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Robin L. Lumsdaine
Eswar S. Prasad

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ABSTRACT

In this paper, we develop an aggregation procedure using time-varying weights for constructing the common component in international economic fluctuations. The methodology for deriving time-varying weights is based on some stylized features of the data documented in the paper. The model allows for a unified treatment of cyclical and seasonal fluctuations and also captures the dynamic propagation of shocks across countries. Based on correlations of individual country fluctuations with the common component, we find evidence for a "world business cycle" as well as evidence for a distinct European common component. We find few systematic differences in international business cycle relationships between the Bretton Woods and post-Bretton Woods periods.

Robin L. Lumsdaine
Department of Economics
Princeton University
Princeton, NJ 08544
and NBER
lumsdain@pucc.princeton.edu

Eswar S. Prasad
Research Department
International Monetary Fund
700 19th Street, NW
Washington, DC 20431
eprasad@imf.org

I. Introduction

The world economy has become more closely integrated in recent years due to increasing trade and financial flows across countries. This has spurred interest in the question of how this phenomenon has affected the transmission and propagation of business cycle fluctuations across national borders. An important question in this context is whether a substantial fraction of economic fluctuations are country-specific or if there exists a "world business cycle", which might be defined as fluctuations that are common for all countries.

This issue has implications in a number of dimensions. From a modeling perspective, the relative importance of country-specific versus common cross-country fluctuations has a bearing on the relevance of different classes of business cycle models. For instance, real business cycle models, where technology shocks are posited to be the main determinant of economic fluctuations, suggest that common international shocks (which could be industry-specific) are relatively more important than country-specific shocks. From a policy perspective, if business cycle fluctuations were highly positively correlated across all countries, the external trade sector would be unlikely to play a significant role in dampening fluctuations. Domestic policies aimed at affecting the real exchange rate and thereby attempting to boost net exports in the short run would then tend to have limited impact.

The objective of this paper is to estimate the common component in international economic fluctuations and to examine its properties. One strand of related literature has attempted to shed light on common fluctuations by looking at bivariate correlations of business cycle indicators and examining changes in these correlations over different time periods (see, e.g., Baxter and Stockman [1989] and Backus and Kehoe [1992]). Another strand of literature has focussed on using time series models to analyze the sources of economic fluctuations. Previous literature in this latter area has focussed on trying to separately identify aggregate, country-specific and industry-specific shocks. For instance, Stockman [1988] and Bayoumi and Prasad [1997] use an error components methodology while Altonji and Ham [1990], Gregory *et. al* [1995], Forni and Reichlin [1996], and Norrbin and Schlagenhauf [1996] use dynamic factor models. A key issue in this literature is the propagation mechanism that allows for lagged feedback effects across various shocks. Although dynamic factor models are able to allow for such feedback effects, this comes at the cost of having to estimate a large number of parameters and restrict the covariance properties of these shocks. In addition, the procedure followed in most of the literature implicitly weights all units of the disaggregated data equally in all periods.

One method for relaxing the equal-weights assumption is to weight by some measure of each country's relative size in total world output. Following this approach, we first examine a measure of the common component of international fluctuations obtained by using a fixed PPP-adjusted weight to aggregate seasonally adjusted industrial production growth rates. The correlations between industrial production growth in each country and this common component are strongly positive for most countries, supporting the notion of a "world business cycle". The fixed-weight measure of the common component is, however, inadequate in many respects. One reason is that the relative economic size of countries changes over time and the weights should reflect this dynamic nature. Another is that countries experience idiosyncratic shocks; these shocks, by definition, should not affect the common component. Fixed weights do not allow for different types of shocks in different periods; all shocks are presumed to have the same influence.

To address these limitations, in this paper, we propose an alternative time-varying weighting scheme for constructing the common component. The modeling strategy that we employ involves estimating univariate models of time-varying conditional variances for industrial production growth fluctuations in each country. The time-varying weights for each country are then derived as a function of the estimated conditional variances.

The weighting scheme is motivated by two empirical regularities that are documented in this paper. The first is the negative relationship between country size and the average volatility of industrial production growth rates. The second feature is the presence of conditional heteroskedasticity in monthly industrial production growth rates for all countries in the sample. We use these two features to determine time-varying weights by noting that each country's volatility relative to that of other countries provides a measure of the degree of idiosyncracy in the observed shock. The weighting scheme developed in this paper implicitly assigns a lower weight to a country when it is subject to a large country-specific shock but leaves the weights unchanged if a common shock occurs. The extent to which the methodology downweights outliers provides a way of distinguishing between idiosyncratic and common shocks.

Our methodology also implicitly captures the effects of the dynamic propagation of shocks across countries. For instance, the country that is first affected by a shock (or where the shock originates) initially would be assigned a lower time-varying weight. As the shock propagated across countries, the relative importance of this shock in the construction of the common component would increase.[1] Thus, the methodology implicitly distinguishes between truly idosyncratic shocks and shocks that affect all countries but with different magnitudes and at different times. There are no restrictions placed on the propagation of shocks across countries, unlike in the case of dynamic factor models that require restrictions on the feedback effects among different shocks.

Another important aspect of economic fluctuations that has gained prominence recently is the importance of seasonal fluctuations and the relationship between seasonal and business cycle fluctuations. The methodology developed in this paper can, in principle, eliminate the effects of idiosyncratic seasonal fluctuations on the common component. On the other hand, common seasonal fluctuations and the part of seasonal variation correlated with the business cycle do enter into the construction of the common component. Thus, the aggregation procedure allows for a unified treatment of seasonal and business cycle fluctuations.

The paper proceeds as follows. Section II briefly describes the dataset and reviews some important considerations for constructing the common component in international fluctuations. Section III motivates the use of time-varying weights in constructing the com-

[1] Intuitively, this might arise because information slowly reveals over time that the shock is of an aggregate nature rather than being country-specific.

mon component and describes the econometric procedure for estimation of these weights. Section IV examines the properties of the estimated time-varying weights and compares the properties of the common component constructed using these weights to that of a benchmark fixed-weight common component. Section V extends the results in two ways: (a) by investigating potential structural change in our specification between the Bretton Woods and post-Bretton Woods periods, and (b) by estimating a European common component. The sensitivity of the aggregation procedure to the treatment of deterministic seasonal effects is also examined. Section VI concludes.

II. Background

This section begins with a brief description of the data used in the analysis, followed by a discussion of a number of issues related to modeling the common component in international fluctuations.

The dataset used in this paper contains seasonally unadjusted monthly indices of industrial production for seventeen OECD economies over the period 1963-1994. The data were drawn from the OECD Analytical Database.[2] On average, industrial production accounts for only about one-third of total output in these economies. However, this index tends to be highly correlated with the aggregate domestic business cycle and, since it represents output in the traded goods sector, is more relevant for examining the transmission and propagation of business cycles across countries. In addition, real GDP is available only at a quarterly frequency, which is inadequate for the implementation of our empirical methodology given the available span of the data.

The data are transformed into logarithms and first differenced to achieve stationarity and are then seasonally adjusted by regressing the log differences on 12 monthly dummy variables. We choose to take first differences in part because, as noted by Baxter and Stockman [1989], this procedure "emphasizes the higher frequencies associated with the

[2] Because of a large outlier associated with the student strike in France in 68:5, we interpolated this observation.

business cycles" relative to linear detrending.[3] The implications of removing deterministic seasonal effects from the data are discussed below.

Table 1 provides summary statistics for the data over the full sample and also for the Bretton Woods (BW) and post-Bretton Woods periods. The results show a significant decline in the mean growth rates of some of the series in the post-BW period.[4] Controlling for this structural shift in the mean, for many countries there is also an increase in the standard deviation but, in most cases, this increase is relatively small.

