (0.16)	-0.05 (0.19)
08Q1-15Q2	0.24 (0.15)	0.42 (0.34)	0.44 (0.38)	0.20 (0.11)	0.20 (0.27)	0.20 (0.30)	0.24 (0.11)	0.36 (0.26)	0.36 (0.29)
[No break model]	[0.11 (0.05)]	[0.28 (0.17)]	[0.29 (0.19)]	[0.02 (0.10)]	[-0.14 (0.27)]	[-0.15 (0.29)]	[0.00 (0.09)]	[0.07 (0.24)]	[0.06 (0.26)]

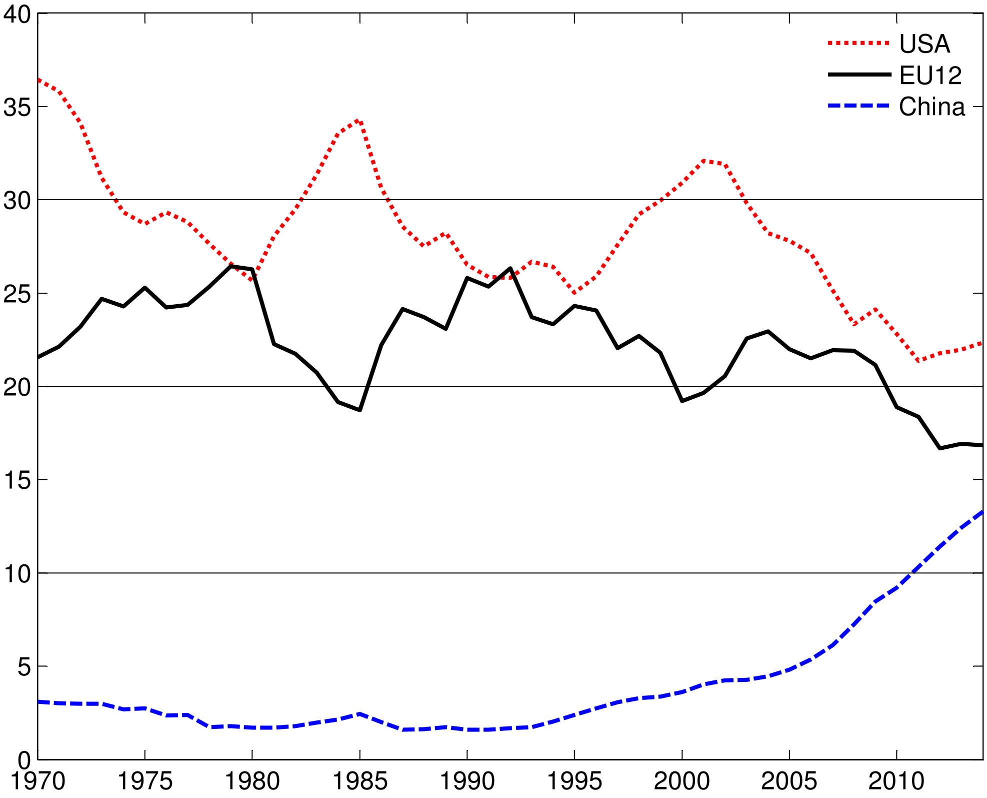
Notes: Net growth spillovers over three horizons (instantaneous, after 1 year, and after 2 years) are defined by equation (15) in the text and refer to the net effect of a one standard deviation shock applying in both economies. Values in parentheses are bootstrap standard errors.

