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Deconstructing The International Business Cycle: Why Does A U.S. Sneeze Give The Rest Of The World A Cold?

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Deconstructing the International Business Cycle: Why does a U.S. sneeze give the rest of the world a cold?[1]

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Abstract

The 2008 crisis underscored the interconnectedness of the international business cycle, with U.S. shocks leading to the largest global slowdown since the 1930s. We estimate spillover effects across major advanced country regions in a structural VAR (SVAR) using pre-crisis data. Our new method freely estimates the contemporaneous correlation matrix for underlying shocks in the VAR and (uniquely, to our knowledge) the associated uncertainty. Our results suggest that the international business cycle is largely driven by U.S. financial shocks with a significant impact from global shocks, mainly reflecting commodity prices. Other advanced economic regions play a much smaller and regional role in growth spillovers. Our findings are consistent with the emerging evidence on the current crisis

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I. INTRODUCTION

The 2008 crisis underscored the importance and interconnectedness of the international business cycle. Shocks apparently emanating in the United States have led to the largest global slowdown since the 1930s. An obvious question, then, is what is the underlying structure of the global business cycle and why are the apparent spillovers from the U.S. to other countries so large?

Obtaining economically sensible answers to this question has proven to be difficult. Technically, it is always tricky to assess causation between highly correlated series—in this context, U.S. and global growth. It is not easy to distinguish between global shocks that drive the U.S. business cycle versus U.S. shocks driving global developments (the "U.S. sneezes and the world catches a cold" view). Indeed, many of the existing statistical techniques used to analyze the global business cycle—such as dynamic factor models—implicitly impose a direction of causation, and obviously cannot be used to answer this question.

This paper addresses these deficiencies by estimating the spillover effects among the major advanced economic regions using minimal identifying conditions in a structural vector auto regression (SVAR), along the lines suggested in Rigobon (2003). Rigobon shows that the contemporaneous correlation matrix of a SVAR can be fully identified by leveraging a single change in the underlying variability of the shocks. Rigobon achieves identification by differentiating, for example, between alternating periods of high financial markets volatility and low financial market volatility.

While this approach works reasonably well for financial data, it is more problematic when applied to macro data, since periods of high and low volatility are more difficult to identify. Moreover, if one thinks of high volatility periods as recessions, they are relatively short compared to the periodicity of the underlying macroeconomic data. Rather, in this paper, we exploit the "great moderation" of macroeconomic uncertainty since the 1980s to identify the contemporaneous correlations in the data using the Rigobon approach. Obviously, the start of the great moderation is uncertain, but this turns out to be an advantage for conducting the empirical analysis.[2] We calculate a series of estimates of contemporaneous correlations based on different assumptions as to when the great moderation started, in a manner similar to using "rolling regressions". This approach not only yields a more accurate estimate of contemporaneous causality, it also allows us to estimate the associated uncertainty around individual coefficients and the associated impulse response functions using a bootstrap approach.

As a result, our desire to identify causality has led to an important technical innovation in SVAR methodology. Our statistical approach allows us to estimate a broader range of uncertainty around the impulse responses from our SVAR, encompassing not only

[2] The source of the great moderation - smaller underlying shocks or better policies - remains a subject of much debate. See, for example, Kim and Nelson (1999), Blanchard and Simon (2001), Stock and Watson (2003, 2005), Kose, Prasad, and Terrone (2003), Heathcote and Perri (2004), Juillard, Karam, Laxton, and Pesenti (2006), and International Monetary Fund (2007).

the "standard" uncertainty coming from the estimated coefficients in the base VAR but also that associated with estimates of the contemporaneous correlations of the shocks. The latter is generally ignored in other identification approaches, such as Cholesky decompositions, which impose a pattern of causality rather than estimating one. To our knowledge, no earlier paper has been able to incorporate the additional uncertainty associated with contemporaneous correlations into impulse response functions.

The Rigobon identification method relies on two critical assumptions of uncorrelated structural shocks and the stability of the contemporaneous correlation matrix through regimes of variability. While the former assumption is standard, the latter raises some concerns. In addition, the stability of the VAR coefficients has also been studied by the great moderation literature.[3] We use a number of existing tests for structural change to examine the stability of VAR coefficients and of the contemporaneous correlation matrix. The results reveal no substantial evidence of an existing structural change in the VAR coefficients but indicate a possible break in the structural correlation matrix dating at the end of the 1970s. Further analysis shows that the shift in the correlation matrix is exclusively associated with the remarkable change in the U.K. economy.

Our empirical results provide a clearer answer on the issue of the underlying structure of the international business cycle. The results suggest that the cycle is primarily driven by U.S. rather than global shocks. The analysis also detects significant correlations in both the upper and lower triangles of the contemporaneous correlation matrix, thus rejecting any Cholesky factorization as an accurate description of the data. Indeed, it finds that the impact of U.S. shocks on Japan is positive, while the reverse impact is negative, a result which would be extremely unusual in any procedure that uses a weighted average of Cholesky factorizations either via sign tests (Uhlig, 2005) or more heuristic approaches (Bayoumi and Swiston, 2009). Strikingly, the U.K. creates more notably spillovers to the euro area than the reverse feedback from the euro area to the U.K. This finding suggests a major role for financial spillovers given that the U.K. is a small part of the European economy but has the main regional financial market.

II. Identification of Structural VARs through Heteroskedasticity

There are a number of approaches used in the VAR literature to identify orthogonal disturbances.[4] By far the most common approach involves the Cholesky decomposition, which assigns all of the correlations between orthogonal errors to the equation that is earliest in the ordering. The Cholesky decomposition approach, however, is known to be sensitive to the ordering of the VAR. In response, Bayoumi and Swiston (2009) suggest a Bayesian-like

[3] Stock and Watson (2005) test for structural breaks in VAR coefficients of G-7 growth data. Doyle and Faust (2005) study the structural change in comovement of shocks using G-7 output, consumption, and investment growth.

[4] A different framework, the Global VAR, also identifies interactions and contemporaneous interrelation among economies but it does not produce orthogonalized errors. See, for example, Pesaran, Schuermann, and Wiener (2004), Dees, Di Mauro, Pesaran, and Smith (2007), and Galesi and Sgherri (2009).

procedure based on a weighted average of the Cholesky decompositions to provide a more nuanced view of the true value of the uncertainty of the impulse responses. Other approaches include exclusion restrictions and/or long-term restrictions to achieve identification—see, for example, Christiano, Eichenbaum, and Evans (1999) and Blanchard and Quah (1989). Alternatively, structural VARs can be identified using sign restrictions as in Uhlig (2005). Though better than a single Cholesky ordering, these alternative approaches are still subject to a number of specific assumptions/restrictions, which can be often theoretically challenged.

By contrast, Rigobon (2003) proposes a far more flexible route to identification that relies only on the heteroskedasticity of the structural shocks. Identification of the structural model is achieved by exploiting the change (if any) in the variance of structural shocks implicit in the data. Rigobon successfully applies his approach to financial data, where he isolates periods of high volatility from periods of low volatility in returns to Latin American sovereign bonds.

Intuitively, identification through heteroskedasticity works in a similar fashion as the (probabilistic) instrument variable approach. The simplest intuition can be developed by looking at a special bivariate case, depicted in figure 1. Assume that we can split the sample into two periods, in which, variance of x_1 variable increases relative to variance of x_2. At the same time, we observe an increase in the covariance between these two series. Everything else constant, this implies that it is shocks to x_1 that are driving the positive correlation with x_2.

Mathematically, let $\varepsilon = Ae$, viz:[5]

$$A_{N\,x\,N}\begin{bmatrix} e_{1,t} \\ . \\ . \\ e_{N,t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1,t} \\ . \\ . \\ \varepsilon_{N,t} \end{bmatrix}$$

where all the structural shocks ε are assumed to have zero correlation at all leads and lags. The contemporaneous correlation A matrix typically has the following form:

$$A_{NxN} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix}$$

[5] Rigobon (2003) allows the inclusion of unobservable common shocks. In this paper, we assume there are no common shocks in the model. For simplicity, we do not present the corresponding formulas. See the original paper for more details.

where the upper (or lower) triangular elements $a_{ij}\left(i \neq j\right)$ are not necessarily equal to zero as required in the Cholesky decomposition.

Assuming there are *S* regimes of variability in the sample data. The model can be estimated by the generalized method of moments (GMM) where moment conditions are:

$$A\Omega_s A' = \Omega_{\varepsilon,s} \qquad s = \{1,2,..,S\}$$

with Ω_s and $\Omega_{\varepsilon,s}$ are the covariance matrices of the estimated reduced-form errors and the structural shocks in each regime s, respectively. In the absence of common shocks, Rigobon shows that only *TWO* regimes are required to achieve exact identification of matrix A irrespective of the number of endogenous variables, *N*.