An important issue that arises in using unadjusted macroeconomic data is the relative importance of seasonal fluctuations. Visual inspection of our monthly industrial production data indicated that there were strong seasonal components in virtually every country in our sample; these were particularly large and noticeable in countries like Italy. Further evidence is provided by time series regressions which show that deterministic seasonal dummies can explain a substantial fraction of variation in monthly industrial production growth rates for most countries.[5]

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[3] We tested the hypothesis that the data are difference stationary by testing for the presence of a unit root in the logarithms of the data using an Augmented Dickey-Fuller regression with twelve monthly seasonal dummy variables included. The results of these tests are given in Appendix Table A1. We find that in only one case is the unit root hypothesis rejected in favor of trend-stationarity – the United States. This is somewhat at odds with previous results for the United States; for example, Nelson and Plosser [1982] did not reject the unit root hypothesis for industrial production using annual data from 1869-1970. Gerlach [1988], who used industrial production data for 1963:9-1986:3, also finds very little evidence against the unit root hypothesis in the BW and post-BW periods for the countries in his sample, including the United States. Hence, we take first differences in order to transform the data for all countries in a uniform manner. As a check that we have adequately purged the data of nonstationarity, we also tested the differenced data for the presence of a unit root. For every country, the null hypothesis of a unit root in the first differences was rejected in favor of stationarity.

[4] This notable decline may be related to the oil shock of the early 1970's and the subsequent productivity slowdown.

[5] For the countries in our sample, regressions on seasonal dummy variables indicated that, on average, about eighty percent of the variation in log differences of unadjusted

The appropriate treatment of seasonal effects is, however, fraught with complications. A simple procedure adopted by many authors (e.g., Beaulieu and Miron [1992], Beaulieu, MacKie-Mason, and Miron [1992]) is to regress the unadjusted data on seasonal dummies. Other deterministic filters such as the Census Bureau's X-11 procedure have also been used widely, although it has been argued that such filters do not necessarily retain the salient features of the data (e.g., Ghysels and Perron [1993]). On the other side of the debate are authors such as Franses, Hylleberg, and Lee [1995] who argue that stochastic seasonality in the form of seasonal unit roots is the appropriate characterization of seasonal fluctuations. These authors recommend seasonal differencing in order to eliminate unit roots at seasonal frequencies.

We prefer to remain agnostic on the appropriate characterization of seasonal variation in the data. We recognize that patterns of seasonal variation could change over time. In addition, as noted by Beaulieu, MacKie-Mason, and Miron [1992], seasonal cycles may be correlated with business cycles. Furthermore, care must be taken not to remove a potential common seasonal component; Engle and Hylleberg [1996], for instance, find evidence of common seasonal patterns in unemployment among some OECD countries. For these reasons, rather than attempting to remove the entire seasonal component, we are interested in eliminating seasonality only to the extent that it interferes with our ability to measure the common component of fluctuations. Because such a large fraction of the variation is due to deterministic seasonal components (see footnote 5), we regress the unadjusted data on deterministic seasonal dummies and use the residuals from these regressions in our analysis. The sensitivity of the results to this procedure is examined later by repeating the analysis using unadjusted data.

Another important consideration in estimating the common component of international fluctuations is the propagation of shocks across countries. Error component models

monthly industrial production could be explained by these seasonal factors. The R^2 from these regressions ranged from 53 percent for Greece to 95 percent for Sweden. In most cases, the seasonal effects remained as important even when quarterly averages of the unadjusted data were used.

typically ignore this issue while dynamic factor models attempt to capture this phenomenon by allowing for feedback effects across country-specific and aggregate fluctuations. This comes at the cost, however, of having to estimate a large number of parameters and having to impose stringent restrictions on the covariance properties of the shocks. In addition, the structure of the transmission mechanism for these shocks is generally assumed to remain unchanged over time. An alternative approach is the common trends and common cycles method developed in Engle and Kozicki [1993], although this methodology requires restrictions on the factor loadings of the common cycles in order to allow for additional idiosyncratic behavior.[6]

This discussion suggests that an ideal weighting scheme for constructing a measure of the common component would be capable of distinguishing between country-specific and common fluctuations. In principle, the weights chosen for constructing the aggregate measure should reflect fluctuations only in the common components in each series. The relative weight of a particular country should decrease when that country experiences a largely idiosyncratic shock. If, on the other hand, a country's shock is of the common component type, its relative weight should remain unchanged. If it were possible to separately identify the two types of shocks for each country, we could compute time-varying weights which took into account both the relative across-country weight and the relative within-country weight (between common and idiosyncratic shocks). Because these are not observable, however, it is necessary to determine a mechanism for distinguishing between these two effects without having to impose unwieldy restrictions.

The above discussion suggests a role for time-varying weights in the construction of a common component. In the next section, we propose a methodology for constructing these time-varying weights.[7]

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[6] Lippi and Reichlin [1994] have a useful discussion of alternative concepts of comovements of variables in the short run and the long run when different trend-cycle decompositions are considered.

[7] The notion of aggregating using time-varying weights has been used in models of combining forecasts; for example, Deutsch, Granger, and Teräsvirta [1994] use rolling regres-

III. Aggregation using Time-Varying Weights

This section first presents evidence on some empirical regularities that could be exploited to devise a procedure for constructing time-varying weights. The econometric procedure used to derive these weights and construct the resulting common component is then described.

We begin by documenting the relationship between the fixed OECD weights (W_i), which are interpretable as a measure of relative country size, and the standard deviations of the individual industrial production growth rates (std_i).[8] This relationship is summarized in the following regression (standard errors are in parentheses):

$$W_i = \underset{(4.49)}{14.72} - \underset{(78.95)}{178.56} std_i \qquad (1)$$

There is clearly a strong negative relationship between country size and volatility in industrial production growth rates.[9] This result is consistent with the view that larger economies tend to be more diversified, thereby tending to have lower aggregate volatility, and are also less affected by external shocks emanating from other economies.[10] The methodology developed in this paper exploits this negative relationship between country

sions to estimate time-varying weights.

[8] The OECD weights are derived from gross domestic product originating in the industrial sector and the GDP purchasing power parity for 1990.

[9] The results were similar when we excluded the United States and/or other outliers such as Luxembourg. We obtained virtually identical results using 1985 OECD weights (earlier weights were not available). Head [1995] also documents a similar negative relationship between country size and the variance of real GDP among industrial economies. In related work, we also have examined this relationship for U.S. states using annual real gross state product over the period 1977-92. We find a similar, although less strong, negative relationship between the standard deviation of annual gross state product and relative state size.

[10] Gerlach [1988] makes a similar observation.

size and business cycle volatility. The above observation also suggests, however, that if volatility in individual industrial production growth rates were constant over time, the use of fixed weights (that are related to country size, such as the OECD weights) might be justified.

We therefore investigate whether the individual industrial production growth series display evidence of time-varying volatility, in particular, conditional heteroskedasticity; such evidence would motivate the need for time-varying weights. One way to test for this is to use the Box-Pierce Q-statistic to test for autocorrelation in the *squared* residuals. Results from the computation of this statistic are given in the last column of Appendix Table A1; for all countries, we reject the null hypothesis of no autocorrelation (conditional homoskedasticity of the residuals) in favor of the alternative. In all cases, autocorrelations up to order 12 were used for the computation of the statistic; under the null hypothesis, this is distributed as a $\chi^2(12)$ random variable. The corresponding 1% critical value is 26.2.