TABLE 4. VOLATILITY SPILLOVERS

	Regimes	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
		Panel A. Generalized forecast error variance decompositions and net volatility spillovers							
		US shock		EU12 shock		Chinese shock		**FROM OTHERS**	
US	75q3-83q4	99.15 (1.37)	98.68 (2.14)	4.06 (3.75)	4.74 (4.33)	0.93 (2.14)	1.00 (2.37)	0.85 (1.37)	1.32 (2.14)
	84q1-93q3	93.52 (6.93)	90.28 (9.39)	9.40 (7.52)	12.92 (10.38)	2.40 (5.16)	2.65 (6.35)	6.48 (6.93)	9.72 (9.39)
	93q4-07q4	98.66 (2.15)	97.97 (3.17)	4.41 (3.96)	5.28 (4.76)	1.24 (2.82)	1.37 (3.35)	1.34 (2.15)	2.03 (3.17)
	08q1-15q2	97.22 (3.50)	95.69 (5.13)	23.27 (15.70)	25.84 (16.46)	20.84 (13.21)	22.01 (13.43)	2.78 (3.50)	4.31 (5.13)
	[No break model]	[97.98 (2.21)]	[96.88 (3.12)]	[8.07 (4.72)]	[9.58 (5.38)]	[0.55 (1.89)]	[0.67 (2.25)]	[2.02 (2.21)]	[3.12 (3.12)]
EU12	75q3-83q4	16.81 (8.45)	23.33 (10.83)	88.96 (6.84)	83.44 (9.34)	1.03 (1.94)	1.06 (2.41)	11.04 (6.84)	16.56 (9.34)
	84q1-93q3	5.41 (4.00)	6.81 (4.72)	97.94 (1.97)	96.89 (3.04)	1.48 (2.31)	1.72 (2.97)	2.06 (1.97)	3.11 (3.04)
	93q4-07q4	13.39 (7.16)	18.57 (9.32)	91.49 (5.47)	87.14 (7.80)	1.50 (2.54)	1.65 (3.23)	8.51 (5.47)	12.86 (7.80)
	08q1-15q2	23.45 (15.48)	26.38 (15.93)	97.60 (2.57)	96.17 (3.95)	37.31 (15.29)	37.12 (15.14)	2.40 (2.57)	3.83 (3.95)
	[No break model]	[13.07 (6.07)]	[16.96 (7.29)]	[94.71 (3.28)]	[91.88 (4.67)]	[0.52 (1.65)]	[0.64 (2.10)]	[5.29 (3.28)]	[8.12 (4.67)]
China	75q3-83q4	0.52 (2.38)	0.56 (2.82)	0.53 (1.41)	0.56 (1.68)	99.86 (1.99)	99.77 (2.73)	0.14 (1.99)	0.23 (2.73)
	84q1-93q3	0.51 (1.68)	0.51 (1.69)	0.51 (1.42)	0.53 (1.69)	99.98 (0.76)	99.96 (1.24)	0.02 (0.76)	0.04 (1.24)
	93q4-07q4	0.50 (1.88)	0.51 (2.05)	0.52 (1.42)	0.54 (1.59)	99.93 (1.00)	99.89 (1.44)	0.07 (1.00)	0.11 (1.44)
	08q1-15q2	16.36 (12.50)	16.21 (12.72)	37.11 (15.14)	36.89 (15.09)	99.75 (4.21)	99.56 (6.14)	0.25 (4.21)	0.44 (6.14)
	[No break model]	[0.07 (1.43)]	[0.11 (1.67)]	[0.01 (1.27)]	[0.02 (1.59)]	[99.93 (1.06)]	[99.87 (1.65)]	[0.07 (1.06)]	[0.13 (1.65)]
		Net US to EU12		Net US to China		Net EU12 to China		**AVERAGE**	
	75q3-83q4	12.75 (7.86)	18.59 (10.80)	-0.41 (2.15)	-0.44 (2.88)	-0.50 (1.70)	-0.50 (2.52)	4.01 (2.30)	6.04 (3.10)
	84q1-93q3	-3.98 (6.99)	-6.11 (10.40)	-1.88 (4.81)	-2.14 (6.12)	-0.97 (1.96)	-1.19 (2.92)	2.85 (2.32)	4.29 (3.14)
	93q4-07q4	8.99 (6.36)	13.29 (9.23)	-0.74 (2.22)	-0.86 (2.99)	-0.99 (2.20)	-1.11 (3.12)	3.31 (1.86)	5.00 (2.62)
	08q1-15q2	0.18 (5.80)	0.54 (8.44)	-4.48 (4.67)	-5.80 (6.26)	-0.20 (4.71)	-0.24 (6.60)	1.81 (2.03)	2.86 (2.98)
	[No break model]	[5.01 (4.75)]	[7.38 (6.73)]	[-0.48 (1.69)]	[-0.56 (2.27)]	[-0.51 (1.58)]	[-0.61 (2.31)]	[2.46 (1.23)]	[3.79 (1.73)]
		Panel B. Orthogonalized forecast error variance decompositions and net volatility spillovers							
		US shock		EU12 shock		Chinese shock		**FROM OTHERS**	
US	75q3-83q4	99.15 (1.37)	98.68 (2.14)	0.61 (1.06)	1.03 (1.80)	0.24 (0.87)	0.30 (1.21)	0.85 (1.37)	1.32 (2.14)
	84q1-93q3	93.52 (6.93)	90.28 (9.39)	4.70 (5.83)	7.61 (8.63)	1.78 (4.63)	2.11 (5.91)	6.48 (6.93)	9.72 (9.39)
	93q4-07q4	98.66 (2.15)	97.97 (3.17)	0.84 (1.42)	1.41 (2.37)	0.50 (1.73)	0.62 (2.36)	1.34 (2.15)	2.03 (3.17)
	08q1-15q2	97.22 (3.50)	95.69 (5.13)	2.71 (3.44)	4.23 (5.07)	0.07 (0.26)	0.08 (0.34)	2.78 (3.50)	4.31 (5.13)
	[No break model]	[97.98 (2.21)]	[96.88 (3.12)]	[1.56 (1.77)]	[2.56 (2.63)]	[0.46 (1.23)]	[0.56 (1.65)]	[2.02 (2.21)]	[3.12 (3.12)]
EU12	75q3-83q4	16.81 (8.45)	23.33 (10.83)	82.51 (8.54)	75.85 (10.87)	0.68 (1.32)	0.82 (1.88)	17.49 (8.54)	24.15 (10.87)
	84q1-93q3	5.41 (4.00)	6.81 (4.72)	93.83 (4.20)	92.22 (5.11)	0.75 (1.49)	0.96 (2.24)	6.17 (4.20)	7.78 (5.11)
	93q4-07q4	13.39 (7.16)	18.57 (9.32)	85.55 (7.37)	80.13 (9.53)	1.06 (1.91)	1.29 (2.74)	14.45 (7.37)	19.87 (9.53)
	08q1-15q2	23.45 (15.48)	26.38 (15.93)	76.50 (15.45)	73.56 (15.89)	0.05 (0.15)	0.07 (0.23)	23.50 (15.45)	26.44 (15.89)
	[No break model]	[13.07 (6.07)]	[16.96 (7.29)]	[86.33 (6.19)]	[82.30 (7.44)]	[0.60 (1.17)]	[0.74 (1.67)]	[13.67 (6.19)]	[17.70 (7.44)]
China	75q3-83q4	0.52 (2.38)	0.56 (2.82)	0.70 (1.61)	0.72 (1.82)	98.78 (3.02)	98.72 (3.50)	1.22 (3.02)	1.28 (3.50)
	84q1-93q3	0.51 (1.68)	0.51 (1.69)	0.70 (1.58)	0.72 (1.81)	98.78 (2.42)	98.77 (2.60)	1.22 (2.42)	1.23 (2.60)
	93q4-07q4	0.50 (1.88)	0.51 (2.05)	0.70 (1.61)	0.71 (1.75)	98.80 (2.66)	98.77 (2.88)	1.20 (2.66)	1.23 (2.88)
	08q1-15q2	16.36 (12.50)	16.21 (12.72)	23.66 (12.27)	23.59 (12.37)	59.97 (14.06)	60.20 (13.89)	40.03 (14.06)	39.80 (13.89)
	[No break model]	[0.07 (1.43)]	[0.11 (1.67)]	[0.00 (1.34)]	[0.01 (1.59)]	[99.93 (1.94)]	[99.88 (2.32)]	[0.07 (1.94)]	[0.12 (2.32)]
		Net US to EU12		Net US to China		Net EU12 to China		**AVERAGE**	
	75q3-83q4	16.20 (8.74)	22.30 (11.46)	0.28 (2.59)	0.26 (3.15)	0.02 (2.14)	-0.10 (2.73)	6.52 (2.87)	8.92 (3.59)
	84q1-93q3	0.72 (7.32)	-0.79 (10.35)	-1.26 (4.92)	-1.60 (6.18)	-0.05 (2.19)	-0.24 (2.94)	4.62 (2.61)	6.24 (3.38)
	93q4-07q4	12.56 (7.47)	17.16 (10.06)	0.00 (2.54)	-0.11 (3.13)	-0.36 (2.51)	-0.58 (3.28)	5.66 (2.54)	7.71 (3.23)
	08q1-15q2	20.74 (16.51)	22.15 (17.75)	16.30 (12.53)	16.14 (12.77)	23.61 (12.25)	23.52 (12.36)	22.10 (8.52)	23.52 (8.53)
	[No break model]	[11.51 (6.53)]	[14.40 (8.13)]	[-0.39 (1.86)]	[-0.45 (2.33)]	[-0.60 (1.83)]	[-0.74 (2.37)]	[5.26 (2.18)]	[6.98 (2.62)]

