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Identifying the Common Component in International Economic Fluctuations: A New Approach

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Abstract

This paper develops an aggregation procedure using time-varying weights for constructing the common component of 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. Correlations of individual country fluctuations with the common component provide evidence of a "world business cycle" and a distinct European common component. The results suggest that macroeconomic fluctuations have become more closely linked across industrial economies in the post–Bretton Woods period.

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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 the ongoing phenomenon of "globalization" 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. More generally, the comovement of macroeconomic aggregates across different countries has become a topic of increasing interest in both academic and policy circles.

These issues have 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 synchronization of business cycles across countries also has important implications for short-run international policy coordination and for assessing the feasibility of monetary unions. Therefore, identifying and analyzing the common component of international economic fluctuations is relevant from a number of different perspectives.

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], Stock and Watson [1989, 1993], Forni and Reichlin [1996], Norrbin and Schlagenhauf [1996] and Gregory et al [1997] 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 restricting 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 a new methodology that incorporates a time-varying weighting scheme for constructing the common component.[2] 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 idiosyncrasy in the observed shocks. 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.

The objective of the methodology developed in this paper is to identify the common component rather than to distinguish among different sources of shocks (global or country-specific). Hence, the methodology is designed to implicitly capture the effects of the dynamic propagation of shocks across countries but without placing restrictions 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. However, as is the case with other techniques, the approach in this paper does not permit us to distinguish between global

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[2]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 regressions to estimate time-varying weights. Also see Diebold and Pauly [1990].

shocks and shocks that might initially appear to be country-specific but that eventually propagate to other countries through trade or other links. Since we are interested in identifying the common component of international fluctuations, irrespective of the sources of shocks to this common component, this distinction is not important for our purposes.

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.[3] 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 motivates the use of time-varying weights in constructing the common component and describes the econometric procedure for estimation of these weights. Section III 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 IV 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 V concludes.

II. AGGREGATION USING TIME-VARYING WEIGHTS

This section first sketches a time series model that clarifies the identification issues involved in measuring the common component of fluctuations across countries. The methodology introduced here is more broadly applicable to situations where construction of an aggregate from a collection of individual time-series is desirable, but we will focus on the details in the context of fluctuations in growth. Evidence is then presented 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.

Our choice of aggregation methodology is motivated by three considerations. First, an ideal weighting scheme should be capable of distinguishing between country-specific and

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[3]See, e.g., Beaulieu and Miron [1992], Beaulieu, Mackie-Mason, and Miron [1992], Canova and Ghysels [1994], Cecchetti and Kashyap [1996], and Cecchetti, Kashyap, and Wilcox [1997].

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.

Second, another important consideration in estimating the common component of international fluctuations is to allow for the propagation of shocks across countries. Error component models 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.[4]

Third, monthly industrial production data typically display a high degree of seasonality, an aspect that could potentially complicate econometric work. 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. In a similar vein, Cecchetti and Kashyap [1996] and Cecchetti, Kashyap, and Wilcox [1997] have documented that, in the OECD economies, patterns of seasonal fluctuations in industrial production vary with the state of the business cycle. 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.

The above discussion suggests a role for time-varying weights in the construction of a common component. In what follows, we propose a methodology for constructing these time-varying weights.

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

A. A Basic Model

Consider the following time-series representation for output growth:

$$y_{it} = \mu_i + \beta(L)e_{it} + \sum_{j \neq i} \gamma_j(L)e_{jt} + \eta(L)e_t \qquad (1)$$

where y_{it} indicates the growth rate of industrial production in country i at time t, μ_i is a country specific mean, e_{it} represents a country-specific shock to country i, e_{jt} represents a country-specific shock to country j, and e_t is a global shock. The lag polynomials β, γ_j, and η capture the propagation, within each country, of the different types of shocks. Distinguishing between these shocks in a reduced-form framework is clearly a difficult task, especially if β, γ_j, and η differ across countries.

Error component models typically impose an assumption of orthogonality between country-specific shocks and global shocks while dynamic factor models make a similar assumption but also allow for dynamic effects of these shocks. In either case, e_{jt} and e_t cannot be identified separately except under very restrictive assumptions about the propagation structure. Further, there is no reason to believe that the lag polynomials governing the propagation of shocks are the same across all countries or that these are constant over time.

We take a different approach since our aim is not to identify the shocks themselves but to construct a measure of the common component that could include global shocks as well as country-specific shocks that eventually propagate to all, or a subset of, other countries. The approach, described in greater detail in subsection C below, involves the construction of a weighted average measure of high frequency output fluctuations in each country, where the weights are allowed to vary over time. To do this, we first measure the conditional volatility of output growth for each country. Second, we interpret a single country's specific increase in conditional volatility as arising from a country-specific shock and, consequently, reduce the weight attributed to such a fluctuation when computing the common component. Thus, the methodology in this paper does not require strong assumptions about the correlation structure across different types of shocks or about the propagation mechanisms for different shocks.

One issue that arises here is whether taking an average is in fact an appropriate approach for constructing the common component. We discuss the intuition here and provide a more formal illustrative example in Technical Appendix A. Consider the case where both e_{it} and e_{jt} have zero mean and are drawn from distributions with similar second moments but are serially and mutually uncorrelated for all i, j. Also assume, for the moment, that the lag polynomials in equation (1) are all equal to unity. In this case, it is fairly easy to see that a simple average would in fact yield the common component e_t, if the sample contained a sufficiently large number of countries, so that the sum of e_{it} and e_{jt} over all these countries was equal to their respective unconditional means of zero.

If each country's shocks had different variances or were correlated, a simple average weighting scheme would not necessarily be optimal. The optimal weights would then be inversely related to the unconditional volatility of these shocks. The intuition behind this is similar to why, in a regression, GLS is efficient relative to OLS when the errors are heteroskedastic. Similarly, if the coefficients in the lag polynomial η were not equal to unity then a simple average of the y_{it} would not yield e_t, while a weighted average of y_{it}, where the weights were inversely related to these coefficients, would.