Since all series display evidence of conditional heteroskedasticity, we estimate univariate GARCH(1,1) models for each series and use the predicted values of the conditional variance to construct time-varying weights for the aggregate series. The GARCH model (developed by Bollerslev [1986]) is a variant of the autoregressive conditional heteroskedasticity (ARCH) model introduced in Engle [1982]. The GARCH(1,1) model expresses the conditional variance as a function of lagged squared residuals and past conditional variance. We select this model because it has been shown empirically to capture the volatility dynamics in a wide variety of data and because quasi-maximum likelihood estimators of this model are consistent and asymptotically normal (Lumsdaine [1996]). The precise specification, for each country i, is as follows:

$$(2a) \qquad y_{it} = C_i + \epsilon_{it}, \qquad \epsilon_{it}|I_{t-1} \sim N(0, h_{it})$$

$$(2b) \qquad h_{it} = \omega_i + \alpha_i \epsilon_{it-1}^2 + \beta_i h_{it-1},$$

where y_{it} represents industrial production growth in country i at time t, C_i is a country-specific mean, and I_t denotes information available at time t. The parameters ω_i, α_i, and

β_i are constrained to be positive; the likelihood is also penalized to ensure that $\alpha + \beta \leq 1$, a constraint which never binds in the estimation. In addition, the unconditional mean and variance of country i's industrial production growth rate are chosen as starting values for C_i and ω_i, respectively, and the initial value of the conditional variance, h_{it}, is 1.[11]

We estimate model (2) and compute $\hat{h}_{it}$ for each series, $i = 1, \ldots, 17$. Based on (1), $h_t^{-1/2}$ can be interpreted as a time-varying measure of relative country size. The time-varying weights W_{it} are then expressed as a fraction of the total weight, so that

$$W_{it} = \frac{1}{\sqrt{h_{it+1}}} \Big/ \sum_{i=1}^{17} \frac{1}{\sqrt{h_{it+1}}}. \tag{3}$$

Note that h_{it+1} is in the information set I_t. The aggregate series representing the common component of international fluctuations is then constructed as $Z_t^G = \sum_{i=1}^{17} W_{it} y_{it}$.

Note that the key assumption underlying our methodology is that the relative conditional standard deviation is a measure of the degree of commonality among fluctuations in different countries between series. If volatility is shared across countries, this suggests that shocks are less idiosyncratic. This differs from the assumptions underlying factor models (which assume orthogonal idiosyncratic errors) and error components models (which assume orthogonality between the common and idiosyncratic components). In this context, it is worth re-emphasizing that our objective is to estimate the common component in international fluctuations rather than to identify a global "shock" that is orthogonal to all country-specific shocks.

In constructing the common component using time-varying weights, we have not specified the transmission mechanism between fluctuations in the aggregate series and in individual countries. We interpret country-specific increases in conditional volatility as reflecting

[11] The above parameter restrictions are standard in estimation of GARCH models. Given these restrictions, as long as the initial value of h_{it} is assumed to be drawn from the stationary distribution, dependence on this initial value diminishes exponentially. We experimented with different sets of starting values. None of the results reported below were sensitive to the choice of starting values.

country-specific fluctuations. Thus, holding other shocks constant, a shock that hits only one country would increase that country's conditional volatility alone. This would result in a decline in the weight attributed to that country in constructing the common component for that period. If the shock propagated to other countries over time, however, the conditional volatility of fluctuations in other countries would increase, and the weights would then depend on how widely and over what time horizon the shock was propagated across countries. Thus, the methodology is capable of accounting for the propagation of shocks across countries without imposing any structure on the dynamics of this propagation.

An illustrative numerical example of how the weights adjust to capture the propagation of shocks is presented in the Appendix. It is also important to note that a more restrictive time series model such as an ARCH(1) specification could capture contemporaneous transmission but would not allow for the dynamic propagation of shocks. In contrast, the GARCH model provides a flexible functional form capable of capturing propagation dynamics and allows for persistence in the weights via the coefficient β in (2).

The endogeneity between the aggregate series and the individual countries is captured in the conditioning information of the GARCH model; in particular, since $h_{t+1} \in I_t$, the time-varying weights are in the conditioning information set and can thus be thought of as known at time t. Therefore, the GARCH model also provides a mechanism for forecasting future relative fluctuations.

To summarize, our time-varying weighting scheme has the following characteristics: (i) the weights vary over time in a manner that minimizes the impact of country-specific fluctuations on the common component; (ii) the weights reflect relative country size; (iii) the methodology allows for a unified treatment of seasonal and business cycle flucutations, and also (iv) captures the propagation of shocks across countries without placing restrictions on the transmission mechanism for the shocks.

IV. Results

In this section, we first examine the correlations of fluctuations in individual country industrial production growth rates with a benchmark fixed-weight common component. Some properties of the time-varying weights estimated using the univariate GARCH estimates are then discussed, followed by an analysis of the common component constructed using these weights.

A. Fixed-weight common component

To construct a benchmark common component, we use the 1990 OECD weights as given in the first column of Table 1 to aggregate the data into a single series.[12] The second column of Table 1 summarizes the correlations of this fixed-weights benchmark common component with industrial production growth rates of the individual countries. Not surprisingly, many of the countries with large weights are also highly correlated with the aggregate series, but there is also substantial correlation with countries that have low weights but high levels of variability. In particular, Luxembourg has a correlation of around 0.5, higher than the correlation for the United States. In addition, the correlation between the benchmark and the individual countries does not appear to be constant; for example, industrial production in Finland and France is negatively correlated with the benchmark in the Bretton Woods period (column 3) and is highly positively correlated in the post-Bretton Woods period (column 4). While some European countries witnessed a post-Bretton Woods decline in correlation with this fixed-weight benchmark, many countries in fact experienced an increase. These results differ from those of Baxter and Stockman [1989], who conclude that cross-country correlations of industrial production growth rates have declined markedly in the post-Bretton Woods period. However, they base their

[12] Forni and Reichlin [1996] use a dynamic factor approach and show that the optimal weights in such a framework are the eigenvalues corresponding to the maximum eigenvector. This fixed-weight approach implicitly assumes that the variance of the idiosyncratic component is a constant proportion of the variance of the total. Even with "optimal weights", however, their approach does not allow these relationships to change over time.

conclusions on bilateral correlations with U.S. industrial production growth rates, while the benchmark measure used here is more comprehensive.

The problem with the fixed-weights measure of the common component, as noted earlier, is that it might in fact partly reflect country-specific fluctuations. In particular, large idiosyncratic fluctuations experienced by countries with relatively small weights would tend to unduly influence the fixed-weight common component. Hence, we now turn to an examination of the time-varying weights.

B. Time-varying weights

Table 2 (center panel) presents summary statistics for the estimated time-varying weights for each country. The weights are volatile and generally quite skewed. Nonetheless, the means and the ranges of the weights are of some interest.

In comparing the averages (over time) of the time-varying weights to the fixed OECD weights used in the benchmark model, the time-varying weights attribute much less importance to smaller, more highly volatile countries such as France and Spain, and relatively more importance to the United States and Canada. In a few cases, the time-varying weights may be at first glance surprising. In particular, Italy has the smallest weight in the aggregate series; this is due to large seasonal fluctuations (in higher moments) associated with the vacation structure in Italy.[13] Because of this, Italy's shocks are inherently more idiosyncratic. The time-varying weights model implicitly accounts for the importance of idiosyncratic shocks relative to common shocks when determining the weights, something the benchmark model cannot do (unless the share of idiosyncratic to total shocks remains

[13] Note that the seasonal adjustment procedure used in this paper eliminates seasonal fluctuations only in the conditional mean of each series. Idiosyncratic seasonal fluctuations in the variance, as in the case of Italy, are important for the identification of our time-varying weights. Seasonal fluctuations that are common to all countries will have no effect on the weights with this structure. As will be discussed subsequently, common seasonal fluctuations are evident in our time-varying aggregate.

constant over time).[14] The other surprising case is that of Germany, which has a small weight relative to its fixed OECD weight. In addition, Austria and Belgium have larger average time-varying weights than their OECD fixed weights, suggesting that these countries may pick up part of the "German business cycle" since these economies are closely related to that of Germany and face similar shocks.[15] The average weights are somewhat misleading as the weights tend to be very volatile. For instance, in the case of the United States, the weights attain a minimum as low as 14.8 and a maximum of 52.0 percent of the total. The weights for other countries also exhibit a wide range of variation.