A clear advantage of this approach is that it does not rely on a specific ordering of variables in the VAR. As such, the Rigobon identification method is preferred to the Cholesky decomposition for VAR analysis. It estimates rather than imposes the pattern of contemporaneous correlations between structural shocks.

Macroeconomic data are often of lower frequency and with shorter time spans than financial data. As a result, it may not be feasible to exactly identify multiple variability regimes in the sample. Moreover, it is often difficult to identify the exact lengths of specific variability regimes in the data sample. Fortunately, however, Rigobon (2003) shows that the contemporaneous correlation matrix is still identified and its estimators are consistent even if the heteroskedasticity is misspecified. In other words, his method is robust to either misspecification of the regime windows or under-specification of the number of regimes.

We propose a new and powerful extension of Rigobon's approach when it is applied to macroeconomic data. First, we do not impose the exact timing of the sample break, yet still get consistent estimates of the structural coefficients. Second, our approach yields empirical estimates of the inherent uncertainty of the estimated VAR coefficients including the contemporaneous matrix coefficients.

For the purpose of estimation, we assume that there are only two regimes in the data. We also assume that there is no common shock in the model so that the order condition is always satisfied and independent of number of exogenous variables. We apply the original Rigobon (2003) identification to all possible sample divisions within a window of time, yielding a set of valid (unbiased) estimates for the contemporaneous correlation matrix.

The procedure generates a set of estimated contemporaneous correlation A matrices, one for each possible division of the sample.[6] The inverse of A is of particular interest because it contains information about contemporaneous correlations between structural shocks. Given the available A matrices, we use a bootstrap procedure to estimate the inverse

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[6] The procedure reports the matrix A only if the Gauss GMM estimation converges and returns a matrix A with values of off-diagonal elements less than one.

of the average A matrix as the mean of all of the inverses of A and calculate standard errors with respect to this average A-inverse matrix.

Using the consistent estimates of VAR coefficients and the average A matrix, we then calculate the (average) impulse response functions of variables in the VAR to orthogonal shocks ε. We use the bootstrap procedure (described in the appendix) to consider two types of uncertainty affecting the impulse response functions: the usual uncertainty derived from the VAR estimation and the specific uncertainty of the A matrix from using our identification approach.

III. VAR Specification and Parameter Stability Tests

To illustrate our approach, we investigate growth spillovers across major industrial regions, defined as the U.S., the euro area, Japan, the U.K., as well as an aggregate of smaller developed and emerging market countries (henceforth, "ROW").[7] Note that the latter aggregation contains countries that are diverse in terms of both geography and industrial structure. Because the individual economies are both varied and relatively small, any one country is unlikely to have significant impact on the other major economic regions included in the estimation. Hence, we take the residuals from this group as a proxy for a global shock.

Our sample includes quarterly data on real GDP of the five regions from 1970:Q1 to 2007:Q4, and hence covers the floating exchange rate system that emerged after the breakup of the Bretton Woods fixed exchange rate system. In the base case, we end the sample at the end of 2007, although we have also calculated results through the entire period. By excluding the great recession we can test whether the spillovers we identify prior to this event appear consistent with what we have seen in recent years. Figure 2 shows the quarter-to-quarter output growth of each region. From the graphs, we can see reductions in growth volatility in the U.S., the U.K. and the euro area since the late 1970s. It is less obvious for Japan and the ROW.

Table 1 reports standard errors of growth rates for each decade in the sample. The last column shows the ratio of volatility between the first two decades and the later half. Estimated growth volatility in all five regions has been declining steadily and at unequal rates since the 1970s, with a much larger fall in the Anglo-Saxon part of the sample (the U.S. and the U.K.) than the rest. This is consistent with findings of the great moderation literature (for example, Doyle and Faust (2005), Stock and Watson (2005)). Similar results (not reported for the sake of brevity) are true of the residuals from the VAR, which are the actual inputs to the Rigobon procedure.

We estimate a reduced-form VAR on the quarter-to-quarter output growth rates of these five regions. Four lags are used in the VAR estimation, following Perez, Osborn, and

[7] The group contains 11 small industrial countries given the availability of quarterly data. Description of data and the aggregation method of the ROW economy are in the appendix.

Artis (2006).[8] While the existence of a fall in variance is the consensus in the literature, whether there is a shift in either the SVAR coefficients and/or the instability of covariance matrix of structural shock are issues that are still under debate.[9]

In order to address these questions, we perform a series of parameter stability tests. First, we test for the structural break in the VAR coefficients. Given the size limitations of existing tests for structural change in multivariate time series, we tested for a break in each equation separately following Stock and Watson (2005).[10] Assuming there is one break in each equation, we calculate the Quandt-Andrews Likelihood Ratio F-statistics to test for structural change with an unknown break date.[11] The test statistics also indicate the most likely break point in each equation. We then apply the Chow forecast test taking the indicated break as given. Test results are summarized in Table 2.

For all equations, the test results consistently indicate there is no structural break in the VAR coefficients. The indicated break points (corresponding to maxima of supLR F-statistics) are between the late 1970s and the early 1980s. These dates are also different among five equations. The Chow forecast test results reinforce the conclusion of no structural break in the VAR coefficients during the sample period.

Next, we test for the structural shift in the contemporaneous correlation A matrix. This is another challenging task because there is lack of formal statistical tests (Doyle and Faust, 2005). We consider two types of stability test for A matrix. The first one is the Hausman test. Because our procedure is able to calculate standard errors of the A matrix coefficients, we can directly compare estimates of the matrix A from different subsamples using the Hausman test. Test results show no indication of a structural change in the A matrix.[12] However, it is known that Hausman tests have low power and often under-reject the null hypothesis of no structural change.

The second test we consider is a likelihood ratio (LR) test suggested by Lanne and Lütkepohl (2006). In order to perform the LR test, the VAR system must be over-identified, i.e. there must be more than one break. We choose two break points at the end of the 1970s and the 1980s. These choices of breaks are ad hoc but consistent with observations from our sample. The first break corresponds to the ending of the period of intense macroeconomic

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[8] Differing formal statistical tests indicate a range of optimal lag lengths (between 0 and 8 lags). Thus, we choose to follow existing literature in selecting number of lags used in VAR estimation.

[9] Results of Goldfeld-Quandt tests for heteroskedasticity are included in the appendix.

[10] We consider two other tests developed by Bai, Lumsdaine, and Stock (1998) and Qu and Perron (2007). The former method allows testing for and dating a common break in multivariate case. The latter test allows for changes in the covariance matrix. However, both methods are limited by either a number of series which have a common break or a number (not more than 10) of parameters that can be changed at once. These limitations make the test results of our model more difficult to interpret and less reliable.

[11] The asymptotic distribution of test statistics is obtained by Andrews (1993) and Andrews and Ploberger (1993). Approximate asymptotic p-values are calculated following Hansen (1997).

[12] Results of the Hausman test are omitted here for space saving and available upon request.

instability following the 1973 oil price shock while the second corresponds to many people's views of the start of the great moderation, as well as the collapse of Japanese stock markets and the beginning of the unification of Germany and then the euro area as the whole.

Results of the LR tests are reported in Table 3. They indicate a possible change in the A matrix dating at the end of the 1970s. We believe that it is due to the inclusion of the U.K. as testing when the U.K. is excluded from the VAR finds no change in comovement among the other four regions during the whole sample period. Repeating the LR test for the benchmark VAR specification using the subsample 1980:Q1–2007:Q4 finds no indication of instability in the A matrix.

IV. International Spillovers: Directions and Sizes

Taking into account the test results in the previous section, we estimate the reduced-form VAR with all five variables using the whole sample of 1970:Q4–2007:Q4 but only using the estimated errors from 1980:Q1 onward to identify the contemporaneous correlations (the A matrix). We choose to keep the 1970s in the sample because of this period's importance in international business cycle analysis. The 1970s contained two major oil price shocks, which have been viewed variously as exogenous events associated with political tensions or as consequences of expansionary monetary policies and ample global liquidity. The results from this analysis can help to shed light on these alternative explanations.