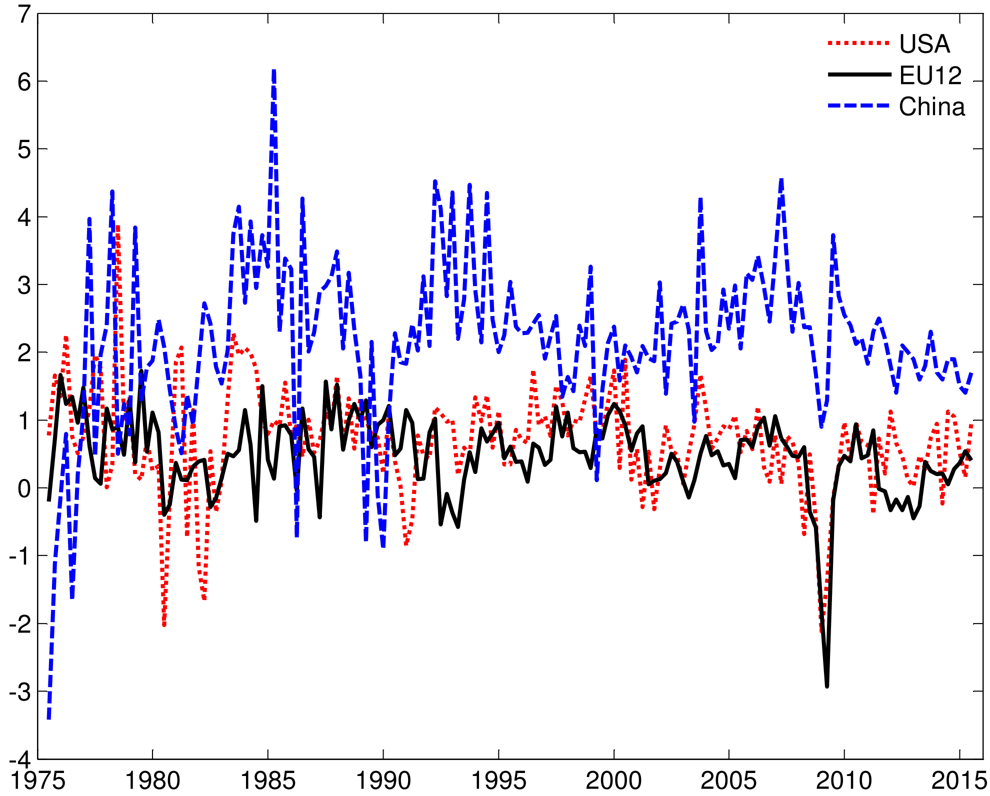
Notes: Spillovers are shown at horizons $h = 1, 4$. The ij^{th} FEVD is the percent of forecast error variance of series i associated with shocks to series j. Quantities estimated over the whole sample without allowing for structural breaks are shown in square brackets. Net spillovers are defined as the difference (to minus from), while Average spillovers are defined in (16) in the text.

Figure 1. Shares of World GDP



Note: Shares of World GDP for each economy where annual World Bank GDP is at market prices (current US$ for each year).