In economic terms, it is plausible that country-specific shocks hitting larger countries are more likely to be eventually propagated to smaller countries than vice versa. Similarly, global shocks would tend to have a larger impact on smaller economies, especially since smaller industrial economies are generally more open to international trade than larger industrial economies. Therefore, we would expect the coefficients β and γ_j to be inversely related to some measure of country size. In fact, as discussed below, we find a strong negative relationship between country size and the volatility of industrial production growth and exploit this empirical relationship in developing our methodology.

B. Some Stylized Facts

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).[5] This relationship is summarized in the following regression (standard errors are in parentheses):

$$std_i = 0.059 - .0014W_i \quad R^2 = 0.25$$
$$(.0064) \quad (.0006)$$

(2)

There is clearly a strong negative relationship between country size and volatility in industrial production growth rates.[6] This result is consistent with the view that larger

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

[6]Although the explanatory power of this regression is not large, it is in fact rather striking since the estimated relationship is an unconditional one that does not control for any other exogenous factors. 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). In related work, we have also 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. Head [1995] documents a similar negative relationship between country size and the variance of real GDP.

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.[7] The methodology developed in this paper is motivated by this negative cross-sectional relationship between country 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 from a regression of industrial production growth rates on a constant and twelve lags. 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 squared 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 percent critical value is 26.2.

C. The Methodology for Constructing Time-Varying Weights

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:

$$y_{it} = c_i + \varepsilon_{it}, \qquad \varepsilon_{it}\big|I_{t-1} \sim N(0, h_{it}), \tag{3a}$$

$$h_{it} = w_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1}, \tag{3b}$$

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 w_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 that never binds in the estimation. In addition, the unconditional mean and

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[7]Gerlach [1998] makes a similar observation.

variance of country i's industrial production growth rate are chosen as starting values for c_i and w_i, respectively, and the initial value of the conditional variance, h_{it}, is 1.[8]

We estimate model (3) and compute $\hat{h}_{it}$ for each series, $i = 1,\ldots,17$. Based on the stylized fact summarized in equation (2), $h_t^{-1/2}$ can then be interpreted as a time-varying measure of the contribution of the fluctuations in a particular country to fluctuations in the international common component. Alternatively, we could use factor analysis to decompose the conditional variance into the sum of a common component conditional variance and an idiosyncratic component. This approach also requires restrictive orthogonality assumptions. Instead, we use the conditional variance for a given country relative to the average across countries as a measure of the idiosyncratic variance. Based on the empirical motivation given earlier for our weighting scheme, the time-varying weights W_{it} are then related to the inverse of the estimated conditional standard deviations and are expressed as a fraction of the total weight, so that

$$W_{it} = \frac{1}{\sqrt{h_{it+1}}} \bigg/ \sum_{i=1}^{17} \frac{1}{\sqrt{h_{it+1}}} \tag{4}$$

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

$$Z_t^G = \sum_{i=1}^{17} W_{it} y_{it}. \tag{5}$$

The key assumption underlying our methodology is that the relative conditional standard deviation is a measure of the degree of commonality among fluctuations shared across countries. This differs from the assumptions underlying factor models 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 fluctuations rather than to identify a global "shock" that is orthogonal to all country-specific shocks. Technical Appendix A presents a simple and highly stylized

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[8]The above parameter restrictions are standard in the 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. None of the results reported below were sensitive to the choice of starting values.

illustrative example that provides further motivation for the methodology used here to construct time-varying weights.[9]

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 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.[10]

An illustrative numerical example of how the weights adjust to capture the propagation of shocks is presented in Technical Appendix B. 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 equation (3).

Further, since we use conditional volatilities in constructing these weights, positive and negative shocks that are specific to a particular country are treated symmetrically since both these shocks would increase country-specific conditional volatility, thereby resulting in a lower weight for that country in the construction of the common component.[11]

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[9]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.

[10]An alternative approach would be to estimate a multivariate GARCH model. To make such a model more tractable would, however, require additional assumptions on the conditional correlations of the shocks (see, e.g., Diebold and Nerlove [1989], and Bollerslev [1990]).

[11]We note that there is a literature which has explored asymmetries in business cycle variation (e.g., Hamilton [1989]; also see the discussion in Pagan [1997]). Our methodology could, in principle, be extended to allow for asymmetric effects of positive and negative shocks. However, for the purposes of identifying the common component, the interpretation of such asymmetries is much less straightforward. There is little evidence that the propagation of positive and negative shocks across countries is different or that positive and

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 fluctuations; and also (iv) captures the effects of the propagation of shocks across countries without placing restrictions on the transmission mechanism for the shocks.

III. RESULTS

The dataset used in this paper contains seasonally unadjusted monthly indices of industrial production for seventeen OECD economies over the period 1963–94. 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 regressed on 12 monthly dummy variables. Reasons for this choice of transformation, along with descriptive statistics and a discussion of other issues related to the data, are given in the Data Appendix.

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 a more detailed 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. 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

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negative common shocks have different effects. Nevertheless, this is an interesting topic that we leave for future research.

Table 1. 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
United Kingdom	6.3	0.31	0.23	0.35	4.91	1.23	7.67	0.20	0.37	0.45
Unites States	36.2	0.35	0.19	0.43	38.92	14.84	51.99	0.63	0.45	0.71

Notes: The 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.

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. For instance, 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 growth in Finland and France is negatively correlated with the benchmark in the Bretton Woods period (column 3) and is strongly 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 conclusions on bilateral correlations with U.S. industrial production growth rates, while the benchmark measure used here is more comprehensive.

One 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 even 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 1 (center panel) presents summary statistics for the estimated time-varying weights for each country. The weights are volatile and generally quite skewed. Nevertheless, 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 at first glance be 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.[12] Because of this, Italy's fluctuations are inherently more idiosyncratic. The time-varying weights model implicitly accounts for the importance of

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[12]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. Consequently, common seasonal fluctuations, if any, would be reflected in the time-varying aggregate.