We analyze the contemporaneous impacts and the impulse responses of GDP levels over the business cycle horizon of a positive growth shock in each region. Table 4 reports the estimate of the average contemporaneous A-inverse matrix (that translates the underlying orthogonal shocks to the shocks observed in the VAR) with the corresponding standard errors and t-statistics. Given the size and significance of the entries on the leading diagonal we take these regions as an indicator of the geographic origin of the structural shocks (what types of spillovers they might represent is discussed further below). For example, the first structural shock has its most significant immediate impact on the estimated reduced-form residuals corresponding to U.S. equation. Similarly, the other structural shocks seem to be closely linked to estimated residuals in other regions. Hence, we call them the U.S. shock, the euro area shock, and so forth. Unsurprisingly, all of these entries on the leading diagonal are highly significant. However, of more interest are the off-diagonal elements, which indicate immediate spillovers across regions.[13]

The off-diagonal coefficient *(i,j)* of the A-inverse matrix contains specific information about the contemporaneous spillover effect between any pair of countries or regions studied in this paper. In particular, it provides both signs and relative magnitudes of immediate contribution of an orthogonal shock in region i^{th} to growth in region j^{th}. Looking

[13] The contemporaneous correlations are consistently estimated irrespective of the ordering of variable in the reduced-form VAR. Changing the variable ordering amounts to a permutation of the corresponding rows and columns of the average inverse A-matrix reported in the Table 4.

down the first column, which indicates how U.S. shocks spillover to other countries in a contemporaneous fashion, the results find that U.S. shocks matter to the world. Positive shocks to U.S. growth significantly increase real output in all other regions. Turning to the first row, which reports the impact of other regions' shocks on the U.S., we see that Japan growth causes immediate negative spillovers to the U.S. while other regions do not exert any significant impact on the U.S. growth.

Turning to other significant contemporaneous spillovers, the second column indicates that euro area shocks only have a significant contemporary effect on the rest of the world, while the second row indicates that there is a significant positive impact from the U.K. that is actually somewhat larger than the one from the U.S. As Japan has no significant contemporaneous inward or outward spillovers except for with the U.S., the other significant spillovers in the matrix concern the U.K. and the rest of the world, with the rest of the world creating a positive spillover to the U.K. but receiving a similarly-sized negative spillover in return.

The statistical results have two important implications for existing studies of spillover effects that use standard VAR methodology. First, as both upper and lower of diagonal elements are significant and non-symmetric, any Cholesky decomposition would be rejected as an accurate representation of underlying international spillover. In addition, some of the relationships involve positive correlations in one direction but negative ones back (e.g., the U.S. and Japan or the U.K. and the ROW), a result that would be extremely unlikely to occur using a weighted average of Cholesky decompositions (of the type proposed in Uhlig, 2005, or in Bayoumi and Swiston, 2009).

The accumulated impulse response functions associated with a one-standard-error positive shock to real GDP growth in each region are plotted in Figures 3a and 3b.[14] The Figures shows the dynamic responses for a time horizon of 2 years, which we regard as a feasible period for inference on short-run macroeconomic dynamics, as well as 90 percent confidence intervals, calculated using a bootstrap procedure with 1000 replications. Two intervals reported. In Figure 3a, the "inner" solid lines represent the confidence interval when only the (new) uncertainty we have introduced that is associated with the estimation of the A matrix is included (corresponding to the results in Table 4), while the "outer" dotted lines show the results of the combined uncertainty in both the A-matrix estimation and the (more standard) uncertainty associated with estimation of the coefficients on lagged variables in the VAR. Figure 3b repeats this exercise, except that the "inner" solid lines now represent the uncertainty associated with estimation of the coefficients on lagged variables while the outer lines again represents the combined uncertainty from coefficient and A-matrix uncertainty.

Comparing Figures 3a and 3b two features stand out. First, at least in this estimation, the volatility in impulse response functions coming from uncertainty in the A-matrix is generally larger than the uncertainty over coefficients (particularly in the short run and for

[14] The standard deviations of structural shocks are calculated using the average A-matrix and the reduced-form estimated variance-covariance matrix for the period of 1980:Q1–2007:Q4.

off-diagonal elements) suggesting that standard VAR analysis ignores a significant source of underlying uncertainty in responses. Second, overall volatility of the impulse responses is larger than would be implied if the two sources (the A-matrix and coefficients on lagged variables in the VAR) were independent. This is because uncertainty about (say) VAR coefficients introduces addition variance in estimates of the A-matrix, and vice versa—uncertainty in one area of the VAR leads to greater uncertainty in the other.

Taking account of both sources of uncertainty, Figure 2 finds that U.S. shocks matter for all four other regions. Although initial effects are relatively modest, ranging from 0.1 percent in the euro area to 0.3 percent in Japan, spillovers from the U.S. gradually increase over time. At the end of the 2-year horizon, for example, a one standard deviation increase in the U.S. real GDP (about 0.8 percent) raises output in other regions by 0.4 percent to almost 0.7 percent, with the largest effect on Japan. These effects are significant for all four regions. The estimated multipliers of one-half to almost one underscore how important the U.S. is as the driver of the global growth.

By contrast, shocks to other major advanced economies' growth generally generate small and insignificant spillovers that die out over time. In the case of the euro area, there is a (marginally) significant positive spillover to the rest of the world. For Japan, there is a positive spillover to the euro area over time, but other effects are small and statistically insignificant. The U.K. has a modest positive (although not significant) impact on the euro area. As discussed earlier, however, the direction of causation between the U.K. and the euro area shocks is notable, with the relatively small U.K. economy having a positive growth impact on the larger euro area that continues over time while the euro area has a small spillover to the U.K. that rapidly dies out. As discussed further below, one interpretation of this result is that the U.K. proxies a financial market shock, and that the spillover from the U.K. to the euro area illustrates the importance of U.K. financial markets for the rest of Europe.

Spillovers from the rest of the world are also sensitive to the uncertainty inherent in estimating the A matrix. Strikingly, we find that over time the rest of the world has negative impacts on other regions that, like the U.S. shocks, build steadily over time and are relatively similarly sized across regions—although only significant in the case of the U.S. and U.K. This is consistent with the notion that this is mainly reflecting a commodity price shock. The view that the ROW group proxies for commodity effects is consistent with the nature of spillovers from other regions to the rest of the world group. Their size reflects the importance of the regions in global commodity demand, of which the U.S. is largest, followed by the euro area, then Japan, and a negative and insignificant effect from the U.K.

These empirical results use average variances of shocks across the whole period. However, given that we have used changes in volatility of shocks over the great moderation (Table 1) to identify the A-matrix, it is interesting to examine how these changes in volatility affect the nature of spillovers. Table 5 reports the standard errors of estimated structural shocks over time. While there was a moderation in the size of shocks across all regions, it was much more pronounced in the Anglo-Saxon countries than elsewhere. Comparing the 1970s and 1980s with the 1990s and 2000s, the average shock in the U.K. has fallen by almost two-thirds and halved in the U.S. By contrast, the comparable numbers for Japan, the rest of the world, and the euro area are one-tenth, one-fifth, and one-third, respectively. The U.K. also has an exceptionally large reduction in volatility between the 1970s and the 1980s, which may explain why it was difficult to identify stable contemporaneous spillovers for the U.K. when data for the 1970s were included in the sample.

Table 6 reports the variance decomposition of the impact of shocks after 8 quarters for 1980–2007 and Table 7 the equivalent concept for individual decades. The results for the entire sample indicate that the U.S. is the most important driver of the business cycle, accounting for one-fifth of volatility in Japan output and about one-third of the other regions' output variability. By contrast, the euro area, Japan, the U.K., and the ROW (representing a global shock) appear to be insignificant drivers of the global business cycles, with each country shock accounting for less than 10 percent of output volatility in other regions.

The results across decades repeat this story.[15] Despite the notable decrease of U.S. growth variability since 1990, the U.S. shock still explains at least 16 percent of output volatility elsewhere except Japan in the 1990s, where the figure is 11 percent. By contrast, the *maximum* spillover from all of the euro area, Japanese, U.K., and ROW shocks—the spillover from ROW to U.S. in the 1990s—is 18 percent. Strikingly, spillovers from the ROW are estimated to have been largest in the 1990s, not the 1970s. Hence, this analysis finds that it was U.S. instability that drove global volatility in the 1970s, not commodity shocks.

V. Sources of Spillovers

We next use some simple techniques to explore the relative importance of three potential transmission channels of spillovers—international trade, commodity prices, and financial conditions—within our framework. We do this by adding exogenous variables representing each possible spillover channels separately to the baseline VAR.[16] The responses of GDP to foreign activity in the augmented VAR can be thought of as the size of the spillover once the impact of this channel is excluded from the VAR. We measure each individual type of spillover as the difference between the identified responses from the initial VAR and the augmented VAR, formally:

$$c_{i,j} = r_i - r_j$$

where $c_{i,j}$ is the contribution of channel j in period i and r_i and $r_{i,j}$ are the overall response and the response from the augmented VAR with channel j included, respectively. The sum of

[15] We report results for the 1970s despite the fact that the A-matrix was found to be unstable for the U.K., but blanking out the U.K. spillovers. Even for other regions, the results for the 1970s are only an approximation as the uncertainty about the U.K. A-matrix coefficients matters for other entries. However, give the limited link between the U.K. and other regions, the reported results are probably relatively accurate.