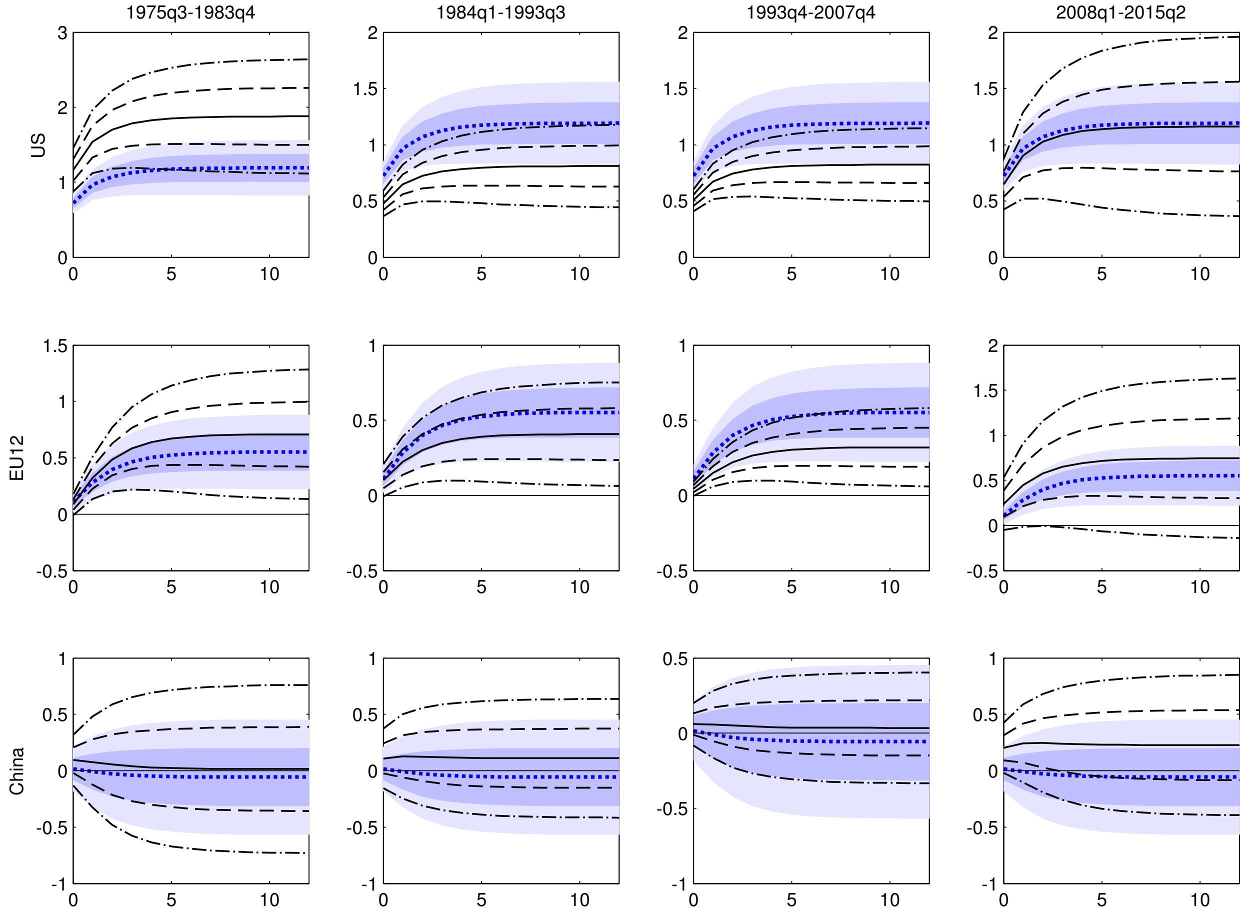
Figure 2. Quarterly GDP Growth Rates



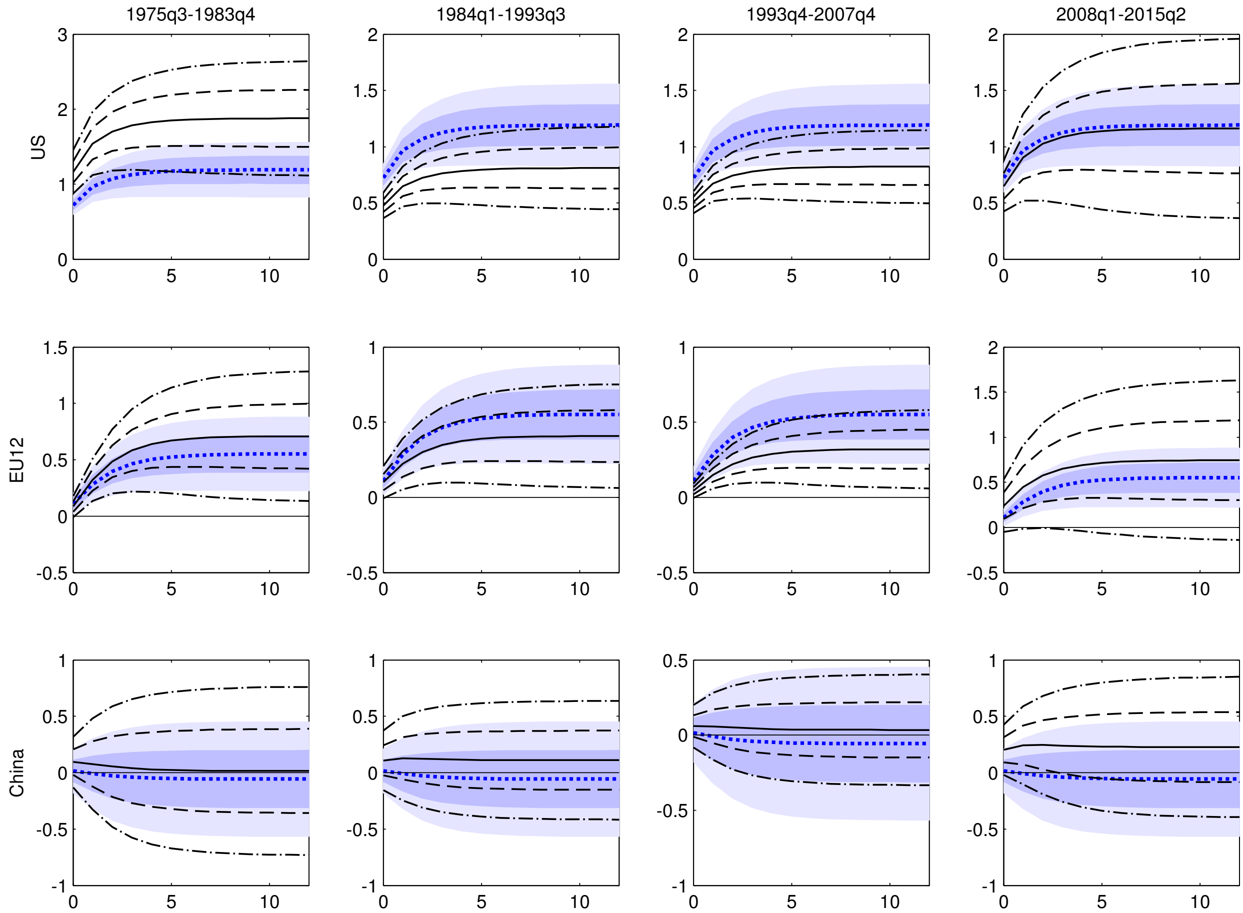
Notes: EU12 is an aggregate of the twelve countries that were members of the Euro area in 2001. See text for data sources.