The time-varying weights in each time period are principally determined by the *relative* fluctuations in industrial production growth across countries. A common seasonal fluctuation will have little effect on the relative weights in a given time period, whereas an idiosyncratic seasonal component (as in the case of Italy) will receive a smaller weight and will, therefore, have a smaller influence on the fluctuations of the overall aggregate. This is apparent in Figure 1, which plots the deseasonalized log differences of monthly industrial production and the estimated time-varying weights for Italy. The deseasonalizing procedure leaves a significant amount of residual higher moment seasonality, which leads to downward spikes in the time-varying weights. Figure 2, which shows the deseasonalized log differences of industrial production and the time-varying weights for the United States illustrates that such seasonal effects are absent in this case.

Both figures demonstrate that the time-varying weights are quite volatile. In mid-1974, the U.S. weight has a sharp downward spike, apparently reflecting the sharp effect of the oil price shock on the U.S. economy. The mirror image of this, of course, is an

[14] Since it dampens the effects of idiosyncratic shocks, the common component constructed using time-varying weights has an average volatility, as measured by the standard deviation, that is about 40 percent lower than the average volatility of the fixed-weight aggregate.

[15] Both Belgium and Austria have relatively strong positive correlations with Germany, suggesting the presence of a common cycle in these countries. Pairwise correlations among all countries are given in Appendix Table A2.

increase in the relative weights of most other countries, including Italy, in this period. Note, however, that the U.S. weight rises quickly thereafter, reflecting the propagation of this shock to other countries.

Correlations between the time-varying weighted aggregate series and the individual countries' industrial production growth rates are reported in the last panel of Table 2. There are a few countries for which the correlations are different when compared to the correlations with the fixed-weight aggregate. For instance, the correlation of U.S. fluctuations with the time-varying common component is much higher than its correlation with the fixed-weight common component. On the other hand, the correlation for Italy drops sharply when using the time-varying rather than the fixed-weight common component. This reflects the (substantially) lower average weight of Italy in constructing the time-varying common component, which reduces the effect of its idiosyncratic seasonal fluctuations on the common component. In the case of France, however, the full sample correlation with the time-varying component is much higher than with the fixed-weight common component, even though the average time-varying weight for France is much lower than its fixed OECD weight.

A question that arises at this juncture is the relative importance of global versus country-specific shocks for macroeconomic fluctuations. As noted in the introduction, this has implications for the relevance of different classes of business cycle models (e.g., Stockman [1988]) and also for current account dynamics (e.g., Glick and Rogoff [1995]). Unlike in an error components framework that imposes the assumption of orthogonality between global and country-specific shocks, however, we cannot directly answer this question in our framework. In particular, we are interested in estimating the component that is common to *all* countries. Thus, there are still possibly significant correlations between subsets of countries. Most previous literature (e.g., Forni and Reichlin [1996], Kwark [1996]) has focused on identifying common "shocks". We do not separately identify the nature of individual countries' shocks but instead attempt to identify the extent to which shocks of any type – seasonal, business cycle, etc. – are common across countries. Nevertheless, the strong positive correlations between individual country industrial production growth fluctuations and the common component indicate that global shocks are quantitatively quite important.[16]

V. Sensitivity of Results

This section explores the sensitivity of the results discussed in the previous section. First, we separately examine the properties of the time-varying weights common component over the Bretton Woods and post-Bretton Woods periods. Examining correlations of individual country fluctuations with the common component in international fluctuations enables us to address the question of whether the correlation of business cycles across countries has changed significantly in the post-Bretton Woods period. Second, we construct a measure of the European common component and examine its properties. There has been growing interest in the relative importance of common economic fluctuations in Europe as European Monetary Union comes closer to becoming a reality. The exchange rate plays a potentially useful role as an adjustment mechanism in response to country-specific shocks. Hence, the relationship between country-specific and common fluctuations could have important implications for the success of a currency union. Finally, we examine the sensitivity of the results to our choice of deseasonalizing procedure. In particular, the time-varying weights methodology implicitly accounts for common seasonal fluctuations. Thus, the effects of deseasonalizing should be less important with our time-varying aggregate than with the benchmark aggregate. In addition, residual seasonality should also be lower.

A. Bretton Woods

In Table 1 it was documented that industrial production growth has slowed in all countries during the post-Bretton Woods period. Based on standard deviations of the data, however, there did not seem to be a systematic commensurate change in volatility. We investigate this more thoroughly in this section. Failure to control for the mean-

[16] A principal components analysis of our dataset indicated that the first common component obtained using this technique had an R^2 contribution of about 0.25.

change could result in misleading inference about the conditional variance (Lumsdaine and Ng [1996]) which, in turn, could affect the accuracy of the time-varying weights. To investigate this possibility, we estimate a modified version of equation (2):

$$(4a) \qquad y_{it} = C_i + C_{1i}\mathbf{1}(t > 1973:6) + \epsilon_{it}, \qquad \epsilon_{it}|I_{t-1} \sim N(0, h_{it})$$

$$(4b) \qquad h_{it} = \omega_i + \alpha_i \epsilon^2_{it-1} + \beta_i h_{it-1},$$

where $\mathbf{1}(A)$ is an indicator variable equal to 1 if event A is true and 0 otherwise. That is, in the deseasonalized data, we allow for a change in mean associated with the end of Bretton Woods.[17] With the exception of Italy, in no case was the coefficient C_1 statistically significantly different from zero. In addition, the change in the mean of the associated time-varying weights was negligible.

The correlations of individual country industrial production growth fluctuations with the time-varying weight common component for the Bretton Woods and post-Bretton Woods periods are reported in the last two columns of Table 2. For most countries, the correlations are similar across the two sub-periods. The United States and certain European countries including Finland, France, Norway, and Spain have more strongly positive correlations with the common component in the post-Bretton Woods periods. On the other hand, the correlations with the common component decline in the post-Bretton Woods period for some countries such as Belgium, Germany, Portugal, and Sweden. Thus, the results using either the fixed or the time-varying weights do not provide unequivocal support for the view that business cycle fluctuations across countries have become more closely linked in the post-Bretton Woods period (see, e.g., Gerlach [1988]). But neither do our results confirm that economic fluctuations have become substantially more country-specific in the post-Bretton Woods period (see, e.g., Baxter and Stockman [1989]). In our view, the main conclusion to be drawn from these results is that virtually all countries have a strong pos-

[17] Alternatively, we could estimate separate GARCH(1,1) models for the two subperiods; such a procedure is problematic due to the diminished number of observations. Accurate estimation of the GARCH(1,1) model typically requires a large number of observations; see, for example, Hong [1987] and Lumsdaine [1995].

itive correlation with the common component in international fluctuations, particularly in the post-Bretton Woods period, confirming the existence of a "world business cycle".

B. European Common Component

This section examines alternative measures of the common component in European economic fluctuations, constructed using all countries in the sample except Canada, Japan, and the US. The fixed weight component uses the same OECD 1990 weights discussed earlier while the time-varying component is constructed using equations (2) and (3); both sets of weights are multiplied by 100 in each time period. Table 3 reports summary statistics for the time-varying weights and the correlations of each country's industrial production growth rate with both the fixed and variable weight measures, for the full sample and also for the Bretton Woods and post-Bretton Woods subsamples. As in the case of the world common component, Italy and Spain experience many idiosyncratic shocks and thus receive substantially less weight using our time-varying method than in the fixed-weight aggregate.