[16] In a similar approach, Dees and Vansteenkiste (2007) treat the financial conditions and oil prices as endogenous variables to identify the trade effects of a U.S. demand shock on the rest of the world using the GVAR framework. They find that the overall effects of a U.S. demand shock are between 1.5 to 5 times larger than of the trade channel only.

the spillovers coming from the individual sources is not constrained to equal the overall spillover estimated in the base VAR.

We use the contribution of exports to GDP growth to measure trade channel, as these are mainly driven by foreign income and exchange rates and can be considered exogenous to domestic growth. To save degrees of freedom, the contemporaneous and first lag of exports contribution to GDP growth for the U.S., euro area, Japan, and U.K. are included (rest of the world data are not includes as this is supposed to reflect a global shock). Spillovers from financial channels are captured by including short-term interest rates (the yield on three-month government securities), long-term interest rates (the yield on 10-year government securities), and equity prices for the same four countries. Equity prices are deflated by the country's GDP deflator and expressed in quarterly percentage changes. We again include only the contemporaneous and first lag of each variable in the augmented VAR estimation. The commodity prices used are the oil price and the non-energy component of the Goldman Sachs Commodity Index. Because commodities are priced in U.S. dollars, they are converted in real terms using the U.S. GDP deflator. The current values and four lags of quarterly percentage changes in prices are included.

Figure 4 presents the estimated contributions of each of these three channels. The line in each graph represents the direct estimate of the average response, as in the Figure 2. Contributions of three main channels are presented in the stacked bar graphs, and correspond reasonably closely to the aggregate spillovers from the initial estimation. The results for contribution of each channel can be summarized as follows. *Financial variables* often have a significant contribution compared to *trade links*. These effects are always positive for the U.S. and almost always for the U.K., the two major financial centers in the sample, where they account for a significant part of the spillovers. The impact of *commodity prices* on real GDP spillovers is generally limited, but they tend to be relatively more important for the ROW and are also always negative for this group. In addition, commodity prices are almost always a source of positive spillovers to the rest of the world, again consistent with our view of this region as primarily reflecting commodity shocks. In short, U.S. and U.K. spillovers appear to largely reflect financial shocks, ROW shocks largely commodity prices.

VI. Explaining the Great Recession

Our final experiment is to use the model to examine the causes of the great recession of 2008 and 2009 by running the model through end-2009. The resulting shocks for each country since 2000—so as to look at both the build-up proceeding the recession as well as the event itself—are reported in Figure 5. Each country's shocks are standardized by dividing them by the standard deviation of shocks since 1990 to get a sense of how they compare with experiences over the great moderation.

The results indicate that after a period of relative stability since 2000, the great recession reflects a series of large and correlated negative shocks starting in the third quarter of 2008 in the U.S. and U.K., generalizing to other regions in the subsequent quarter, and peaking for the U.S. and U.K. in the first quarter of 2009. Compared to the experience during the great moderation, these shock are implausibly large—the shocks are some 5 standard deviations away from normal for the U.S. and U.K. in 2009Q1, implying infinitesimal joint likelihoods. Measured by the size of the shocks over the 1970s and 1980s, however, the shocks are closer to 2–2½ standard deviations (i.e. around a one to five percent probability), which is much more plausible. Hence, to some extent, the great recession can be seen as a return to the kind of instability experienced in the Anglo-Saxon counties with major financial centers before the great moderation. Note, also, that after the first quarter of 2009 the negative shocks ended, and indeed became large positive shocks in the euro area and Japan (where the major impact on activity was through relatively fleeting trade effects). In short, the global recession reflected a few quarters of large negative shocks mainly emanating in the U.S. and U.K. and likely spread to other advanced economies through financial channels.

The intuition that the crisis period is largely a return to the instability of the 1970s and 1980s can be further illustrated by adding the post-2007 sample in our estimation. When we plausibly include these data assuming that they are part of the first "unstable" part of the sample, the estimates of the A matrix and impulse response functions remain broadly unchanged although the role of the U.K. in global spillvoers is modestly enhanced (details available upon request). If, however, we implausibly include them as part of the great moderation the results find major changes in the A matrix of contemporaneous spillovers, with (for example) Japan becoming a major source of global spillovers. This illustrates the importance of linking the Rigobon identification approach to actual events, rather than simply using it in a mechanistic manner.

VII. Conclusions

This paper has explored the nature of growth spillovers across the main advanced country regions using a new identification method for VARs that accounts for the uncertainty associated with the estimation of the contemporaneous correlation matrix across shocks. As a result, the VAR identification involves only two assumptions—the variables included in the VAR and the chosen lag length.

The results from 1970 through the end of 2007 describe a relatively coherent picture for international growth spillovers. First, U.S. shocks dominate the international business cycle. European financial market shocks—proxied by U.K. spillovers—may also matter for the euro area. Commodity price shocks—proxied by a grouping of smaller advanced and emerging markets—create negative effects on the major advanced country regions. Lastly, euro area shocks matter primarily through commodity prices. It is also striking that this description of global spillovers through end-2007 fits the experience of the great depression in 2008 and 2009 so well, as a disturbance largely emanating out of the U.S. had major global consequences.

These results suggest that work on international spillovers should focus more on the role of financial markets as conduits for shocks, at least across the major advanced economy regions. The next challenge is thus to build realistic models of international macro-financial linkages that can create the size of spillovers apparently prevalent in the underlying data.

Figure 1. Identification through Heteroskedasticity Example

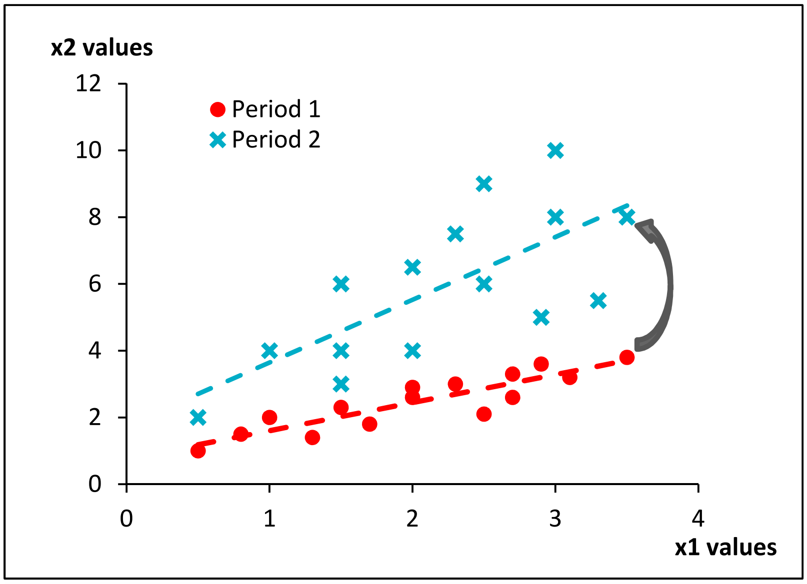


Figure 2. Quarter-to-Quarter Real GDP Growth (1970–2007)