Figure 3. Response to a US shock

(a) Generalized impulse responses



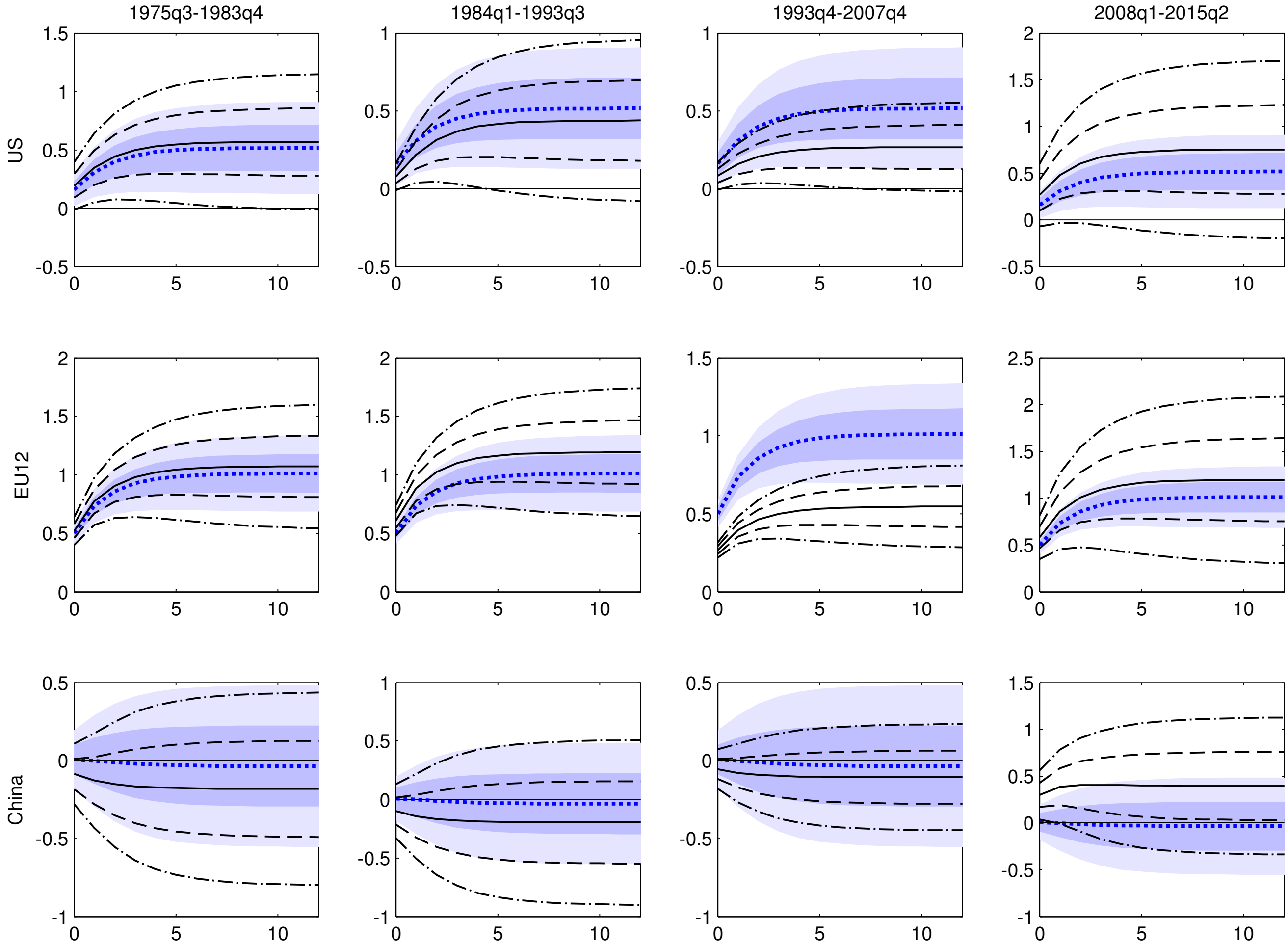
(b) Orthogonalized impulse responses



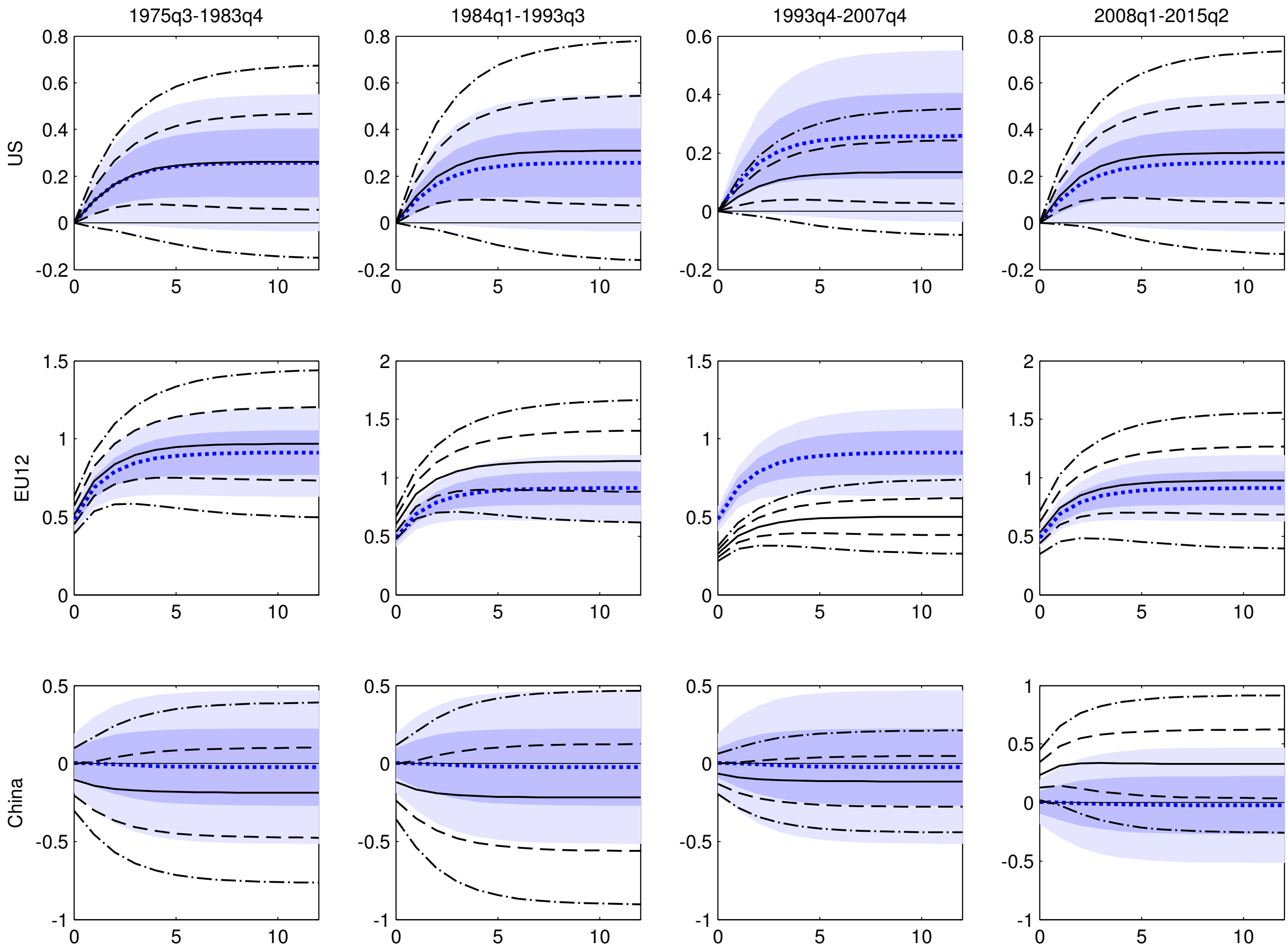
Notes: Cumulated impulse responses to a one standard deviation US shock are shown to three years (horizontal axis). Rows indicate the variables that respond to the shock. Closely dotted blue lines with shaded confidence intervals assume parameter constancy. A response in solid black line with dotted and dashed confidence intervals is specific to the sub-regime specified on the top. For each plot a one and two standard-deviation-wide confidence interval is obtained using a bootstrap procedure explained in the Appendix.