The correlations of individual country fluctuations with the European common component are strongly positive for virtually all of the European countries. The last column of Table 3 indicates that this result is more evident in the post-Bretton Woods sample and confirms the existence of a "European business cycle".[18] For most European countries, the full sample correlation with the European common component is significantly stronger than the correlation with the world common component. An interesting finding is that, despite their relatively large weights in the construction of the European common component, both France and the United Kingdom have higher correlations with the world common component than with the European common component. Fluctuations in the United States were negatively correlated with the European common component during the Bretton Woods period but are positively correlated in the post-Bretton Woods period.

[18] Artis and Zhang [1995] arrive at a similar conclusion by examining cross-country correlations of industrial production growth fluctuations and using a number of different detrending techniques.

Fluctuations in Japan and Canada are positively correlated with the European component in both periods. Also, perhaps not surprisingly, the aggregate constructed with time-varying weights is more highly correlated with the time-varying world component than with its fixed-weight counterpart.

C. Seasonal Adjustment

As discussed in section II, the procedure for deseasonalizing unadjusted data could potentially have a large impact on the empirical results. The time-varying weights methodology developed in this paper should, in principle, discriminate between country-specific and common seasonal fluctuations and adjust each country's weights accordingly. But, as noted earlier, we removed seasonal means from each country's data by regressing on a set of seasonal dummies in order to avoid the problems that could result from the misspecification of conditional means. To examine the sensitivity of the results to this procedure, we recomputed the time-varying weights and the international common component using unadjusted data. The use of unadjusted data may be viewed as allowing for common deterministic seasonal fluctuations to be reflected in the common component.

To conserve space, we summarize only the main results here.[19] The relative ranking in terms of average weights was roughly similar to that in Table 2 although there were some differences. The mean weight for the United States was much higher at 53.1 percent while the weights for Canada and Japan were smaller, suggesting that seasonal fluctuations in the latter two countries are idiosyncratic. The correlations between individual country fluctuations and the common component were generally higher than those reported in Table 2, indicating that a substantial fraction of the fluctuations that are captured by deterministic seasonal dummies is similar across countries. We are reluctant to make too much of these results because of the possible misspecification problems that could arise from the use of unadjusted data. Nevertheless, our principal result about the existence

[19] A table detailing these results is available from the authors on request.

of a substantial common component in international fluctuations is confirmed by these correlations.

VI. Conclusion

This paper has proposed a new methodology for estimating the common component in international economic fluctuations. The methodology accounts for relative country size but is simultaneously capable of distinguishing between idiosyncratic and common shocks, without imposing a formal structure on the dynamic propagation of these shocks across countries. In addition, it provides a unified treatment of seasonal and business cycle fluctuations, allowing for correlations between these fluctuations while eliminating the impact of idiosyncratic seasonal variation on the common component.

The methodology is based on two properties of fluctuations in industrial production growth rates that were documented in this paper. The first is the negative relationship between country size and the volatility of industrial production growth rates. The second property is that industrial production growth rates in all countries exhibit evidence of conditional heteroskedasticity. Combining these two features suggests a time-varying weighting scheme for measuring the common international component where the time-varying weights are inversely proportional to the conditional variance of industrial production growth rates for each country.

The methodology has potential applications for aggregation in a wide variety of other contexts where conditional volatility provides a natural stochastic specification with which to form time-varying weights. Possible applications might include the construction of stock market indices and aggregate price indices. Another natural application is in the construction of measures of the "world interest rate".

In the empirical example considered here, we found that industrial production growth fluctuations in virtually all countries in the sample have strong, positive correlations with the common component of international fluctuations constructed using time-varying weights. This phenomenon was more apparent in the post-Bretton Woods period. In general, however, we did not find systematic differences in these correlations across the Bretton Woods and post-Bretton Woods periods. Similar results were obtained when we constructed a time-varying measure of the common component in European economic fluctuations. Virtually all European countries in the sample had strong, positive correlations with this common component, which was distinct from the world common component. These results confirm the importance of common international influences in driving business cycle fluctuations in the main industrial economies.

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APPENDIX

This appendix provides a few numerical examples that illustrate two points made in the text. The first set of examples shows how the common component constructed using time-varying weights from the GARCH(1,1) model captures the dynamic propagation of shocks across countries. The second example illustrates that time-varying weights constructed using a more restrictive model such as an ARCH(1) specification can not capture these feedback effects.

Assume that there are two countries, A and B. The parameter values (corresponding to equation 2a in the text) are assumed to be $\omega_i = 0.1$, $\alpha_i = 0.4$, $\beta_i = 0.5$, for $i = A, B$, that is, for simplicity, assume that the two countries are driven by the same conditional volatility process. Also assume that shocks are normally of magnitude equal to 1, so that $h_t = 1$, implying that, initially, both countries are weighted equally, with weights equal to $\frac{1}{2}$. We will examine the effects of the arrival of a shock of magnitude 2.

Example 1: GARCH(1,1) model

Case 1: Both countries experience a simultaneous shock of the same magnitude.

In this case, the weights will not change, demonstrating that common fluctuations do not alter the relative weights.

Case 2: Country A receives an idiosyncratic shock of magnitude 2; shocks return to normal magnitude in the following period.

Period 1:

$$h_{A1} = 0.1 + (0.4)(2)^2 + (0.5)(1) = 2.2$$
$$h_{B1} = 0.1 + (0.4)(1)^2 + (0.5)(1) = 1$$
$$W_{A1} = \frac{\frac{1}{\sqrt{2.2}}}{1 + \frac{1}{\sqrt{2.2}}} = 0.4$$
$$W_{B1} = 1 - W_{A1} = 0.6$$

Period 2:

$$h_{A2} = 0.1 + (0.4)(1)^2 + (0.5)(2.2) = 1.6$$
$$h_{B2} = 0.1 + (0.4)(1)^2 + (0.5)(1) = 1$$
$$W_{A2} = \frac{\frac{1}{\sqrt{1.6}}}{1 + \frac{1}{\sqrt{1.6}}} = 0.44$$
$$W_{B2} = 1 - W_{A2} = 0.56$$

Period 3:

$$h_{A3} = 0.1 + (0.4)(1)^2 + (0.5)(1.6) = 1.3$$
$$h_{B3} = 0.1 + (0.4)(1)^2 + (0.5)(1) = 1$$
$$W_{A3} = \frac{\frac{1}{\sqrt{1.3}}}{1 + \frac{1}{\sqrt{1.3}}} = 0.47$$
$$W_{B3} = 1 - W_{A3} = 0.53$$
$$\vdots$$

In this case, the relative weight of country A is reduced due to the idiosyncratic shock but, as the shock does not propagate, the weights move back to their original levels, with country A approaching this level from below and country B from above.

Case 3: Country A receives a shock of magnitude 2; this shock is propagated to country B in the following period.