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 constant over time). The other surprising case is that of Germany, which has a small weight relative to its fixed OECD weight. Note that 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.[13] 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 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.

Figure 3 shows a plot of the estimated common component.[14] The top panel of this figure shows the common component constructed as described in equation (5), while the lower panel shows a cumulated measure of this component. The lower panel provides a clear indication of how the common component reflects, for instance, the global recession in 1974-75, around the time of the first OPEC oil shock, and the recession in the early 1980s. The

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[13]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.

[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.

Figure 1. Italy
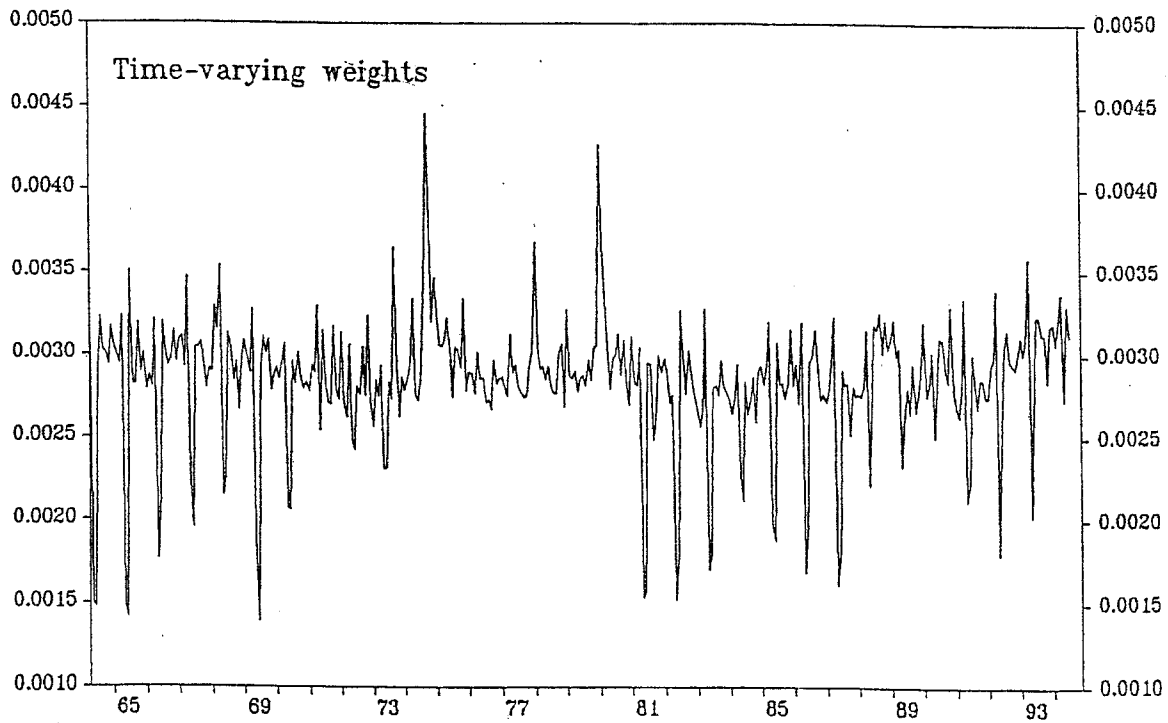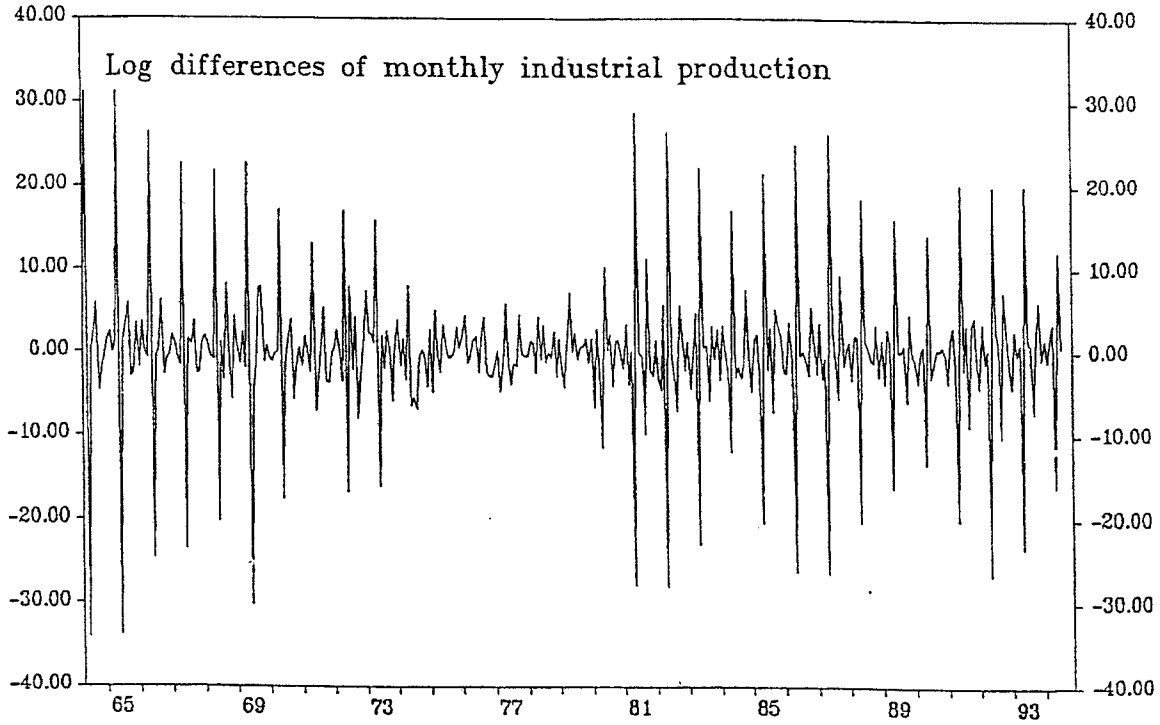
Log differences of monthly industrial production

Time-varying weights

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.