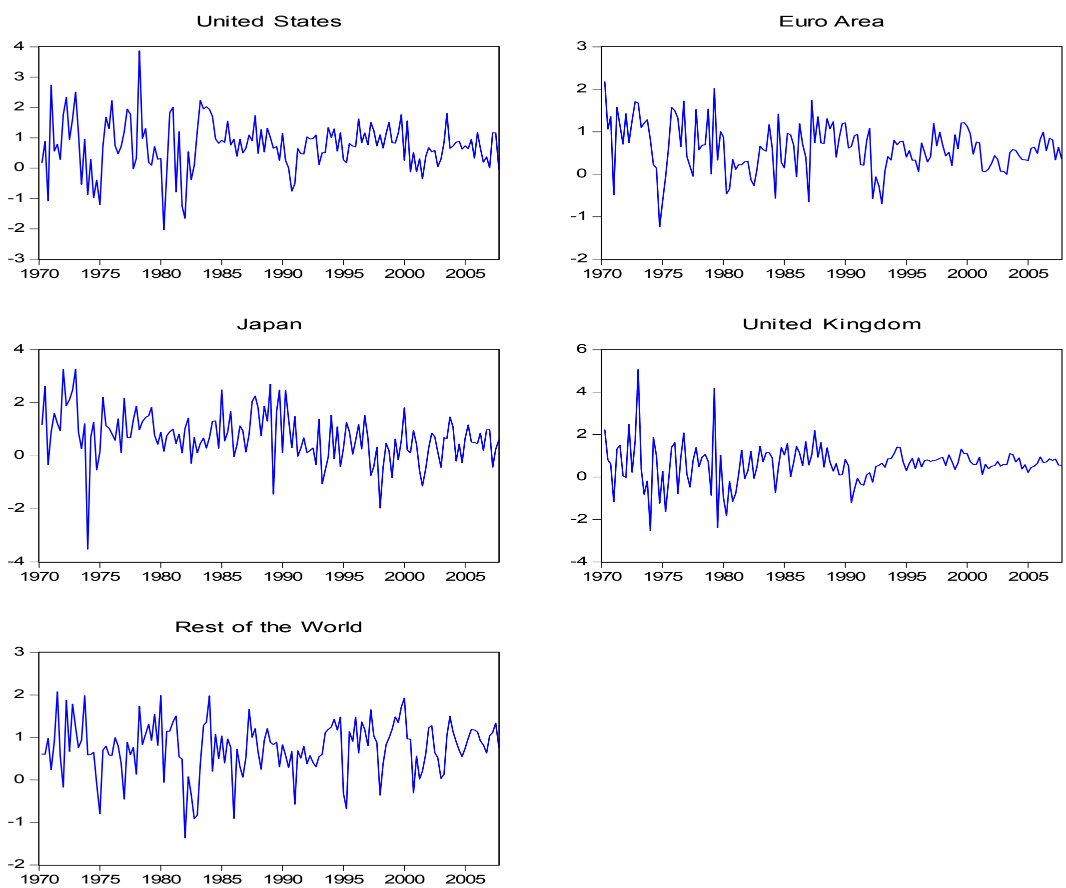


Figure 3a. (Accumulated) Impulse Responses of Real GDP to 1-s.d. Structural Shock

(solid CIs: A-matrix estimation uncertainty - dotted CIs: overall uncertainty)

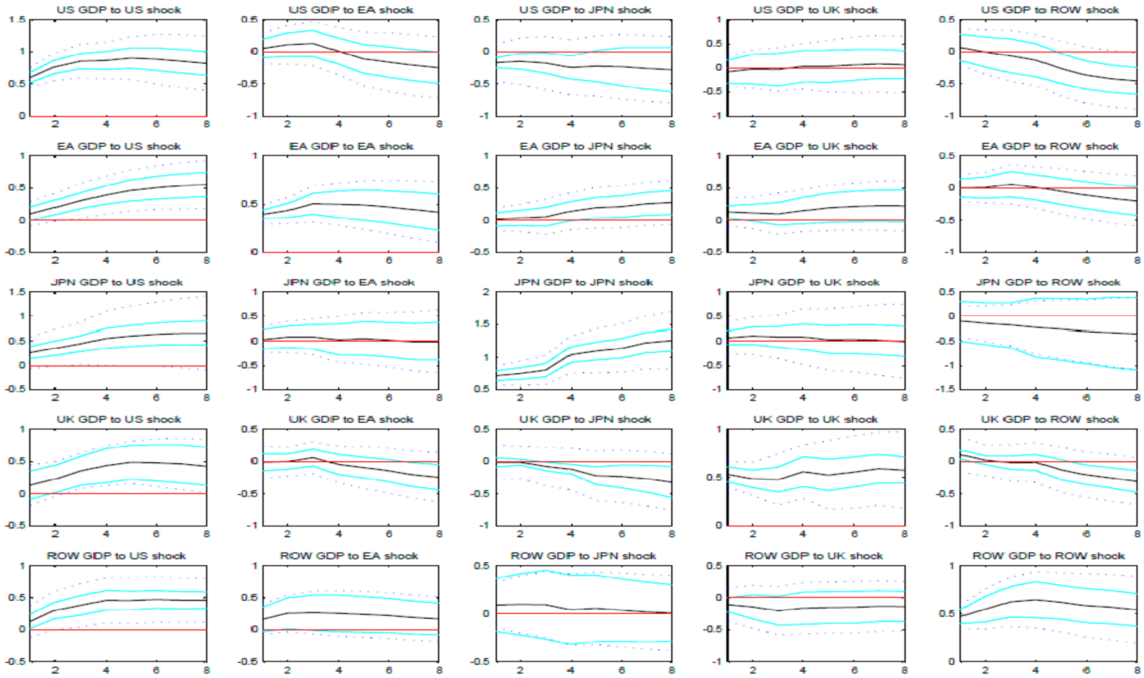
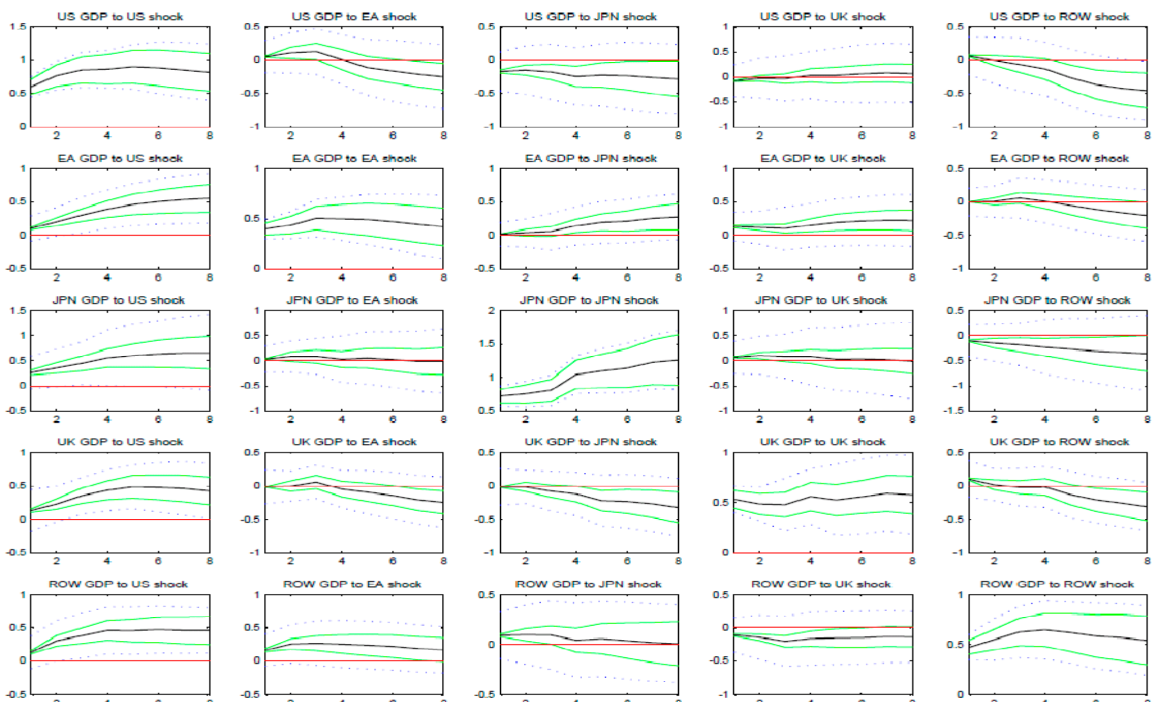


Figure 3b. (Accumulated) Impulse Responses of Real GDP to 1-s.d. Structural Shock

(solid CIs: VAR coefficient estimation uncertainty only - dotted CIs: overall uncertainty)



Leading diagonal graphs: Effects of own shock on GDP—Off-diagonal graphs: Spillovers effect
First column: Spillovers from U.S. to U.S., euro area, Japan, U.K., and ROW (respectively by row)
First row: Spillovers onto U.S. from U.S., euro area, Japan, U.K., and ROW (respectively by column)