Period 1:
$$h_{A1} = 0.1 + (0.4)(2)^2 + (0.5)(1) = 2.2$$
$$h_{B1} = 0.1 + (0.4)(1)^2 + (0.5)(1) = 1$$
$$W_{A1} = \frac{\frac{1}{\sqrt{2.2}}}{1 + \frac{1}{\sqrt{2.2}}} = 0.4$$
$$W_{B1} = 1 - W_{A1} = 0.6$$

Period 2:
$$h_{A2} = 0.1 + (0.4)(1)^2 + (0.5)(2.2) = 1.6$$
$$h_{B2} = 0.1 + (0.4)(2)^2 + (0.5)(1) = 2.2$$
$$W_{A2} = \frac{\frac{1}{\sqrt{1.6}}}{\frac{1}{\sqrt{1.6}} + \frac{1}{\sqrt{2.2}}} = 0.54$$
$$W_{B2} = 1 - W_{A2} = 0.46$$

Period 3:
$$h_{A3} = 0.1 + (0.4)(1)^2 + (0.5)(1.6) = 1.3$$
$$h_{B3} = 0.1 + (0.4)(1)^2 + (0.5)(2.2) = 1.6$$
$$W_{A3} = \frac{\frac{1}{\sqrt{1.3}}}{\frac{1}{\sqrt{1.3}} + \frac{1}{\sqrt{1.6}}} = 0.53$$
$$W_{B3} = 1 - W_{A3} = 0.47$$
$$\vdots$$

In this case, the relative weight of country A is reduced in this first period, just as in case 2. Note that in the initial period of the shock's arrival, we cannot distinguish whether or not the shock is common or idiosyncratic. However, as the shock propagates to country B in the second period, country A receives a higher weight. In addition, country B's weight is not reduced by as much as it would be if the shock hitting it was purely idiosyncratic. Subsequently, the conditional variances and the weights settle back down to their original levels.

The GARCH(1,1) model is preferred to an ARCH(1) because it allows for feedback effects as illustrated above. Without the β coefficient, however, weights would still change but the propagation of the shock to other countries would not be captured. The next example shows this.

Example 2: ARCH(1) model

Assume that the true values of ω_i and α_i are 0.1 and 0.9, respectively, and that $\beta_i = 0$, for $i = A, B$. These values are chosen so that, as in the previous example, the initial values for h_{At} and h_{Bt} are both equal to 1 and the weights for the two countries are equal to $\frac{1}{2}$. This model implies that conditional volatility follows an ARCH(1) process. In this case, a shock to either country will result in that country receiving a lower weight in the current period, but the weight will return to the original level in the following period. Consider case 3 above:

$$
\begin{aligned}
\text{Period 1:} \quad & h_{A1} = 0.1 + (0.9)(2)^2 = 3.7 \\
& h_{B1} = 0.1 + (0.9)(1)^2 = 1 \\
& W_{A1} = \frac{\frac{1}{\sqrt{3.7}}}{1 + \frac{1}{\sqrt{3.7}}} = 0.34 \\
& W_{B1} = 1 - W_{A1} = 0.66
\end{aligned}
$$

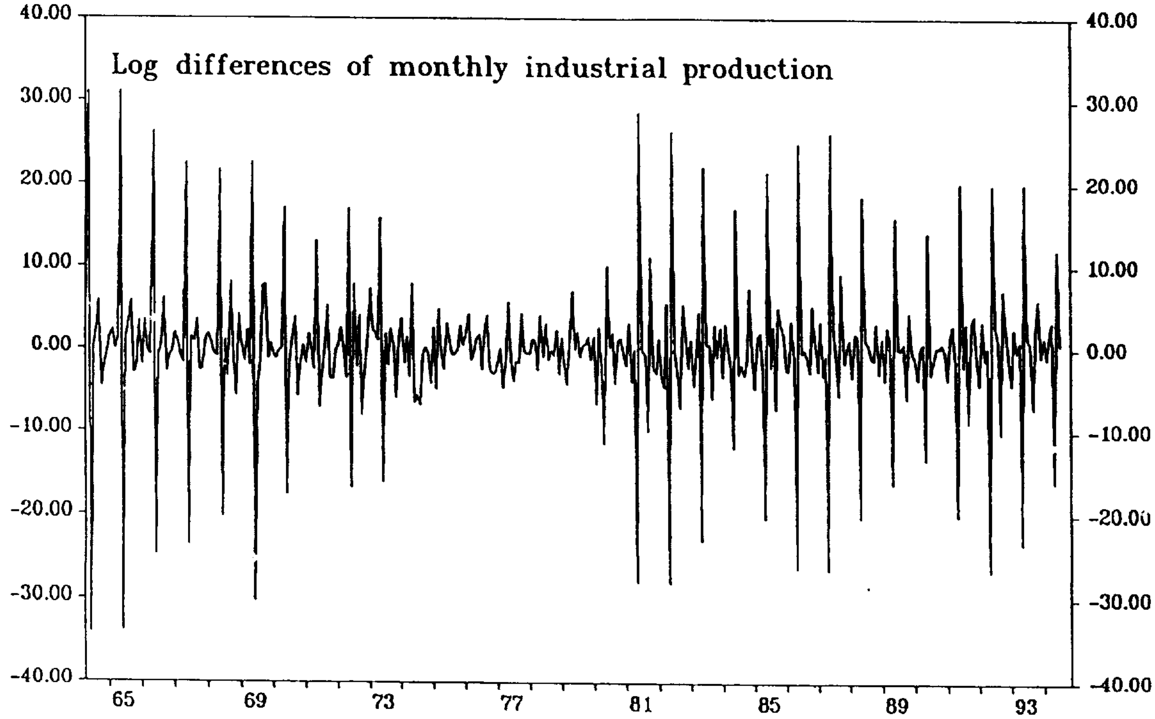
$$
\begin{aligned}
\text{Period 2:} \quad & h_{A2} = 0.1 + (0.9)(1)^2 = 1 \\
& h_{B2} = 0.1 + (0.9)(2)^2 = 3.7 \\
& W_{A2} = \frac{1}{1 + \frac{1}{\sqrt{3.7}}} = 0.66 \\
& W_{B2} = 1 - W_{A2} = 0.34
\end{aligned}
$$

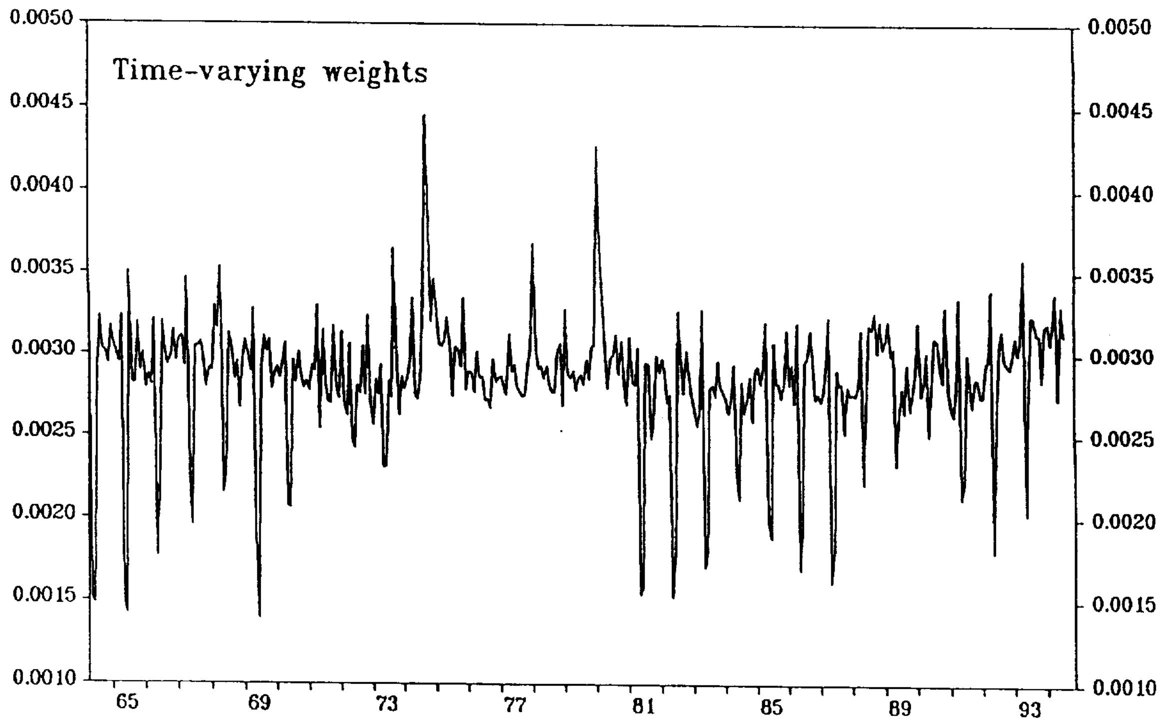
$$
\begin{aligned}
\text{Period 3:} \quad & h_{A3} = 0.1 + (0.9)(1)^2 = 1 \\
& h_{B3} = 0.1 + (0.9)(1)^2 = 1 \\
& W_{A3} = W_{B3} = 0.5 \\
& \vdots
\end{aligned}
$$