Figure 4. Response to a EU12 shock

(a) Generalized impulse responses



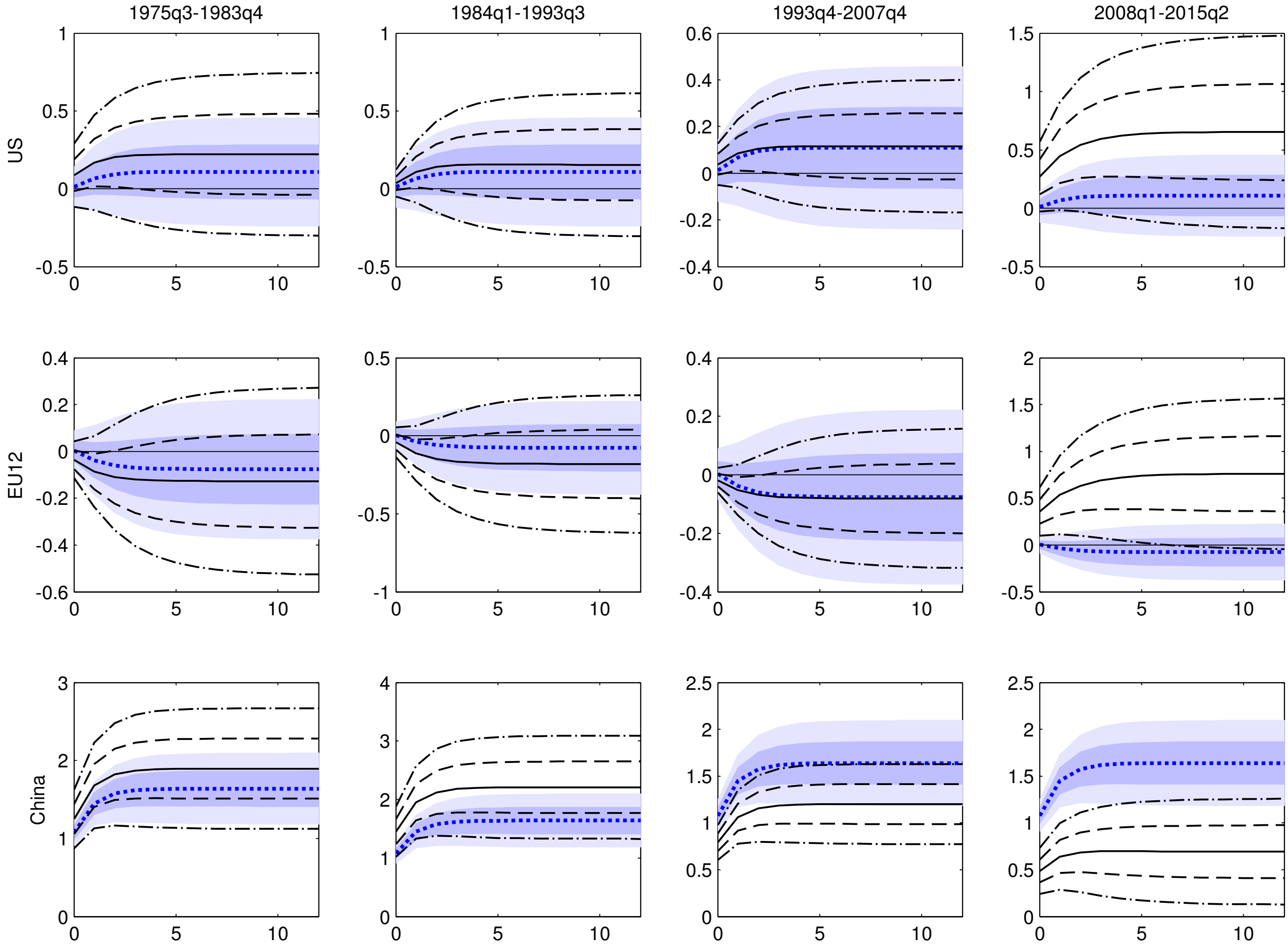
(b) Orthogonalized impulse responses



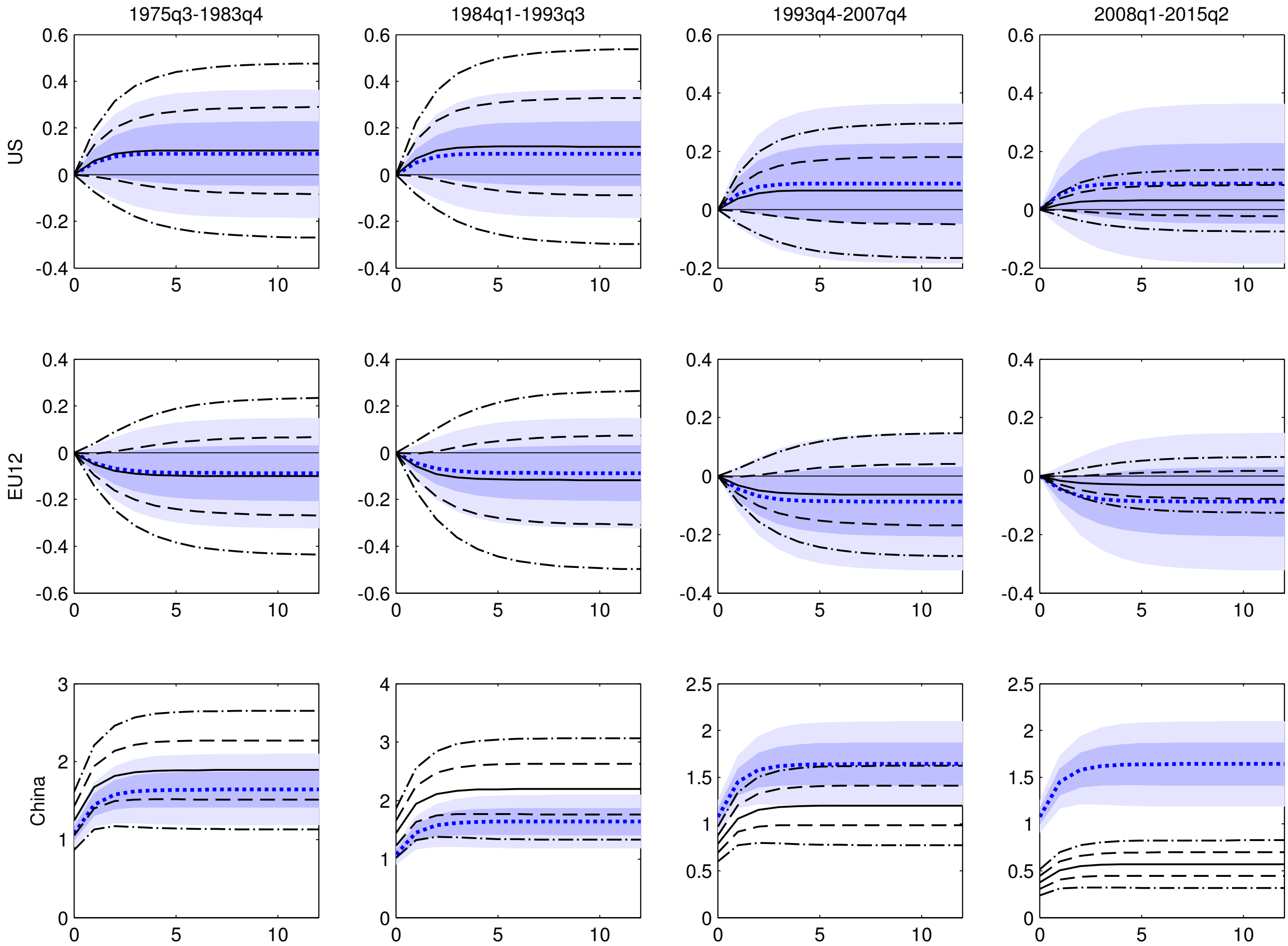
Notes: See Notes to Figure 3, except that the shock is applied to EU12.

Figure 5. Response to a Chinese shock

(a) Generalized impulse responses



(b) Orthogonalized impulse responses



Notes: See Notes to Figure 3, except that the shock is applied to China.

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 the latter are provided in Bataa *et al.* (2013).