Figure 4. Decomposition of Spillover Effects

__Mean Original __Trade __Finance __Commodity

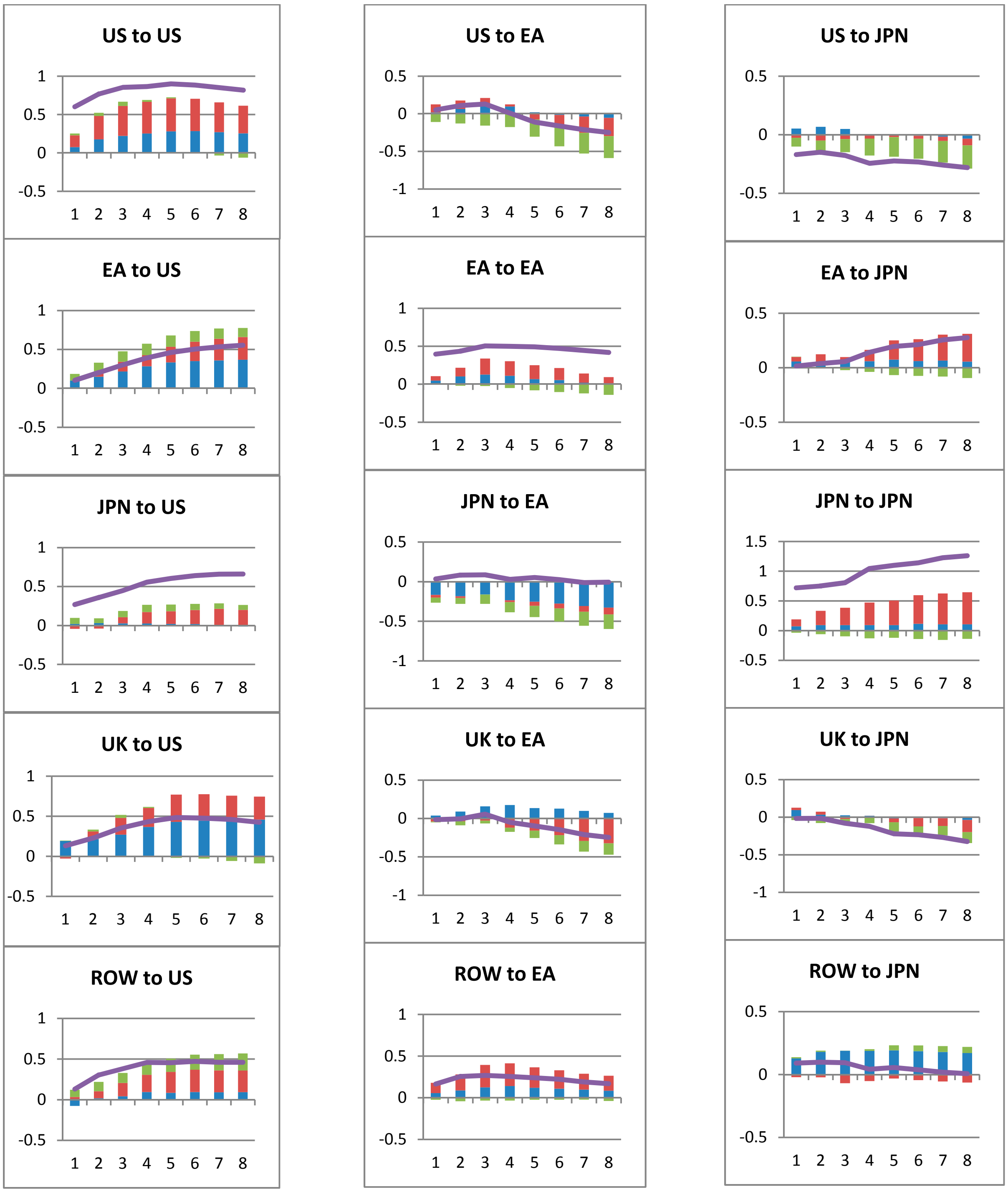


Figure 4 (continued)

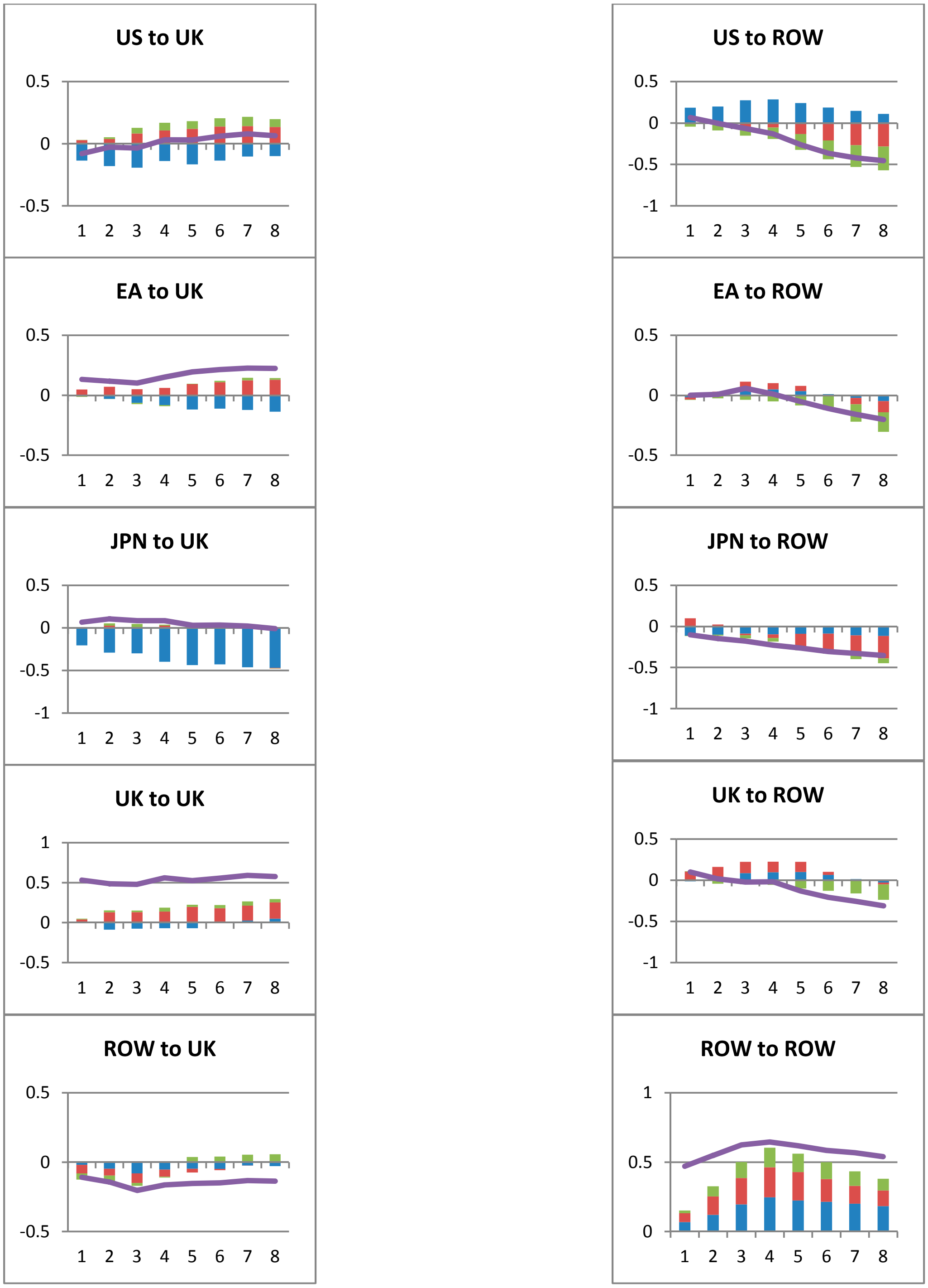


Figure 5. Structural GDP Growth Shocks
(Normalized by 1990-2007 standard errors)