In this case, the relative weight of country A is reduced in the initial period. As the shock propagates to country B, the relative weights are reversed since the shock is interpreted as an idiosyncratic shock to country B in the second period. In the third period, weights immediately return to their pre-shock level.

Figure 1

Italy

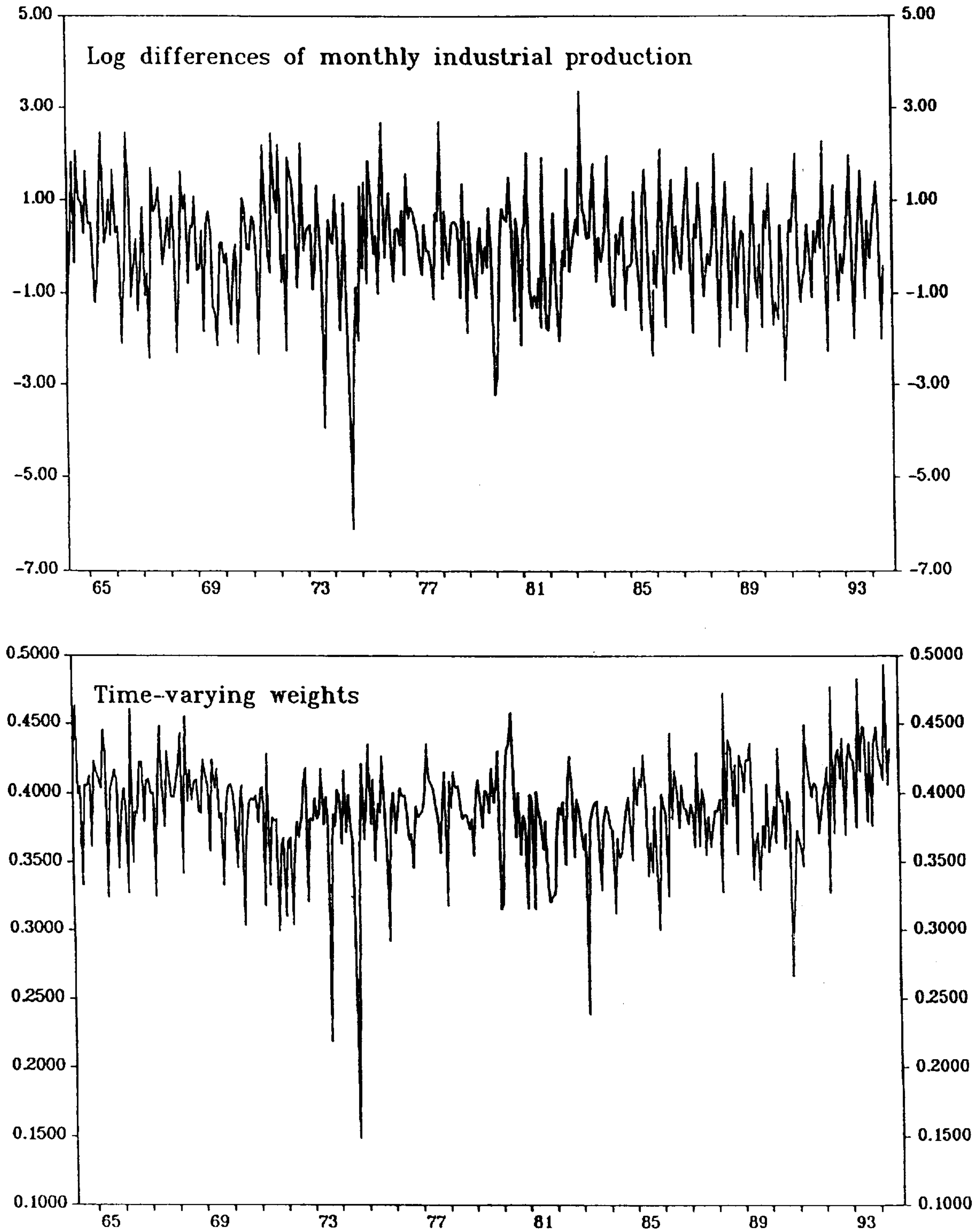




Notes: The log differences of monthly industrial production shown above are residuals from a regression on a constant and eleven seasonal dummies.

Figure 2

United States



Notes: The log differences of monthly industrial production shown above are residuals from a regression on a constant and eleven seasonal dummies.

Table 1
Descriptive statistics for industrial production growth rates

	Annualized mean growth rates (in percent)			Standard deviation		
	Full sample	BW	Post–BW	Full sample	BW	Post–BW
Austria	3.64	5.92	2.54	0.036	0.031	0.029
Belgium	2.50	4.94	1.18	0.040	0.029	0.035
Canada	3.61	6.91	1.83	0.021	0.019	0.017
Finland	4.37	6.76	3.34	0.045	0.022	0.043
France	2.72	5.69	1.09	0.041	0.037	0.029
Greece	4.91	10.09	1.65	0.044	0.030	0.039
Germany	2.37	4.93	0.90	0.038	0.032	0.036
Italy	3.14	5.99	1.67	0.091	0.039	0.059
Japan	5.44	11.47	2.47	0.022	0.016	0.021
Luxembourg	2.01	3.23	1.41	0.065	0.024	0.059
Norway	5.44	5.30	5.13	0.082	0.056	0.083
Netherlands	3.51	7.34	1.04	0.041	0.025	0.041
Portugal	4.52	5.90	3.65	0.079	0.051	0.051
Spain	4.61	10.43	1.76	0.085	0.039	0.059
Sweden	2.47	5.19	1.25	0.073	0.034	0.084
U.K.	1.84	3.17	1.08	0.034	0.026	0.036
U.S.	3.35	5.46	2.22	0.012	0.008	0.011

Notes: The descriptive statistics reported in this table are for data that were transformed into logarithms, first differenced, and then deseasonalized by regressing on a set of monthly dummies. The Bretton Woods period covers 1963:1–1973:6 and the post–BW period covers 1973:7–1994:11. The annualized mean growth rate is calculated as 100*((1+MEAN)^12) – 100, where mean is the sum of the coefficients on the deterministic seasonals in the deseasonalizing regression.