Figure 3. The estimated time-varying weight common component

Note: The cumulated common component in the lower panel includes a fixed-weight average of the unconditional mean growth rates for the countries in the sample.

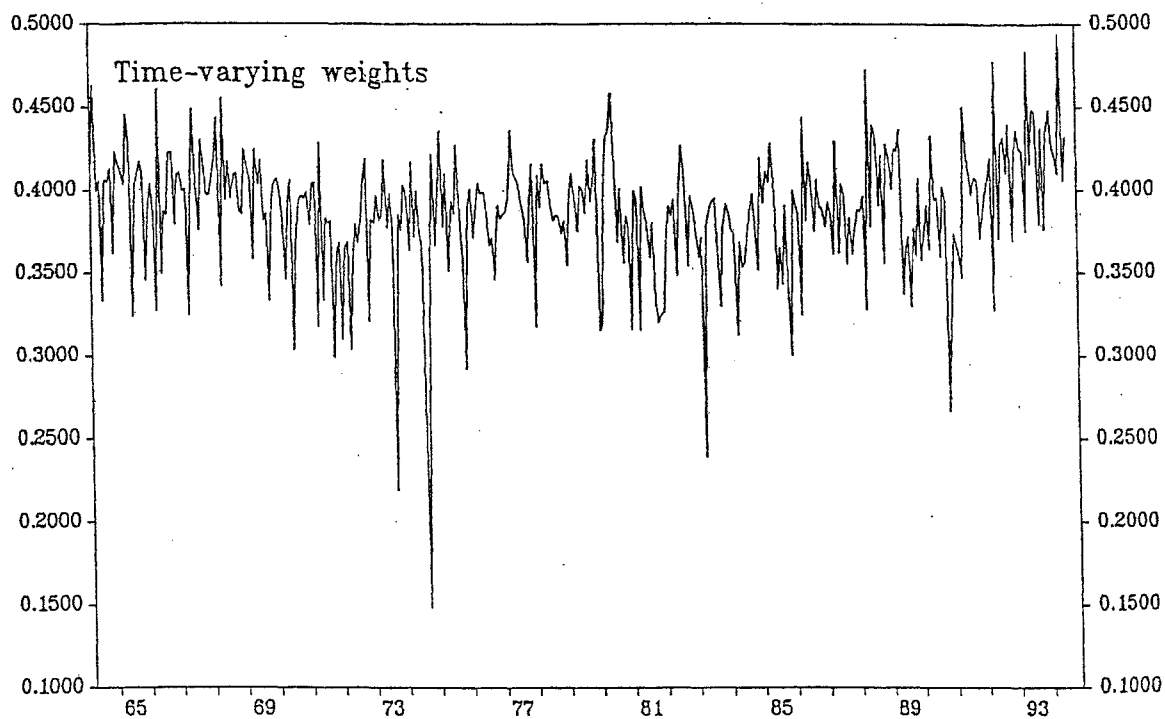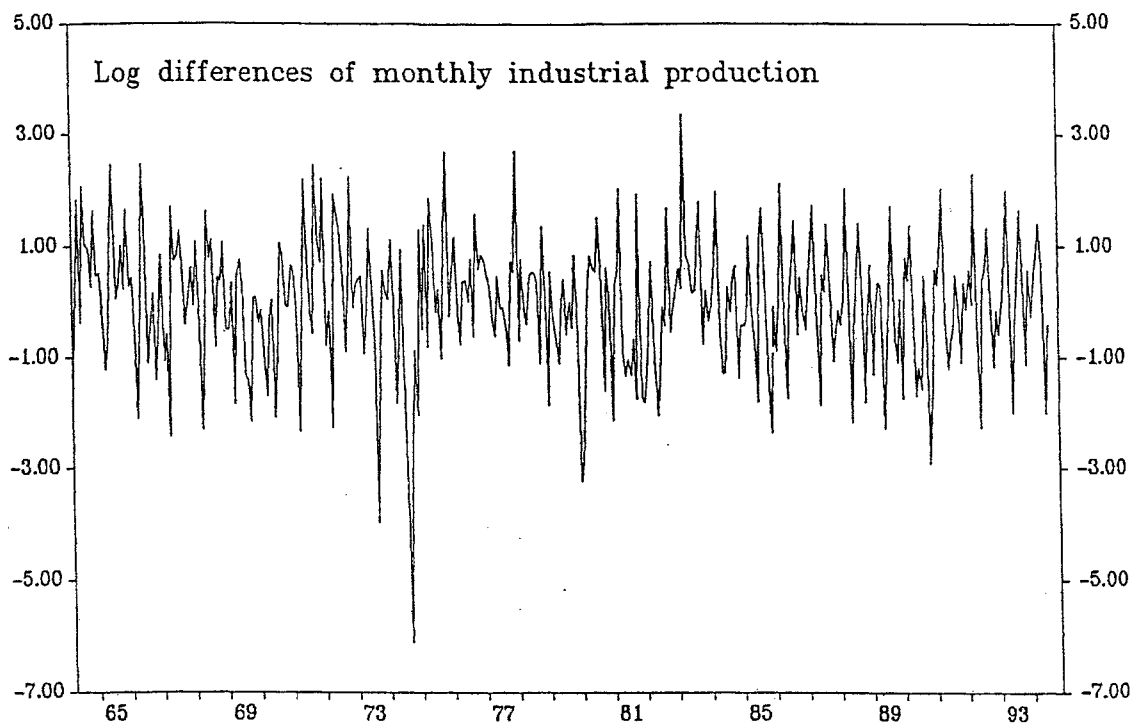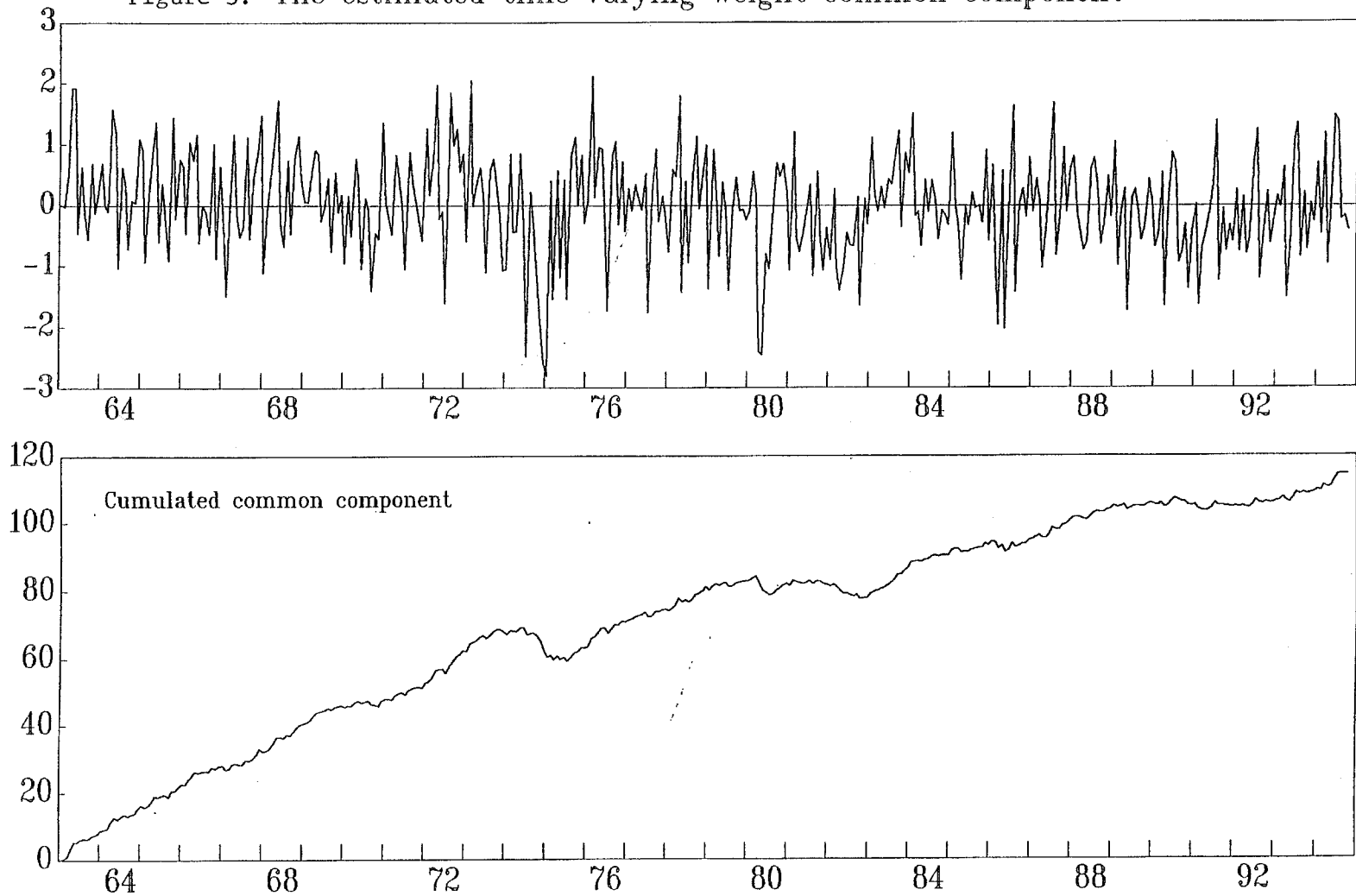effects of the post-1975 productivity slowdown are reflected in the slower trend increase in the cumulated common component after 1975. Further, there are no seasonal patterns evident in this common component, indicating the absence of common seasonal patterns in fluctuations in industrial output among the OECD economies.[15]