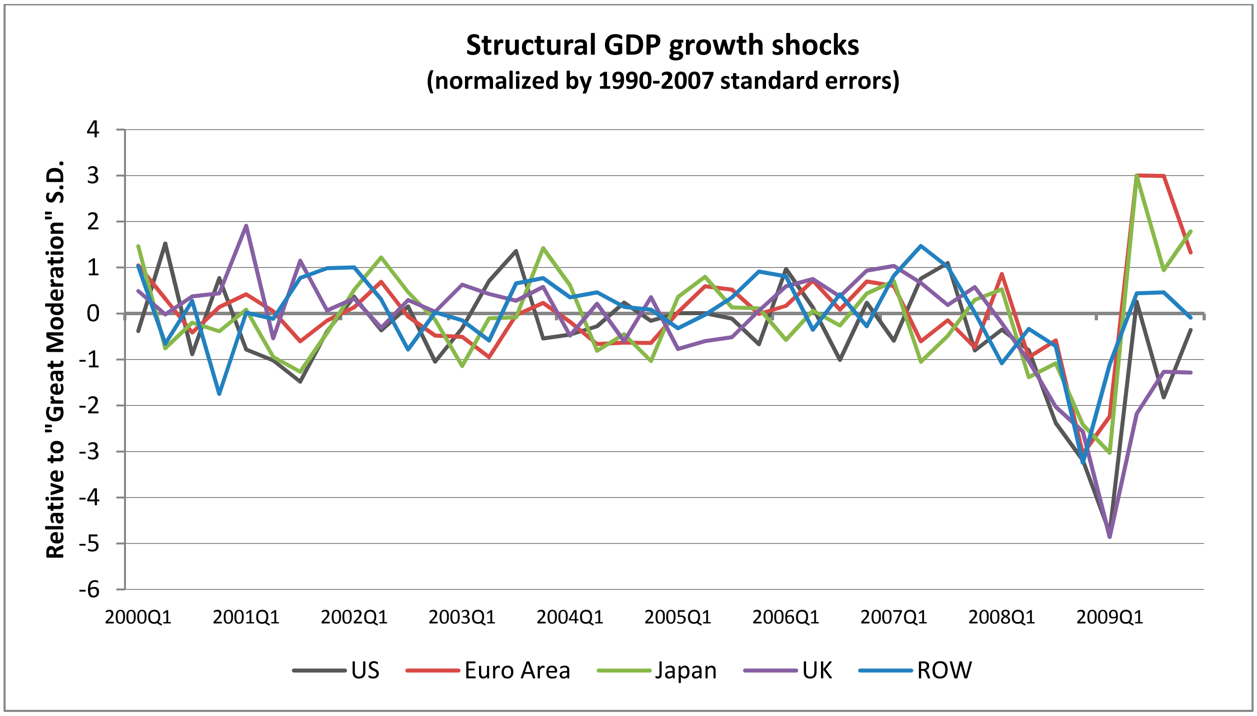


Table 1. Estimated Standard Errors of Quarter-to-Quarter Output Growth by Decade

Last column: ratio of standard errors of 1970-1989 to 1990-2007
Ratio greater than 1 means higher volatility in the earlier period

	1970-1979	1980-1989	1990-1999	2000-2007	1970-89 vs. 1990-2007
U.S.	1.10	0.97	0.53	0.49	1.98
Euro Area	0.76	0.58	0.45	0.30	1.78
Japan	1.14	0.83	0.84	0.63	1.33
U.K.	1.53	0.85	0.54	0.23	2.83
ROW	0.62	0.76	0.58	0.47	1.31

Table 2. Test Results for Structural Breaks in the VAR Coefficients

	Quandt-Andrews test		Chow Forecast test	
	SupLR F-statistics (possible break)	p-value	F-statistic	p-value
U.S.	3.31 (1981Q3)	1.00	0.43	0.997
Euro area	2.66 (1980Q3)	1.00	1.06	0.475
Japan	2.84 (1977Q1)	1.00	2.56	0.322
U.K.	7.35 (1980Q2)	1.00	0.42	0.995
ROW	3.03 (1983Q2)	1.00	0.95	0.591

Table 3. Test Results for Structural Change in the A Matrix

		1970-1979 vs. 1980-1989	1970-1979 vs. 1990-2007	1970-1979 vs. 1990-2007	Whole sample
Full VAR	LR test statistic	21.55	28.77	2.48	35.49
	p-value	0.00	0.00	0.78	0.00
Restricted VAR (excluding U.K.)	LR test statistic	0.90	0.21	0.68	3.68
	p-value	0.92	0.99	0.95	0.88

Table 4. Average Contemporaneous A-Inverse Matrix–1980:Q1–2007:Q4

	U.S.	**Euro Area**	**Japan**	**U.K.**	**ROW**
U.S.	**0.911***** (0.124) [7.325]	0.131 (0.201) [0.655]	**-0.205***** (0.051) [--4.048]	-0.137 (0.188) [-0.725]	0.132 (0.207) [0.636]
Euro Area	**0.157*** (0.086) [1.820]	**0.987***** (0.082) [12.11]	0.018 (0.060) [0.305]	**0.225**** (0.090) [2.504]	-0.001 (0.145) [-0.006]
Japan	**0.407***** (0.108) [3.764]	0.086 (0.256) [0.336]	**0.872***** (0.091) [9.130]	0.115 (0.115) [1.002]	-0.203 (0.430) [-0.471]
U.K.	0.200 (0.152) [1.310]	-0.038 (0.189) [-0.203]	-0.020 (0.049) [-0.416]	**0.906***** (0.140) [6.491]	**0.199***** (0.076) [2.619]
ROW	**0.199**** (0.094) [2.118]	**0.408*** (0.233) [1.755]	0.110 (0.181) [0.605]	**-0.186*** (0.101) [-1.845]	**0.932***** (0.078) [11.954]

Standard errors are inside (.) and t-statistics are reported in [.]
(***, **,* mean statistically significant at 1%, 5%, and 10% levels, respectively)

Table 5. Changes in Standard Errors of Structural Shocks

	1970-1979	1980-1989	1990-1999	2000-2007	1970-89 vs. 1990-2007
U.S.	1.02	0.90	0.48	0.49	1.98
Euro Area	0.47	0.50	0.41	0.22	1.45
Japan	0.91	0.85	0.86	0.71	1.09
U.K.	1.39	0.84	0.42	0.30	2.87
ROW	0.63	0.55	0.56	0.33	1.24

Table 6. Variance Decomposition of Real GDP at 8th–Quarter
Using estimated standard errors from sample 1980:Q1-2007:Q4

Explained by / Forecast variable	**U.S.**	**Euro Area**	**Japan**	**U.K.**	**ROW**
U.S.	0.82	0.03	0.06	0.00	0.09
Euro Area	0.37	0.47	0.07	0.07	0.02
Japan	0.21	0.00	0.74	0.00	0.05
U.K.	0.29	0.03	0.07	0.55	0.06
ROW	0.29	0.09	0.01	0.04	0.58

Table 7. Variance Decompositions of Real GDP at 8th–Quarter (extended)

(Sums of rows may not equal to 1 due to rounding errors)

	U.S.	EA	Japan	U.K.	ROW
1970:Q1-1979:Q4					
U.S.	0.88	0.02	0.03	--	0.07
EA	0.48	0.31	0.04	--	0.02
Japan	0.33	0.00	0.61	--	0.05
U.K.	--	--	--	--	--
ROW	0.35	0.06	0.01	--	0.47
1980:Q1-1989:Q4					
U.S.	0.87	0.02	0.04	0.00	0.07
EA	0.43	0.43	0.04	0.09	0.02
Japan	0.33	0.00	0.63	0.01	0.07
U.K.	0.32	0.03	0.04	0.60	0.04
ROW	0.37	0.09	0.01	0.06	0.48
1990:Q1-1999:Q4					
U.S.	0.68	0.04	0.10	0.00	0.18
EA	0.25	0.58	0.09	0.04	0.04
Japan	0.11	0.00	0.83	0.00	0.06
U.K.	0.25	0.06	0.12	0.46	0.11
ROW	0.16	0.09	0.01	0.02	0.73
2000:Q1-2007:Q4					
U.S.	0.83	0.01	0.08	0.00	0.07
EA	0.49	0.32	0.12	0.04	0.02
Japan	0.16	0.00	0.81	0.00	0.03
U.K.	0.41	0.02	0.14	0.37	0.06
ROW	0.35	0.06	0.01	0.02	0.56

Appendix

I. Data

Data on quarterly growth (measured as the difference in the logarithm of real GDP) of the United States, the Euro area, Japan, the United Kingdom, and the rest of the world group were collected from Haver Analytics. The sample covers the period from 1970:Q1 to 2007:Q4. The official Euro area data extend back to 1991, and earlier data were spliced back to 1970 using the estimates in Fagan, Henry, and Mestre (2005).

The rest of the world group includes Australia, Canada, Denmark, Korea, Mexico, Norway, New Zealand, South Africa, Sweden, Switzerland, and Taiwan. The countries included are based on availability of quarterly GDP data since 1970. These countries are diverse in terms of both geography and industrial structure.

For the rest of the world aggregation, each country's real GDP index (2000=100) is weighted by the size of its GDP in purchasing power parity (PPP) terms. PPP data are available from the IMF's WEO database. The weighted-average index is then used to calculate quarterly growth rate for VAR estimation.

II. Bootstrap procedure

We consider two types of uncertainty affecting the impulse response functions: the usual uncertainty derived from the VAR estimation and the specific uncertainty of the A matrix from using our identification approach. We use the following bootstrap procedure to calculate standard errors of impulse response functions (IRFs).