7.1 Example: Structural Breaks and Impulse Responses

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

$$\mathbf{\Phi} = \begin{bmatrix} 0.8 & -0.4 \\ 0.1 & 0.6 \end{bmatrix}, \; \mathbf{D}_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \; \mathbf{P} = \begin{bmatrix} 1 & 0.6 \\ 0.6 & 1 \end{bmatrix} \tag{17}$$

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 $\mathbf{\Psi}_1^g(h)$, $h = 0, 1, 2, ...$ also double.

For orthogonalized IRFs, and again considering one standard deviation shocks, (4) shows 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,

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

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 $\mathbf{\Phi}_k$) and the covariance matrix $\mathbf{\Sigma}$ 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[9] 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.

After convergence, and conditional on the sub-periods identified by the system-wide coefficient breaks, Granger causality between the output growth series is examined. In particular, in the equation for country i, a joint test is conducted on the significance of all lag coefficients relating to country j, for each $j = 1, ..., n$; this test takes account of the detected volatility changes. Granger causality tests for each equation are conducted recursively, initially eliminating the least significant coefficient and re-estimating until all

[9] 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 from the using the modified BIC criterion proposed by Hall, Osborn and Sakkas (2013) for structural break inference.

the remaining coefficients are significant at 5 percent. Imposition of Granger causality implies that the corresponding coefficients are set to zero when the joint test is not significant at 5 percent.

Turning to the identified covariance breaks, the identity $\mathbf{\Sigma} = \mathbf{DPD}$ 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 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. Tests of Granger causality also employ a bootstrap analysis taking volatility breaks into account.

Confidence intervals and standard errors for IRFs, FEVDs and spillover measures are also 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[10]. 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).

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

TABLE A.1. NET GROWTH SPILLOVERS (Granger causality imposed)

Regime	US to EU12			US to China			EU12 to China		
	$h=0$	$h=4$	$h=8$	$h=0$	$h=4$	$h=8$	$h=0$	$h=4$	$h=8$
Panel A. GIRF spillovers									
75Q3-83Q4	-0.09 (0.06)	0.37 (0.19)	0.41 (0.23)	0.01 (0.03)	0.00 (0.06)	0.00 (0.06)	-0.04 (0.06)	-0.10 (0.10)	-0.10 (0.11)
84Q1-93Q3	0.02 (0.02)	0.25 (0.09)	0.27 (0.10)	0.07 (0.09)	0.10 (0.14)	0.10 (0.14)	-0.05 (0.07)	-0.08 (0.10)	-0.08 (0.10)
93Q4-07Q4	-0.03 (0.02)	0.17 (0.08)	0.19 (0.10)	0.02 (0.03)	0.03 (0.05)	0.03 (0.05)	-0.03 (0.04)	-0.06 (0.07)	-0.06 (0.07)
08Q1-15Q2	-0.04 (0.06)	0.26 (0.14)	0.29 (0.17)	-0.06 (0.09)	-0.10 (0.18)	-0.10 (0.18)	-0.05 (0.07)	-0.23 (0.24)	-0.24 (0.27)
[No break model]	[-0.05 (0.03)]	[0.25 (0.10)]	[0.28 (0.11)]	[0.00 (0.03)]	[0.01 (0.05)]	[0.01 (0.05)]	[0.00 (0.05)]	[0.00 (0.08)]	[0.00 (0.08)]
Panel B. Orthogonalized IRF spillovers									
75Q3-83Q4	0.07 (0.04)	0.63 (0.22)	0.67 (0.26)	0.09 (0.11)	0.14 (0.17)	0.14 (0.17)	-0.09 (0.10)	-0.13 (0.16)	-0.13 (0.16)
84Q1-93Q3	0.09 (0.06)	0.36 (0.14)	0.37 (0.15)	0.10 (0.13)	0.16 (0.20)	0.16 (0.20)	-0.10 (0.12)	-0.16 (0.18)	-0.16 (0.18)
93Q4-07Q4	0.04 (0.02)	0.28 (0.10)	0.30 (0.11)	0.06 (0.07)	0.09 (0.11)	0.09 (0.11)	-0.06 (0.06)	-0.09 (0.10)	-0.09 (0.10)
08Q1-15Q2	0.24 (0.15)	0.69 (0.37)	0.72 (0.41)	0.17 (0.09)	0.26 (0.14)	0.26 (0.14)	0.24 (0.15)	0.37 (0.23)	0.37 (0.23)
[No break model]	[0.11 (0.05)]	[0.49 (0.14)]	[0.52 (0.15)]	[0.02 (0.10)]	[0.02 (0.15)]	[0.02 (0.15)]	[0.00 (0.10)]	[0.01 (0.15)]	[0.01 (0.15)]

Notes: See Notes to Table 3 in the main text.

TABLE A.2. VOLATILITY SPILLOVERS (Granger causality imposed)