Correlations between the time-varying weighted aggregate series and the individual countries' industrial production growth rates are reported in the last panel of Table 1. 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 [1999]) 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 suggest that global shocks are quantitatively quite important.[16]

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[15]Regressions of the common component on seasonal dummies confirmed this visual observation. We also found no evidence of residual ARCH in the estimated common component. The Box-Pierce Q-statistic, computed using twelve autocorrelations, was 16.03, well below even the 10 percent critical value for rejecting the null hypothesis of conditional homoskedasticity of the residuals.

[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.

C. Evaluating the Time-Varying Weight Common Component

This subsection uses two standard approaches to further evaluate the features of the time-varying weight common component. First, to better understand the comovement between individual country fluctuations and the common component, we regress each country's IP growth rate on a constant and a measure of the common component. The slope coefficient from this regression can be interpreted as a country's "beta" (analogous to this concept in the finance literature) in that it measures the sensitivity of a country's IP growth to movements in the common component. The first two columns of Table 2 report the full sample results based on regressions with the fixed-weight and time-varying weight common components, respectively. Not surprisingly, in column 2, most countries (13 of 17) have betas that exceed one, confirming that the time-varying aggregate is less volatile than IP growth in individual countries. Furthermore, countries that experience large seasonal fluctuations—including Italy, Norway and Spain—have correspondingly high betas. It also appears that more of the estimated betas in column 2 are closer to unity compared to those in column 1. Standard F-tests confirmed that the null hypothesis of a slope coefficient equal to unity could not be rejected for only four countries when the fixed-weight common component is used, compared to eight when the time-varying weight common component is used. Thus, the greater degree of comovement obtained using the time-varying weights suggests that these weights provide a better measure of the common component.