Table 2

Correlations with the common component of international ip growth fluctuations

	OECD weights	Fixed–weight measure of the common component			Time–varying weights			Time–varying measure of the common component		
		Full sample	BW	Post–BW	Mean	Min.	Max.	Full sample	BW	Post–BW
Austria	1.1	0.25	0.29	0.22	3.89	0.98	6.27	0.24	0.29	0.21
Belgium	1.1	0.08	0.07	0.08	2.25	1.00	3.32	0.18	0.31	0.12
Canada	3.1	0.28	0.25	0.29	14.71	9.04	21.77	0.62	0.65	0.61
Finland	0.5	−0.07	−0.38	0.09	3.95	0.35	12.00	0.14	0.01	0.20
France	6.6	0.00	−0.15	0.10	2.82	0.43	5.14	0.18	−0.04	0.33
Greece	0.3	0.23	0.20	0.24	3.31	0.90	5.31	0.24	0.21	0.24
Germany	10.9	0.45	0.43	0.46	3.13	0.80	4.93	0.36	0.43	0.33
Italy	7.1	0.67	0.77	0.60	0.29	0.14	0.45	0.20	0.26	0.17
Japan	19.5	0.63	0.63	0.61	14.62	2.63	27.00	0.41	0.35	0.42
Luxembourg	0.1	0.53	0.67	0.46	1.27	0.58	1.96	0.28	0.33	0.26
Norway	0.5	0.45	0.36	0.50	0.63	0.14	0.97	0.35	0.21	0.42
Netherlands	1.6	0.40	0.33	0.43	3.83	1.85	6.41	0.45	0.50	0.43
Portugal	0.7	0.57	0.61	0.54	0.39	0.09	0.60	0.22	0.29	0.18
Spain	3.3	0.69	0.77	0.64	0.31	0.19	0.47	0.26	0.14	0.27
Sweden	1.0	0.06	−0.09	0.10	0.78	0.09	1.25	0.13	0.37	0.14
U.K.	6.3	0.31	0.23	0.35	4.91	1.23	7.67	0.42	0.37	0.45
U.S.	36.2	0.35	0.19	0.43	38.92	14.84	51.99	0.63	0.45	0.71

Notes: The fixed OECD weights reported in the first column are 1990 relative industrial production weights constructed using purchasing power parity exchange rates. The fixed weights are normalized to sum to 100, as are the time–varying weights. The construction of the aggregate components using these weights is described in the text. The BW period covers 1963:1–1973:6 and the post–BW period covers 1973:7–1994:11.

Table 3

Correlations with the common component of European ip growth fluctuations

	OECD weights	Fixed−weight measure of the common component			Time−varying weights			Time−varying measure of the common component		
		Full sample	BW	Post−BW	Mean	Min.	Max.	Full sample	BW	Post−BW
Austria	2.60	0.29	0.28	0.29	12.29	3.67	17.13	0.46	0.41	0.49
Belgium	2.60	0.20	0.20	0.20	7.13	3.51	10.92	0.45	0.54	0.39
Finland	1.30	−0.03	−0.30	0.13	12.07	1.19	22.37	0.29	0.14	0.36
France	16.10	−0.09	−0.22	0.02	8.89	1.34	13.19	−0.04	−0.25	0.11
Greece	0.80	0.30	0.32	0.29	10.51	3.03	15.51	0.47	0.53	0.42
Germany	26.40	0.51	0.48	0.54	9.92	2.68	14.31	0.44	0.54	0.38
Italy	17.40	0.81	0.86	0.76	0.91	0.44	1.23	0.45	0.48	0.43
Luxembourg	0.30	0.61	0.77	0.52	4.03	1.78	5.17	0.45	0.56	0.39
Norway	1.30	0.40	0.27	0.47	2.01	0.51	3.00	0.30	0.07	0.41
Netherlands	3.90	0.45	0.38	0.50	12.06	6.55	17.05	0.67	0.70	0.65
Portugal	1.80	0.68	0.68	0.68	1.22	0.34	1.61	0.44	0.47	0.43
Spain	8.00	0.79	0.83	0.75	0.98	0.57	1.35	0.43	0.42	0.45
Sweden	2.30	0.02	−0.15	0.08	2.46	0.29	3.57	0.24	0.08	0.29
U.K.	15.30	0.19	0.16	0.21	15.52	4.52	22.58	0.25	0.21	0.27
Canada		0.21	0.26	0.16				0.32	0.48	0.20
Japan		0.38	0.43	0.35				0.21	0.14	0.22
U.S.		0.02	−0.11	0.09				0.06	−0.12	0.14
World common component		0.54	0.52	0.56				0.69	0.71	0.68

Notes: The European common component was contructed using all the countries in the sample excluding Canada Japan, and the United States. The fixed OECD weights and the time−varying weights were normalized to sum to 100 for the European countries.

Table A1
Time series properties of industrial production growth rates

Country	ADF statistics		Box–Pierce
	Levels	First dfcs.	Q–statistic
Austria	−1.99	−5.28	103.66
Belgium	−1.78	−6.08	80.51
Canada	−3.38	−3.50	85.70
Finland	−1.72	−4.63	349.29
France	−1.69	−5.34	157.99
Greece	−0.92	−6.44	42.21
Germany	−2.52	−4.04	39.38
Italy	−2.29	−5.12	404.00
Japan	−2.14	−3.76	94.73
Luxembourg	−2.48	−5.04	223.78
Norway	−2.05	−7.95	99.91
Netherlands	−2.35	−6.13	31.20
Portugal	−0.07	−6.25	286.67
Spain	−2.36	−4.73	337.59
Sweden	−2.78	−5.96	311.35
U.K.	−3.32	−5.27	60.51
U.S.	−4.97	−3.84	42.75

Notes: The regressions were run on deseasonalized log differences using data over the period 1963:1–1994:11. The ADF tests were all run with a constant, a time trend, and twelve lags of the dependent variable. The critical values for the ADF statistic are 3.41 (5 percent) and 3.12 (10 percent). The Box–Pierce Q–statistics were computed using twelve sample autocorrelations. Under the null, this statistic is distributed as chi–squared with 12 degrees of freedom. The 1 percent critical value for this statistic is 26.2.

Table A2
Cross–country correlations of fluctuations in industrial production growth rates: Full sample

	AT	BE	CA	FI	FR	GR	GE	IT	JA	LX	NO	NT	PO	SP	SW	UK	US
Austria	1.00																
Belgium	0.14	1.00															
Canada	−0.03	0.25	1.00														
Finland	0.03	0.27	0.30	1.00													
France	−0.28	0.10	0.24	0.17	1.00												
Greece	0.12	0.14	0.23	0.15	−0.13	1.00											
Germany	0.28	0.27	0.23	0.07	0.08	0.03	1.00										
Italy	0.31	0.04	0.02	−0.16	−0.32	0.33	0.12	1.00									
Japan	0.14	−0.10	0.16	0.01	0.05	0.24	0.09	0.37	1.00								
Luxemb.	0.21	0.05	0.12	−0.12	−0.20	0.23	0.14	0.68	0.28	1.00							
Norway	0.13	−0.17	0.03	−0.04	0.03	0.09	0.07	0.27	0.19	0.20	1.00						
Nethlnd.	0.32	0.23	0.26	0.15	−0.06	0.26	0.23	0.29	0.15	0.23	0.29	1.00					
Portugal	0.25	0.04	0.08	−0.13	−0.34	0.31	0.08	0.80	0.34	0.65	0.27	0.37	1.00				
Spain	0.17	−0.05	0.07	−0.16	−0.25	0.38	0.13	0.84	0.43	0.63	0.39	0.29	0.77	1.00			
Sweden	0.19	0.12	0.05	0.42	−0.04	0.10	−0.04	−0.03	0.15	−0.12	−0.01	0.16	−0.06	−0.09	1.00		
U.K.	−0.08	−0.02	0.24	−0.05	0.15	−0.00	−0.02	−0.14	0.14	0.02	0.23	0.05	−0.09	−0.02	−0.01	1.00	
U.S.	0.16	−0.06	0.33	−0.04	0.28	−0.07	0.16	−0.11	0.27	−0.04	0.33	0.11	−0.09	−0.05	−0.01	0.32	1.00