	Regimes	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$	$h=1$	$h=4$
		Panel A. Generalized forecast error variance decompositions and net volatility spillovers							
		US shock		EU12 shock		Chinese shock		**B. FROM OTHERS**	
US	75q3-83q4	100.00 (0.00)	100.00 (0.00)	2.01 (2.68)	2.01 (2.68)	0.51 (1.46)	0.51 (1.46)	-0.00 (0.00)	-0.00 (0.00)
	84q1-93q3	100.00 (0.00)	100.00 (0.00)	2.01 (2.59)	2.01 (2.59)	0.51 (1.49)	0.51 (1.49)	0.00 (0.00)	0.00 (0.00)
	93q4-07q4	100.00 (0.00)	100.00 (0.00)	2.01 (2.51)	2.01 (2.51)	0.51 (1.55)	0.51 (1.55)	0.00 (0.00)	0.00 (0.00)
	08q1-15q2	100.00 (0.00)	100.00 (0.00)	16.95 (14.35)	16.95 (14.35)	11.50 (13.09)	11.50 (13.09)	0.00 (0.00)	0.00 (0.00)
	[No break model]	[100.00 (0.00)]	[100.00 (0.00)]	[4.41 (3.64)]	[4.41 (3.64)]	[0.02 (1.15)]	[0.02 (1.15)]	[0.00 (0.00)]	[0.00 (0.00)]
EU12	75q3-83q4	16.35 (8.68)	23.80 (11.53)	88.98 (7.10)	82.34 (10.31)	0.26 (0.92)	0.24 (0.83)	11.02 (7.10)	17.66 (10.31)
	84q1-93q3	4.69 (3.68)	6.16 (4.52)	98.59 (1.25)	97.56 (2.28)	0.32 (1.17)	0.30 (1.13)	1.41 (1.25)	2.44 (2.28)
	93q4-07q4	12.63 (6.88)	18.40 (9.52)	92.23 (5.19)	87.24 (8.08)	0.27 (1.03)	0.25 (0.93)	7.77 (5.19)	12.76 (8.08)
	08q1-15q2	24.07 (15.59)	27.24 (16.15)	97.37 (2.51)	95.56 (4.19)	34.29 (15.37)	34.03 (14.90)	2.63 (2.51)	4.44 (4.19)
	[No break model]	[12.49 (5.90)]	[16.70 (7.29)]	[95.23 (3.00)]	[92.01 (4.68)]	[0.01 (0.94)]	[0.01 (0.92)]	[4.77 (3.00)]	[7.99 (4.68)]
China	75q3-83q4	0.51 (1.46)	0.51 (1.46)	0.36 (1.19)	0.36 (1.19)	100.00 (0.00)	100.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
	84q1-93q3	0.51 (1.49)	0.51 (1.49)	0.36 (1.25)	0.36 (1.25)	100.00 (0.00)	100.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	93q4-07q4	0.51 (1.55)	0.51 (1.55)	0.36 (1.26)	0.36 (1.26)	100.00 (0.00)	100.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
	08q1-15q2	11.50 (13.09)	11.50 (13.09)	34.26 (16.17)	34.26 (16.17)	100.00 (0.00)	100.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	[No break model]	[0.02 (1.15)]	[0.02 (1.15)]	[0.00 (1.00)]	[0.00 (1.00)]	[100.00 (0.00)]	[100.00 (0.00)]	[0.00 (0.00)]	[-0.00 (0.00)]
		Net US to EU12		Net US to China		Net EU12 to China		**AVERAGE**	
	75q3-83q4	14.34 (7.86)	21.78 (10.94)	0.00 (0.00)	0.00 (0.00)	0.10 (0.41)	0.11 (0.59)	3.67 (2.37)	5.89 (3.44)
	84q1-93q3	2.68 (1.82)	4.15 (3.00)	0.00 (0.00)	0.00 (0.00)	0.04 (0.13)	0.05 (0.19)	0.47 (0.42)	0.81 (0.76)
	93q4-07q4	10.61 (5.91)	16.39 (8.79)	0.00 (0.00)	0.00 (0.00)	0.09 (0.34)	0.10 (0.51)	2.59 (1.73)	4.25 (2.69)
	08q1-15q2	7.12 (3.65)	10.29 (5.41)	0.00 (0.00)	0.00 (0.00)	-0.03 (1.83)	0.23 (2.84)	0.88 (0.84)	1.48 (1.40)
	[No break model]	[8.08 (3.86)]	[12.28 (5.68)]	[0.00 (0.00)]	[0.00 (0.00)]	[0.00 (0.18)]	[0.00 (0.25)]	[1.59 (1.00)]	[2.66 (1.56)]
		Panel B. Orthogonalized forecast error variance decompositions and net volatility spillovers							
		US shock		EU12 shock		Chinese shock		**B. FROM OTHERS**	
US	75q3-83q4	100.00 (0.00)	100.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	84q1-93q3	100.00 (0.00)	100.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	93q4-07q4	100.00 (0.00)	100.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	08q1-15q2	100.00 (0.00)	100.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	[No break model]	[100.00 (0.00)]	[100.00 (0.00)]	[0.00 (0.00)]	[0.00 (0.00)]	[0.00 (0.00)]	[0.00 (0.00)]	[0.00 (0.00)]	[0.00 (0.00)]
EU12	75q3-83q4	16.35 (8.68)	23.80 (11.53)	83.65 (8.68)	76.20 (11.53)	0.00 (0.00)	0.00 (0.00)	16.35 (8.68)	23.80 (11.53)
	84q1-93q3	4.69 (3.68)	6.16 (4.52)	95.31 (3.68)	93.84 (4.52)	0.00 (0.00)	0.00 (0.00)	4.69 (3.68)	6.16 (4.52)
	93q4-07q4	12.63 (6.88)	18.40 (9.52)	87.37 (6.88)	81.60 (9.52)	0.00 (0.00)	0.00 (0.00)	12.63 (6.88)	18.40 (9.52)
	08q1-15q2	24.07 (15.59)	27.24 (16.15)	75.93 (15.59)	72.76 (16.15)	0.00 (0.00)	0.00 (0.00)	24.07 (15.59)	27.24 (16.15)
	[No break model]	[12.49 (5.90)]	[16.70 (7.29)]	[87.51 (5.90)]	[83.30 (7.29)]	[0.00 (0.00)]	[0.00 (0.00)]	[12.49 (5.90)]	[16.70 (7.29)]
China	75q3-83q4	0.51 (1.46)	0.51 (1.46)	0.50 (1.35)	0.50 (1.35)	98.99 (2.10)	98.99 (2.10)	1.01 (2.10)	1.01 (2.10)
	84q1-93q3	0.51 (1.49)	0.51 (1.49)	0.50 (1.42)	0.50 (1.42)	98.99 (2.20)	98.99 (2.20)	1.01 (2.20)	1.01 (2.20)
	93q4-07q4	0.51 (1.55)	0.51 (1.55)	0.50 (1.40)	0.50 (1.40)	98.99 (2.20)	98.99 (2.20)	1.01 (2.20)	1.01 (2.20)
	08q1-15q2	11.50 (13.09)	11.50 (13.09)	23.91 (15.50)	23.91 (15.50)	64.58 (14.72)	64.58 (14.72)	35.42 (14.72)	35.42 (14.72)
	[No break model]	[0.02 (1.15)]	[0.02 (1.15)]	[0.00 (1.05)]	[0.00 (1.05)]	[99.98 (1.57)]	[99.98 (1.57)]	[0.02 (1.57)]	[0.02 (1.57)
		Net US to EU12		Net US to China		Net EU12 to China		**AVERAGE**	
	75q3-83q4	16.35 (8.68)	23.80 (11.53)	0.51 (1.46)	0.51 (1.46)	0.50 (1.35)	0.50 (1.35)	5.79 (2.95)	8.27 (3.88)
	84q1-93q3	4.69 (3.68)	6.16 (4.52)	0.51 (1.49)	0.51 (1.49)	0.50 (1.42)	0.50 (1.42)	1.90 (1.40)	2.39 (1.65)
	93q4-07q4	12.63 (6.88)	18.40 (9.52)	0.51 (1.55)	0.51 (1.55)	0.50 (1.40)	0.50 (1.40)	4.54 (2.38)	6.47 (3.24)
	08q1-15q2	24.07 (15.59)	27.24 (16.15)	11.50 (13.09)	11.50 (13.09)	23.91 (15.50)	23.91 (15.50)	19.83 (8.50)	20.89 (8.60)
	[No break model]	[12.49 (5.90)]	[16.70 (7.29)]	[0.02 (1.15)]	[0.02 (1.15)]	[0.00 (1.05)]	[0.00 (1.05)]	[4.17 (2.05)]	[5.57 (2.50)]

Notes: See Notes to Table 4 in the main text.