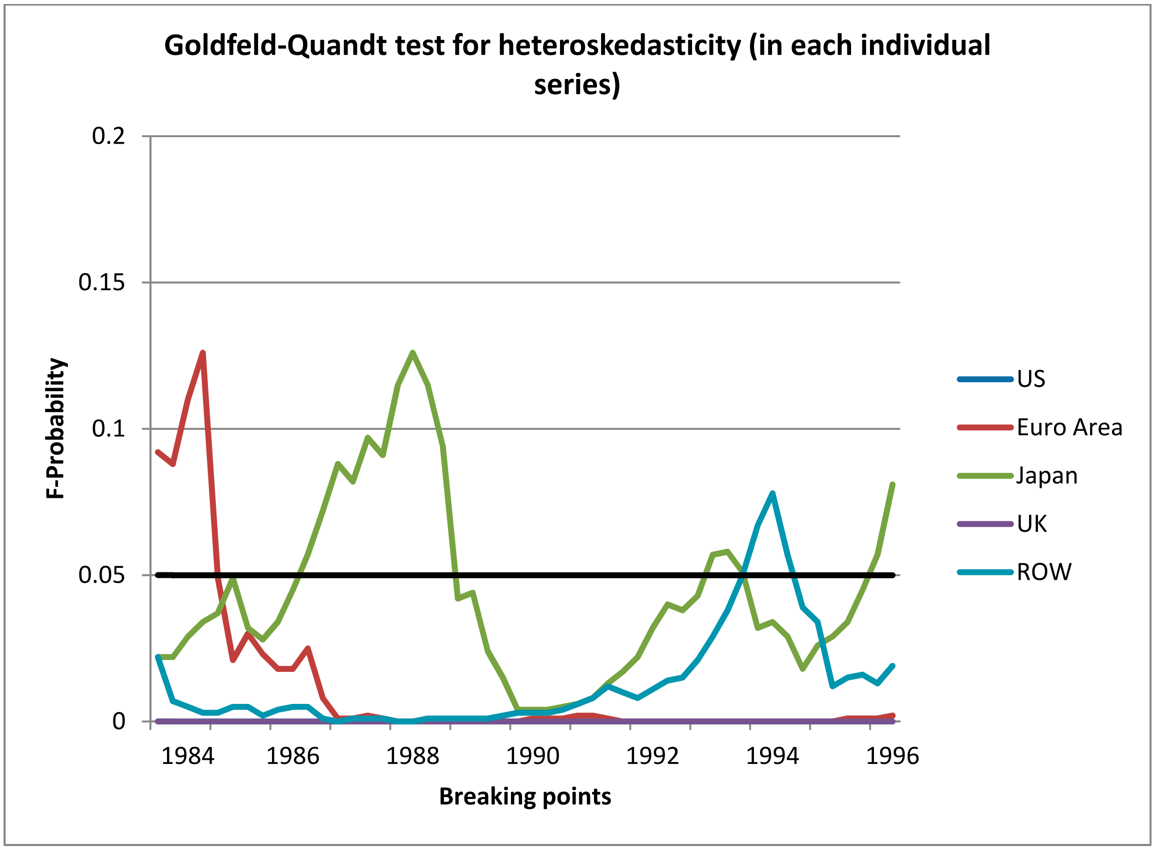
For each sample division point, we randomly draw from original VAR disturbances and generate an artificial dataset and re-estimate VAR.

$$\text{draw } \frac{e_1}{e_2} \xrightarrow{\text{yields}} \frac{\widetilde{e_1}}{\widetilde{e_2}} \xRightarrow{\textit{Original}\,\beta} \tilde{y} \xRightarrow{OLS} \tilde{\beta}_{(1)} \xrightarrow{and} \frac{\widehat{e_1}}{\widehat{e_2}} \xrightarrow{\textit{Identification}} \tilde{A}_{(2)}$$

(1) For the former uncertainty, we use A and $\tilde{\beta}$ to generate a set of IRFs.
(2) The latter uncertainty involves re-identifying the A matrix (accounting for the structural change in the A matrix as found in the empirical data). Using new $\tilde{A}$ and $\tilde{\beta}$, we calculate another set of IRFs. By construction, the second set of IRFs contains both types of uncertainty specified above.

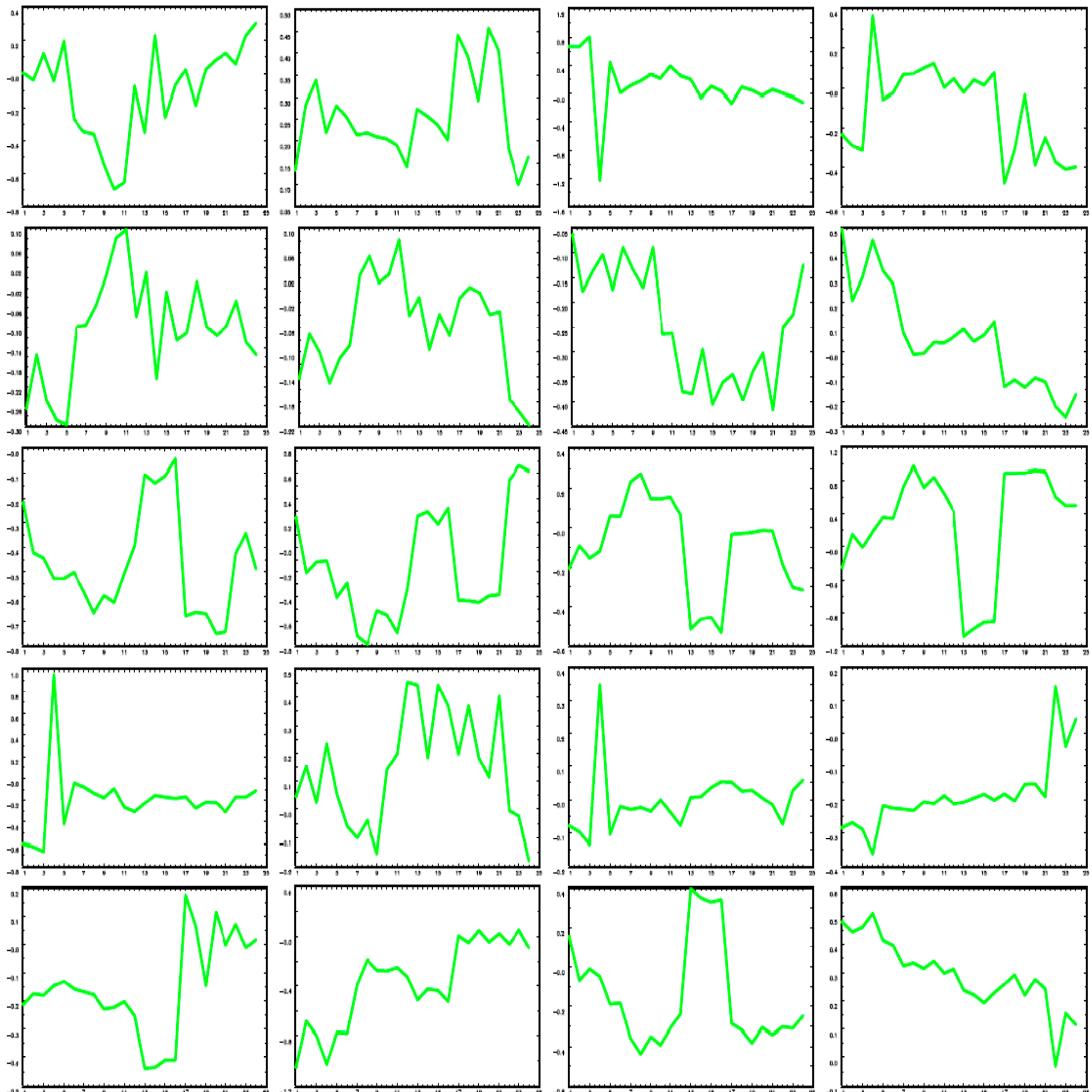
We repeat these steps 1000 times for each division point and calculate the standard errors with respect to the average impulse responses.

III. Goldfeld-Quandt test for heteroskedasticity



The above figure summarizes Goldfeld-Quandt test for heteroskedasticity of individual countries/regions VAR errors series. Heteroskedasticity is significantly present (at 5%) in U.S. and U.K. errors for all sample break points considered (between one-third to two-third of sample) while it can be rejected in periods for euro area, Japan, and ROW data. It is important to note that Rigobon identification relies upon relative heteroskedasticity, such that it does not require changes in each and every series.

IV. Estimated off-diagonal elements of A-matrix over possible break points



Along ROW: Distribution of estimated elements of the corresponding row of A-matrix at each break point considered (excluding the main diagonal element).

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