Next, to characterize the dynamic relationship between the time-varying weight common component (CC) and fluctuations in individual countries, we estimate a set of simple bivariate VARs and use a standard Cholesky decomposition to orthogonalize the shocks.[17] In other words, the structural assumption underlying the VARs is that a shock to country i cannot have a contemporaneous effect on the CC, but a shock to the CC can have a contemporaneous effect on the country. Rather than reporting a plethora of results, we only summarize the main features of the results here. Detailed results are available from the authors.

We cumulated the impulse responses to measure the level responses of the CC and the individual country IP index to shocks. Interestingly, for all countries other than the U.S., the effects of shocks to individual country IP growth on the CC were relatively small and transitory. This was true even for large countries such as Germany and Japan. On the other hand, the CC has large and persistent effects on the levels of the IP indices for all countries, including Japan and the U.S., indicating the importance of the CC for domestic fluctuations in all of the industrial economies.

We also examined the forecast error variance decompositions from the VARs. Over horizons of 12 to 24 months, the contribution of individual country IP growth rates to the

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[17]Bivariate VARs were run separately for each country using a constant and twelve lags each of the respective country's ip growth rate and the time-varying weight common component.

Table 2. Regressions of Each Country's IP Growth on Common Components

	Fixed Weight Common Component	Time-Varying Weight Common Component		
	Full Sample	Full Sample	BW	Post-BW
Algeria	0.64 (0.12)	1.02 (0.21)	1.52 (0.43)	0.80 (0.24)
Belgium	0.23 (0.14)	0.90 (0.24)	1.68 (0.44)	0.54 (0.29)
Canada	0.40 (0.07)	1.54 (0.10)	1.99 (0.20)	1.33 (0.11)
Finland	-0.23 (0.17)	0.81 (0.28)	0.06 (0.50)	1.15 (0.35)
France	-0.22 (0.15)	0.86 (0.25)	-0.26 (0.56)	1.36 (0.24)
Greece	0.72 (0.15)	1.25 (0.26)	1.22 (0.48)	1.22 (0.31)
Germany	1.22 (0.12)	1.65 (0.22)	2.10 (0.38)	1.49 (0.27)
Italy	4.26 (0.24)	2.23 (0.54)	3.70 (1.17)	1.61 (0.58)
Japan	0.98 (0.06)	1.10 (0.12)	0.95 (0.22)	1.12 (0.51)
Luxembourg	2.41 (0.20)	2.17 (0.38)	2.63 (0.65)	2.06 (0.48)
Norway	2.60 (0.26)	3.43 (0.46)	1.92 (0.78)	4.30 (0.58)
Netherlands	1.14 (0.13)	2.19 (0.22)	2.27 (0.34)	2.18 (0.29)
Portugal	3.15 (0.23)	2.11 (0.47)	3.69 (1.03)	1.45 (0.49)
Spain	4.09 (0.22)	2.65 (0.49)	3.30 (1.06)	2.39 (0.54)
Sweden	0.29 (0.26)	1.18 (0.44)	0.75 (0.45)	1.38 (0.63)
United Kingdom	0.75 (0.12)	1.73 (0.19)	1.43 (0.31)	1.93 (0.24)
United States	0.30 (0.04)	0.90 (0.06)	0.66 (0.11)	1.01 (0.06)

Notes: The coefficients reported above are from regressions of each country's IP growth rate on the respective common component and a constant. Standard errors are reported in parentheses.

forecast error variance of the CC is quite small and is generally less than 10 percent, even for relatively large countries such as Germany and Japan. The maximum contribution is about 15 percent in the case of the United States. The results are quite similar at longer forecast horizons. On the other hand, the relative importance of the CC for the forecast error variance of IP growth rates over a one to two-year horizon is much larger and is in the range of 15 percent for large countries such as Germany and Japan as well as many of the smaller countries. The maximum is for the United States, at about 50 percent. Interestingly, for countries such as Italy and Spain that have large idiosyncratic seasonal fluctuations, the relative importance of domestic fluctuations for the forecast error variance of the CC is barely 5 percent, similar to that of far smaller countries. Further, the CC explains a relatively small fraction of the forecast error variance of IP growth in these economies. Thus, the time-varying weight common component that we have constructed appears to have reasonable properties.

IV. EXTENSIONS

This section extends and 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. However, with the reduced-form approach adopted here, we can document these stylized facts but cannot directly attribute changes in the patterns of these correlations to changes in exchange rate regimes or other factors.

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, particularly in the context of European Economic and Monetary Union (EMU). 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

Table A1 documents that industrial production growth has slowed in all countries during the post-Bretton Woods period.[18] Based on standard deviations of the data, however,

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[18]This decline is also related to the oil shock of the early 1970's and the subsequent productivity slowdown.

there does not seem to be a systematic commensurate change in volatility. We investigate this more thoroughly in this section. Failure to control for the mean change could result in misleading inference about the conditional variance (Lumsdaine and Ng [1999]) which, in turn, could affect the accuracy of the time-varying weights. To investigate this possibility, we estimate a modified version of equation (3):

$$y_{it} = c_i + c_{1i} \mathbf{1}(t > 1973:6) + \varepsilon_{it}, \qquad \varepsilon_{it}|I_{t-1} \sim N(0, h_{it}) \tag{6a}$$

$$h_{it} = w_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1}, \tag{6b}$$

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.[19]

The means of the associated time-varying weights estimated using this specification were similar across the Bretton Woods and post-Bretton Woods periods. The correlations of individual country industrial production growth fluctuations with the time-varying weight common component for these two periods are reported in the last two columns of Table 1. For most countries, the correlations are similar across the two subperiods. 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.

Of particular interest is the comparison of the betas (as before, these are the coefficients from regressions of individual country IP growth on the common component and a constant) between the BW and post-BW periods, as shown in the last two columns of Table 2. In the post-BW period, 13 of the 17 countries have betas that are closer to (in 12 cases) or equal (in 1 case) to unity than the betas in the earlier period. This suggests that, in the post-BW period, fluctuations in IP growth in industrial countries have been driven more by common fluctuations, as measured by the time-varying common component, and have been less subject to idiosyncratic fluctuations. This provides some evidence to support the theory that macroeconomic fluctuations have become more closely linked in the post-BW period (see, e.g., Gerlach [1988]). We do not find evidence to support the notion 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 positive correlation with the

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[19]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].

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 United States. The fixed weight component uses the same OECD 1990 weights discussed earlier while the time-varying component is constructed using equations (4) and (5); both sets of weights are normalized to sum to 100 for the European countries 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."[20] 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. 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 common component than with the 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

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[20]Artis and Zhang [1999] arrive at a similar conclusion by examining bivariate cross-country correlations of industrial production growth fluctuations and using a number of different detrending techniques.

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
United Kingdom	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
United States		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.

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.[21] The relative ranking in terms of average weights was roughly similar to that in Table 1 although there were some differences. The mean weight for the United States was higher at 53.1 percent while the weights for Canada and Japan were smaller, suggesting that the deterministic components of 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 1, indicating that part 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, the principal result about the existence of a substantial common component in international fluctuations is confirmed by these correlations.

V. CONCLUDING REMARKS

This paper has proposed a new methodology for estimating the common component of international economic fluctuations. The methodology accounts for relative country size and also captures the effects of the cross-national propagation of 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 among OECD industrial countries. The second property is that industrial production growth rates 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 relative conditional variance of industrial production growth rates for each country.

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

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 further applications include the construction of stock market indices and aggregate price indices. Another interesting extension of this approach would be to examine if there is systematic variation in the conditional volatility of output growth over different phases of the business cycle (see the discussion in Diebold and Rudebusch, 1996). This could have implications for business cycle modeling as well as forecasting. The model developed in this paper could also be extended to test for business cycle asymmetries, although, as noted earlier, we do not see compelling reasons why the weighting scheme itself should treat positive and negative shocks asymmetrically.

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. 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.

Technical Appendix A

This appendix provides a simple and highly stylized illustrative example to motivate the methodology for constructing time-varying weights. Consider the following model:

$$y_{it} = \alpha_i u_t + \varepsilon_{it}$$

where y_{it} is country i's IP growth rate, which can be decomposed into a piece based on the common component u_t and an idiosyncratic component ε_{it}. In vector form, the model is written as:

$$Y_t = \alpha U_t + \varepsilon_t$$

where Y_t, α_t and ε_t are of dimension n x 1, and U_t is of dimension 1 x 1. Also, as in a standard factor model, assume that U_t and ε_t are independent. The variance covariance matrix is given by

$$E[\varepsilon_t \varepsilon_t'] = D = [d_{ii,t}] \quad where \quad d_{ii,t} = f(y_{it-1})$$

that is, its elements are functions of lagged IP growth, which vary across equations.
Now consider the special case where α = an n x 1 vector of ones and the variance of u_t,

denoted σ_u^2, is constant. The least squares estimator of u_t is then given by $\hat{u}_t = \dfrac{1}{n}\sum_{i=1}^{n} y_{it}$.

This estimator is not optimal, however, due to the heteroskedasticity of ε_t. In this case, GLS is optimal and is equivalent to the LS estimation of $\tilde{y}_{it} = \tilde{\alpha}_i u_t + \tilde{\varepsilon}_{it}$

where $\tilde{\varepsilon}_{it}$ is spherical, $\tilde{y}_{it} = \dfrac{y_{it}}{\sqrt{d_{ii,t}}}$ and $\tilde{\alpha}_i = \dfrac{1}{\sqrt{d_{ii}}}$. Thus, $\hat{u}_t = \sum_{i=1}^{n} w_i y_{it}$, where the weights are given by

$$\frac{\tilde{\alpha}_i}{TR(D)} = \frac{\dfrac{1}{\sqrt{d_{ii,t}}}}{\sum_{i=1}^{n} \dfrac{1}{d_{ii,t}}}$$

and TR(D) is the trace of the matrix D.

Technical Appendix B

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 3 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 ½. We will examine the effects 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.

$$
\begin{aligned}
\text{Period 1:} \quad h_{A1} &= 0.1 + (0.4)(2)^2 + (0.5)(1) = 2.2 \\
h_{B1} &= 0.1 + (0.4)(1)^2 + (0.5)(1) = 1 \\[2mm]
w_{A1} &= \frac{\frac{1}{\sqrt{2.2}}}{1 + \frac{1}{\sqrt{2.2}}} = 0.4 \\[2mm]
w_{B1} &= 1 - w_{A1} = 0.6
\end{aligned}
$$

$$
\begin{aligned}
\text{Period 2:} \quad h_{A2} &= 0.1 + (0.4)(1)^2 + (0.5)(2.2) = 1.6 \\
h_{B2} &= 0.1 + (0.4)(1)^2 + (0.5)(1) = 1 \\[2mm]
w_{A2} &= \frac{\frac{1}{\sqrt{1.6}}}{1 + \frac{1}{\sqrt{1.6}}} = 0.44 \\[2mm]
w_{B2} &= 1 - w_{A2} = 0.56
\end{aligned}
$$

$$
\text{Period 3:} \quad h_{A3} = 0.1 + (0.4)(1)^2 + (0.5)(1.6) = 1.3
$$

$$h_{B3} = 0.1 + (0.4)(1)^2 + (0.5)(1) = 1$$

$$w_{A3} = \frac{\frac{1}{\sqrt{1.3}}}{1 + \frac{1}{\sqrt{1.3}}} = 0.47$$

$$w_{B3} = 1 - w_{A3} = 0.53$$

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:
$$h_{A2} = 0.1 + (0.4)(1)^2 + (0.5)(2.2) = 1.6$$
$$h_{B2} = 0.1 + (0.4)(1)^2 + (0.5)(1) = 2.2$$

$$w_{A2} = \frac{\frac{1}{\sqrt{1.6}}}{\frac{1}{\sqrt{1.6}} + \frac{1}{\sqrt{2.2}}} = 0.54$$

$$w_{B2} = 1 - w_{A2} = 0.46$$

Period 3:
$$h_{A3} = 0.1 + (0.4)(1)^2 + (0.5)(1.6) = 1.3$$
$$h_{B3} = 0.1 + (0.4)(1)^2 + (0.5)(2.2) = 1.6$$

$$w_{A3} = \frac{\frac{1}{\sqrt{1.3}}}{\frac{1}{\sqrt{1.3}} + \frac{1}{\sqrt{1.6}}} = 0.53$$

$$w_{B3} = 1 - w_{A3} = 0.47$$

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 such 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 ½. 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:

Period 1:
$$h_{A1} = 0.1 + (0.9)(2)^2 = 3.7$$
$$h_{B1} = 0.1 + (0.9)(1)^2 = 1$$

$$w_{A1} = \frac{\frac{1}{\sqrt{3.7}}}{1 + \frac{1}{\sqrt{3.7}}} = 0.34$$

$$w_{B1} = 1 - w_{A1} = 0.66$$

Period 2:
$$h_{A2} = 0.1 + (0.9)(1)^2 = 1$$
$$h_{B2} = 0.1 + (0.9)(2)^2 = 3.7$$

$$w_{A1} = \frac{1}{1 + \frac{1}{\sqrt{3.7}}} = 0.66$$

$$w_{B2} = 1 - w_{A2} = 0.34$$

Period 3:
$$h_{A3} = 0.1 + (0.9)(1)^2 = 1$$
$$h_{B3} = 0.1 + (0.9)(1)^2 = 1$$
$$w_{A3} = w_{B3} = 0.5$$

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.

Data Appendix

This appendix briefly describes the data used in the analysis, and elaborates on some of the issues discussed in Section II, including that of seasonality.

Monthly indices of industrial production (not seasonally adjusted) for 17 OECD economies over the period 1963-94 were taken from the OECD Analytical Database.[22] 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 business cycles" relative to linear detrending.[23] Table A1 provides summary statistics for the data over the full sample and also for the Bretton Woods (BW) and post-Bretton Woods periods.

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.[24]

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

[23]We tested the hypothesis that the raw 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 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 Bretton Woods (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.

[24]For the countries in our sample, regressions on seasonal dummy variables indicated that, on average, about 80 percent of the variation in log differences of unadjusted monthly industrial production could be explained by these seasonal factors. The R^2 from these regressions

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.

As mentioned in the text, we prefer to remain agnostic on the appropriate characterization of seasonal variation in the data. Hence, we deal with seasonality only to the extent that it could potentially interfere with identification. As a practical matter, we take out only the deterministic seasonal component by regressing the raw data on 12 monthly dummies and using the residuals in our empirical work. In Section IV of the paper, we test the robustness of our results to this transformation by using seasonally unadjusted data.

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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.

Table A1. Descriptive Statistics for and Time Series Properties of Industrial Production Indexes

	Annualized Mean Growth Rates (in percent)			Standard Deviation			ADF Statistics		Box-Pierce
	Full sample	Bretton Woods	Post-BW	Full sample	Bretton Woods	Post-BW	Levels	First differences	Q-statistic
Austria	3.64	5.92	2.54	0.036	0.031	0.029	-1.99	-5.08	103.66
Belgium	2.50	4.94	1.18	0.040	0.029	0.035	-1.78	-5.88	80.51
Canada	3.61	6.91	1.83	0.021	0.019	0.017	-3.38	-3.48	85.70
Finland	4.37	6.76	3.34	0.045	0.022	0.043	-1.72	-4.51	349.29
France	2.72	5.69	1.09	0.041	0.037	0.029	-1.69	-5.13	157.99
Greece	4.91	10.09	1.65	0.044	0.030	0.039	-0.92	-4.80	42.21
Germany	2.37	4.93	0.90	0.038	0.032	0.036	-2.52	-3.97	39.38
Italy	3.14	5.99	1.67	0.091	0.039	0.059	-2.29	-5.02	404.00
Japan	5.44	11.47	2.47	0.022	0.016	0.021	-2.14	-3.58	94.73
Luxembourg	2.01	3.23	1.41	0.065	0.024	0.059	-2.48	-5.05	223.78
Norway	5.44	5.30	5.13	0.082	0.056	0.083	-2.05	-7.96	99.91
Netherlands	3.51	7.34	1.04	0.041	0.025	0.041	-2.35	-5.38	31.20
Portugal	4.52	5.90	3.65	0.079	0.051	0.051	-0.07	-6.01	286.67
Spain	4.61	10.43	1.76	0.085	0.039	0.059	-2.36	-3.98	337.59
Sweden	2.47	5.19	1.25	0.073	0.034	0.084	-2.78	-5.91	311.35
United Kingdom	1.84	3.17	1.08	0.034	0.026	0.036	-3.32	-5.29	60.51
United States	3.35	5.46	2.22	0.012	0.008	0.011	-4.97	-3.83	42.75

Notes: The descriptive statistics reported in the first two panels of 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 is calculated as $100 \ast ((1+\text{MEAN})^{12}) - 100$, where MEAN is the sum of the coefficients on the deterministic seasonals in the deseasonalizing regression. The ADF regressions for the levels included a constant, a time trend, and twelve lags of the dependent variable--deseasonalized log differences of monthly industrial production. The critical values for the ADF statistic in this case are -3.41 (5 percent) and -3.12 (10 percent). The ADF regressions for the differences were similar except that no trend term was included. The 5 percent critical value for the ADF statistic in this case is -2.92. Using residuals from a regression of ip growth on a constant and 12 lags of ip growth, the Box-Pierce Q-statistics for the squared residuals 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 test statistic is 26.2.

Table A2. Cross-Country Correlations of 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								
Luxemborg	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						
Netherlands	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		
United Kingdo	-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	
United States	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

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